Automation in Construction 180 (2025) 106574

Contents lists available at ScienceDirect

Automation in Construction

journal homepage: www.elsevier.com/locate/autcon

Integrating ontology and computer vision for intelligent monitoring of unsafe conditions in hot work

Zhengwen Zhou [a], Shan Chen [a], Junhui Kou [a], Siqi Chen [b], Jiaxin Liu [a], Liangjie Guo [a,*]

[a] *Faculty of Engineering, China University of Geosciences, Wuhan 430074, China*
[b] *Automotive Engineering Institute, BYD Auto Industry Co., Ltd, Shenzhen 518100, China*

ARTICLE INFO

Keywords:
Ontology
Computer vision
Hot work
OCR
Unsafe conditions monitoring

ABSTRACT

Special operations are a significant source of accidents in the construction industry, making intelligent monitoring crucial for safety management in the context of Industry 4.0. This paper focuses on hot work and proposes an integrated risk management framework that combines computer vision (CV), optical character recognition (OCR), and ontology to monitor unsafe conditions of workers and provide emergency measures. The ontology knowledge base and rule set are developed from existing regulations and accident analyses, providing a structured foundation for risk assessment. To address challenges such as variable lighting and small object detection in hot work scenarios, the proposed ATFL-YOLO model achieves a recognition accuracy of 97.7 %. In addition, PaddleOCR is used to identify area labels, linking operational hazards with contextual text data and bridging the "logic gap" between intelligent risk assessment and emergency response. The framework can initiate emergency measures within an average of 12.3 s across diverse conditions, enhancing autonomous human–machine collaboration and delivering a reliable approach to safety management and emergency decision-making in Industry 4.0.

1. Introduction

Special operations are tasks associated with a high risk of injury or fatality, posing significant threats to operators, others, and nearby facilities [1]. Among these, hot work is the most hazardous and accident-prone, involving welding and cutting processes in production facilities, pipelines, and chemical storage tanks that generate flames, sparks, and high temperatures [2]. On construction sites, hot work is frequently performed during building activities, often on a weekly basis or even more frequently. Without adequate preventive measures, hot work can cause fires, explosions, and severe burns, accounting for 43.1 % of special operation accidents. In the United States, 60 fatal hot work accidents were reported over a 20-year period [3], while in China, more than 50 % of special operation accidents involve hot work [4]. To protect operators, numerous safety regulations and procedures have been established, for example, "hot work is allowed only in fire-safe or fire-proofed areas." [5] Nevertheless, despite these policies and protective measures, accidents caused by hot work remain a persistent issue, particularly on construction sites.

The rapid development of Industry 4.0 has introduced innovative approaches to enhance the safety supervision of hot work and other special operations [6]. In this context, the integration of advanced technologies such as 3D printing, artificial intelligence (AI), and the Internet of Things (IoT) has significantly improved production efficiency and operational performance [7]. However, this technology-driven transformation presents new challenges and opportunities in safety management. While mechanized and intelligent construction sites still rely on workers to carry out operations [8], the application of intelligent technologies can significantly improve operational safety [9]. For instance, the deployment of smart cameras, wearable devices, sensors, and robotic technologies enables real-time monitoring of workers' activities [10]. When combined with supervision by backend personnel, this enables effective human–machine collaborative management. Such collaboration allows for the implementation of effective control measures before potential risks escalate, thereby reducing the likelihood of accidents [11].

Among intelligent technologies, computer vision (CV) based on smart cameras is particularly popular in the construction industry because of its low cost and non-intrusive nature compared with invasive wearable sensor devices. The CV involves the use of cameras and computational algorithms to replace human vision in recognizing, tracking, and measuring targets. Collaboration between computer vision

* Corresponding author at: Lumo Road 388, Wuhan, Hubei 430074, China.
E-mail address: guoliangjie@cug.edu.cn (L. Guo).

https://doi.org/10.1016/j.autcon.2025.106574
Received 13 May 2025; Received in revised form 23 September 2025; Accepted 27 September 2025
Available online 4 October 2025

systems and personnel improves the detection of workers' tasks and personal protective equipment (PPE), supporting operational compliance and facilitating appropriate control measures [12]. At present, CV has been applied to ergonomic risk assessment [13], PPE detection [14], and the intelligent identification of work phases [15].

Additionally, optical character recognition (OCR), which is based on image and text analysis, has been widely applied in fields such as transportation and industrial production [16,17], demonstrating its potential for analyzing safety signs and assessing work area risks. By integrating OCR technology with CV, intelligent systems can not only perceive workers' behaviors but also identify on-site warning signs to determine whether workers are in hazardous areas. This integration enables appropriate control measures, thereby enhancing the accuracy and real-time capabilities of risk monitoring. Although CV and OCR provide a foundational perception layer for intelligent risk assessment systems, a significant "logical gap" remains in analyzing the relationships between operational behavior and objects in a scene and in performing reasoning.

Ontology modeling is essential for addressing this "logical gap," as it enables intelligent systems to evaluate the relationships between operational behaviors, environmental factors and associated risks. As a formal and standardized method for representing knowledge, ontology provides a means of structuring and organizing complex domains, thereby facilitating information sharing, reasoning, and decision-making [18]. Ontology has been widely applied in fields such as law [19], agriculture [20], medicine [21], and history [22], and it is increasingly being adopted in real-world production scenarios [23–25]. In the context of safety management, ontology offers a robust mechanism for integrating diverse data sources, interpreting situational information, and inferring potential risks in dynamic work environments [26,27]. Additionally, it serves as the foundation for risk reasoning and emergency control following computer perception. A growing number of scholars have begun constructing ontology models in the safety domain. For example, Huang et al. [28] developed an ontology model for blast furnace fault diagnosis, while Su et al. [29] created one for the manufacturing of aircraft engine casings. In construction safety, Farghaly et al. [30] applied ontology to automate production and control processes on construction sites. Goetz et al. [31] proposed an ontology for identifying sources of workplace stress, helping to improve occupational mental health. Although research increasingly focuses on the development of ontology models for workplace safety management, studies on ontology knowledge libraries for specialized operations remain limited. In particular, there is a notable gap in the construction of ontology knowledge libraries specifically related to hot work operations.

Therefore, this paper aims to propose an integrated risk management framework that combines visual monitoring with reasoning capabilities to detect unsafe conditions in special operation contexts and to implement automated emergency responses. Within this framework, ontological technology is used to establish computer-readable standards for operational processes, while CV and OCR technologies are employed to automatically execute risk perception and emergency response reasoning. Two research questions guide this study: (1) How can ontological technology be applied to establish standards for identifying unsafe conditions during operations? (2) How can CV and OCR technologies be dynamically integrated for risk perception and emergency management? In response, the objectives of this study are as follows: (1) To develop a computerized depiction of the ontological standards for assessing unsafe conditions during operations; (2) To establish an intelligent risk assessment framework that dynamically integrates CV and OCR technologies for unsafe condition evaluation; and (3) To evaluate the proposed framework to validate its effectiveness in risk perception and emergency response management.

The remainder of the paper is structured as follows: Section 2 reviews relevant literature to identify research gaps. Section 3 describes the construction of the ontology–driven risk management module, the development of the target detection module based on CV and OCR, and the proposed risk management framework. Section 4 presents the results of ontology reasoning, evaluates the effectiveness of target detection, and validates the proposed framework through assessments. Section 5 examines the results, future directions, challenges, and limitations. Finally, Section 6 concludes this paper with a summary of key findings and future directions.

2. Literature review

This review is based on literature retrieved from previous publications, and employs a two-step review methodology: literature retrieval and literature selection. This paper used two search tools, "Web of Science" and "Google Scholar," to perform a systematic search targeting "article titles, abstracts, and keywords." This search retrieved various types of publications, including journal articles, conference papers, and academic reports relevant to the field. Separate and combined searches were performed using the following keywords: "hot work," "ontology," "computer vision," "OCR," "special operations," "construction industry," "Industry 4.0," and "emergency management." This process yielded a total of 73 articles were initially considered relevant to the topic. These articles were imported into Zotero for literature selection, where titles and abstracts were screened, duplicates removed, and only English articles were retained. Articles that contained relevant keywords but were unrelated to the content were excluded. Ultimately, 29 articles were selected for full–text reading, covering the period from 2011 to 2025, to identify themes highly relevant to the paper's content. Among these, 10 articles were deemed particularly relevant and were used for comparative analysis.

Although various methods have been proposed to address the safety risk challenges of special operations, most focus on proactive measures such as the compliance with operational processes, quantitative risk assessment, and big data risk analysis. However, limited amount of paper directly addresses dynamic risk assessment and emergency response in special operations, particularly in the context of hot work. Thus, three highly relevant topics are reviewed in this section: hot work risk management, intelligent risk perception in construction operations, and ontology-based knowledge libraries for risk management, to identify and clarify the research gaps.

2.1. Hot work risk management

To further reduce hot work accidents at construction sites, researchers have proposed using data tables [3], big data analysis [32], risk assessment [33], and other methods to improve safety management. Prateepasen and Aumpiem [34] conducted interviews to investigate the risk factors of welding engineering in Thai construction projects and analyzed the risk priorities using failure mode and effects analysis (FMEA). He et al. [35] proposed a quantitative risk assessment method for hot work based on the analytic hierarchy process (AHP) and fuzzy comprehensive evaluation (FCE), and they applied it to evaluate a spring hot work case for a natural gas pipeline. Li et al. [2] employed adaptive bow-tie (ABT) and Petri nets (PNs) to conduct a comprehensive risk evolution analysis and quantitative risk assessment for hot work. The key to preventing the escalation of hot work accidents lies in timely emergency response and risk alerts. Xu et al. [36] adopted a deep learning approach to automatically classify and predict accident causes using text features and text mining. The accident causes identified in previous research include lack of continuous monitoring, failure to remove flammable and explosive materials, improper protective measures, and worker violations. While researchers have identified the main causes of hot work accidents, they also highlight concerns regarding workers' habitual violations [1]. Studies further indicate that the failure of rescue personnel to wear protective equipment contributes to casualties during hot work. Although increasing the frequency of safety training can enhance the safety awareness of workers and rescue personnel, the lack of real-time monitoring systems makes on-site violations difficult to detect. Moreover, the subjective judgment of supervisory staff responsible for hot work lacks effective decision-making support. It is therefore necessary to adopt objective methods to monitor the behavior of hot work personnel and improve the efficiency of safety management. To date, no ontology models for risk management or computer vision–based monitoring systems for hot work have been reported in the literature.

2.2. Intelligent risk perception in construction operations

With the rapid adoption of Industry 4.0 in the construction sector, scholars have begun exploring computer vision–based safety monitoring systems. These systems use CV technology for real-time monitoring of construction sites, aiming to improve safety management, reduce accident rates, and ensure worker protection. Gan et al. [37] developed a three-phase collision risk warning model for construction vehicles and workers using CV technology. The model identifies and locates vehicles and workers with YOLOv5, tracks trajectories with the DeepSort algorithm, and evaluates collision risk levels through multi-factor assessment criteria. Fang et al. [38] applied Faster R-CNN to recognize workers without safety harnesses in fall-from-height (FFH) situations and introduced an algorithm to detect FFH among construction workers, enabling automatic hazard identification and distance calculation. Vukicevic et al. [39] suggested using dynamic environment recognition and posture estimation to monitor compliance with PPE. Wang et al. [40] incorporated human risk identification into CV to enable safety monitoring. Soltani et al. [41] developed the iSAFEGuard risk detection platform, which includes 127 scenarios, and uses CV and sensor technology to detect unsafe worker behaviors. Additionally, Wang et al. [42] proposed a method for automatic hazard identification through visual–text semantic similarity using CV and dense image captioning technology. This method effectively identifies hazardous behaviors and unsafe conditions by comparing them with a textual safety knowledge base. Despite significant paper on hazard recognition using CV, new monitoring algorithms are still required to identify targets under unstable lighting and complex environmental conditions [43]. Moreover, most vision–based studies focus on risk assessment and prevention without addressing how computers can autonomously implement emergency management to mitigate risks after identifying hazards.

Additionally, the recognition warning signs using OCR can help monitoring systems identify hazardous areas and verify the presence of safety warnings. The OCR technology has been widely employed in transportation [44] and industrial production [45]. In industrial settings, OCR is used to identify printed symbols on labels [46]. However, in the construction industry, OCR has rarely been used to identify safety signs, despite its potential to help monitor personnel determine whether an area is hazardous.

2.3. Ontology-based knowledge library of risk management

Risk management is inherently cross-disciplinary and requires multiple types of information to evaluate the risk status of objects. However, the absence of explicit knowledge representation methods complicates the sharing, exchange, and retrieval of information pertinent to risk management [47]. The introduction of ontology can help computer-based risk management overcome the existing "logical gap" between risk perception and risk reasoning, thereby enabling the integration of perception and reasoning. Consequently, significant number of studies have focused on utilizing ontology modeling to improve the efficiency of the risk management process, particularly in the construction industry. Wang et al. [48] applied ontology modeling to organize job hazard analysis (JHA) knowledge and developed XML-formatted JHA documents for automatic reasoning and evaluation of applicable safety rules, allowing safety personnel to quickly adjust JHA when construction conditions change. Lu et al. [49] developed a meta-model (CSCOntology) for construction safety inspection, extracted safety constraint rules from regulations using the Semantic Web Rule Language (SWRL), and implemented safety inspections in JESS. Zhang et al. [50] formalized safety management knowledge through a construction safety ontology, enabling ontology-based JHA. Fang et al. [51] integrated CV with ontology models to identify FFH hazards under various contexts. Jiang et al. [52] introduced an ontology-based reasoning approach for safety risk cases, developed a safety risk ontology model for subway construction, and proposed corresponding risk management strategies. Park and Liu [53] developed an ontology model for fall accidents based on safety rules provided by the Occupational Safety and Health Administration (OSHA), supporting and extending the development of automated construction safety detection systems. Hong et al. [54] constructed an accident hazard ontology by analyzing accident-related textual data within a natural language framework and applied it to accident tracking and forecasting. Zeng et al. [55] developed the Construction Semantic Enrichment ontology (ConSE), which provides an integrated visual information representation for construction sites, narrowing the gap between low-level visual information and high-level semantics by introducing context-relevant image content. Bavaresco et al. [56] proposed a multi-agent framework that combines vision-based deep learning and ontology knowledge models to assess workers' health and well-being, using video stream monitoring information to understand the operational environment. Their study demonstrates that integrating intelligent monitoring with situational reasoning rules contributes to long-term support for hazard identification, evaluation, and control in the industry. Chan et al. [57] integrated multimodal visual–language models into video analysis, using a framework driven by construction safety ontology to infer unsafe behaviors that violate aerial work regulations.

Numerous ontologies in the construction domain have been proposed for intelligent safety management applications, such as safety inspection, safety design, and safety supervision. However, despite some progress in knowledge management within construction safety, few studies have emphasized on-site safety monitoring and automated emergency response. Moreover, challenges remain in specialized areas such as risk management for hot work and other specific operations. Table 1 summarizes and compares the differences between existing studies and this paper using six descriptive attributes.

2.4. Research gap

According to the above-mentioned review of existing studies, it is concluded that current hot work risk management primarily relies on static risk assessment methods and passive monitoring techniques, with clear gaps in the closed-loop management of risk perception, reasoning, and response. Compared with the current research aim, the following research gaps still exist. Firstly, there is a lack of dynamic ontology reasoning mechanisms specifically for hot work operations, as the specific risk rules of hot work have not been encoded into ontology models. Secondly, CV and OCR technologies are limited in forming closed-loop risk perception capabilities. The CV technology is often constrained to single-object detection and is not integrated with scene understanding to make judgments, while OCR technology is rarely applied in construction safety to parse safety signs and cannot dynamically update danger zones. Moreover, CV and OCR technologies are used in isolation, with no collaborative perception framework for integrating visual and textual information. Finally, the cross-technology collaboration framework for automated emergency response remains underdeveloped. Existing systems are limited to risk identification and have failed to establish decision-making mechanisms, resulting in a disconnect between ontology reasoning and the computer perception layer and creating a "logic gap" where low-level data cannot directly drive emergency response measures.

Therefore, this paper focuses on creating a risk management framework that integrates visual monitoring and reasoning to identify unsafe conditions in specialized work environments, enhance

Table 1
Summary and comparison between directly related studies.

Reference	Year	Industry	Goal	Knowledge source	Combined	Reasoning
Wang et al. [48]	2011	General	Quickly adjust the JHA plan	Process safety resources	None	No
Lu et al. [49]	2015	Construction	Automated construction safety checking	Safety regulations	None	Yes
Zhang et al. [50]	2015	Construction	Automating the JHA process.	OSHA regulation	BMI	Yes
Fang et al. [51]	2020	Construction	Hazard detection related to FFH	Regulations	CV	Yes
Jiang et al. [52]	2020	Construction	Risk assessment of subway construction	Regulations; Expert evaluation	None	Yes
Park and Liu [53]	2020	Construction	Recognizing and understanding the construction safety knowledge	Textual information	None	Yes
Hong et al. [54]	2024	Construction	Predict and understand construction accidents	Accident reports	NLP	Yes
Zeng et al. [55]	2024	Construction	Develop a semantically enhanced visual analysis system	Regulations	DL	Yes
Bavaresco et al. [56]	2024	General	Avoid excessive fatigue, injuries, and illnesses among workers	Documentation	CV	Yes
Chan et al. [57]	2025	Construction	Hazard detection related to FFH	Regulations	VLM	Yes
Current study	2025	Construction	Implementation of assessment and emergency control reasoning	Regulations; Accident reports	CV and OCR	Yes

operational management, and minimize accident risks. Firstly, using hot work scenarios as an example, an ontology knowledge library and rule base were constructed based on legal regulations and case studies. Furthermore, the ATFL-YOLO model was developed for object detection in complex environments, and PaddleOCR with the Baidu Translation API was used to recognize and translate on-site signs, enabling the ontology model to generate corresponding control measures. Finally, the effectiveness of the proposed framework was validated using images from real-world hot work scenarios, demonstrating its potential for supervision and risk mitigation. The internal components for target detection and ontology in the framework can be replaced according to actual needs and can also be applied to other types of special operations.

3. Methodology

To extract semantic information about detected objects, activities, PPE and the working environment, and to connect this information with a domain knowledge base for identifying unsafe conditions in hot work. This framework comprises two main modules:

3.1. Ontology-based risk management module

Ontology methods provide a formal approach to representing concepts and their relationships within a domain using reasoning rules [58]. When a domain can be described through classification, a hierarchical structure of classes is developed by constructing specific property connections to form an ontology [59]. In an ontology library, classes represent categories of entities that share similar characteristics, while subclasses denote more specific concepts under high-level concepts, with relationships described through object and data properties. Instances refer to concrete entities that belong to a particular class or concept. Together, these structures provide a framework for reasoning, querying, and organizing ontological knowledge in the field [60].

3.1.1. Seven-step improvement method

The currently prevalent methods for ontology construction include the Skeletal Method [56], the TOVE Method [61], and the Seven-Step Method [62], with the Seven-Step Method being the most widely used. In this paper, the Seven-Step Method was refined based on process safety principles and relevant literature [63]. A top-down approach was adopted to streamline the methodology by merging step three, “List important terms,” with “Define classes and the class hierarchy” into a single step termed “Structure definition.” Similarly, “Define class properties” and “Define properties” were combined into a new step called “Property definition.” Additionally, an “Ontology evaluation” step was introduced to assess the constructed ontology. The improved Seven-Step Method is as follows:

(1) Objective

The purpose of constructing the ontology model is to define its scope and represent risk management knowledge using standardized, structured terminology, enabling efficient storage, transmission, and reuse over the internet [64]. In addition, ontology rules are established from textual knowledge and management experience, which can be combined with computer vision and text recognition to semi-automatically input information. This integration facilitates intelligent control of operational risks, supports operators and supervisors in decision-making for imminent risks, and provides appropriate emergency control measures.

(2) Ontology reuse

For hot work, China and the United States have established numerous standards to ensure safety, such as the Occupational Safety and Health Administration (OSHA) regulations [65] and the *Special Operations Safety Regulations for Hazardous Chemicals Companies* (GB 30871–2022) [66].These standards define the safety requirements for hot work and provide a basis for constructing the knowledge base. According to GB 30871–2022 [66] and previous studies [30,37,49,50], five classes of indicators were selected as the top-level concepts for hot work risk management. The reasonableness of the constructed top-level concepts was validated using real-world hot work accident cases retrieved from the EHSPlanet website [67], as shown in Table 2.

Case 1. At 14:01 on April 17, 2023, at a certain industrial and trade company in Jinhua City, Zhejiang Province, high-temperature welding slag from illegal electric welding work on the second floor fell to the first floor, igniting combustible materials and drawing modulation paint used next to the paint spraying table, which caused a fire. This accident resulted in 11 deaths, a burned area of approximately 9000 square meters.

Case 2. At 9:47 on April 7, 2021, in a company in Dingyuan County, Chuzhou City, while workers were performing welding work on top of a slurry storage tank, a flammable and explosive gas mixture of acetylene and carbon monoxide, which had accumulated inside the tank over a

Table 2
Top-level concepts of the hot work risk ontology model.

Class	Definition	Case analysis
Work activity	Activities involved in hot work	Welding work, Cutting work
Work resource	Resources required for hot work	Slurry storage tank, Workers
Precursor	Factors that may lead to risk events when using construction resources during hot work	Combustible material, Explosive gas
Risk event	Potential risk events caused by hazardous factors	Deaths, Injuries, Economic loss
Control measure	Measures taken to prevent or control risk events	(Detection output)

long period, encountered metal sparks produced by the welding work, causing a flash explosion. This accident resulted in 6 deaths and a direct economic loss of 9.3537 million.

Case 3. At 8:45 on April 6, 2021, in a square in Guichi District, Chizhou City, during the dismantling of an escalator, high-temperature molten material produced during the gas cutting work fell to the northwest side of the escalator shaft on the negative first floor, igniting oil stains and decorative boards, which resulted in a fire. The accident caused 4 deaths and 2 injuries.

These cases highlight the key risks and hazards associated with hot work, reinforcing the need for comprehensive risk management frameworks and validating the relevance of the selected top-level concepts for risk assessment.

(3) Structure definition

This step merges "List important terms" and "Define classes and the class hierarchy" from the traditional Seven-Step Method. In ontology definition, this step is generally carried out using either a top-down or a bottom-up method. In this paper, a top-down approach was employed [68], in which top-level concepts were gradually decomposed to construct the conceptual structure of the hot work risk ontology model, as shown in Fig. 1. This simplification streamlines the original process, removes redundant definitions, and improves the efficiency of ontology model construction. The structure of the ontology model is as follows:

(a) "Work activity" is divided into two categories: "Hot work" and "Other works."

- Hot work is categorized into welding work, cutting work, and other hot work.
- Other works include sampling work and other related tasks.

(b) "Work resource" is classified three categories: "Machinery," "Personnel," and "Tools."

- Machinery mainly refers to the mechanical equipment used during hot work and the nearby mechanical equipment, such as welding machines, acetylene cylinders, etc.
- Personnel refer to management personnel and operating personnel.
- Tools refer to the implements used by operators during hot work, mainly divided into protective equipment and other tools. Protective equipment is categorized into body, ear, eye, head, and others. Other tools include safety work permits and operation permits.

(c) "Risk factors" are categorized into "Unsafe condition factors," "Unsafe behavior factors," "Unsafe environment factors," and "Unsafe management factors."

- Unsafe condition factors refer to the unsafe conditions in hot work that may lead to risk events, including lack of emergency equipment, lack of supervision, etc.
- Unsafe behavior factors refer to unsafe behaviors in hot work that may lead to risk events, including not wearing safety helmets, not wearing protective gloves, etc.
- Unsafe environment factors refer to work environments during hot work that may cause risks, including hot work in flammable and explosive areas, etc.
- Unsafe management factors refer to management practices that may cause risks, such as lack of regular risk inspections, etc.

(d) "Risk events" are categorized into three types: "Human-machine-environment damage risk," "Fire and explosion risk," and "Other risks."

- Human-machine-environment damage risks include fatalities, injuries, equipment malfunctions, and the release of harmful gases, etc.
- Fire and explosion risks encompass fires, explosions, and ignition, etc.
- Other risks refer to economic losses, etc.

(e) "Control measures" are categorized into "Pre-incident protection," "During-incident control," and "Post-incident handling."

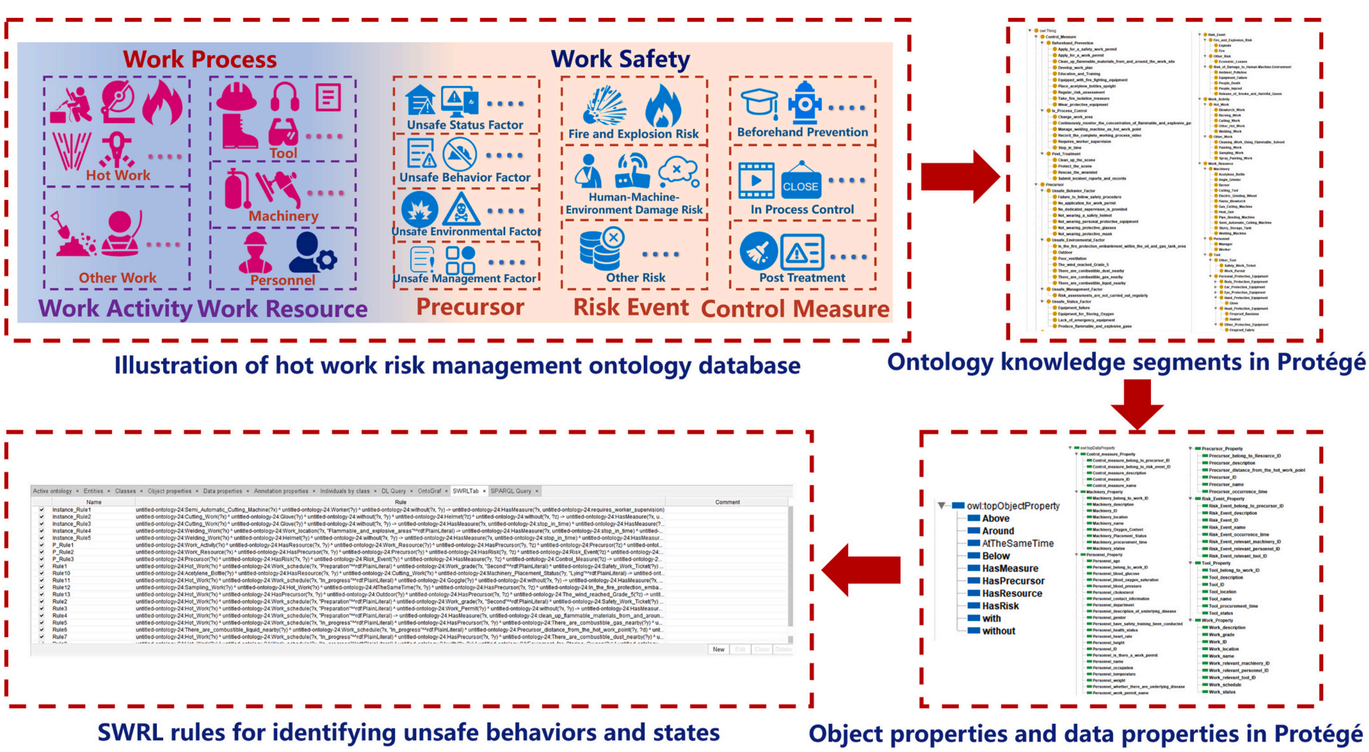

Fig. 1. Visualization of hot work risk management ontology and rule library in Protégé.

- Pre-incident protection involves education and training, obtaining work permits, equipping with firefighting equipment, and wearing protective gear, etc.
- During-incident control includes recording work videos and stopping work promptly, etc.
- Post-incident handling includes site cleanup and site protection, etc.

(4) Property definition

This step integrates “Define class properties” and “Define properties” from the traditional Seven-Step method. Defining classes alone cannot fully capture the risk conditions of hot work operations, whereas property definitions allow for describing the relationships both among classes and between classes and data [69]. By dividing properties into object properties and data properties, the process is streamlined and redundant definitions are avoided. In addition, by defining spatiotemporal relationships and related operational attributes, it becomes possible to more accurately capture the spatiotemporal characteristics of hot work scenarios, thereby offering more comprehensive information for subsequent reasoning. The property definition of the ontology model is as follows:

(a) “Object properties” describe the relationships between classes. In this paper, two types of object properties are defined: one representing the relationships between top-level concepts and the other representing spatiotemporal relationships.

- The object properties that represent relationships between top-level concepts include “HasResource,” “HasPrecursor,” “HasRisk,” and “HasMeasure.” HasResource represents the resources needed in operational activities; HasPrecursor denotes the existence of hazardous factors in resources; HasRisk refers to risk events resulting from hazardous factors; HasMeasure indicates the control measures that need to be taken for risk events.
- The object properties representing spatiotemporal relationships are divided into “Temporal relationship” and “Spatial relationship.” Temporal relationships are represented by “AtTheSameTime,” Spatial relationships are defined by “Above,” “Below,” and “Around,” which describe positional relationships such as above, below, and surrounding, and by “With” and “Without,” which denote the presence or absence.

(b) “Data properties” refer to the attributes that link classes and data. To represent spatiotemporal logic and provide specific data descriptions of instances, this paper defines seven types of data properties: operational data properties, personnel data properties, machine data properties, tool data properties, hazardous factor data properties, risk event data properties, and control measure data properties. Examples are shown in Table 3.

- Operational data properties aim to convert the basic information involved in actual hot work into a formatted computer language. It includes relevant information such as the operation name, operation number, operation description, operation progress, and location.
- Personnel data properties consist of basic data such as personnel ID, department, job ID, etc. Additionally, physiological data properties like body temperature, heart rate, etc.
- Mechanical data properties comprise mechanical number, mechanical name, etc.
- Tool data properties primarily consist of the tool name, tool description, etc.
- Hazardous factor data properties mainly include risk factor name, risk factor description, and the distance of the risk factor from the hot work point, etc.
- Risk event data properties include risk event ID, risk event name, risk event time, etc.

Table 3
Some examples of data properties.

Data properties	Data property name	Value range
Operational data properties	Work_location	xsd: string
	Work_grade	Data range expression: {Second, First, Superior}
Personnel data properties	Personnel_ID	xsd: int
	Personnel_temperature	xsd: float
	Personnel_wrok_permit_name	Data range expression: {Yes, No}
Mechanical data properties	Machinery_location	xsd: string
	Machinery_status	Data range expression: {Faulty, Normal, Warning}
Tool data properties	Tool_name	xsd: string
	Tool_status	Data range expression: {Faulty, Normal, Warning}
Risk event data properties	Risk_Event_name	xsd: string
	Risk_Event_description	xsd: string
Control measure data properties	Control_Measure_name	xsd: string
	Control_Measure_description	xsd: string

- Control measure data properties include control measure name, control measure description, and the associated risk factor ID, etc.

Using the above data properties to express hot work in detail, where “xsd” denotes XML structure definitions, including int, string, dateTime, etc. Data range expression refers to a data range expression that can customize constraint values, allowing predefined value options to standardize input for management and querying.

(5) Instance creation

After constructing the knowledge model of the hot work risk ontology and defining the classes and related properties of hot work risks, it is necessary to create relevant instances of hot work scenarios to illustrate the actual situations represented by abstract classes. This paper proposes two methods for constructing instances. The first method generates instances for work activities, work resources, risk factors, and risk events based on the outputs of computer vision detection models. The second method predefines SWRL instance rules for control measures derived from hot work standards, such as *GB30871–2022* [66] and *GB50484–2019* [70]. These methods enable the ontology to reason over heterogeneous data and provide domain-specific, customized reasoning capabilities, thereby enhancing its ability to address the demands of complex risk management in dynamic environments.

(6) Ontology evaluation

The framework proposed in this paper evaluates the constructed ontology across five dimensions, as summarized in Table 4 [71]. The ontology's top-level concepts and the hierarchical relationships between related classes were developed through literature review, case analysis, and relevant legal and regulatory standards. This framework facilitates ontology browsing, sharing, and reasoning. The SWRL rule language used is fully compatible with ontology standards and supports the addition of instances through a computer vision detection model, providing extensibility. Furthermore, the consistency of the ontology was evaluated using the Pellet reasoner, which completed the consistency check in 62 ms, meeting the required standards. By applying a structured ontology evaluation framework and conducting consistency checks, the logical consistency and stability of the constructed ontology were validated, ensuring the reliability of the model for intelligent hot work risk management.

Table 4
Description of ontology evaluation dimensions.

Evaluation dimensions	Definition
Completeness	To evaluate whether the classes, class hierarchy, and the domain and range of relationships defined in the ontology are complete.
Accuracy	To evaluate whether actual concepts can be correctly expressed.
Extensibility	To evaluate whether the ontology is conducive to adding classes and their relationships or applying it to another specific domain.
Clarity	To evaluate whether the ontology clearly and explicitly expresses the defined classes and their relationships, including the following three aspects: 1) Is there subjectivity? 2) Is natural language used for documentation? 3) Is it easy for users and computers to understand?
Consistency	To evaluate whether there are contradictory logical errors in the ontology, the Pellet reasoner can be used to infer and check for inconsistencies in the class hierarchy, domain, and range.

3.1.2. *Visualization of ontology structure based on OntoGraf*

After completing ontology construction, the ontology is stored in OWL format, which is not convenient for understanding or reading. Protégé [72] provides two tools for visualizing ontology structures: OWLViz and OntoGraf, which can display the complete view and hierarchy of the ontology knowledge library. This paper adopts OntoGraf as the visualization method [73], which not only provides detailed node information but also allows filtering to hide or show different classes and relationships.

3.1.3. *Rule base for unsafe behavior and condition identification in hot work*

The SWRL is a combination of OWL DL and OWL Lite, based on the OWL Web Ontology Language and the Rule Markup Language (Rule ML). It is designed to represent inference mechanisms for the OWL language and supports ontology rule reasoning [74]. Integrating SWRL rules into the ontology knowledge library after its construction enhances the formal representation of knowledge and improves the completeness of the ontology [56]. In this paper, SWRL rules are represented as axioms in the hot work risk ontology knowledge library to regulate and constrain class behaviors in classification and relational connections. The SWRL Tab plugin was used to edit the rules and dynamically link them with the ontology model. The rule base integrates domain knowledge with computer reasoning, providing an intelligent, inference-based solution for dynamic risk management.

(1) Construction of SWRL Property Rules

The ontology library for hot work risks is structured using logic-based descriptions and organized through class-to-class structural relationships. Top-level concepts are connected through object properties, such as linking activities to resources via the "HasResource" property and associating risk events with control measures via the "HasMeasure" property. The detailed attribute rules are shown in Fig. 2, where solid lines represent prerequisites and dashed lines represent inference results.

P_Rule 1: If *x*∈Work_Activity, *y*∈Work_Resource, *z*∈Precursor, *a*∈Risk_Event, *b*∈Control_Measure; And *x* (HasMeasure) *y*, *y* (HasPrecursor) *z*, *z* (HasRisk) *a*, *a* (HasMeasure) *b*; Then *x* (HasPrecursor) *z*, *x* (HasRisk) *a*, *x*(HasMeasure) *b*.

The SWRL rule is expressed as: Work_Activity(*?x*)^HasResource (*?x*,*?y*)^Work_Resource(*?y*) ^HasPrecursor(*?y*,*?z*)^Precursor(*?z*)^HasRisk(*?z*,*?a*)^Risk_Event(*?a*)^HasMeasure(*?a*,*?b*)^ Control_Measure(*?b*)–⟩HasPrecursor (*?x*,*?z*)^HasRisk(*?x*,*?a*)^HasMeasure(*?x*,*?b*).

P_Rule 2: If *x*∈Work_Resource, *y*∈Precursor, *z*∈Risk_Event, *a*∈Control_Measure; And *x* (HasPrecursor) *y*, *y* (HasRisk) *z*, *z* (HasMeasure) *a*; Then *x* (HasRisk) *z*, *x* (HasMeasure) *a*.

The SWRL rule is expressed as: Work_Resource(*?x*)^HasPrecursor(*?x*,*?y*)^Precursor(*?y*)^ HasRisk(*?y*,*?z*)^Risk_Event(*?z*)^HasMeasure(*?z*,*?a*) ^Control_Measure(*?a*)–⟩HasRisk(*?x*,*?z*)^ HasMeasure(*?x*,*?a*).

P_Rule 3: If *x*∈Precursor, *y*∈Risk_Event, *z*∈Control_Measure; And *x* (HasRisk) *y*, *y* (HasMeasure) *z*; Then *x* (HasMeasure) *a*.

The SWRL rule is expressed as: Precursor(*?x*)^HasRisk(*?x*,*?y*)^Risk_Event(*?y*)^ HasMeasure(*?y*,*?z*)^Control_Measure (*?z*)–⟩HasMeasure(*?x*,*?z*).

(2) Construction of SWRL instance rules

Instance rules are an important component of the SWRL, facilitating risk and control measure reasoning through instance inputs from computer vision–based object detection [55]. Typical methods for risk assessment in operations include both qualitative and quantitative evaluations. Furthermore, the operational processes incorporate procedural qualitative requirements, such as safety-related procedures and behavioral protocols, which are essential for ensuring operational safety. Accordingly, this paper categorizes instance rules into procedural, quantitative assessment, and qualitative assessment types.

(a) Procedural instance rules

In the actual process of hot work, although documents and procedures for safety inspections exist, many workers still rely on subjective experience to carry out operations. This paper builds SWRL process instance rules according to *GB30871–2022* [66] to enable reasoning with the Pellet reasoner. For example, the rule *"The validity period for the safety work permit applied for before secondary hot work must be within 72 hours"* can be expressed in SWRL as follows:

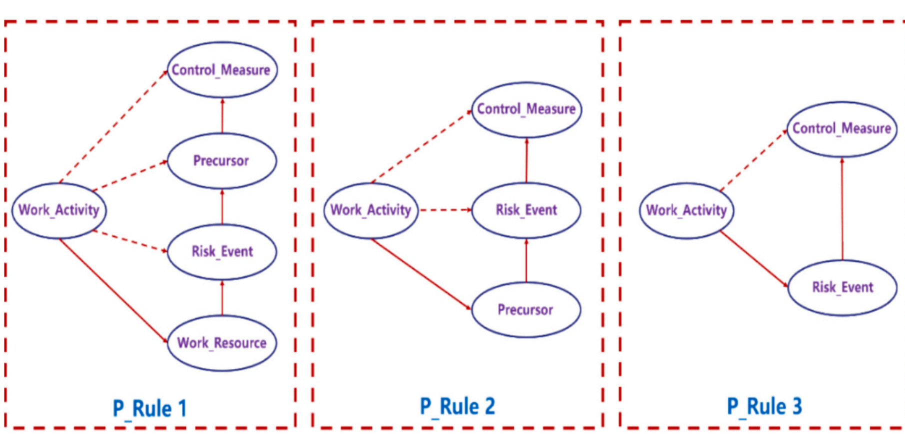

Fig. 2. Three categories of SWRL property rules in the ontology rule base of hot works.

SWRL Rule: Hot_Work(?x)^Work_schedule(?x, "Preparation") ^Work_grade(?x, "Second")^ Safety_Work_Ticket(?y)^with(?x,?)^Tool_-procurement_time(?y,?t)^swrlb: greaterThan(?t, 72)–⟩ HasMeasure(?x, apply_for_a_safety_work_permit).

(b) Qualitative assessment instance rules

Qualitative determination rules describe operational behavior according to standards to identify risk events qualitatively. For example, the rule *"Welding work cannot be performed in flammable or explosive areas; otherwise, the work must be stopped, and the work area must be changed."*

SWRL Rule: Welding_Work(?x)^Work_location(?x, "Flammable_and_explosive_areas")–⟩HasMeasure(?x, stop_in_time)^HasMeasure (?x, change_work_area).

(c) Quantitative assessment instance rules

Quantitative determination rules involve assessing operational behavior using quantified descriptions from relevant standards to identify risk events. For instance, the rule *"During hot work, flammable gases should not be emitted within 20 meters of the hot work site."*

SWRL Rule: Hot_Work(?x)^Work_schedule(?x, "In_progress") ^HasPrecursor(?x,?y)^ There_are_combustible_gas_nearby(?y)^Precursor_distance_from_the_hot_work_point(?y,?d)^ swrlb: lessThan(?d, 20)–⟩HasMeasure(?x, stop_in_time).

To extract semantic information about objects, activities, and signage related to hot work and to link this information to the ontology knowledge library for hazard identification and control, the system integrates two primary modules: an object detection module and a text recognition module. The object detection module applies the ATFL-YOLO algorithm to identify relevant objects, while the text recognition module uses the OCR algorithm to extract textual information from signage.

3.2. Object detection module

This module is composed of CV and OCR technologies to detect targets in hot work sites, identify safety management elements related to the targets, such as work type, workers, PPE, and safety signs. Transform image data into textual data for integration into risk management module.

3.2.1. ATFL module and ATFL-YOLO structure

The YOLO series is one of the mainstream algorithms for object detection, with YOLOv5 and YOLOv8 widely applied across various scenarios. The latest YOLOv11 algorithm updated in 2024, uses an anchor-free, center-point-based strategy that incorporates square roots to process width and height loss, thereby improving balance across targets of different sizes [75]. However, in environments such as factory hot work, where background features are dominant and lighting conditions are complex, the disproportionate nature of the image's central region often affects the gradient update direction, leading to reduced training speed and accuracy [76]. To address these challenges, this paper adopted a recently developed feature network for single-frame infrared small target detection. By incorporating the adaptive threshold focal loss (ATFL) function [77], the method effectively decouples the target from the background. An adaptive mechanism is employed to adjust loss weights, enabling the model to focus more on difficult-to-classify samples during training. The focal loss (FL) function handle both easy and difficult-to-classify samples through a focal mechanism. Specifically, it reduces the influence of easily classified samples while increasing the focus on difficult ones. The function is defined as follows:

$$\mathscr{L}_{BCE} = -(\mathrm{y}\log(p) + (1-\mathrm{y})\log(1-p)) \tag{1}$$

$$p_t = \begin{cases} p, if\ y = 1 \\ 1-p, other \end{cases} \tag{2}$$

$$FL(p_t) = (1-p_t)^{\gamma} L_{BCE} \tag{3}$$

Where p represents the predicted probability, y represents the true label and γ represents the focusing parameter. Although the FL function can adjust the value of γ to reduce sample loss, this approach simultaneously diminishes the loss for both easily and difficult-to-classify samples, which is detrimental to identifying difficult samples. To address this issue, the threshold focal loss (TFL) function reduces the loss weight of easy samples while increasing the loss weight of difficult samples, thereby mitigating the impact of easy samples. By setting a threshold p_t, prediction probabilities exceeding 0.5 are classified as easy samples, whereas those below this threshold are considered difficult samples. Additionally, this paper also incorporates the predicted probability value of the actual target, denoted as $\widehat{p}_c$, to inform the model training process.

$$\widehat{p}_c = 0.05 \times \frac{1}{t-1} \sum_{i=0}^{t-1} \overline{p_i} + 0.95 \times p_t \tag{4}$$

Here, p_t represents the current average predicted probability value, while $\overline{p_i}$ denotes the average predicted probability value for each training iteration. According to Shannon's information theory, as the probability value of an event increases, its information content decreases; conversely, a lower probability results in greater information content. This principle underpins the development of the ATFL function. The structure of the ATFL-YOLO is illustrated in Fig. 3:

$$\mathrm{ATFL} = \begin{cases} -(\lambda - p_t)^{-\ln(p_t)} \log p_t, p_t \le 0.5 \\ -(1-p_t)^{-\ln(\widehat{p}_c)} \log p_t, p_t > 0.5 \end{cases} \tag{5}$$

The ATFL-YOLO framework enables the identification of object information within images, converting the detection outcomes into textual data that can be integrated into ontology software for further analysis.

3.2.2. OCR-based text recognition for signage at hot work sites

In the context of hot work, numerous on-site signs assist automatic supervision devices in defining the scope and area of hot work and in confirming whether employees violate safety regulations. The OCR [78] provides a robust solution for extracting textual information from signs at hot work sites, dividing the recognition process into two steps: text detection and text translation. The first step identifies, while the second converts cropped text instance images into string representations. The OCR enables the conversion of text in image data into recognizable text. It uses a custom dictionary to translate recognized text, while text not included in the dictionary is translated using the Translate API, thereby providing essential support for semantic reasoning.

3.3. Ontology-driven risk management framework with object detection integration

The proposed risk management framework is designed as an integrated system incorporating three modules: target perception, ontology reasoning, and monitoring actions to address risks associated with hot work. Fig. 4 provides an overview of the framework, illustrating how the components interact to enable intelligent risk management. The framework is organized into three main levels: the perception layer, the reasoning layer, and the action layer. Notably, the modules within each of layer can be substituted with different algorithms or ontology libraries.

3.3.1. Perception layer

The perception layer includes an image acquisition module. It also includes an object detection and text recognition module, which capture and interpret real-world data from the work environment.

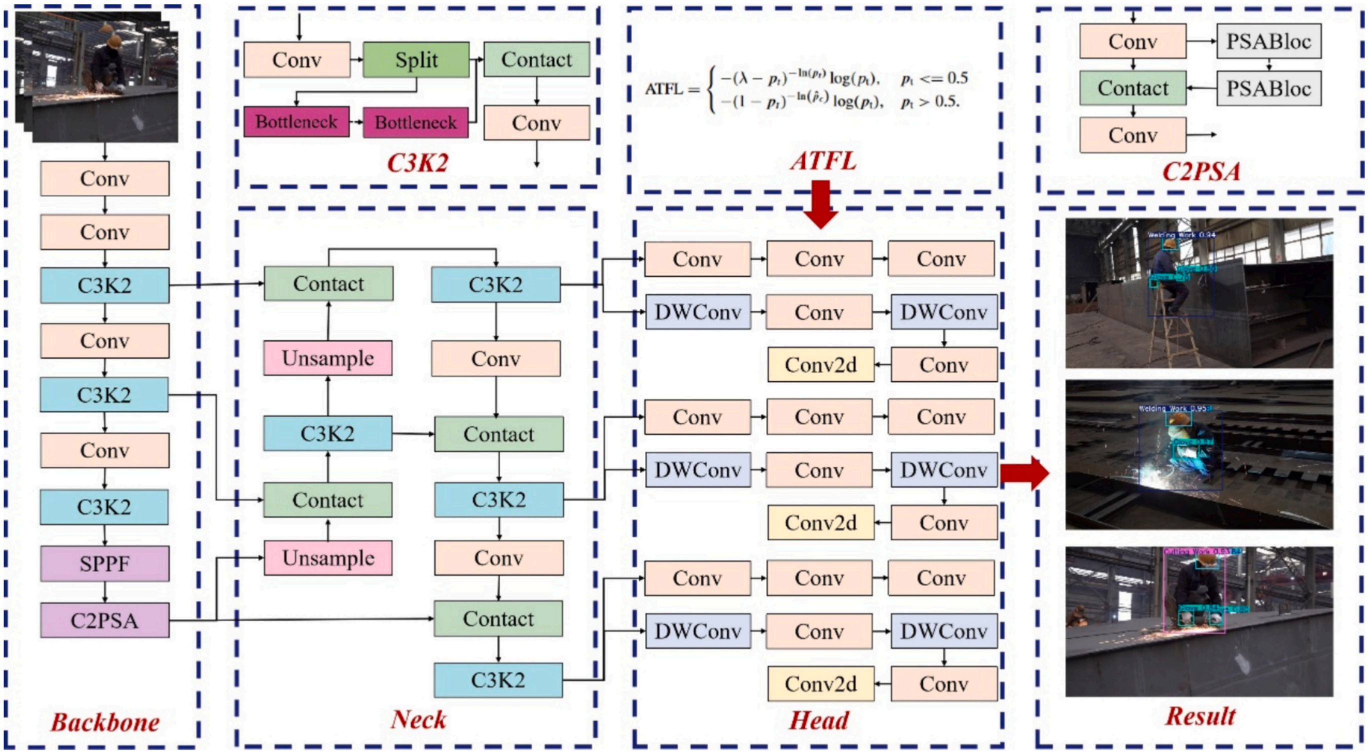

Fig. 3. ATFL-YOLO model structure diagram.

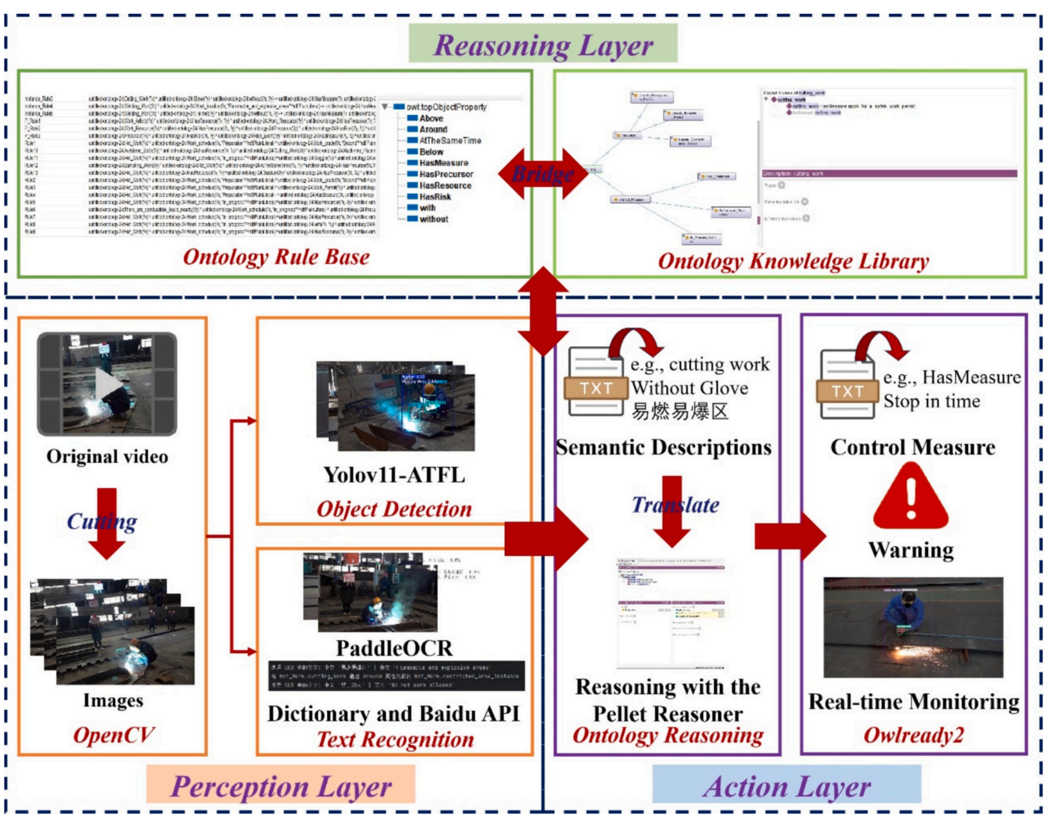

Fig. 4. Flow diagram of the proposed framework in this paper.

(1) Image acquisition module

This module captures real-time video data through cameras or supervisory robots deployed in the work environment. The video data is periodically segmented into single-frame images (e.g., one frame every 30 s) and stored in designated folders. This method ensures continuous monitoring of the work environment, optimizes data storage, and allows direct input of images or videos from external sources for testing and evaluation. The captured images are then transferred to subsequent processes for object detection and text recognition.

(2) Object detection and text recognition module

The ATFL-YOLO model is applied to detect objects in images, identifying key elements in the work environment such as workers, equipment, and PPE. Simultaneously, PaddleOCR is used for text recognition, extracting and interpreting text information from warning signs, safety instructions, or operational requirements in the environment (e.g., *"No hot work is allowed in this area"*). The algorithm outputs detected objects, their spatial locations, and relevant textual information. These outputs are linked to predefined labels in the ontology library, thereby integrating the detection results into the reasoning process.

3.3.2. Reasoning layer

The reasoning layer consists of an ontology knowledge library and an ontology rule base, which are used to store existing regulations and rule reasoning conditions. Together, they provide central support for enabling reasoning functionalities within the framework. They are developed from laws, regulations, and accident cases, defining critical concepts (e.g., workers, PPE, and operational scenarios) as well as their interrelations and attributes. Semantic annotation connects the reasoning layer with the perception layer by assigning labels to detected objects. These labels correspond to ontology concepts, enabling the integration of perception and reasoning.

3.3.3. Action layer

The action layer covers processes detected data, outputs alarm information, and applies the rule base to infer risks and suggest control measures. Information captured by the perception layer is transformed into structured text and input into the ontology model. The Pellet inference engine compares the detected data with the knowledge stored in the ontology and applies SWRL rules to identify unsafe conditions. For example, if the signs *"No hot work allowed"* and *"Flammable and explosive area"* are detected alongside hot work activities, the inference engine recognizes this as a breach of safety regulations and issues a warning. In addition, the system provides tailored control measures based on the specific violations to safety monitoring personnel, enabling supervisors to make swift and informed decisions.

4. Experiment and result

This section aims to validate the effectiveness of the proposed intelligent framework through a series of experiments that evaluate its performance in dynamic risk assessment and multimodal data integration. To this end, this paper focused on validating the ontology-based reasoning module (reasoning layer), object detection module, and text recognition module (perception layer), along with the overall reasoning performance of the framework (action layer). By leveraging collaboration among these layers, the framework can accurately identify potential safety risks in complex hot work environments and generate real-time emergency response measures.

4.1. Ontology-driven module of hot work

Based on the improved Seven-Step method, the ontology model for managing risks in hot work visualized through the OntoGraf plugin in Protege is depicted in Fig. 5.

The reliability of the Pellet reasoner was verified using defined Rule 15 as an example. Instances were created for "cutting work" and "glove", and the object property "without" was added to the "cutting work" instance with "glove" as the target object. The reasoner deduced that the "cutting work" instance lacked "glove" and determined that, according to Rule 15, the required control measures were "stop in time" and "Wear protective equipment". The reasoner's runtime was 151 ms, demonstrating good consistency and reasoning capability, as depicted in Fig. 6. This implementation shows that the module achieves automated generation from risk identification to control measures through dynamic reasoning, addressing the limitations of traditional static rule-based systems and enabling the computerized representation of unsafe states in hot work based on ontology standards.

Rule 15: *"Gloves must be worn during cutting work; otherwise, operation should be stopped and protective equipment must be donned."*

The SWRL rule is expressed as: Cutting_Work(*?x*)^Glove(*?y*)^without (*?x*,*?y*)→HasMeasure(*?x*, stop_in_time)^HasMeasure(*?x*, wear_protective_equipment).

4.2. Object detection module of hot work

This section covers the design, implementation, and evaluation of the object detection module for hot work scenarios. It describes dataset construction, model selection, performance comparison and OCR

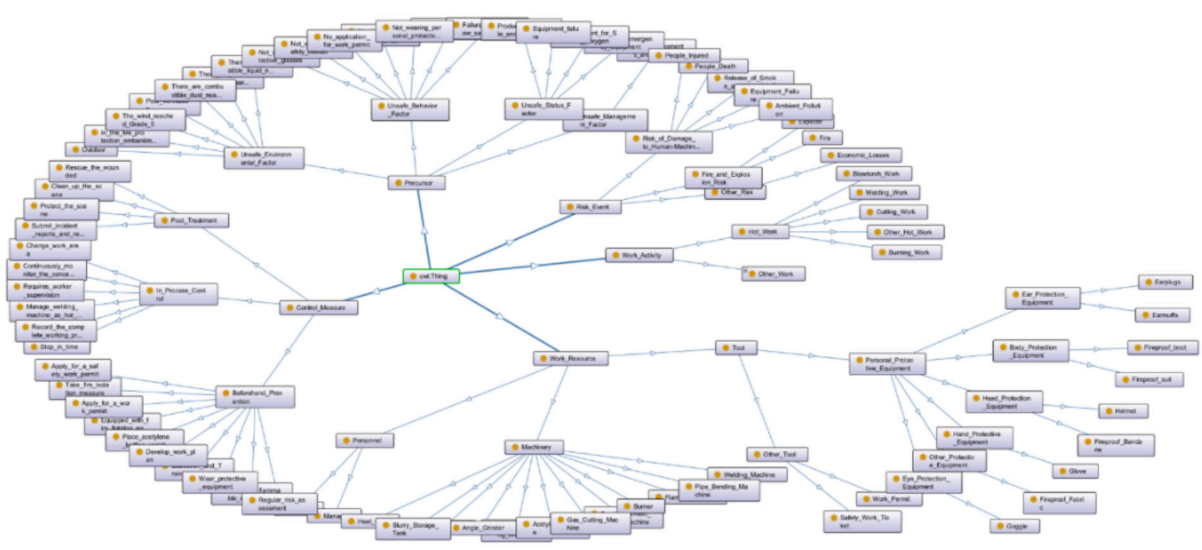

Fig. 5. Ontology-driven entity module for managing risks in hot work.

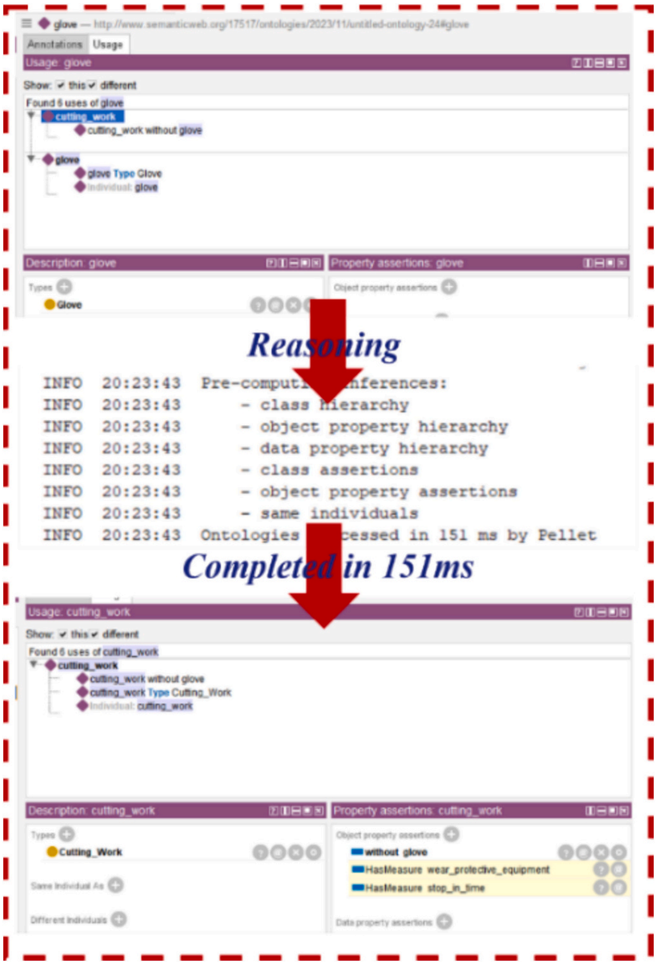

Fig. 6. Instance of cutting work inferred and evaluated using Pellet.

evaluations. The results support reliable perception and risk assessment in complex industrial environments.

4.2.1. Data collection

This paper focuses on scenarios of workers performing hot work in a construction site to explore the feasibility of the proposed visual monitoring method, as illustrated in Fig. 7. Considering the interactions between people and tools, people and machines, and people and environment in safety management, the following four hot work scenarios were captured:

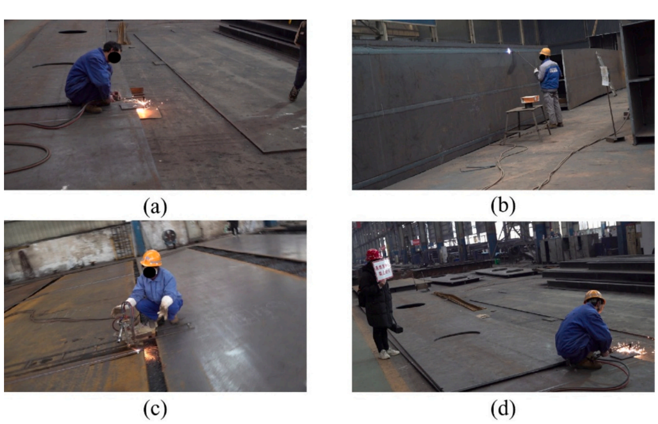

Fig. 7. Scenarios of hot work.

(a) Workers performing cutting work with and without safety helmets and protective gloves.
(b) Workers performing welding work with and without safety helmets and protective gloves.
(c) Semi-automatic cutting work with or without worker supervision.
(d) Workers conducting hot work near flammable and explosive zones or in allowable work zones.

The above scenarios involve three types of hot work: "cutting," "welding," and "semi-automatic cutting"; two types of protective equipment: "safety helmets" and "protective gloves"; two work environments: "flammable and explosive areas" and "permissible hot work areas"; and a machine: "semi-automatic cutting machine (SACM)." Items (a) and (b) represent the relationship between humans and tools in different hot work scenarios, focusing on whether workers wear helmets or gloves during operations. Item (c) reflects the relationship between humans and machines, exemplified by the presence or absence of worker supervision during operation of the semi-automatic cutting machine. Item (d) addresses the relationship between humans and the environment, examining whether workers operate in flammable or explosive areas or in designated hot work zones, as distinguished by site signage.

This paper recorded 139 video clips of different workers at various times across the eight scenarios. By using video segmentation and capturing images of actual on-site workers in the factory, the dataset was expanded to a total of 2745 images with a resolution of 1920 × 1080. These datasets were obtained through collaboration with a metal processing construction company engaged in hot work, capturing videos and photos of hot work scenes in the facility. All videos and photos in this paper were taken on-site under specialized supervision, reflecting worker's behavior during hot work, and simulated unsafe behaviors conditions based on on-site activities.

4.2.2. Data preparation

Using the LabelImg tool [79] to annotate images, a total of 2745 images and their annotation data were randomly divided into a training set, test set, and validation set in a ratio of 8:1:1. The proposed framework for monitoring unsafe conditions in hot work scenarios was trained on Windows operating system using the PyTorch framework. The software and hardware used for dataset training are detailed in Table 5.

4.2.3. Evaluation results of ATFL-YOLO

To evaluate the performance of the ATFL-YOLO and other models, overall mAP@0.5, per-class mAP@0.5, and the loss function were employed as evaluation metrics [80]. The loss function serves as an indicator of the model's fit to the data. Specifically, the training loss and validation loss are used to assess how well the model fits the training data and validation data. The mAP@0.5, mAP@0.75 and mAP@[0.5:0.95] are defined as follows:

$$AP = \int_0^{-1} P(R)dR \tag{6}$$

$$mAP = \frac{\sum_{i-1}^{N} AP_i}{N} \tag{7}$$

Table 5
Experimental environment.

Type	Name	Details
Hardware	CPU	13th Gen Intel(R) Core (TM) i9-13900F
	GPU	NVIDIA GeForce RTX 4070 with 12GB
Software	Operation	Windows 11
	Programing Language	Python 3.9.18
	Deep learning Framework	PyTorch 1.11.0
	CUDA	CUDA 12.6.65
	Protégé	Protégé 5.6.4

where mAP@0.5, mAP@0.75 and mAP@[0.5:0.95] are the Average Precision (AP) of all classes when Intersection over Union (IoU) is set to 0.5, 0.75 and [0.5:0.95], and the AP value will decrease as IoU increases.

Table 6 compares the detection results of Faster R-CNN, YOLOv5, YOLOv8, YOLOv11, and ATFL-YOLO on various detection targets. Compared with the other detection schemes, the ATFL-YOLO showed significant improvements in detecting "Glove" and "No Glove." The precision for "Glove" increased by 0.9 % relative to YOLOv11, while for "No Glove" it improved by 8.2 %. This demonstrates that the focus mechanism incorporated in the ATFL module enhances the model's ability to detect small objects. Although performance decreases slightly for some easily classifiable samples, the model prioritizes "Glove" and "No Glove" cases that other models struggle to classify under imbalanced category conditions.

Table 7 provides a comparison of the mean average precision (mAP@0.5), small object detection accuracy (mAP@0.75 and mAP@[0.5:0.95]), and training cycles for Faster R-CNN, YOLOv5, YOLOv8, YOLOv11, and ATFL-YOLO. While the YOLOv11 exhibits certain advantages in small object detection, the ATFL-YOLO model, optimized using the ATFL module, shows improvements in mAP@0.5, mAP@0.75, and mAP@[0.5:0.95]. This demonstrates that the ATFL module, with its adaptive thresholding mechanism, not only reduces training cycles but also enhances small object detection accuracy, and is better suited for hot work scenarios. Compared with the YOLOv11, the ATFL-YOLO achieved accuracy improvements of 1.1 %, 1.9 %, and 1.2 % for mAP@0.5, mAP@0.75, and mAP@[0.5:0.95], respectively, alongside a reduction in training Epochs.

To further verify the effectiveness of the ATFL loss function, we compared it with Complete IoU (CIoU) and Normalized Wasserstein Distance (NWD), two approaches that previous papers has shown to improve the accuracy of small target detection [81,82]. The comparison of loss functions and mAP@0.5 across different training models is illustrated in Figs. 8 (a) and (b). As training epochs increase, both training loss and validation loss gradually decrease and eventually stabilize. Compared with other models, the ATFL loss function exhibited faster loss reduction, achieved higher accuracy, and completed training earlier. By contrast, the CIoU and NWD loss functions performed poorly on the hot work training dataset and did not show significant improvement. These findings indicate that the proposed model demonstrate excellent fitting performance on both training and validation datasets, making it more suitable for target detection in hot work scenarios. The normalized confusion matrix of the ATFL-YOLO is presented in Fig. 8 (c).

and (c) Confusion matrix of ATFL-YOLO.

Although the overall performance improvement of ATFL appears relatively less (1.1 %), it is achieved on a strong baseline (YOLOv11) applied to a challenging dataset. More importantly, in scenarios with small targets and class imbalance, ATFL significantly improves detection accuracy for harder-to-classify objects such as "No Glove," which is critical for ensuring safety in hot work environments. This highlights its practical value in real-world applications where reducing false negatives can help prevent potential accidents. However, for the "No Glove" dataset, while detection accuracy shows considerable improvement over other models, there remains potential for further enhancement. Developing a more robust model with an expanded training dataset represents a key direction for future work. Identifying the absence of protective measures in hot work scenarios is crucial, as it forms the foundation for ontology reasoning.

Table 7
Comparison of detection performance and training processes.

Models	mAP@0.5 (%)	mAP@0.75 (%)	mAP@[0.5:0.95] (%)	Epochs at End
FasterRCNN (resnet50)	92.8 %	–	–	300
FasterRCNN (vgg)	94.9 %	–	–	300
YOLOv5	96.2 %	70.8 %	65.6 %	300
YOLOv8	96.8 %	72.0 %	66.2 %	300
YOLOv11	96.6 %	72.3 %	66.4 %	300
ATFL-YOLO	**97.7 %**	**74.2 %**	**67.6 %**	**284**

The comparison among YOLOv11, YOLOv11- CloU, YOLOv11- NWD and ATFL-YOLO on the test set reveals differences in detecting blurry targets under variable illumination and small, distant objects. The improved algorithm shows enhanced confidence levels or the same targets, detects more protective equipment in complex scenarios, and achieves better recognition of distant objects. The detection results are shown in Fig. 9.

The complex lighting conditions and small object detection requirements in hot work scenarios pose challenges for traditional object detection models. To address this issue, the improved ATFL-YOLO model is proposed, introducing an adaptive threshold mechanism and a focal loss function to enhance detection capabilities for small objects and hard-to-classify samples, while reducing training time and model size. These improvements make the model more suitable for real-time safety monitoring and applications in resource-constrained environments. As more advanced algorithms emerge, this module can be replaced within the framework. This module supports research objective (2), addressing the challenge of perception reliability in complex scenarios.

4.2.4. Evaluation results of OCR

PaddleOCR, EasyOCR and Tesseract are used to perform text recognition on safety signs in hot work scenarios, thereby assisting contextual decision-making within the overall framework. By extracting eight segments of video that included signs and workers operating under various scenes and angles, a total of 392 images were obtained. These collected images are processed using PaddleOCR, EasyOCR and Tesseract for text extraction and recognition, as shown in Table 8.

According to the comparison presented in Table 8, PaddleOCR demonstrated superior performance in recognizing fire operation scene signs. The average confidence of PaddleOCR in recognizing the *"Area Permitting Hot Work"* sign was 94.8 %, while the average confidence for the *"Flammable and Explosive Zone"* and *"No Ignition"* signs was 98.97 % and 99.13 %, respectively. The overall recognition confidence reached 97.63 %, indicating that the model can effectively extract textual information from signs at hot work sites. Therefore, this paper adopts

Table 6
mAP@0.5 of each model on the eight-class dataset.

Models	Worker	Helmet	SACM	Glove	Welding Work	Cutting Work	No Helmet	No Glove
Faster R-CNN (resnet50)	97.3 %	94.4 %	**100 %**	84.9 %	98.3 %	100 %	95.4 %	72.08 %
Faster R-CNN (vgg)	**97.6 %**	94.5 %	99.7 %	89.8 %	99.2 %	100 %	99.0 %	79.4 %
YOLOv5	94.8 %	97.5 %	99.3 %	95 %	99.4 %	99.5 %	**99.1 %**	85.1 %
YOLOv8	95.9 %	98.1 %	99.3 %	95.1 %	99.4 %	99.4 %	**99.1 %**	88.3 %
YOLOv11	96.1 %	98.3 %	99.5 %	95.3 %	99.4 %	99.5 %	99.0 %	85.5 %
ATFL-YOLO	95.7 %	**98.7 %**	99.4 %	**96.1 %**	**99.5 %**	99.5 %	99.0 %	**93.7 %**

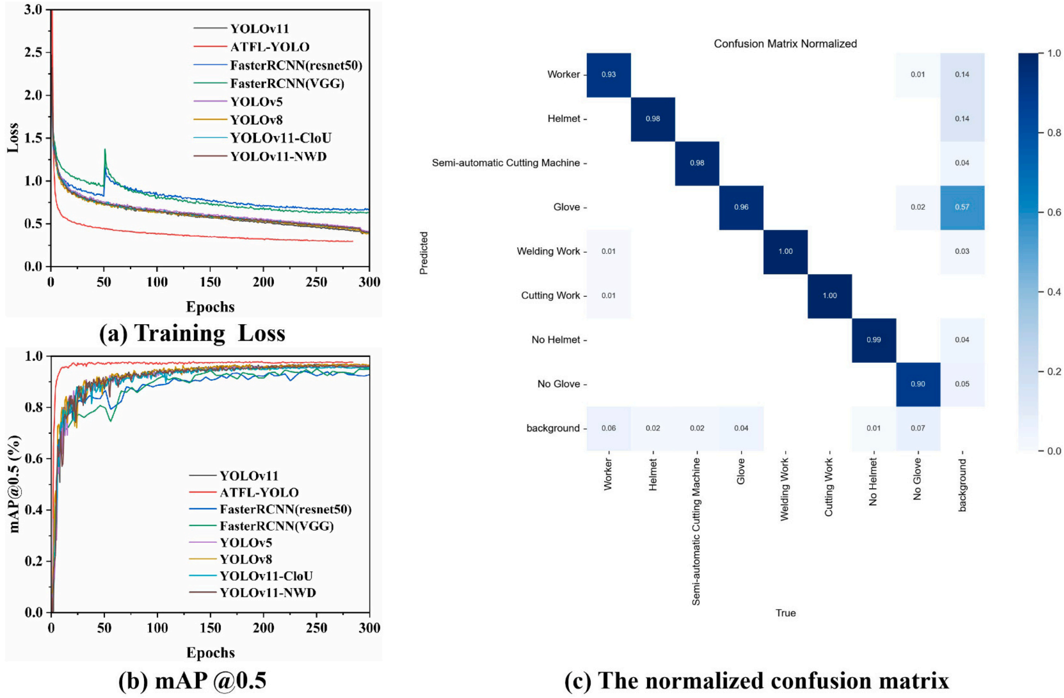

Fig. 8. Experimental results of ATFL-YOLO model performance on a customized hot work dataset: (a) Comparison of training losses. (b) mAP@0.5 among Faster R-CNN, YOLOv5, YOLOv8, YOLOv11, YOLOv11- CIoU, YOLOv11- NWD and ATFL-YOLO.

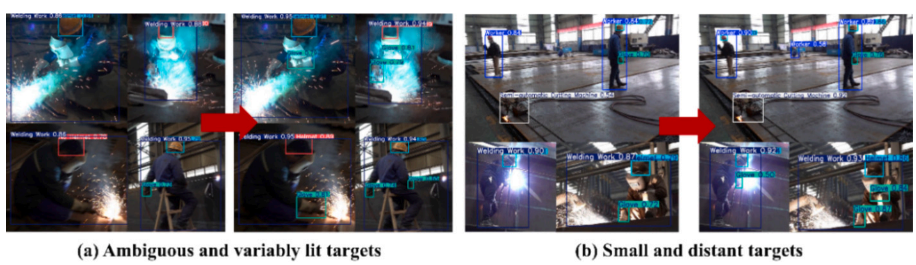

Fig. 9. Comparison of detection results of YOLOv11 and ATFL-YOLO algorithms in real hot work scenarios: (a) Ambiguous and variably lit targets. (b) Small and distant targets.

Table 8
Comparison of recognition efficiency and time between Tesseract, EasyOCR, and PaddleOCR.

Models	Confidence
Tesseract	86.42 %
EasyOCR	95.03 %
PaddleOCR	97.63 %

PaddleOCR as the text recognition tool, with the recognized text shown in Fig. 10. This module efficiently extracts on-site textual information, providing reliable support for multimodal data integration and risk assessment. It enhances the text perception aspect of research objective (2), achieving an in-depth understanding of scene semantics.

4.3. Detection performance of the intelligent monitoring framework for unsafe conditions

To improve the transparency and interpretability of reasoning results, the proposed framework incorporates a textual explanation module and a flowchart visualization module. Specifically, the framework instantiates the detection results into the ontology by visualizing the targets detected by the ATFL-YOLO and OCR. For instance, when inputs such as “No hot work allowed” and “Flammable and explosive areas” are detected, the system links the instance *hot_work_cutting_work* to *hot_work_restricted_area* through the property “Around.” According to the ontology rules: If the instance *hot_work_cutting_work* is detected to be around the instance *hot_work_restricted_area*, it is inferred that the work area needs to be changed. This rule is automatically executed by the Pellet, producing the inference result “The work area must be changed.”

The textual explanation module and the flowchart module document and present each step of the reasoning process while visually generating dynamic flowcharts to help users in tracking the reasoning process and its foundations. Fig. 11 shows a reasoning flowchart of specific cutting task, where the flowchart module is constructed using the directed graph functionality in NetworkX. Nodes represent significant input data and applied rules, while edges represent data flow and logical connections. The Matplotlib module renders the flowchart using dynamic layout algorithms and enables the expansion and visualization of nodes. Through the textual explanation module and the flowchart module, the system provides clear reasoning bases for various hot work scenarios.

The above process validates the system’s accuracy and reliability in integrating multi-source inputs (object detection and text recognition) and generating decision recommendations, while demonstrating its dynamic adaptability in work scenarios. The following will verify the performance of the framework in typical scenarios. To evaluate the

Fig. 10. Examples of text recognition output for hot work signage by PaddleOCR.

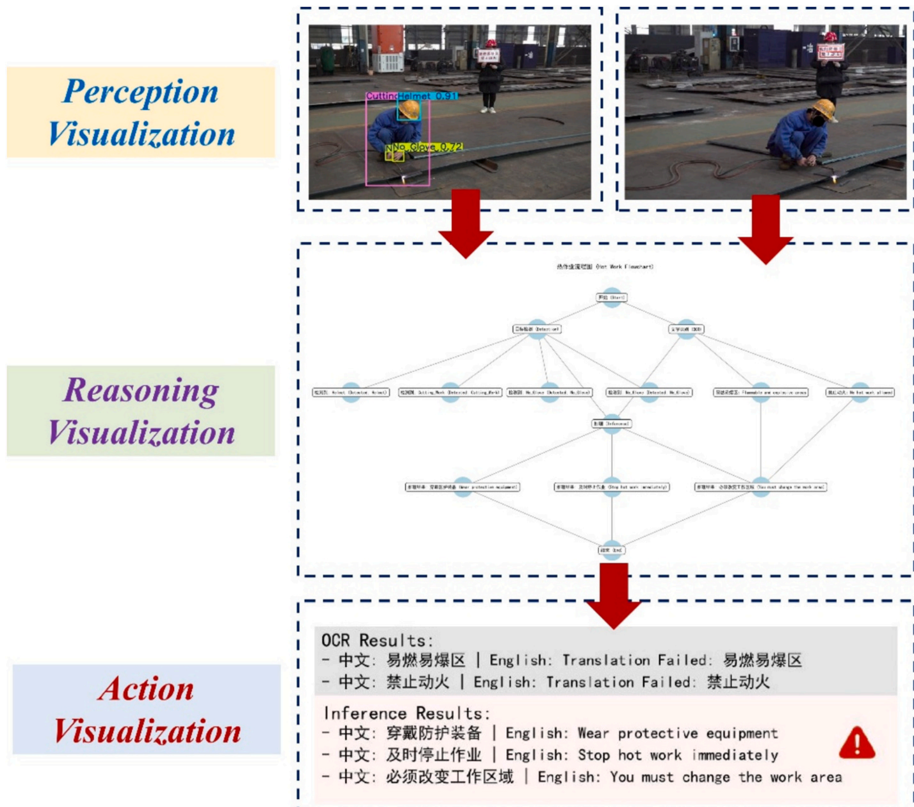

Fig. 11. Reasoning flowchart for hot work monitoring and safety assessment (Using *"Not wearing protective equipment in prohibited areas"* as an example).

overall performance of the intelligent monitoring framework, four representative hot work scenarios were designed: (a) "Normal operation", (b) "Not wearing protective equipment", (c) "Hot work in prohibited areas", (d) "Not wearing protective equipment in prohibited areas."

Fig. 12 presents the validation results. The average time for target detection and reasoning-based emergency management measures is 12.3 s. In the "Normal operation" scenario, text recognition identified the text "Movable fire zone," while target detection verified the presence of protective equipment, outputting "Safe". In the "Not wearing protective equipment" scenario, no text was recognized and only target detection results were processed by the ontology, which provided control actions for the absence of protective equipment and issued a warning icon. In the "Hot work in prohibited areas" scenario, text recognition detected "No hot work allowed" and "Flammable and explosive areas", while target detection confirmed the presence of protective equipment. The framework output control measures that the work area must be changed and issued a warning. In the "Not wearing protective equipment in prohibited areas" scenario, text recognition recognized the text "No hot work allowed" and "Flammable and explosive areas", while target detection detected the lack of protective equipment. The framework identified two issues based on target detection and text recognition, and proposed control measures while issuing warnings accordingly. The results indicate that the developed framework is accurate in the representation and recognition of hot work knowledge. It integrates and distinguishes input textual information and object detection data to generate corresponding control measures.

The framework demonstrates the effectiveness of an intelligent risk assessment system that integrates CV and OCR technologies for dynamic safety monitoring. Validation of the collaborative application framework for research objective (3) resulted in a closed-loop system for risk perception and emergency response. By perceiving risk information, the

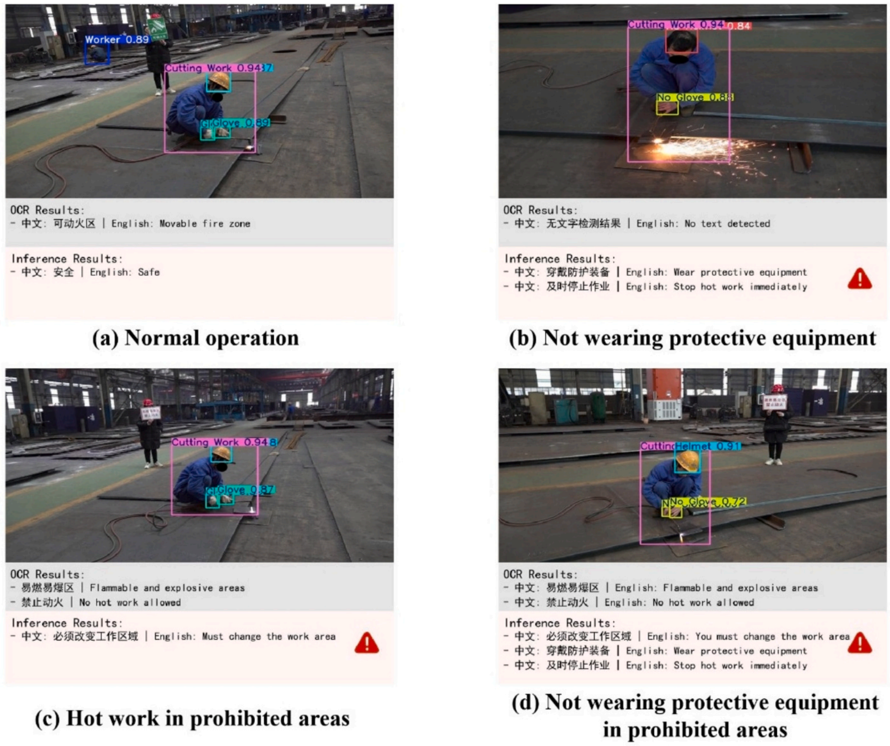

Fig. 12. Example validation of the hot work monitoring.

system generates corresponding emergency management solutions, providing a reliable approach to intelligent risk management in the context of Industry 4.0.

5. Discussion

Intelligent monitoring of unsafe conditions based on computer systems has been continuously evolving. In order to accelerate this evolution, this section discusses the challenges and limitations of the framework based on its contributions. Furthermore, it explores how these challenges can open up new pathways for broader advancements in this domain by tapping into their full potential.

5.1. Contributions of the proposed framework

Safety in modern hazardous chemical industries and contemporary construction is not merely about identifying risks but about dynamically responding and guiding the handling of risks. While real-time monitoring of safety incidents is crucial, it represents only the surface of the solution. The real challenge lies in preventing supervisory errors, assisting supervisors in recognizing situations, and enabling them to take appropriate and timely interventions. Once a safety alarm is triggered, a one-size-fits-all approach is only a suboptimal solution, as such actions may lead to severe accidents or disrupt workflows. Ideally, an intelligent decision-making mechanism should be implemented to address specific situations. For instance, upon detecting workers without protective gear near hazardous zones, the system should not only issue warnings but also guide them with appropriate measures and, if necessary, take control of relevant administrative processes to manage emergencies. Ultimately, however, objective of intelligent systems is not complete automation but the realization of human–machine collaborative autonomy, where intelligent guidance supports supervisors and workers in executing emergency measures more efficiently.

Compared with existing approaches, this paper introduces several key innovations. First, the improved Seven-Step method simplified the ontology library construction process, and, for the first time, an ontology knowledge base and rule base related to hot work operations were established based on laws, regulations, and case studies. Case-based reasoning validation was conducted to enable the computerized representation of unsafe conditions in hot work operations through ontology technology. Second, the ATFL-YOLO detection model was developed to improve target detection capabilities in hot work scenarios. Additionally, a risk management framework integrating CV and OCR technologies was created, allowing dynamic identification of specific targets and background information for risk evaluation and emergency management, effectively bridging the "logic gap" between recognition and reasoning. Third, four scenarios involving hot work operations were validated through the proposed framework, demonstrating its reasoning effectiveness in simulated real-world environments. This framework not only enhances existing automated monitoring methods but also provides a reliable approach to safety management and emergency decision-making in the context of Industry 4.0. The main findings are presented in Table 9.

5.2. Challenges and limitations

However, certain challenges and limitations were encountered

Table 9
Main findings.

Module	Main Findings
Ontology reasoning module	An ontology knowledge base and rule base for monitoring hot work safety conditions were established using ontology, achieving the computerized representation of hot work standards.
Target detection module	Improved the object detection capability in hot work scenarios under challenging lighting conditions. Integrated ATFL-YOLO and PaddleOCR to combine visual and textual information.
Framework performance	Achieved a 12.3-s contextual emergency response linkage, demonstrating the effectiveness of multimodal data integration and ontology-driven reasoning in dynamic risk assessment.

during the research process. First, the lack of adequate attention to hot work and specialized operations in industry is a key limitation. In China's construction and chemical industries, oversight is typically limited to safety supervision and maintaining safety logs, without actual monitoring footage of hot work operations. This creates considerable challenges for data collection. Although a dataset of hot work in real scenarios was collected and corresponding hot work rules were meticulously designed, they may still deviate from actual conditions. Extreme behaviors under specific circumstances were not addressed, and the dataset primarily encompasses a limited range of hot work activities. Additionally, it lacks unique activities from diverse contexts, such as hot work in chemical plants or high-altitude tasks during power grid maintenance.

Second, the rule base is currently defined primarily from regulations and case studies, requiring manual organization. The capability to automatically extract knowledge from textual data and generate rules remains limited. In addition, the rules are simplistic and lack adaptability to dynamic situations. They rely on basic if–then logic, which is insufficient for managing complex spatiotemporal interactions or conducting risk assessments under multivariate conditions. In fast-evolving operational environments, such static rules may not adequately support flexible risk management. Nonetheless, the field of safety production requires strict compliance with laws, regulations, and industry standards, which are typically fixed and predictable.

The advent of generative artificial intelligence has introduced new opportunities. It can construct hypothetical scenarios to expand knowledge libraries and rule bases, thereby providing additional cases to enhance datasets. In addition, ontology reasoning rules remain relatively simple and are primarily based on predefined logic. Future work may focus on integrating ontology models, CV, and large language models (LLMs) such as GPT-5 and DeepSeek to move beyond basic matching and enable more nuanced compliance reasoning. However, caution must be exercised regarding the phenomenon of AI hallucination in LLMs.

Third, although the framework achieved an average inference time of 12.3 s during experimental testing, this response time remains relatively high for practical industrial scenarios. Moreover, real-world conditions such as network latency, hardware performance limitations, and operational complexities may further hinder the system's real-time performance. Therefore, research into edge optimization and lightweight solutions is required to improve response speed.

Fourth, this human–machine collaboration framework is designed to support supervisors in decision-making through intelligent systems. In practice, developing intuitive and user-friendly interfaces for human–machine interaction, as well as ensuring that supervisory personnel can quickly comprehend and adopt system suggestions, remains an area for further exploration. In addition, although program instance rules such as *hot work permits* have been established in the rule base, their implementation still requires integration with enterprise management systems, such as electronic work permit systems to enable ontology reasoning. Within this framework, sensor data and enterprise system data will be matched with the rule base to enable broader multimodal monitoring and reasoning for professional emergency measures.

Lastly, the collection and analysis of monitoring video and personnel behavior data in hot work scenarios raise concerns regarding privacy protection and data security. In addition, the reliability and trustworthiness of AI inference results warrant further validation. Addressing these limitations and exploring these areas for improvement will enhance the effectiveness and applicability of the proposed autonomous risk management framework.

6. Conclusions

This paper established an ontology knowledge library and an ontology rule base, integrating object detection and text recognition technologies. Using hot work as an example, it proposes a framework for intelligently monitoring unsafe conditions in operational scenarios. The significance and contributions of this paper are as follows:

1) An ontology knowledge library for unsafe behavior and condition identification in hot work was proposed. Based on relevant laws and regulations, the hot work risk ontology library was established using the improved Seven-Step method, which optimizes traditional ontology development processes by simplifying redundant steps, incorporating case-driven modeling, and adding systematic ontology evaluation. Starting from the top-level concepts of work activity, work resource, precursor, risk event, and control measure, a top-down construction of the hot work ontology library was achieved. This approach not only improves the efficiency and quality of ontology construction but also provides a foundation for the subsequent establishment of the rule base and target detection objects.
2) A rule base for unsafe behavior and condition identification in hot work was constructed. Three types of instance rules were developed using SWRL to define unsafe spatiotemporal interaction patterns and to establish the interactive relationships between human, machine, and environment, as well as between risk events and emergency measures in hot work.
3) The ATFL-YOLO target detection model was proposed to address the complex challenges of hot work scenarios. Compared with other models, it demonstrates clear advantages on the collected hot work scenario dataset, with significant improvements in small object detection accuracy. Specifically, the accuracy for *No Glove* improved by 8.2 % compared with the original YOLOv11 model, while the overall mAP@0.5 increased by 1.1 %. Meanwhile, PaddleOCR effectively recognized text labels in the work area, achieving an overall confidence level of 97.63 %. Together, these results show that the system can effectively identify targets in hot work scenarios.
4) An intelligent monitoring framework for unsafe conditions in operational scenarios was proposed based on ontology, ATFL-YOLO and PaddleOCR. This framework integrates target information detected by ATFL-YOLO and text information recognized by PaddleOCR into an ontology model, thereby overcoming the "logic gap" between recognition and reasoning in computer systems. With the predefined rules of the internal ontology model and the results of target detection, the average inference time for emergency management measures across four different scenarios was 12.3 s. The framework enables multi-factor risk state assessment and provides appropriate emergency management measures to assist supervisors in making quick decisions. It strengthens existing automated monitoring methods for hot work and offers a reliable approach to safety management and emergency decision-making in Industry 4.0.

Although this paper has achieved some progress, several limitations remain that warrant further exploration and improvement in future work. The following directions are proposed for future research:

1) **Extending the applicability and refinement of the ontology model.** The ontology model in this paper was primarily designed for hot work scenarios, but future research could expand it to other specialized work areas such as working at heights or electrical operations. This would require integrating industry regulations, case studies, and the unique characteristics of each work scenario to redefine the ontology's top-level concepts and rule base, thereby ensuring its adaptability and generalizability across different fields.
2) **Incorporating advanced perception technologies to enable multimodal data integration.** Future research could extend the framework to multimodal data monitoring, employing multiple sensors to enhance multidimensional perception and real-time risk analysis in dynamic environments, thereby establishing a more comprehensive system for risk prediction and management.
3) **Combining skeleton recognition and posture analysis applications.** Currently, target detection mainly focuses on identifying

unsafe conditions, but workers' posture is equally important. Future studies could incorporate 2D skeleton recognition technology to analyze workers' detailed behaviors, such as whether welding postures meet standards or if fatigue-related operations are present, significantly enhancing the accuracy of risk assessments.

4) **Integrating LLMs to achieve more complex semantic reasoning.** By transmitting text, image information, and other data to LLMs, these models can be used to analyze and provide safety suggestions, which is expected to become a mainstream direction in the future. However, attention must still be given to the issue of hallucination. In addition, the automatic generation and dynamic updating of ontology rules is a promising area for exploration. By combining knowledge graphs with LLM technologies, the ontology rule base could be enhanced through automatic rule extraction and continuous updating. For example, LLMs could automatically extract critical safety rules from legal texts and convert them into ontology rules, or assist in constructing more intricate reasoning chains to provide intelligent support for risk management in dynamic environments.
5) **Optimizing model performance and expanding dataset scale.** Future research should focus on developing lighter detection models to improve both detection speed and accuracy.
1) In addition, expanding the training dataset for hot work scenarios is essential, particularly by incorporating more samples from extreme or complex environments (e.g., low-light or obstructed work conditions), to enhance the model's adaptability and robustness in real-world applications.
6) **Validation in practical applications and industrial promotion.** For real-world deployment, long-term experiments should be conducted in environments such as construction sites, chemical plants, or hazardous material warehouses. These experiments would involve collecting data from actual operational scenarios to evaluate the framework's performance under diverse conditions. This is a challenging endeavor that requires collaboration with industry partners to explore pathways for industrial implementation, develop user-friendly interfaces and platforms, and ensure the practical adoption of research findings.

By exploring the above future research directions, the intelligent capabilities and practical value of the proposed framework can be further enhanced, providing stronger theoretical support and practical guidance for automated safety management in Industry 4.0 scenarios.

CRediT authorship contribution statement

Zhengwen Zhou: Visualization, Supervision, Software, Writing – review & editing, Writing – original draft. **Shan Chen:** Project administration, Investigation. **Junhui Kou:** Methodology, Writing – review & editing. **Siqi Chen:** Validation, Methodology. **Jiaxin Liu:** Investigation, Data curation. **Liangjie Guo:** Resources, Project administration, Funding acquisition, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

This paper was supported by the Production Safety Special Fund Science and Technology Project of Hubei Province (Grant No. SJZX2023090), the Knowledge Innovation Program of Wuhan-Shuguang (Grant No. 2022020801020209), and Knowledge Innovation Program of Wuhan -Basic Research. The conclusions herein are those of the authors and do not reflect the views of the sponsoring agencies.

Data availability

The raw data used in this paper are available from the corresponding authors upon reasonable request.

References

[1] J. Zhou, L. Liu, Y. Su, R. Liang, J. Feng, X. Wang, Statistical investigation on the characteristics of hazardous chemical accidents in special work in China from 2008 to 2021, Process. Saf. Prog. 43 (1) (2024) 195–208, https://doi.org/10.1002/prs.12526.
[2] W. Li, Q. Sun, J. Zhang, L. Zhang, Quantitative risk assessment of industrial hot work using adaptive Bow tie and petri nets, Reliab. Eng. Syst. Saf. 242 (Feb. 2024) 109784, https://doi.org/10.1016/j.ress.2023.109784.
[3] N.D.A. Majid, A.M. Shariff, N.A.M. Zaki, Compliance of hot work permit to process safety management (PSM) regulation, Appl. Mech. Mater. 625 (2014) 418–421, https://doi.org/10.4028/www.scientific.net/AMM.625.418.
[4] X. Wang, Analysis and improvement of hot work management in China, Process. Saf. Prog. 42 (1) (2023) 72–78, https://doi.org/10.1002/prs.12433.
[5] S. Hedrick, D. Hisey, J. Petkovsek, Fire prevention during hot work, Weld World 59 (4) (Jul. 2015) 585–587, https://doi.org/10.1007/s40194-015-0233-4.
[6] D. Koh, A. Tan, Applications and impact of industry 4.0: technological innovations in occupational safety and health, Saf. Health Work 15 (4) (Dec. 2024) 379–381, https://doi.org/10.1016/j.shaw.2024.09.001.
[7] Z. Liu, K. Xie, L. Li, Y. Chen, A paradigm of safety management in industry 4.0, Syst. Res. Behav. Sci. 37 (4) (2020) 632–645, https://doi.org/10.1002/sres.2706.
[8] A. Górny, Employee safety in the conditions of industry 4.0, Manag. Syst. Product. Eng. 32 (4) (Nov. 2024) 489–497, https://doi.org/10.2478/mspe-2024-0046.
[9] P. Swuste, J. Groeneweg, C. van Gulijk, W. Zwaard, S. Lemkowitz, Y. Oostendorp, The future of safety science, Saf. Sci. 125 (May 2020) 104593, https://doi.org/10.1016/j.ssci.2019.104593.
[10] M. Beetz, G. Bartels, A. Albu-Schäffer, F. Bálint-Benczédi, R. Belder, D. Beßler, et al., Robotic agents capable of natural and safe physical interaction with human co-workers, in: 2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS), Sep. 2015, pp. 6528–6535, https://doi.org/10.1109/IROS.2015.7354310.
[11] R. Gill, D. Srivastava, S. Hooda, C. Singla, R. Chaudhary, Unleashing sustainable efficiency: the integration of computer vision into industry 4.0, Eng. Manag. J. 0 (0) (2025) 1–19, https://doi.org/10.1080/10429247.2024.2383518.
[12] I. Yousif, J. Samaha, J. Ryu, R. Harik, Safety 4.0: harnessing computer vision for advanced industrial protection, Manufact. Lett. 41 (Oct. 2024) 1342–1356, https://doi.org/10.1016/j.mfglet.2024.09.161.
[13] C. Fan, Q. Mei, X. Li, Real-time ergonomic risk assessment approach for construction workers based on computer vision, in: S. Desjardins, G.J. Poitras, M. Nik-Bakht (Eds.), Proceedings of the Canadian Society for Civil Engineering Annual Conference 2023, Volume 5, Springer Nature Switzerland, Cham, 2024, pp. 113–127, https://doi.org/10.1007/978-3-031-61503-0_9.
[14] L. Yipeng, W. Junwu, M.E. Torbaghan, Data-driven safety management of worker-equipment interactions using visual relationship detection and semantic analysis, Autom. Constr. 175 (Jul. 2025) 106181, https://doi.org/10.1016/j.autcon.2025.106181.
[15] N. Khan, S.F.A. Zaidi, J. Yang, C. Park, D. Lee, Construction work-stage-based rule compliance monitoring framework using computer vision (CV) technology, Buildings 13 (8) (Aug. 2023), https://doi.org/10.3390/buildings13082093. Art. no. 8.
[16] L.A. Glasenapp, A.F. Hoppe, M.A. Wisintainer, A. Sartori, S.F. Stefenon, OCR applied for identification of vehicles with irregular documentation using IoT, Electronics 12 (5) (Jan. 2023), https://doi.org/10.3390/electronics12051083. Art. no. 5.
[17] Q. Peng, L. Tu, Paddle-OCR-based real-time online recognition system for steel plate slab spray marking characters, J. Control Autom. Electr. Syst. 35 (1) (Feb. 2024) 221–233, https://doi.org/10.1007/s40313-023-01062-w.
[18] B. Zhong, H. Wu, H. Li, S. Sepasgozar, H. Luo, L. He, A scientometric analysis and critical review of construction related ontology research, Autom. Constr. 101 (May 2019) 17–31, https://doi.org/10.1016/j.autcon.2018.12.013.
[19] D.A. de Araujo, S.J. Rigo, J.L.V. Barbosa, Ontology-based information extraction for juridical events with case studies in Brazilian legal realm, Artif. Intell. Law 25 (4) (Dec. 2017) 379–396, https://doi.org/10.1007/s10506-017-9203-z.
[20] G.A. Helfer, A.B. Da Costa, J.L.V. Barbosa, SoilBR-onto: an ontology for soil fertility management and classification in Brazil, Appl. Ontol. 20 (2) (May 2025) 181–196, https://doi.org/10.1177/15705838251315571.
[21] A.V. Larentis, E.G. De A. Neto, J.L.V. Barbosa, D.N.F. Barbosa, V.R.Q. Leithardt, S. D. Correia, Ontology-based reasoning for Educational assistance in noncommunicable chronic diseases, Computers 10 (10) (Oct. 2021), https://doi.org/10.3390/computers10100128. Art. no. 10.
[22] I.M.G. Cardoso, J.L.V. Barbosa, B.M. Alves, L.P.S. Dias, L.C. Nesi, Vulcont: a recommender system based on context history ontology, IET Softw. 16 (1) (2022) 111–123, https://doi.org/10.1049/sfw2.12034.
[23] G. Ancione, S.M. Ansaldi, P. Bragatto, P. Agnello, M.F. Milazzo, An ontological approach increasing the knowledge about equipment ageing including the effects of current transitions, J. Loss Prev. Process Ind. 92 (Dec. 2024) 105453, https://doi.org/10.1016/j.jlp.2024.105453.
[24] Y. Hu, C. Liu, M. Zhang, Y. Lu, Y. Jia, Y. Xu, An ontology and rule-based method for human–robot collaborative disassembly planning in smart remanufacturing, Robot.

Comput. Integr. Manuf. 89 (Oct. 2024) 102766, https://doi.org/10.1016/j.rcim.2024.102766.
[25] F. Ocker, B. Vogel-Heuser, C.J.J. Paredis, A framework for merging ontologies in the context of smart factories, Comput. Ind. 135 (Feb. 2022) 103571, https://doi.org/10.1016/j.compind.2021.103571.
[26] C. Cui, M. Xu, C. Xu, P. Zhang, J. Zhao, An ontology-based probabilistic framework for comprehensive seismic risk evaluation of subway stations by combining Monte Carlo simulation, Tunn. Undergr. Space Technol. 135 (May 2023) 105055, https://doi.org/10.1016/j.tust.2023.105055.
[27] F. Ciroku, S. De Giorgis, A. Gangemi, D.S. Martinez-Pandiani, V. Presutti, Automated multimodal sensemaking: ontology-based integration of linguistic frames and visual data, Comput. Hum. Behav. 150 (Jan. 2024) 107997, https://doi.org/10.1016/j.chb.2023.107997.
[28] X. Huang, C. Yang, Y. Zhang, S. Lou, L. Kong, H. Zhou, Ontology guided multi-level knowledge graph construction and its applications in blast furnace ironmaking process, Adv. Eng. Inform. 62 (Oct. 2024) 102927, https://doi.org/10.1016/j.aei.2024.102927.
[29] C. Su, Q. Jiang, Y. Han, T. Wang, Q. He, Knowledge graph-driven decision support for manufacturing process: a graph neural network-based knowledge reasoning approach, Adv. Eng. Inform. 64 (Mar. 2025) 103098, https://doi.org/10.1016/j.aei.2024.103098.
[30] K. Farghaly, R. Soman, J. Whyte, cSite ontology for production control of construction sites, Autom. Constr. 158 (Feb. 2024) 105224, https://doi.org/10.1016/j.autcon.2023.105224.
[31] C. Goetz, R.S. Bavaresco, W.F. Heckler, G.L. Schroeder, R. Kunst, J.L.V. Barbosa, OntoKaire: an ontology-based reasoning for work-related stressors in industrial settings, JUCS - J. Univ. Comput. Sci. 31 (5) (Apr. 2025), https://doi.org/10.3897/jucs.128779. Art. no. 5.
[32] G. Zhang, Y. Wang, B. Mu, T. Wang, Big Data and Safety Management Methods: The Reduction Model of Hot Work Number, in: 2019 IEEE 4th International conference on big data analytics (ICBDA), Mar. 2019, pp. 140–143, https://doi.org/10.1109/ICBDA.2019.8713251.
[33] X. Ding, X. Tian, J. Wang, A comprehensive risk assessment method for hot work in underground mines based on G1-EWM and unascertained measure theory, Sci. Rep. 14 (1) (Mar. 2024) 6063, https://doi.org/10.1038/s41598-024-56230-y.
[34] A. Prateepasen, A. Aumpiem, Problems causing delays and risk factors in welding construction projects of Thailand, EJ 25 (5) (May 2021) 33–44, https://doi.org/10.4186/ej.2021.25.5.33.
[35] S. He, H. Xu, J. Zhang, P. Xue, Risk assessment of oil and gas pipelines hot work based on AHP-FCE, Petroleum 9 (1) (Mar. 2023) 94–100, https://doi.org/10.1016/j.petlm.2022.03.006.
[36] H. Xu, Y. Liu, C.-M. Shu, M. Bai, M. Motalifu, Z. He, et al., Cause analysis of hot work accidents based on text mining and deep learning, J. Loss Prev. Process Ind. 76 (May 2022) 104747, https://doi.org/10.1016/j.jlp.2022.104747.
[37] W. Gan, K. Gu, J. Geng, C. Qiu, R. Yang, H. Wang, et al., A novel three-stage collision-risk pre-warning model for construction vehicles and workers, Buildings 14 (8) (Aug. 2024), https://doi.org/10.3390/buildings14082324. Art. no. 8.
[38] W. Fang, L. Ding, H. Luo, P.E.D. Love, Falls from heights: a computer vision-based approach for safety harness detection, Autom. Constr. 91 (Jul. 2018) 53–61, https://doi.org/10.1016/j.autcon.2018.02.018.
[39] A.M. Vukicevic, M. Petrovic, P. Milosevic, A. Peulic, K. Jovanovic, A. Novakovic, A systematic review of computer vision-based personal protective equipment compliance in industry practice: advancements, challenges and future directions, Artif. Intell. Rev. 57 (12) (Oct. 2024) 319, https://doi.org/10.1007/s10462-024-10978-x.
[40] Y. Wang, P.-C. Liao, C. Zhang, Y. Ren, X. Sun, P. Tang, Crowdsourced reliable labeling of safety-rule violations on images of complex construction scenes for advanced vision-based workplace safety, Adv. Eng. Inform. 42 (Oct. 2019) 101001, https://doi.org/10.1016/j.aei.2019.101001.
[41] M. Soltani, A. Pedro, J. Yang, S.F.A. Zaidi, D. Lee, C. Park, Isafeguard: A proactive solution for construction job site safety monitoring, in: N. Banthia, S. Soleimani-Dashtaki, S. Mindess (Eds.), Smart & Sustainable Infrastructure: Building a Greener Tomorrow, Springer Nature Switzerland, Cham, 2024, pp. 50–65, https://doi.org/10.1007/978-3-031-53389-1_101.
[42] Y. Wang, B. Xiao, A. Bouferguene, M. Al-Hussein, Proactive safety hazard identification using visual–text semantic similarity for construction safety management, Autom. Constr. 166 (Oct. 2024) 105602, https://doi.org/10.1016/j.autcon.2024.105602.
[43] B. Ekanayake, J.K.-W. Wong, A.A.F. Fini, P. Smith, Computer vision-based interior construction progress monitoring: a literature review and future research directions, Autom. Constr. 127 (Jul. 2021) 103705, https://doi.org/10.1016/j.autcon.2021.103705.
[44] H. Moussaoui, N. El Akkad, M. Benslimane, W. El-Shafai, A. Baihan, C. Hewage, et al., Enhancing automated vehicle identification by integrating YOLO v8 and OCR techniques for high-precision license plate detection and recognition, Sci. Rep. 14 (1) (Jun. 2024) 14389, https://doi.org/10.1038/s41598-024-65272-1.
[45] C.-W. Park, V. Palakonda, S. Yun, I.-M. Kim, J.-M. Kang, OCR-diff: a two-stage deep learning framework for optical character recognition using diffusion model in industrial internet of things, IEEE Internet Things J. 11 (15) (Aug. 2024) 25997–26000, https://doi.org/10.1109/JIOT.2024.3390700.
[46] G. Monteiro, L. Camelo, G. Aquino, R. De A. Fernandes, R. Gomes, A. Printes, et al., A comprehensive framework for industrial sticker information recognition using advanced OCR and object detection techniques, Appl. Sci. 13 (12) (Jan. 2023), https://doi.org/10.3390/app13127320. Art. no. 12.
[47] R. Batres, S. Fujihara, Y. Shimada, T. Fuchino, The use of ontologies for enhancing the use of accident information, Process. Saf. Environ. Prot. 92 (2) (Mar. 2014) 119–130, https://doi.org/10.1016/j.psep.2012.11.002.
[48] H.-H. Wang, F. Boukamp, Ontology-based representation and reasoning framework for supporting job Hazard analysis, J. Comput. Civ. Eng. 25 (6) (Nov. 2011) 442–456, https://doi.org/10.1061/(ASCE)CP.1943-5487.0000125.
[49] Y. Lu, Q. Li, Z. Zhou, Y. Deng, Ontology-based knowledge modeling for automated construction safety checking, Saf. Sci. 79 (Nov. 2015) 11–18, https://doi.org/10.1016/j.ssci.2015.05.008.
[50] S. Zhang, F. Boukamp, J. Teizer, Ontology-based semantic modeling of construction safety knowledge: towards automated safety planning for job hazard analysis (JHA), Autom. Constr. 52 (Apr. 2015) 29–41, https://doi.org/10.1016/j.autcon.2015.02.005.
[51] W. Fang, L. Ma, P.E.D. Love, H. Luo, L. Ding, A. Zhou, Knowledge graph for identifying hazards on construction sites: integrating computer vision with ontology, Autom. Constr. 119 (Nov. 2020) 103310, https://doi.org/10.1016/j.autcon.2020.103310.
[52] X. Jiang, S. Wang, J. Wang, S. Lyu, M. Skitmore, A decision method for construction safety risk management based on ontology and improved CBR: example of a Subway project, Int. J. Environ. Res. Public Health 17 (11) (Jan. 2020), https://doi.org/10.3390/ijerph17113928. Art. no. 11.
[53] H. Park, R. Liu, Improving for Construction Safety Design: Ontology Model of a Knowledge System for the Prevention of Falls, Nov. 2020, pp. 463–471, https://doi.org/10.1061/9780784482872.050.
[54] E. Hong, S. Lee, H. Kim, J. Park, M.B. Seo, J.-S. Yi, Graph-based intelligent accident hazard ontology using natural language processing for tracking, prediction, and learning, Autom. Constr. 168 (Dec. 2024) 105800, https://doi.org/10.1016/j.autcon.2024.105800.
[55] C. Zeng, T. Hartmann, L. Ma, ConSE: an ontology for visual representation and semantic enrichment of digital images in construction sites, Adv. Eng. Inform. 60 (Apr. 2024) 102446, https://doi.org/10.1016/j.aei.2024.102446.
[56] R. Bavaresco, Y. Ren, J. Barbosa, G.P. Li, An ontology-based framework for worker's health reasoning enabled by machine learning, Comput. Ind. Eng. 193 (Jul. 2024) 110310, https://doi.org/10.1016/j.cie.2024.110310.
[57] C.-F. Chan, P.K.-Y. Wong, X. Guo, J.C.P. Cheng, J.P.-C. Chan, P.-H. Leung, et al., Context-aware vision-language model agent enriched with domain-specific ontology for construction site safety monitoring, Autom. Constr. 177 (Sep. 2025) 106305, https://doi.org/10.1016/j.autcon.2025.106305.
[58] R. Studer, V.R. Benjamins, D. Fensel, Knowledge engineering: principles and methods, Data Knowl. Eng. 25 (1) (Mar. 1998) 161–197, https://doi.org/10.1016/S0169-023X(97)00056-6.
[59] Z. Guo, D. Zhou, D. Yu, Q. Zhou, H. Wu, A. Hao, An ontology-based method for knowledge reuse in the design for maintenance of complex products, Comput. Ind. 161 (Oct. 2024) 104124, https://doi.org/10.1016/j.compind.2024.104124.
[60] A. Gómez-Pérez, R. Benjamins, Overview of knowledge sharing and reuse components: ontologies and problem-solving methods, in: Proceedings of the 16th International Joint Conference on Artificial Intelligence (IJCAI'99) Workshop KRR5: Ontologies and Problem-Solving Methods: Lesson Learned and Future Trends | 16th International Joint Conference on Artificial Intelligence (IJCAI'99) Workshop KRR5: Ontologies and Problem-Solving Methods: Lesson Learned and Future Trends | 2 August 1999 | Stockholm, Sweden, Facultad de Informática (UPM), Stockholm, Sweden, Aug. 1999. Accessed: Jan. 06, 2025. [Online]. Available: https://oa.upm.es/6468/.
[61] M.S. Fox, M. Barbuceanu, M. Gruninger, An organisation ontology for enterprise modeling: preliminary concepts for linking structure and behaviour, Comput. Ind. 29 (1) (Jul. 1996) 123–134, https://doi.org/10.1016/0166-3615(95)00079-8.
[62] B. Yang, Construction of logistics financial security risk ontology model based on risk association and machine learning, Saf. Sci. 123 (Mar. 2020) 104437, https://doi.org/10.1016/j.ssci.2019.08.005.
[63] M. Uschold, M. Gruninger, Ontologies: principles, methods and applications, Knowl. Eng. Rev. 11 (2) (Jun. 1996) 93–136, https://doi.org/10.1017/S0269888900007797.
[64] Y.A. Tijerino, D.W. Embley, D.W. Lonsdale, G. Nagy, Ontology generation from tables, in: Proceedings of the Fourth International Conference on Web Information Systems Engineering, 2003. WISE 2003, Dec. 2003, pp. 242–249, https://doi.org/10.1109/WISE.2003.1254487.
[65] Occupational Safety and Health Administration (OSHA), U.S. Department of Labor. Process Safety Management of Highly Hazardous Chemicals (29 C.F.R. § 1910.119), Accessed October 15, 2023, https://www.ecfr.gov/current/title-29/subtitle-B/chapter-XVII/part-1910, 2025.
[66] National Standard of the People''s Republic of China, Special operations safety regulations for hazardous chemical companies (GB30871–2022), Accessed November 29, 2024, from, https://www.chemicalsafety.org.cn/article/we07q2774j62mxod, 2022.
[67] EHSPlanet, Accessed: Nov. 05, 2024. [Online]. Available: https://www.ehsplanet.com/#/, 2025.
[68] M. Uschold, M. King, Towards a Methodology for Building Ontologies, Accessed: Jan. 06, 2025. [Online]. Available: https://www.semanticscholar.org/paper/Towards-a-Methodology-for-Building-Ontologies-Uschold-King/bb0f448961bca41e74b803cdb72cc98f89a2c763, 1995.
[69] G. Cui, Y. Zhang, H. Tao, X. Yan, Z. Liu, Ontology-based inference decision support system for emergency response in tunnel vehicle accidents, Heliyon 10 (17) (Sep. 2024) e36936, https://doi.org/10.1016/j.heliyon.2024.e36936.
[70] National Standard of the People''s Republic of China, Safety technical standards for petrochemical construction engineering (GB50484–2019), Accessed November 29,

2024, from, http://www.caec-china.org.cn/zhengcefagui/xzfg/11526014.shtml, 2019.
[71] L. Obrst, W. Ceusters, I. Mani, S. Ray, B. Smith, The evaluation of ontologies, in: C. J.O. Baker, K.-H. Cheung (Eds.), Semantic Web: Revolutionizing Knowledge Discovery in the Life Sciences, Springer US, Boston, MA, 2007, pp. 139–158, https://doi.org/10.1007/978-0-387-48438-9_8.
[72] Z. Zhou, Y.M. Goh, L. Shen, Overview and analysis of ontology studies supporting development of the construction industry, J. Comput. Civ. Eng. 30 (6) (Nov. 2016) 04016026, https://doi.org/10.1061/(ASCE)CP.1943-5487.0000594.
[73] D.L. Nuñez, M. Borsato, OntoProg: an ontology-based model for implementing prognostics health management in mechanical machines, Adv. Eng. Inform. 38 (Oct. 2018) 746–759, https://doi.org/10.1016/j.aei.2018.10.006.
[74] T.M. de Farias, A. Roxin, C. Nicolle, SWRL rule-selection methodology for ontology interoperability, Data Knowl. Eng. 105 (Sep. 2016) 53–72, https://doi.org/10.1016/j.datak.2015.09.001.
[75] R. Khanam, M. Hussain, YOLOv11: An Overview of the Key Architectural Enhancements, Oct. 23, 2024, https://doi.org/10.48550/arXiv.2410.17725.
[76] Y. Li, H. Yan, D. Li, H. Wang, Robust miner detection in challenging underground environments: an improved YOLOv11 approach, Appl. Sci. 14 (24) (Jan. 2024), https://doi.org/10.3390/app142411700. Art. no. 24.
[77] B. Yang, X. Zhang, J. Zhang, J. Luo, M. Zhou, Y. Pi, EFLNet: enhancing feature learning network for infrared small target detection, IEEE Trans. Geosci. Remote Sens. 62 (2024) 1–11, https://doi.org/10.1109/TGRS.2024.3365677.
[78] W. Cao, Z. Chen, X. Deng, C. Wu, T. Li, An identification method for irregular components related to terminal blocks in equipment cabinet of power substation, Sensors 23 (18) (Jan. 2023), https://doi.org/10.3390/s23187739. Art. no. 18.
[79] Y. Ding, X. Chen, Z. Wang, Y. Zhang, X. Huang, Human behaviour detection dataset (HBDset) using computer vision for evacuation safety and emergency management, J. Safety Sci. Resilien. 5 (3) (Sep. 2024) 355–364, https://doi.org/10.1016/j.jnlssr.2024.04.002.
[80] X. Zhang, X. Chen, Y. Ding, Y. Zhang, Z. Wang, J. Shi, et al., Smart real-time evaluation of tunnel fire risk and evacuation safety via computer vision, Saf. Sci. 177 (Sep. 2024) 106563, https://doi.org/10.1016/j.ssci.2024.106563.
[81] Z. Zheng, P. Wang, W. Liu, J. Li, R. Ye, D. Ren, Distance-IoU loss: faster and better learning for bounding box regression, in: THIRTY-FOURTH AAAI CONFERENCE ON ARTIFICIAL INTELLIGENCE, THE THIRTY-SECOND INNOVATIVE APPLICATIONS OF ARTIFICIAL INTELLIGENCE CONFERENCE AND THE TENTH AAAI SYMPOSIUM ON EDUCATIONAL ADVANCES IN ARTIFICIAL INTELLIGENCE, in AAAI Conference on Artificial Intelligence 34, Assoc Advancement Artificial Intelligence, Palo Alto, 2020, pp. 12993–13000.
[82] X. Yang, J. Yan, Q. Ming, W. Wang, X. Zhang, Q. Tian, Rethinking rotated object detection with Gaussian Wasserstein distance loss, in: M. Meila, T. Zhang (Eds.), International Conference on Machine Learning Vol 139, Jmlr-Journal Machine Learning Research, San Diego, 2021 in Proceedings of Machine Learning Research, vol. 139.