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AI-POWERED GESTURE RECOGNITION FOR OCCUPATIONAL SAFETY IMPROVEMENT IN THE SRI LANKAN CONSTRUCTION INDUSTRY: A CONCEPTUAL MODEL

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ABSTRACT

It is generally accepted that the construction business is one of the most critical industries in which the safety is a paramount need. Even though the traditional safety management measures have been adopted, construction sites still record a high level of occupational accidents. Even though the Artificial Intelligence (AI)-powered gesture recognition has become an option in identifying the unsafe behaviours of workers and facilitating real-time safety interventions, yet it remains a less mature field. As the previous research lacks their focus on AI-based safety monitoring in the construction industry, this paper seeks to conceptualise an AI-powered gesture recognition model to enhance the occupational safety in the Sri Lankan construction sector. A non-systematic literature review was adopted under qualitative phenomenon, drawing on peer-reviewed journals, conference papers, and industry reports from databases including IEEE Xplore, ScienceDirect, Scopus, and Google Scholar, published from 2010 to 2026. The important technological elements, application fields, and implementation strategies of gesture recognition systems in the construction setting were first identified through thematic analysis. Based on these results, an AI-powered gesture recognition model for the Sri Lankan construction sites was conceptualised. The research indicates the possibilities of gesture recognition systems to achieve proactive safety management by real-time identification of dangerous behaviour, better communication, and automatic warnings The study does not involve empirical testing however, it develops a conceptual model based on literature synthesis. Lastly, the paper discusses on the practical issues that are related to the adoption of AI technology in Sri Lankan construction setting and a way forward for future research and practice directions.

Keywords: *Artificial Intelligence; Construction Industry; Gesture Recognition; Occupational Safety Improvement.*

1. INTRODUCTION

The construction industry can be recognised as one of the most unsafe occupational sectors worldwide due to the presence of heavy machinery, complex operations, and

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continuously changing work environments (Zhou et al., 2012; Li et al., 2015). Construction activities often encompass dynamic and temporary site conditions that upsurge the likelihood of accidents and injuries compared with many other industries. Globally, construction accidents remain a major concern since they often result in severe injuries, fatalities, project delays, and financial losses for construction organisations (López-Arquillos et al., 2012). Occupational safety management in construction has become a main requisite in national and international safety policies, procedures, where protective practices can be implemented to prevent injuries, accidents, and health risks among workers during construction operations (Lingard & Rowlinson, 2005). Therefore, improving occupational safety management has become a key priority for the construction industry. Research emphasises the fact that safety management using technological interventions is becoming a more crucial factor to minimise the risks and improve efficiency in operations within a construction setting (Qin et al., 2024).

Modern digital technologies, including Artificial Intelligence (AI), computer vision, and machine learning, have started to be used in the construction industry (in recent years) to enhance occupational safety. Safety monitoring strategies used in the past are mainly based on manual supervision, safety training and written safety procedures. Consequently, scholars have examined technology-based interventions that can be used to automatically detect violations of safety and risky behaviours. The use of AI-based systems, especially deep learning algorithms, has demonstrated promising outcomes in the detection of the use of safety equipment, the control of the activities of workers, and the recognition of the possible risks in the construction site (Islam et al., 2024). Further to the authors, the gesture recognition is one of the new technological methods in this field that is being used to allow computers to learn human gestures using machine learning algorithms and sensors. Gesture recognition technology can recognise movements of hands or body and convert it into commands or safety signs in real time. Hand gestures are widely used in construction settings as workers interact with crane operators, equipment drivers and other workers within the same group of people, especially in a noisy setting where they cannot easily communicate verbally. It has been shown that it is possible to use automated gesture recognition algorithms based on computer vision or wearable devices to identify worker gestures and recognise them to command the machine or monitor safety including heavy machinery operation, crane and heavy equipment signalling and fall hazard detection (Bangaru et al., 2020; Wang and Zhu, 2021; Wei et al., 2025). To illustrate, the frameworks of gesture recognition have been constructed to automatically decode construction worker hand signals and facilitate the human-machine interaction in construction activities (Wang et al., 2021).

Thus, there is still a gap in research in the application of AI-based gesture recognition systems to enhance occupational safety management in the Sri Lankan construction sector. Although gesture recognition frameworks have advanced significantly in global construction research since 2021, there remains a lack of implementation within the Sri Lankan construction industry. This gap is largely attributed to contextual constraints such as financial limitations, regulatory conditions, and site-level operational differences specific to Sri Lanka (Maduwage et al., 2025). The study positions its contribution as a conceptual model rather than an applied system. In addition, the limitations related to practical implementation are explicitly addressed in the discussion section to ensure transparency and contextual relevance. To this end, the current study aims to adopt the AI-based gesture recognition technology for occupational safety improvement in construction, and this paper presents the development of an AI-based gesture recognition model to improve the occupational safety practices in the Sri Lankan construction industry. Accordingly, three objectives were formulated as; (1) review the modern technologies use for occupational safety improvement in construction emphasising AI-powered gesture recognition technology, (2) identify the different applications of AI-powered gesture recognition for occupational safety improvement, and (3) propose an AI-powered gesture recognition model to enhance the occupational safety in the Sri Lankan construction sector. While Objectives 1 and 2 focus on synthesising knowledge to establish contextual relevance, Objective 3 constitutes the primary contribution of this study by conceptualising an AI-powered gesture recognition model specifically for Sri Lankan construction industry.

2. LITERATURE REVIEW

2.1 OCCUPATIONAL SAFETY RISKS IN CONSTRUCTION

Construction business is universally known as one of the main drivers of the world economic growth, but it has a longstanding image of being among the most dangerous industries to human labour force. Most recent statistics show that the construction industry plays a significant role in the development of a country, with the contributing figures of about 13% to the Gross Domestic Product (GDP) in the world (Bilim, 2025). Nevertheless, a high number of incidents at the workplace regularly dampens this economic vitality, with the sector contributing to some 35 percent of all occupational deaths in the world (Kamalruzaman et al., 2026). Building sites are dynamic as they are associated with changing hazards that change depending on the project stage (Jayasundara & Eranga, 2025). Falls, struck by, caught-in/between, and electrocution still prevail in the field of safety across the world (Weerakoon, et al, 2025). Common risks caused by scaffolds and lifting equipment continue to be seen on any site despite any existing safety measures (Wei et al., 2025). The use of heavy machinery poses serious threats to the workers, which is a characteristic feature of high-rise buildings construction and results in long-term disability and loss of income. On the job, employees become exposed to awkward working postures and manual handling of materials, which causes musculoskeletal diseases including neck strains and back pains (Sarathkumar & Boopathi, 2026). As summarised in Table 1, the construction industry involves constant activity in high-force and high-exertion activities that around unpredictable areas.

Table 1: Types of safety risks in construction and their health outcomes

Trade/Activity	Primary Ergonomic/Physical Risks	Health/Safety Outcome	Reference
Excavation	Vibration, awkward postures	Back injuries, lower body stress	Schneider and Susi, (2023)
Masonry	Heavy lifting, repetitive bending	Lower back stress, sprains	Schneider and Susi, (2023)
Steel Work	Squatting, kneeling	Musculoskeletal strain	Dhakal and Giri, (2024)
Finishing	Repetitive movements	Musculoskeletal pain	Sarathkumar and Boopathi, (2026)

An example of this is structural steel work, which entails welding work that is usually performed in squatting or kneeling. In addition to physical trauma, construction employees work in stressful conditions that also lead to a very high probability of psychological trauma (Rahman et al., 2024). The situation can lead to accidents because the heavy machinery caused high noise levels, which can affect communication and situational awareness.

2.2 USE OF AI TECHNOLOGIES FOR OCCUPATIONAL SAFETY IMPROVEMENT IN CONSTRUCTION

Modern AI technologies incorporated in the construction sector have greatly enhanced occupational safety in that it allows to manage risks proactively, as well as to increase the competency of workers. The use of AI-based systems has demonstrated favourable outcomes in revealing the use of safety equipment, the control of the activities of workers, and the recognition of the possible risks in the construction site (Islam et al., 2024; Qin et al., 2024). Additionally, convolutional neural networks and object detection systems are examples of AI devices utilised in autonomously processing visual data that have been obtained with cameras or sensors, thus enhancing compliance with safety and lowering the risk of human error in safety supervision (Qin et al., 2024). The gesture recognition has been one of the new technological methods in this field that is being used to allow computers to learn human gestures using machine learning algorithms and sensors (Cui et al., 2025).

2.3 SYSTEM ARCHITECTURE OF AI-POWERED GESTURE RECOGNITION TECHNOLOGY

A gesture recognition system architecture based on AI, presented in Figure 1, is a hierarchical process that converts physical hand movements into a digital command. The general idea of this architecture is a data-acquisition module, pre-processing and feature-extraction module, deep learning-based recognition, and command execution are usually included in the pipeline between sensing and action (Cui et al., 2025).

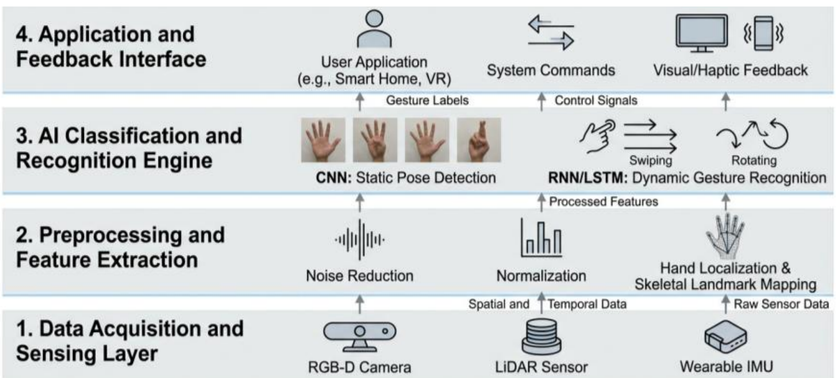

Figure 1: AI-powered gesture recognition for human interaction - system architecture (Author constructed)

The input and data acquisition module forms the base of the system and is charged with the duty of receiving raw gesture data of different sensors. The typical hardware will be RGB-D cameras and motion capture devices, which are able to address spatial and depth details that are important in precise hand tracking. As an example, the Leap Motion and the like depth cameras can measure the three-dimensional position of the hand joints, which allows the precise detection of gestures. Inertial Measurement Units (IMUs) or radar sensors can also be employed to capture motion features in the environment in which camera data might be constrained. After this, the raw data is sent to the pre-processing and feature extraction module that pre-processes the data ready to be analysed by removing noise and identifying meaningful patterns. Image pre-process normally involves background subtraction, normalisation and segmentation to isolate the region of the hand. Spatial characteristics including the positions and movements of fingers are then removed. These features are usually learned by deep learning models; however, traditional methods can take engineered descriptors in feature selection followed by classification (Cui et al., 2025; Nogales & Benalcázar, 2023). The AI-based recognition unit consists of deep learning structures to recognize certain gestures. Convolutional neural networks (CNNs) are designed to learn spatial patterns, which are based on image data, and recurrent or hybrid networks also incorporate temporal information in the dynamic gesture sequences. Research shows that a CNNs-temporal network such as LSTM can be used to enhance the accuracy of dynamic gesture recognition in real time (Cui et al., 2025).

There is a command execution and interface module where the identified gestures are mapped to system actions. The gesture recognition output is connected to external devices or software through protocols and middleware including the Robot Operating System (ROS). Visual or auditory and haptic feedback on this module could also be used to show a successful gesture recognition to enhance the user interface and system stability in real time usage. Systems that are designed based on these principles have been implemented at consumer interfaces, and robotics as well as assistive technologies (Cui et al., 2025).

2.4 OCCUPATIONAL SAFETY IN SRI LANKAN CONSTRUCTION INDUSTRY

The Sri Lankan construction industry has been on a boom in the past decade, with the GDP reporting a large growth (Melagoda & Rowlinson, 2022). Over 600,000 people earn their livelihoods through the industry, which accounts to over 7% of the number of active workforce (Jayasundara & Eranga, 2025). Nonetheless, it has a dismal safety track record, which has caused 30% of all industrial accidents in the country (Weerakoon, et al, 2025). Overall applicability of sustainable practices to manage construction wood waste is very low in Sri Lanka because of the prevailing barriers. One of the significant obstacles that have been highlighted to hinder the application of sustainable management in local locations is financial constraints (Maduwage et al., 2025). It was found that health and safety training carried out on large-scale projects does not allow reaching the necessary level (Kumara, 2023).

To modify the attitude of workers, changes in the policy, legislation, and institutional framework were necessary to impose temperature checks and a one-meter social distance on all locations during the COVID-19 pandemic (Construction Industry Development Authority, [CIDA], 2024). These instructions require appointing special supervisors to control the following hygiene standards (CIDA, 2024). The cast in-situ and bored reinforced concrete piles have safety requirements that ensure that all the open boreholes should be covered to avoid accidents (CIDA, 2016). There is several key legislations and policies in Sri Lanka for occupational health and safety in construction. For example, the CIDA (2016) Guidelines introduce piling operations and site-specific safety measures, which is issued jointly by CIDA and ICTAD (CIDA, 2016). The Factories Ordinance (1942) also provides general occupational health, safety and welfare provisions. This ordinance regulates the registration of factories including construction organisations, and daily removal of refuse to maintain workroom cleanliness (Factories Ordinance, 1942). However, the practical adaptation of the modern technology for safety improvements to the local industry context remains a challenge.

Although there are existing regulations in place regarding occupational health and safety within the Sri Lankan construction industry, the successful implementation of safety management practices is limited by some systemic barriers (Weerakoon, et al, 2025). The overall adoption of sustainable management practices in the sector is relatively low, primarily attributed to financial constraints which limit investment in upgrading technologies, training programmes and safety infrastructure (Maduwage et al., 2025). This is compounded by the lack of good skills development, with current health and safety training on large scale projects being found lacking in providing the competence of workers and supervisors (Kumara, 2023). Many construction firms have therefore continued to use traditional safety management practices which restricts their capacity to embrace innovative and technology-driven solutions for hazard identification, risk mitigation, and behavioural safety monitoring (Kumara, 2023; Weerakoon, et al, 2025). All these barriers together help to perpetuate unsafe work environments and slow the advancement of a more proactive and sustainable culture for safety within the industry (Maduwage et al., 2025; Weerakoon, et al, 2025).

Accordingly, the VOSviewer map in Figure 2 presents the main ideas behind the study. The VOSviewer visualisation revealed the clusters of the world safety technologies, and their low relationship with the local construction industry, which reflected the gap in research.

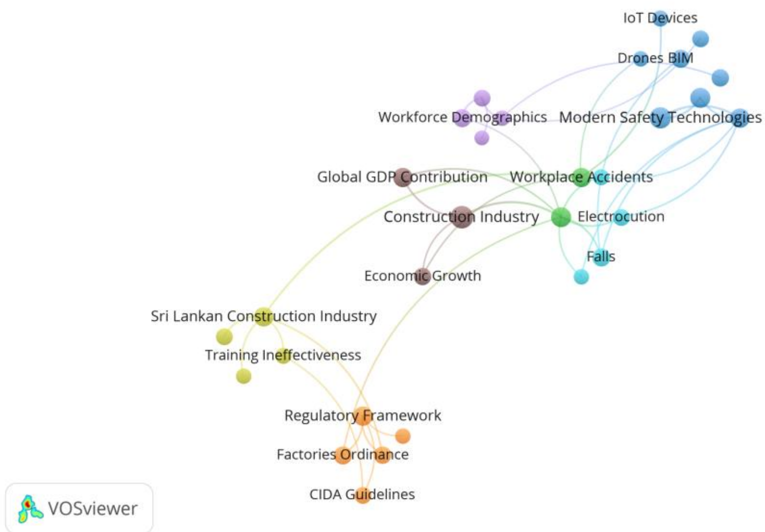

Figure 2: Research gaps visualisation

At the middle in the map are the construction industry and workplace accidents, which connect different research themes. In the top-right, a dark blue cluster characterises modern safety technologies, such as Building Information Modelling, Drones, and IoT devices (Manzoor et al., 2025). This indicates how digital tools can assist to manage the safety risks in real time. In contrast, the bottom-left yellow and orange cluster focuses on the safety risks in the Sri Lankan construction industry, where issues such as poor training and old regulations dominate. The weak connection between these two clusters shows the research gap while the global industry uses advanced technology for safety. Sri Lanka still relies on basic rules and thus this study focuses on an AI-powered gesture recognition as a new opportunity to modernise safety monitoring locally.

3. RESEARCH METHODOLOGY

The research approach chosen in this study was qualitative research because it focused on studying the opportunities of gesture recognition based on AI to increase occupant safety in the Sri Lankan construction sector. The qualitative approach was adopted because it can be used to gain a deeper understanding of the research phenomenon (Yin, 2018) into the technological, organisational, and regulatory conditions that influence the implementation of AI-based safety interventions in construction.

The emerging and multidisciplinary nature of AI gesture recognition for construction safety, the narrow scope of directly relevant literature, and the requirement for a flexible and exploratory synthesis made a non-systematic literature review more appropriate than a protocol-driven systematic review (Yin, 2018). In addition, the literature search process followed the recommendations of Xiao and Watson (2019) who stated the necessity of systematic search procedures, transparency of inclusion and exclusion criteria and detailed consolidation of results when constructing conceptual contributions. Literature review is useful for summarising existing information, being able to pinpoint the holes in the research and creating conceptual models for new areas of study, according to Snyder (2019). A thematic analysis technique was used to identify, organise and interpret the common themes from literature reviewed. Themes were identified in an emergent way, rather than predetermined by a coding matrix, following the inductive coding process proposed by Braun and Clarke (2006). The search initially retrieved 124 publications. Following screening against the inclusion and exclusion criteria, 58 studies were retained for detailed review.

The keyword search string [("gesture recognition" OR "activity recognition" OR "human activity recognition") AND ("construction safety" OR "construction health and safety") AND ("artificial intelligence" OR "AI" OR ''computer vision" OR "machine learning" AND ("Sri Lankan construction industry" OR "global construction industry")] was used to conduct the queries on a variety of peer-reviewed journals, conference papers, and industry reports on the IEEE Xplore, ScienceDirect, Scopus and Google Scholar databases. The search included only English-language peer-reviewed sources that were published from 2010 to 2026. Only papers related to construction safety, AI-based gesture recognition, or activity recognition and Sri Lankan or global construction practices were selected from the initial pool of papers retrieved, while non-peer-reviewed papers, non-English papers and out of scope papers were excluded. Findings were synthesised emergently from the literature and analysed using the thematic analysis technique. The keyword co-occurrence analysis was used to analyse the relationships between the common research keywords. Three occurrences of the keywords were used as the minimum threshold to increase the reliability and clarity of the network visualisation. The VOSviewer software was chosen, as it is well-known and used for bibliometric mapping and offers a good tool for the visualization of thematic clusters, research relations, and emerging gaps in knowledge in multidisciplinary research fields. The resulting visualisation helped to pinpoint the lack of linkage between the global developments in

AI-enabled construction safety technologies and their application in the Sri Lankan construction industry, which aided in the development of the research gap of the study.

4. DATA ANALYSIS AND FINDINGS

4.1 APPLICATIONS OF AI-POWERED GESTURE RECOGNITION FOR OCCUPATIONAL SAFETY IMPROVEMENT

Gesture recognition using AI is becoming more commonly used in occupational safety systems to track worker movements, detect potentially unsafe behaviour and allow a safer approach to working with machinery and equipment in hazardous settings like construction and manufacturing industries. Such systems are usually based on computer vision and sensor-related technologies to track human body movements and convert them into digital signals that can activate safety warning systems or equipment control. Among the most popular technologies is the use of vision-based gesture recognition, which is based on an RGB camera, RGB-D camera, or infrared camera along with a neural network that detects the gestures of workers, their body position, and adherence to safety rules in real time (Zhou et al., 2023). Wearable sensing technologies are widespread, especially Inertial Measurement Units (IMUs) that combine accelerators, gyroscopes, and magnetometers to measure body motions including climbing, bending, or falling, hence AI models can classify the activities of workers and determine the possible dangers (Park et al., 2025). Moreover, through motion capture systems and optical tracking technologies, there are multicamera or markers which are used in rebuilding the 3D body movements to ensure accurate gesture recognition in dynamic work settings (Menache, 2010). Additional new creative technologies are the ElectroMyoGraphy (EMG) sensors, LiDAR, capacitive sensors, and smart gloves, which will be able to detect finer finger movements and enhance the interpretation of more complex gestures used to control a machine or communicate with a crane (Wei et al., 2025). Example applications of AI-powered gesture recognition for safety Improvements including related technologies and safety functions are summarised in Table 2.

Table 2: Applications of AI-powered gesture recognition technology for safety

Applications in Occupational Safety	Technology Used	Safety Function	Key References
Worker posture and activity monitoring	Computer vision using RGB cameras and deep learning algorithms	Detects unsafe worker movements and monitors compliance with safety procedures	Zhou et al., 2023
Contactless machinery operation	RGB-D cameras and vision-based gesture recognition systems	Enables workers to control equipment using predefined hand gestures, reducing physical interaction with hazardous machines	Rena and Kim, (2025)
Crane and heavy equipment signalling	AI-based hand signal recognition with video analytics	Automatically interprets standard crane hand signals and improves communication	Wei et al., (2025)

Applications in Occupational Safety	Technology Used	Safety Function	Key References
		between operators and workers	
Worker falls and abnormal motion detection	Wearable sensors such as inertial measurement units (IMU), accelerometers, and gyroscopes	Identifies slips, falls, and unusual body movements that may indicate accidents or fatigue	Park et al., (2025)
Ergonomic and motion risk analysis	Optical motion capture and three-dimensional tracking systems	Evaluates body movement patterns to prevent musculoskeletal injuries in physically demanding tasks	Menache, (2010)

Accordingly, based on the literature reviewed, an AI-based gesture recognition model is conceptualised expecting to close the distance between the safety technologies that are already available globally and their application to the Sri Lankan construction sites.

4.2 AI-POWERED GESTURE RECOGNITION FOR OCCUPATIONAL SAFETY IMPROVEMENT IN CONSTRUCTION INDUSTRY (PROPOSED MODEL)

Based on the reviewed key literature, the AI-powered gesture recognition model was conceptualised consisting of four stages; (1) Data acquisition, (2) AI processing, (3) Real-time action, and (4) Compliance management as shown in Figure 3.

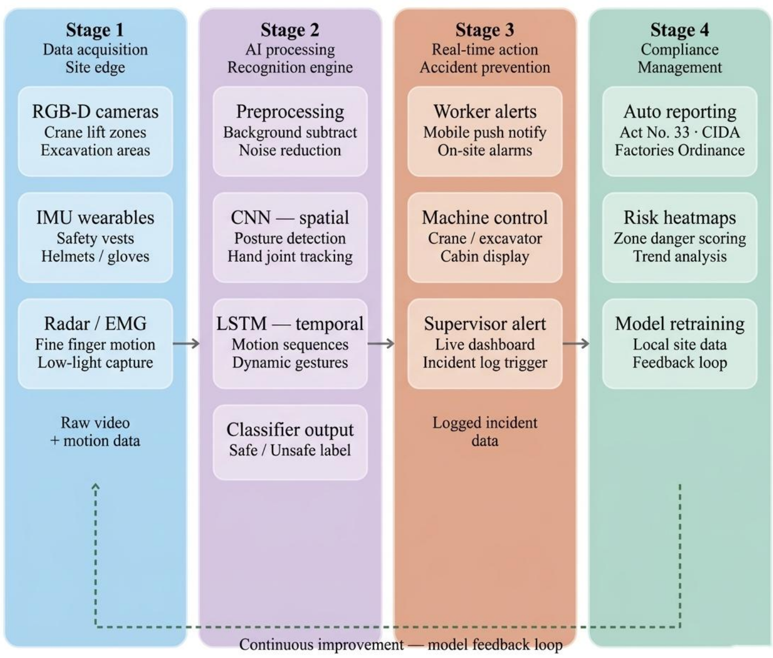

Figure 1: AI-powered gesture recognition - proposed model

Stage 1 is inspired by the sensor architectures proposed by Cui et al. (2025) and Wang and Zhu (2021). The CNN-LSTM recognition frameworks reported by Cui et al. (2025)

are used for Stage 2. Islam et al. (2024) identified the real-time intervention approaches in Stage 3. Stage 4 includes compliance requirements as per Factories Ordinance (1942), Construction Industry Development Act No. 33 of 2014 and CIDA guidelines. In the proposed model, Stage 1 is the sensory base, which captures physical movement and positional data based on RGB-D cameras mounted at the crane lifting points and excavation periphery, IMU wearables integrated in the safety vests and helmets, as well as auxiliary radar and EMG sensors which identify fine-grained finger movements during obstructed or low-light operations (Rena and Kim, 2025). This multimodal sensor fusion design guarantees that none of the failure points of any sensor in the system can cause the system to go blind to the unfolding hazard, which offers the rich and redundant data streams with which the downstream AI engine will operate with sufficient reliability in the unpredictable conditions of an active construction site. The raw data input here directly drives into the Stage 2, which is the AI recognition engine, then pre-processing routines, such as background subtraction, normalisation, and silhouette segmentation, purify the incoming streams and then input into the hybrid deep learning architecture. Each frame is fed to a Convolutional Neural Network (CNN) to obtain spatial posture and hand joint configuration information and the sequence of CNN outputs over time is fed to a Long Short-Term Memory network to obtain the temporal sequence of changing gestures: Is this an incidental arm movement or an intentional crane signaller stop gesture? The CNN-LSTM classifier together gives a binary safe or unsafe result, which is used as the trigger of all downstream intervention. When a dangerous gesture or posture is detected, Stage 3 instigates three parallel response lines in parallel without needing any intermediary action of a human such as is necessary in the traditional safety management based on supervision, which is the key difference between this system and the traditional safety management of the system which relies on supervision. Mobile push notifications and on-site audible alarms ensure that workers in the hazard zone are alerted immediately when a warning is needed and, in those situations, when a worker is not looking at the screen. At the same time, the system communicates directly with the control systems of the surrounding heavy equipment, sending stop or slow-down signals to crane and excavator operators cabs, and in some settings, automatically stopping the system before any physical contact may happen. A third channel also informs supervisors via a live dashboard, recording every incident in a time-stamped record of the type of gesture, location, and the workers and the machinery in operation that provides an audit trail directly to the compliance functions of Stage 4.

Stage 4 completes the loop of operation by transforming accumulated incidents data to automated compliance reports in line with the Construction Industry Development Act No. 33 of 2014 of Sri Lanka (Construction Industry Development Act, 2014), the Factories Ordinance of 1942 and the CIDA Guidelines. Heatmaps of risk zones created on the basis of aggregated location data allows visual identification of locations on a site that continually lead to unsafe behaviours, based on which redesign, supervision, or training intervention can be targeted, and a trend analysis allows the safety managers with the evidence base to understand whether the frequency of harmful incidents is decreasing with time.

Most importantly, the feedback loop between Stage 4 and Stage 1 is the constant improvement loop of the system, as the deployed model receives more and more labelled incident data, reflecting local hand signals, local site-specific postural patterns and local environmental conditions, this data is used to periodically induct the Stage 2 classifier, gradually minimising the number of false positives that cause unnecessary perturbations to the system and false negatives that lets real hazards escape detection. It makes the system no longer a fixed deployment of technology, yet an adaptive safety infrastructure gradually becoming more effective as it spends time in. As the underlying AI concepts used on the proposed model were mostly derived from international research, the model was conceptualised to be adopted in the Sri Lankan construction industry by aligning its stages to reduce the occupational safety risks. However, additional empirical validation through industry expert feedback and real industry cases studies are required to further strengthen the applicability of the model within the Sri Lankan construction industry, which will be carried out as the next stage of the research.

5. DISCUSSION

While the proposed model is technically robust and contextually informed, the application in the Sri Lankan construction sector is associated with a very specific set of structural, financial, and institutional difficulties that should not be ignored in case the implementation process can be taken outside the realm of the conceptual phase. The barrier that is most readily visible is the financial constraint. As Maduwage et al. (2025) remark, financial constraints are one of the greatest inhibiters to the implementation of sustainable and technology-driven practice in Sri Lankan construction, and the capital investment to implement RGB-D camera networks, IMU wearables, and deep learning infrastructure in many of the active locations would be cost-prohibitive to the small and medium-sized contractors that form the bulk of the local industry. The human capital aspect is equally a big issue outside of the cost dimension. Even on large-scale projects in Sri Lanka, health and safety training has been identified lower than the required standard (Kumara, 2023). Further, it can be inferred that the current workforce and the supervisory cadres lack the necessary digital literacy and technical familiarity with an AI-driven safety system to operate, analyse, and maintain. The model of gesture recognition that is introduced here does not only require that the hardware itself works properly but also that the site supervisors can properly react to the dashboard alerts and that the workers learn to see the significance of monitoring their movements in the first place and that the maintenance personnel can competently act as trouble-shooters of the sensor malfunctions, which can hardly be assumed of the local community under the present conditions without significant and long-lasting financing of the training (Weerakoon, et al, 2025). It may be possible that workers will consider constant gestures tracking as a form of surveillance, not protection, and create resistance to adoption that may ruin the efficiency of the system in case the technical infrastructure is implemented successfully. The technical challenges to the performance of the system also arise due to the dynamic and volatile nature of construction sites, where work zones, sightlines, and personnel layouts vary on a daily basis, which means that the classifier trained on one set of conditions will show higher rates of false positive or false negative results when presented with a different set of conditions, especially at the beginning of deployment when the feedback retraining loop does not have enough local data to work with (Cui et al., 2025). The combination of these issues highlights the fact that the successful implementation of AI gesture recognition into the Sri Lankan construction is not merely an issue of technology acquisition but a structural change management issue that needs to be addressed on a coordinated basis in the financial, institutional, regulatory, and human capital sectors. However, since this study confirms a non-empirical contribution through a secondary data analysis and by conceptualising the AI-powered gesture recognition model, the next stage will be focused on validating the proposed model in a real construction industry context for further strengthening and generalising the contribution of this research.

6. CONCLUSIONS AND A WAY FORWARD

This paper has presented a conceptual AI-driven gesture recognition model which is specifically targeted to enhance occupational safety in the Sri Lankan construction sector. Based on a substantial literature review, the study highlighted a great gap in the research and practice whereas the global construction industry has been increasingly embracing innovative digital safety tools and AI-based computer vision, in Sri Lanka yet it remains a less mature field. Hence, a four-stage model was suggested by the authors, including the multimodal site data acquisition, hybrid CNN-LSTM gesture detection, real-time multi-channel safety intervention, and compliance-consistent management reporting, with the feedback loop constituting the fourth stage, which can be viewed as a context-related response to this gap, incorporating the technical architecture of the offerings in the international literature and the regulatory framework in Sri Lanka.

To take a step into the future, several recommendations are suggested in both research and practice. Pilot deployments on larger scale infrastructure projects where budgets, technical oversight, and regulatory review are stronger, would supply the gestures datasets localised to the locals that would allow Stage 2 classifier to be intuitively retrained to the Sri Lankan context to overcome the data localisation issue that the existing conceptual model would fail to overcome by design alone. The next step of this research will be focused on the evolution of the qualitative and conceptual methodology chosen here into the empirical analysis, such as the quantitative field studies which will estimate the accuracy of gesture categorisation under the conditions of real Sri Lankan sites, the ergonomic research on the wearable sensor compatibility with the current personal protective equipment, and the cost-benefits studies that will be able to model the safety investment payback at various levels of deployment. Finally, the shift in occupational safety management in the construction industry of Sri Lanka between being reactive and proactive will need not only the technical systems outlined in this model, but also a more extensive cultural and institutional reorientation towards occupational safety as a measurable and technology-driven performance goal.

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