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Computer vision and IoT research landscape for health and safety management on construction sites

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ABSTRACT

Aims: Perform a systematic review of current literature to evaluate and summarise the health and safety hazards on construction sites.
Methods: Science Direct, SCOPUS and web of science databases were searched for research articles published from 2013 to 2021. From an initial search of 350 research articles, we removed the duplicate articles and carried out an analysis of the abstract and full text that focused on health, safety, hazards, behaviour, on-site health and safety and the digital technologies leaving a total of 66 studies included.
Results: Computer vision and Internet of Things (IoT) are the dominant technologies for health and safety management. A comparison of the two technologies reveals that computer vision is dominant because of its non-intrusive approach to data collection; thus, supporting the scalability of computer vision approach at the expense of cost and development time. It will help to prevent on-site health and safety hazards and injuries on construction site.
Conclusion: Computer vision offers non-intrusive benefits over Internet of Things (IoT); being able to detect the health and safety hazards. Computer vision has proved to be beneficial for better accuracy prediction, real time data monitoring, and model development for onsite health and safety analytics on the construction site.

1. Background

Construction industry is one of the most hazardous industries with a high rate of onsite injuries and fatal accidents. Evidence suggests that there are about 61,000 non-fatal injuries recorded in the UK construction every year [1]**.** The construction industry experiences an average of 41 fatalities per year and ~81,000 work-related health problems per year due to the health and safety hazards [1]. Further, there have been ~59,000 non-fatal injuries per average over the years from 2019 to 2022 and 30 fatal injuries to the construction workers in 2021–2022. Also, it has been estimated that ~78,000 work related illness of the workers on the construction site [2]. The high rate of accident is because of the dynamic nature on construction sites where various equipment and site workers interact in various ways. It has been argued that the high rate of accidents in the construction industry is major bottleneck in project performance leading to margin erosion, project delays, cost over-runs, and loss of productivity (Abas et al., 2020).

A large body of knowledge evidenced that digital technology adoption has huge potential to improve productivity and safety on the construction sites [3–5]. As such, various research and development studies have surfaced in the last decade on the use of digital technologies for minimising health and safety hazards on construction sites. The emerging trends include the use of computer vision, sensor-based technologies (wireless sensor networks and internet of things), wearable technologies, LIDAR, building information modelling, immersive technologies (augmented and virtual realities), etc. [6,7]. However, the choice of an appropriate technology for

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health and safety management requires an understanding of construction site peculiarities, safety hazards of interest, level of decision accuracy, implementation requirements and process, and limitations.

The authors have absolutely made the efforts to identify and collect the health and safety hazards associated with the emerging technologies in the construction industry. The paper addresses those health and safety hazards which have been found in the literature. Although, the authors believe that an exhaustive list of health and safety hazards have been found in the literature. They also acknowledge that there may be additional health and safety hazards on the construction sites that were not included in the review. Therefore, there is a need for further data analysis to research the potential additional health and safety hazards. Besides this, the subsequent study, the authors plan to work on additional health and safety hazards that were not covered in the initial review. This effort will contribute to broaden the knowledge of the health and safety hazards associated with the emerging technologies in the construction industry.

It is on the aforementioned premise that a systematic literature review of the emerging technologies for on-site health and safety management was carried out. Relevant research works in the field of health and safety management were collected from research databases and reviewed. The focus of the study is to understand the relevance of the technologies in health and safety management and to provide a comparison of the most relevant digital technologies. As such, the specific objectives of the study are.

1) To review relevant scholarly publications on the use of digital technologies for health and safety management on construction sites.
2) To identify the trend of digital technologies adoption and provide a comparison of the dominant technologies.
3) To discuss the current research gaps and opportunities in the adoption of the dominant technologies for construction health and safety management.

The remainder of this paper has four sections. The next section, Section 2 contains the systematic literature review, which addresses the identification of research articles and health and safety hazards with respect to the digital technologies. Section 3 contains a discussion of computer vision and IoT in the construction industry. It also discusses the comparison of computer vision and IoT based on key features, the key techniques, and the limitations of computer vision and IoT for on-site health and safety analytics. The final section, section 4, presents the conclusion and future research.

2. Research methodology

A systematic review was carried out by collecting articles from acknowledged scholarly journals from January 2013 to December 2021. The emergence of digital technologies has played a pivotable role in the implementation of information technology in the construction industry [8,9]. highlights the importance of technological innovation and sustainable growth in the construction industry. The digital technologies have adopted the tools and techniques to revolutionise the construction industry. Digital technologies have been adopted in the construction industry because of the technological innovation. These technologies have the potential to streamline the processes, improve safety and enhance the productiveness in construction projects.

PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses) method adopted for the systematic review [10]. The PRISMA method supports the precise flow and reporting of information through the different phases of a systematic review or meta-analyses [11]. The PRISMA process starts with the identification of the research articles through the search of databases and additional resources. If there exists duplication of articles, they are removed. Then, the records are screened by title/abstract with the relevance of the research. Emphasis was placed on papers within the scope of on-site health and safety hazards management and the digital technologies. The PRISMA flow diagram is presented in Fig. 1. The selected literature databases are ScienceDirect, SCOPUS, and web of science and six search rounds were conducted. The inclusion criteria for selecting the papers include the keywords such as 'health', '*safety', 'hazards', 'on-site health and safety', 'behaviour', and the 'digital technologies*. Further, the exclusion criteria include research articles that focus on construction safety management, risk management, construction waste, health diseases in construction and demographic data. The systematic review data was then explored and analysed across the following dimensions: (i) onsite health and safety application area, (ii) digital technologies adopted, and (iii) research methods used. A total of 66 research articles identified for the research. The research roadmap for the identification of research articles is captured in Fig. 2.

3. Results and discussion

The results of the systematic review show that computer vision and IoT are the two widely adopted digital technologies in the construction health and safety management. Figs. 3 and 4 show the distribution of the papers with respect to the year of publication and the digital technologies adopted respectively. The trend of digital technologies adoption reveals that computer vision (CV), Internet of

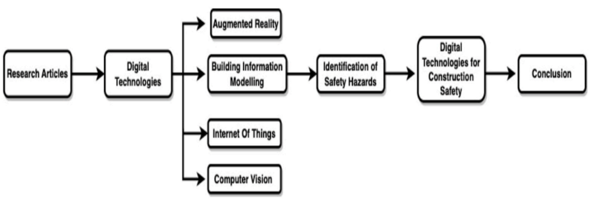

Fig. 1. Prisma flow diagram (Adapted from Ref. [12]).

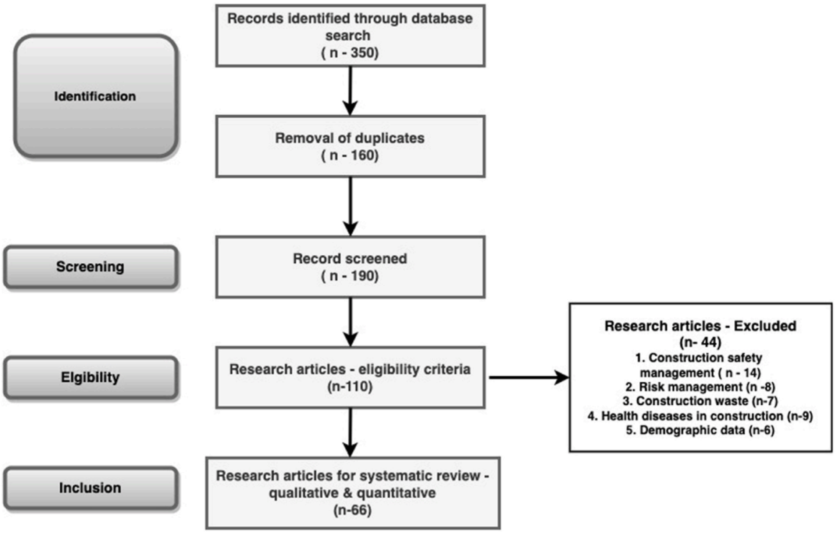

Fig. 2. Research roadmap for the identification of research articles.

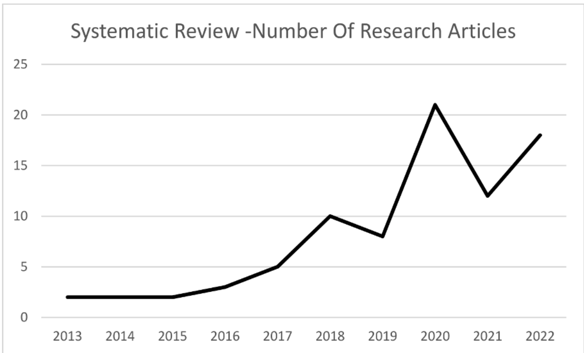

Fig. 3. Distribution of research articles with respect to year.

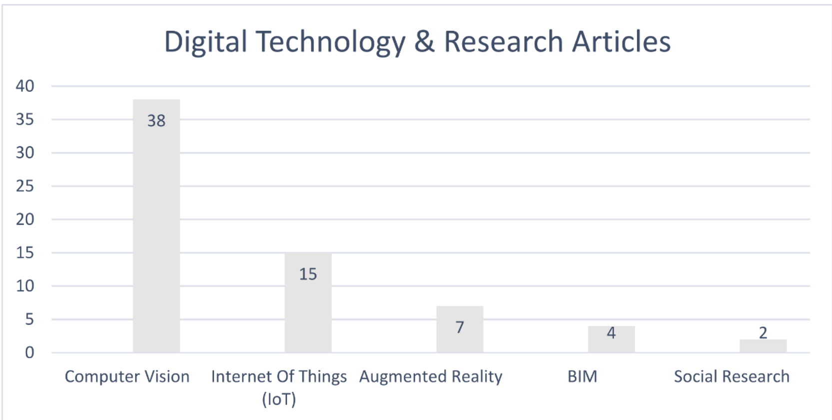

Fig. 4. Digital technologies adoption for construction health and safety.

Things (IoT), Augmented Reality (AR), and Building Information Modelling (BIM), are the top technologies adopted for construction health and safety management. However, computer vision and IoT stood out as the most adopted technologies across the papers. As such, a critical look was taken to explore the peculiarities of the two technologies with a focus on their areas of strengths in health and safety management and areas of research opportunities.

Fig. 3 shows the number of research articles from 2013 to 2021. Also, Fig. 4 shows the number of research articles in the digital technologies such as computer vision, internet of things (IoT), augmented reality, building information modelling (BIM), and social research. Fig. 5 shows the health and safety hazards addressed in the research articles. The top five safety hazards addressed with digital technologies in the systematic literature review includes unsafe behaviour and worker conditions, hazardous conditions and equipment, absence of PPE, behaviour-based safety, and construction accident.

3.1. Computer vision for construction health and safety

Computer vision is renowned for solving issues pertinent to construction health and safety due to its ability to automate tasks using non-intrusive approaches to replicate human visual system (Seo et al., 2015). Computer vision can detect objects and their special relationships, track the movement of objects, and understand actions of people and equipment on a construction site (Yang et al., 2016). A major strength of computer vision for onsite health and safety is its capability to identify multiple objects' information from complex and dynamic construction sites without the need of a hardware tag. Computer vision detects, recognizes, and track objects' movement and the interactions among them using moving images captured by a camera [13]. has argued that these capabilities as building blocks of computer vision technologies are relevant for on-site health and safety analytics to determine unsafe conditions and safety hazards on the construction sites. Since the tracked objects, their categories, locations, and interactions can be monitored to isolate safety concerns using images (Saluser et al., 2016).

A recent trend in onsite health and safety management is the integration of computer vision with an ontology to address the semantic gap [14–16]. An ontology is a definite description of a knowledge domain, its entities, and the relationships among the entities [17,18]. Ontologies provide the knowledge representation of a specific domain and it enables the sharing of a common understanding of the knowledge [19,20]. Ontology development tools accelerate the validation process of the knowledge representation process. Example of such tools include Protégé ontology library [21,22], IEEE Standard Upper Ontology [23], UMLS Semantic Net [24], Gene Ontology [25], etc.

The combination of computer vision and ontology enables classification, and extraction of attributes of detected objects. Some example applications include ontology for image and video classification [26,35,70,44]. Meanwhile, Semantic image segmentation modelling is a challenge in object detection and classification [27,28]. The combination of ontology based semantic image segmentation with object detection and image segmentation achieves spatial segmentation for on-site safety objects [16]. investigated that the annotated set of images can be calculated through the image retrieval approach. To determine computer vision for site safety monitoring a framework was proposed by Ref. [14] for the identification of unsafe behaviour and on-site safety worker condition. The framework comprised of the four steps which includes ontological safety hazards, computer vision attributes detection, extraction of spatial and temporal relation from the on-site videos and interpretation of hazard identification.

3.2. Internet of things (IoT) for construction health and safety

Internet of Things (IoT) is a system of interrelated computing devices, mechanical and digital machines that are provided with unique identifiers (UIDs) and the ability to transfer data over a network without requiring human-to-human or human-to-computer interaction' (Margaret 2019). The major components of the IoT include sensors, connectivity, platform, analytics, governance standard and a user interface [29,30] (Desai et al., 2015). investigated that IoT architecture enables semantic web enabled interoperability at application level which provides interoperability between sensors using low-level sensor data. The communication of wireless protocols and IoT nodes enable the information transmission on the construction site [31]. IoT sensors require identity and authentication management which includes data confidentiality and integrity, heterogeneity, access control and privacy issues to detect malicious activity in the IoT ecosystem (Anthi et al., 2018). IoT devices operate in the construction industry to collect the data through sensors and edge devices to obtain informed decisions on a construction site [32,33].

IoT connected devices have been deployed on the construction site to detect accidents and safety hazard. In a recent study [34,35] investigated that the site workers use wearable instruments to achieve the data such as temperature, health, humidity, air quality,

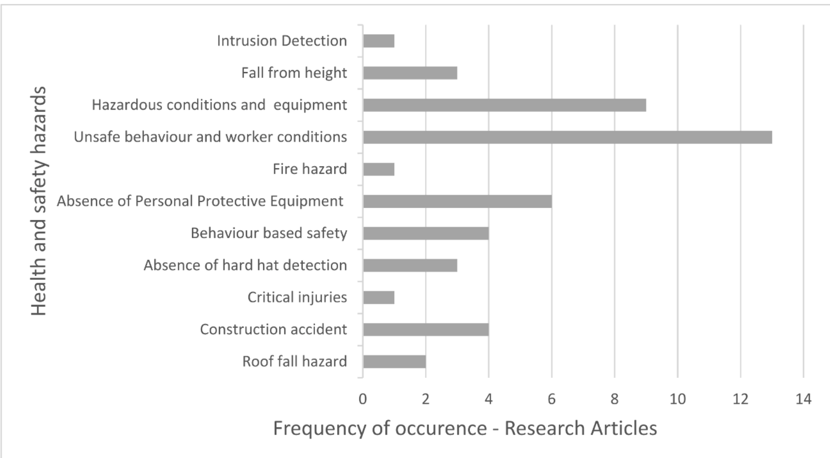

Fig. 5. Safety hazards addressed in the research articles.

heart rate and outdoor location. The data is securely transmitted through the gateways and IoT security for further data analytics. The integration of different IoT technologies provides better tracking of the dangerous equipment and the site worker hazard conditions for on-site health and safety analytics [36] such as wearable sensing devices [37], RFID smart tracking [38–40], scientific tool development [41].

IoT is an evolutionary technology which provides solutions for Big Data analytics, business optimization and multiple concurrent access of the IoT devices. Remote site monitoring such as facial recognition, radio frequency (RFID) tags, sensors installed on machines and vehicles, wearable devices recognize the movement patterns, authorised workers, and intrusion detection for on-site health and safety analytics [42]. The IoT solutions enable the site workers to manage the hazardous equipment before it reaches to the critical breaking point [43,44]. Therefore, it is important to prevent on-site accidents such as fall from height (FFH) [39]. The use of IoT based hybrid smart safety hook helps to monitor on-site multiple workers status in real-time. Also, the use of fuzzy logic systems helps to assess the real-time risk situations associated with fall from height (Rey-Merchan et al., 2022). Furthermore, the IoT enabled drones adopt the use of sensors for abnormality detection and site inspection without the need for human intervention [45,46]. The scalability of IoT platform measures the capability of the system to handle the computation processes for the growth of the network in health and safety analytics. According to KPMG survey, the 95% of the construction organizations conclude that the adoption of the digital technologies such as IoT in the construction industry will impact the profitability of the business processes [47].

3.3. Comparison of Computer Vision and Internet of Things

A major challenge in the adoption and implementation of technologies for onsite health and safety determine the capabilities and relevance of the digital technologies. As such, it is important to draw a comparison between IoT and computer vision across an evaluative metrics [48]. identified the choice of metrics, which includes (a) implementation approach, (b) health and safety hazard detection accuracy, (c) safety hazard type, (d) techniques, and (e) key limitation. The comparison of IoT and computer vision across these metrics is shown in Table 1.

3.4. Health and safety hazard on construction sites

Various health and safety hazards in construction management have been identified in the research articles. According to Fig. 5, the health and safety hazards on construction site include roof fall hazard, construction accident, critical injuries, absence of hard hat, behaviour-based safety, absence of personal protective equipment, fire hazard, intrusion detection, unsafe behaviour and worker conditions, hazardous condition and equipment and fall from height. According to Table 1, the techniques identified to detect health and safety hazards include RFID, optical sensors, Henrich's domino theory, fast R–CNN, naïve Bayes, bounding box image classification amongst others. Hence, Table 2 depicts the identification of the health and safety hazards in the digital technologies using Internet of Things (IoT) and Computer Vision (CV).

Table 2 shows the identification of the health and safety hazard in Computer Vision and Internet of Things. The internal numbers in the table indicate the identification of the type of health and safety hazards with respect to the digital technology i.e., computer vision and Internet of things in the literature. Computer vision performs better on health and safety hazards; the data extraction is achieved from the on-site surveillance cameras which provides better solution for confined construction sites and achieve a higher level of accuracy prediction for on-site health and safety analytics.

3.5. Health and safety hazard identification accuracy

The construction sites require to be observed to discover unsafe behaviour and the protection of the site workers from injuries, fatal accidents, and weather conditions in real time manner. Choudhry in 2014 opined that using inter-observer reliability (IOR) with safety performance of 94% helps to improve the behaviour-based safety on the construction sites. IOR checks are carried out when the writer and an observer independently checklists completed for a construction site using percentage agreement method. The safety performance measures 94% on the construction projects in the construction industry with the use of (IOR) which helps to improve the behaviour-based safety on the construction site. Also, Wang et al., 2019 employed that the detection model based on Faster RCNN to obtain an accuracy of 93% for detecting worker and equipment on construction site and a precision of 87% using spatial temporal relations for site worker safety. For the spatial temporal relations, a precision of 87% achieved on site worker safety. Recently, Wu et al., in 2021 achieved a precision of 75% and recall of 90% on the spatial relationship of images and videos on construction sites using computer vision with semantic reasoning. Also, the unsafe behaviour which includes fall from height can be predicted using computer vision and mobile scaffolds [52]. used deep neural network, Mask R–CNN to detect unsafe behaviour which includes fall from height and obtained a precision of 92% and accuracy of 87% for image detection. As the Personal protective equipment (PPE) protects the site worker against the hazardous conditions on the construction site, therefore detecting PPE on construction site is a great safety concern. The absence of PPE in real-time detects the unsafe conditions and achieves a precision of 90% and recall value of 93% [13]. Computer vision and deep learning techniques enable PPE detection for on-site health and safety analytics. In this vein [65], classified as an unsafe behaviour for site worker to remove hard hat while on construction site. The robustness of the trained YOLO model achieved an accuracy of 96% which validates the performance of the site worker PPE. The model tested on trained images and videos which validated the performance of the algorithm. Furthermore, Deep learning model and LSTM used by Ref. [60] to measure safe and unsafe action achieved accuracy of 97% and 92% respectively [60]. Also, an intelligent helmet identification model using image-based analytics segmentation to determine the presence of helmet on site workers by Ref. [61] provided an accuracy of 91%. The computer vision-based techniques provide real-time monitoring of the spatial relation on the construction site. Furthermore [66], employed computer vision-based techniques to monitor spatial relation achieving precision and recall value of 1 and 0.816 with error estimation less than 0.8 m in 3D spatial proximity. Also, Isleyen et al., 2020 adopted an Artificial Intelligence detection system to detect

Table 1
The performance measure of the comparison of Computer Vision and Internet of Things.

S.no	Evaluative metric	Internet of Things (IoT)	Computer Vision (CV)
1	Implementation approach	- Dependent of the number of connections and hardware devices - Sensor data required. - IoT implementation requires more effort to scale - Require active component connectivity using Wi-Fi, bluetooth, cellular, RFID - Employs intrusive sensors	- Dependent on the nature of data and approach of information visualization - Images and video data required. - Computer vision requires less effort to scale. - Dependent on image capture and model capabilities - Non-intrusive sensors
2	Health and safety hazard detection accuracy	- 65% detection of smoke detector and air quality monitoring for confined spaces.	- 88% detection of unsafe action in the videos [49] - 85% Vision based activity recognition [50] - 87.45% Worker and equipment detection (S.-C [51]. - 86% workers unsafe behaviour [52] - 93% workers proximity detection [53]
3	Safety hazards type	- Personal Protective Equipment (PPE) - Fire hazard - Intrusion detection - Accident prevention - Safety monitoring and compliance - Hazardous condition and equipment	- Roof fall hazard - Critical injuries - Fire Hazard - Intrusion Detection - Unsafe behaviour and worker condition - Accident prevention - Hazardous condition and equipment - Construction quality and safety - Behaviour based safety. - Falls from height. - Hardhat and Helmet detection - Personal Protective Equipment (PPE) - Health and safety monitoring and compliance - Construction accident
4	Techniques	- RFID for intrusion detection [36] - Optical sensors for smoke detection and monitor air quality [13] - Fishbone method to detect hazardous equipment [54] - Heinrich's domino theory to measure the perspectives of the cause of accident [55]	- Naïve Bayes provides better performance for prediction modelling and robustness to measure the accident severity (Eds et al., 2021). - Text segmentation to identify the safety risk factors (Martuser et al., 2018) - Fast R–CNN accurately object identification for the location of the tracked object (Edde et al., 2017) - Position probability grid to model worker location and movement (Anjum et al., 2020) - CNN to measure workers activity (Mark et al., 2018; Vanesse, 2019) - Ontological model for detection of fall from height [56] - Bounding box image classification (Wang et al., 2021)
5	Key Limitations	- Lack of subsystem integration (Baker et al., 2020) - Fixed sensor for each PPE tool result in faulty alarm and the Wi-Fi module is not an energy saver option [57] - Lack of calculation of time and quality in construction projects [58] - Inadequacy of video interface in the fire monitoring system [52] - Identification of restricted zones for accident prevention using image processing techniques [59] - Lack of worker's understanding of personal protective equipment (Mneymneh et al., 2018)	- Requires expertise with training of model. - Inaccurate feature extraction due to shape of hard hat [60] - Reduction in computation power [55] - Lack of regulation of workers wearing helmets on risk sites [61] - Low video resolution for object detection [13,54] - Lack of sub-system integration [62] - Lack of noise cancellation feature [59,63] - Lack of identification of danger zones (M [51]. - Lack of prediction and interpretation for ML models such as support vector machines and artificial neural network [64]

Table 2
Literature - The health and safety hazard types in Computer Vision and Internet of Things.

	Roof fall hazard	Construction accident	Critical Injuries	Absence of Hardhat	Behaviour Based Safety	Absence of Personal Protective Equipment (PPE)	Fire Hazard	Intrusion Detection	Unsafe behaviour and worker conditions	Hazardous Conditions and Equipment	Fall from height
Computer Vision	3	1	1	3	5	1		1	14	6	5
Internet of Things						2	1	1		3	

roof fall hazard which achieves an accuracy of 86%. The model data trained on hazardous and non-hazardous roof conditions. The model predicted an accuracy of 80% hazardous roof condition and 89% accuracy of non-hazardous roof conditions. The prediction of health and safety hazard determines the hazardous conditions and their mitigation on the construction site. The fall-from-height hazards includes all risk of objects that fall from height [64]. used computer vision approaches to reduce the likelihood of the fall from height safety hazard on the construction site. The safety measures were employed for the reduction of fall from height. The average precision and recall value achieved an accuracy of 58% and 74%.

[31] investigated the efficiency and robustness of the IoT system in the lab environment with time lag [31]. The signal strength of safety glasses recorded lower than that of not wearing the safety glasses. The time lag of 1 s was recorded on the construction site which does not over utilize the user threshold. Also, Park et al., 2017 investigated that the position of the site worker determines the severity of the safety hazard. The precise classification of the health and safety hazard could not be achieved. Although, the specificity value of 8% and reliability of the hazard at 98% on the construction site. Therefore, the precise detection of health and safety hazard is an important factor on construction sites. Furthermore [38], investigated that the performance of the intrusion detection for on-site health and safety monitoring include error detection, intrusion distance error and the time delay for the reception of the alarm. An increase in the intrusion detection distance indicates that the mean error and variation will also increase [57]. developed an innovative health and safety model which reduces the cost analysis for on-site worker in real-time. The model predicted cost cut back of 78% and cost saving of 65% compared to the usage of traditional manual and sensor system.

3.6. Key techniques in system development

The key techniques used in Computer Vision and Internet of Things (IoT) to detect health and safety hazard on construction site have been identified. Computer vision uses machine learning algorithms which are used to detect the robustness and measure the severity of the accident. The simple binary classification, logistic regression and Naive Bayes yield good performance while the multi classification problem, the algorithms does not produce good performance on the severity of the construction accidents [67]. Also, the rule operation method helps to assess the risk factors of other health and safety hazards on the construction site. The severity of the accident is dependent on the nature of the occurrence of the accident. The attribute based framework with Natural Language Processing (NLP), predicts safety analysis to deal with the large amount of data in injury prediction [68]. The construction safety risk factors analysed using text mining approach [69]. It will help to prevent the future accidents on the construction site. The framework designed to determine vision based unsafe detection to measure the unsafe actions on the construction site [49]. The distance and location-based proximity enables to predict the risk proximity and alerts the collision hazard to the site worker [50]. The pro-active struck by risk estimates the exposure stability to measure the next worker of the site worker.

Convolutional Neural Network (CNN) based object detection used to detect the wearing of hardhat and assessing worker activities on the construction site. It is an effective mechanism in the risk reduction of brain injury and provides better results for the construction site conditions such as occlusion, visual range, and individual posture [70,71]. Also, the method improves the accuracy of object detection for on-site objects. The Faster Region based convolution neural network (R–CNN) used to capture the semantic relationships and spatial relations of on-site entities (M [51,63]. It enabled to identify the hard-hats, site-worker equipment, and large holes. The large holes are a safety hazard on the construction site. Computer vision and ontology establishes a knowledge graph that leverages the automatic detection and mitigation of safety hazards for on-site safety analytics [58,72]. Mask R–CNN provides good performance on image segmentation which is used to identify unsafe actions such as fall from height achieves an acceptable level of detection accuracy for on-site entities. The images trained to Mask R–CNN stored in Microsoft's Common Objects in Context (MS COCO) which will extract features to test the model [13]. The site inspection ensures quality and safety analytics which reveals the safety hazards and risks on the construction site. Deep learning model and long-term short memory (LSTM) provides a robust solution to identify unsafe behaviour improves safety performance on the construction sites [14,60]. The unsafe action is identified; injury, accidents, and near-miss reports. The human object interaction and computer vision inspects the on-site health and safety analytics from site images and videos [73]. The model validates site worker hand protection and vision-based health and safety through compliance checks. The detection of health and safety hazards and objects in real-time provides an efficient mechanism for the health and safety managers to recognize the hazardous conditions. The detection of unsafe behaviour and mobile scaffolding achieved through Mask R–CNN and object correlation detection (OCD) module [52]. The module enables to identify the co-relation among the working condition and the bounding boxes of the construction objects. Monitoring of the spatial relationship prevents the hazards between on-site and heavy vehicle. The 3D spatial relationship enables to detect the vehicle in real-time and provides proximity estimation among the construction equipment [66]. The roof fall hazards identify the roof conditions which protects the on-site construction objects. An artificial intelligence based system provides detection of hazardous and non-hazardous roof conditions [56]. The roof fall index determines the occurrence of the roof fall hazards. The integrated gradient which is a deep learning technique provides image prediction for the geologic features. The barricades prevent the construction site from the hazards. The missing of barricades gives rise to the health and safety hazards such as fall from height on the construction site. The computer vision detection approaches; masks comparison approach (MCA) and missing object detection approach (MODA) developed to detect the missing barricade [64]. The approaches identify the missing barricades and mitigate the probability of missing barricades. The performance of the computer vision methods evaluated using the approaches, average precision, average recall, and detection frames per second.

Computer vision and deep learning techniques detect personal protective equipment (PPE) using YOLOv3 deep learning network [65]. PPE includes hardhat, shoes, harnesses, gloves, eye protection, safety footwear, etc [74]. The hardhat categorization into safe, not safe, no hardhat and no jacket enabled time stamp and real-time alarm on the construction site. Protection of site worker is important to measure the health and safety hazard on the construction site. The videos accessed from video surveillance system identified the presence of site worker helmet [61]. Image extraction achieved using local binary pattern, hu moment invariants and colour histogram to differentiate the various helmet colours. The intelligent helmet identification detects proactive risk identification and assessment of security hazards on the construction site. In addition, computer vision detects whether the site worker has fully worn the PPE or not which includes helmet, masker, vest, and glove [75]. The experiment conducted in various workplace areas which includes construction site, entrance, and the worksite of the construction machinery. This helped to increase the safety of on-site workers [76]. detected the presence of PPE from real time video input and webcam feed on the construction site using YOLO v4 object detection model. The model detected the presence of mask, face shield and gloves.

The behaviour-based safety (BBS) analysed through requirement gathering, survey and interviews on the constructions site [77]. The measurement result has shown an improvement in the performance of health and safety analytics. Behaviour based safety tracking system and supervisory based intervention cycle developed for BBS safety proved improvement on the construction site [55,78]. The quantitative assessment and cost analysis implemented to achieve persistent safety improvement. The personal protective equipment (PPE) helps in reducing the severity of the accidents, injury prevention and fatal on-site accidents [79]. The framework helped in the identification of the PPE role on the construction projects. The building information modelling (BIM) based intelligent site model for improving the practices in construction management [80]. The built-in safety helmets and other wearable devices provide real time monitoring of the location. It predicts the performance and efficiency of the health and safety hazards and the weather conditions on the construction site.

The internet of things (IoT) connected with other Wi-Fi module achieves the connectivity and productivity on the platform. An automated PPE- Tool pair checking system developed to analyse the health and safety analytics using IoT and wireless Wi-Fi modules tagged on the PPE [31]. The study determines the health and safety of the site worker when working with danger handheld devices on the construction site. The health and safety risks identified through the use of Bluetooth low-energy (BLE) based location detection technology, BIM based hazard and the cloud based platform [36,81]. The real time data collection achieved through cloud-based monitoring system [36]. The integration of IoT with wireless sensor network enable to determine the intelligent real time monitoring and fire control on the construction site [82]. The framework uses fuzzy logic algorithm which analyse the faulty fire nodes and reduction of false alarms. The proactive detection of fire will enable to prevent from severe disaster on the construction sites. A real time intrusion detection framework enhance the health and safety management such as unauthorized intrusion on the construction site [38,57]. The intelligent hardhat enables to alarm the location and identification of the intruder for on-site health and safety analytics. The thermal sensor detects the accurate wear and position of the hardhat on the registered site worker for the construction site. Another health and safety hazard which needs attention is the prevention of the accidents on the construction site. Heinrich's accident-causation theory employed to measure the perspectives of the causation of the accident. The occurrence of the health and safety hazard such as falling from height considered as an unexpected accident on the construction site [83]. detected unexpected accidents on the construction site using convolutional neural network. The model identifies the presence of the construction worker; the distance of the site worker with the concrete which determines the presence of the site worker on the construction site. Also, the model successfully detects the object detection and unsafe behaviour of the safety hazards on the construction site.

3.7. Implementation process of Computer Vision and Internet of Things

The construction sector greatly benefits from data annotation which enables construction experts to identify the construction objects which are present on the construction site, this identification is fundamental to track and understand the construction objects including site worker, roadblocks, barricade, roller, mini dumper etc. Accurate identification of the construction objects and their movement is necessary for conducting the health and safety analytics which ensures the security of on-site workers. The construction site involves a range of tasks, including digging the surface, moving the equipment such as construction pipes, roadblocks, materials loading and off-loading, removal of dangerous materials from site, assembling the barricades etc. Considering a use case when the on-site objects are constantly moving during construction operations, health and safety hazards arise. Some of these health and safety hazards identified in Fig. 5 and existing literature include lack of PPE practice by the site workers, improper demarcation of the danger zones, fire hazards, unsafe behaviour, fall from height etc.

When on-site objects such as excavator, site worker are in close proximity to each other, it can yield to a health and safety hazard leading to substantial risk of injury. Therefore, it is necessary to identify the danger zones and the detection of the proximity of the interrelated on-site objects on the construction site. The IoT retrofitted on the wearable devices such as the PPE worn by the site worker can be used to detect the site activities on the construction site. However, this solution can be costly and requires proper infrastructure to interact with IoT and other Wi-Fi modules on the construction site. An alternative approach is computer vision for health and safety analytics. Computer vision models can be trained to analyse the photos and videos from the construction site detecting the potential health and safety hazards. By coupling computer vision with IoT, it is possible to improve the construction site health and safety analytics.

[53] investigated the state-of-the art framework that encapsulates the image segmentation (computer vision) and sensor-based techniques (Internet of Things) to provide proximity warnings for the health and safety hazards. The framework achieved workers proximity with an accuracy of 93% to detect the static and dynamic hazards [59]. used convolutional neural network to extract the images and identification of the fatal accidents on the construction site. To develop computer vision models, image and Video labelling is a fundamental activity. Fig. 6 shows the screenshot of the Computer Vision Annotation Tool (CVAT) editor after object segmentation. The figure colours correspond to various construction objects which are visible on the construction site which helps to train computer vision models.

Fig. 6. Identification of construction objects on construction site (CVAT).

3.8. Limitations of computer vision and IoT for on-site health and safety management

The nature of the construction site is dynamic as the objects are constantly moving. Due to the dynamic and prevalent on-site working conditions, the site worker safety is a challenging task in the construction industry [60]; M [51]. Therefore, the sites need to be monitored continuously to detect the unsafe action and proactive identification of the fatal accidents and injuries on the construction site [62]. The limitations of using computer vision and IoT to detect health and safety hazards on construction site gathered from the systematic literature in section 3 and described in Fig. 7.

To create a secure and robust health and safety environment on the construction site involves addressing several challenges. Fig. 7 illustrates that occlusion, access to video surveillance data, risk identification of safety hazards and understanding of PPE are the prominent limitations addressed in literature. The occlusion occurs on the construction site when the site vision is not visible due to the construction equipment, hazardous conditions, or the site worker. This requires the use of advanced technologies which shall monitor the construction site, even in obstructed areas. The surveillance cameras are used on the construction site to identify the health and safety hazards has become widespread. In computer vision approaches, a challenging task is to acquire the video surveillance data. Currently, the widespread installation of surveillance cameras on the construction sites captures the image and the videos to monitor and identify the potential health and safety hazards on the construction site (M [51]. To train the model, the images and video are required. Hence, there is minimal human interaction. The appropriate risk identification of the health and safety hazards include the machinery, equipment, danger zones, environmental conditions etc. Understanding the importance of proper PPE is crucial in construction as it provides a barrier between the site worker and potential health and safety hazard. The safety precautions aids to prevent injuries, illnesses, and the vulnerability of the hazard. The danger of the accidents, falls, injuries, and other work-related health concerns can be considerably reduced by wearing the appropriate PPE.

Though, accuracy is not the only measure to predict health and safety hazard [56]. As discussed, the accuracy prediction of the detection of health and safety hazard in computer vision approaches yields higher accuracy as compared to Internet of Things (IoT) as discussed in Table 1. The accuracy of the CV model is dependent on the capture of the image and the implementation of the model. Also, computer vision uses location-based methods to automatically monitor the working conditions of the site worker [70]. On the other hand, IoT requires sensor data and the active connectivity of Wi-Fi, Bluetooth, Cloud infrastructure, Cellular and Radio Frequency Identification (RFID) [84–86]. Automated health and safety monitoring on the construction site enable accurate observation of the conditions on the construction site [81]. Hence, IoT is dependent on the number of active connections and hardware devices.

The Wi-Fi module not considered to be an energy efficient for Internet of Things [31]. The hazard assessment for PPE requires the appropriate selection of the tool pair kit for the identification of on-site health and safety hazards. The results showed that the PPE

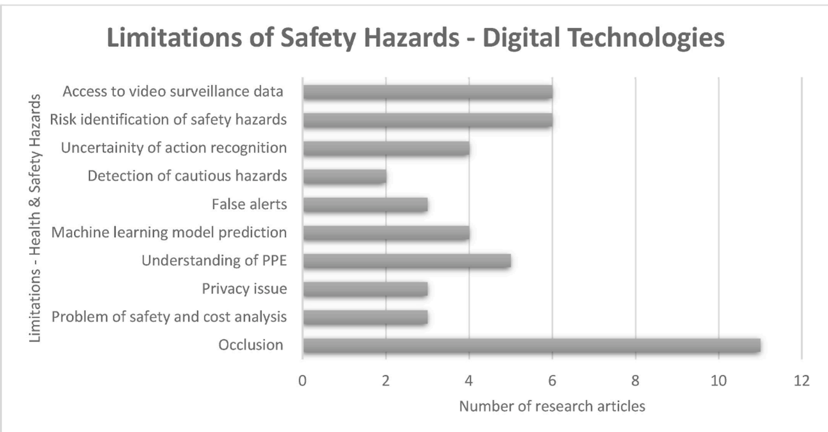

Fig. 7. Limitations of the health and safety hazard in digital technologies.

tool pair kit achieves low cost, portable and identified the PPE requirements for the site worker. In comparison, computer vision based hardhat detection requires high computation and identifies specific risk categories for on-site health and safety hazards. The prediction of health and safety hazards in initial phases of the construction improves the prediction modelling of on-site health and safety hazards using model stacking in machine learning [87].

4. Conclusion and future research

This paper contributes to the construction industry in relation to the on-site health and safety hazards. Firstly, it addresses the dynamic nature of the construction sites, as the objects on the construction site are continuously moving, leading to the hazards for the health and safety. The paper conducts a systematic literature review to investigate the health and safety trends and associated hazards with the digital technologies used in construction applications. Through the identification of the key scholars, the health and safety hazard types, research themes and relevant topics, the review provides valuable insights about the use of digital technologies for on-site health and safety.

Secondly, the paper highlights the specifications and the evaluative metrics for the technologies: Computer Vision and the Internet of Things (IoT). Table 1 in the paper presents the specification and the evaluative metrics, which play a crucial role in the selection of the appropriate technology for on-site health and safety analytics on the construction site. The paper recognizes that IoT is not a standalone technology and highlights the relevance of a stable IoT network connectivity for data transfer. Furthermore, the paper evaluates the prospects of computer vision for on-site health and safety analytics in the construction industry. It suggests that computer vision provides benefits such as improved accuracy prediction, real-time data monitoring, and model development. By analysing these capabilities, the paper highlights the improvement of the health and safety practices on the construction sites.

Although the above results indicate the advantages of computer vision has some advantages over IoT for on-site health and safety analytics in the construction industry, it also recognizes certain limitations. One of the limitations is the computational resource requirement for processing videos acquired from on-site cameras. The study also acknowledges the large amount of data collected from the construction sites to improve the performance of health and safety hazards on the construction site. Therefore, the video analytics can observe the temporal and spatial relationships of the on-site objects on the construction site. Furthermore, the study proposes the inclusion of multistage detection and the integration of 3D depth perception cameras with motion tracking to enhance the accuracy in the detection of the proximity of on-site construction objects. This indicates potential future research direction to integrate these technologies to develop high-level applications to detect the danger zones and alarm for the impending hazards on the construction site.

Author statement

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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.

Data availability

No data was used for the research described in the article.

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