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Indoor Safety Monitoring for Falls or Restricted Areas Using Wi-Fi Channel State Information and Deep Learning Methods in Mega Building Construction Projects

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Abstract: With the trend of sustainable development growing worldwide, both the numbers of new mega building construction projects and renovations to existing high-rise buildings are increasing. At such construction sites, most construction workers can be described as performing various activities in indoor spaces. The literature shows that the indoor safety protection measures in such construction sites are often imperfect, resulting in an endless stream of incidents such as falls. Thus, this research aims at developing a flexible indoor safety warning system, based on Wi-Fi-generated channel state information (CSI), for monitoring the construction workers approaching restricted areas or floor openings. In the proposed approach, construction workers do not have to carry any sensors, and each indoor space only needs to have the specified Wi-Fi devices installed. Since deep learning methods are employed to analyze the CSI data collected, the total deployment time, including setting up the Wi-Fi devices and performing data collection and training work, has been measured. Efficiency and effectiveness of the developed system, along with further developments, have been evaluated and discussed by 12 construction safety experts. It is expected that the proposed approach can be enhanced to accommodate other types of safety hazards and be implemented in all mega building construction projects so that the construction workers can have safer working environments.

Keywords: channel state information (CSI); deep learning; fall accident; construction safety

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1. Introduction

As the global population escalates, the number of new skyscrapers around the world is increasing [1,2]. Although there is no universally accepted definition, a skyscraper can be regarded as a very tall high-rise building with at least 100 m high and has become a common sight where the land is expensive (e.g., in the centers of big cities) [3]. Another trend with rising populations is that more and more existing, old high-rise buildings need to be renovated to accommodate new dwellers in communities in a short period of time [4]. Indeed, all such construction or renovation work can be classified into the mega building construction project type since there can be thousands of construction workers performing their jobs at the same time.

Previous literature shows that in the United States, approximately 20% of job-related deaths occur in the construction industry [5]. On top of that, the construction sites located in commercial and residential areas account for 30% of all such fatal accidents [5]. Falls remain the most common cause of deaths, and the literature shows that one-third of all fatalities is a result of falls or related accidents [5]. Since a mega building construction project can involve more construction workers at the same time than a typical construction site, it can be estimated that there are more construction safety incidents in these types of projects [6–8]. Nevertheless, nowadays governments and/or organizations worldwide are eager to achieve various Sustainable Development Goals (SDGs) [2,4], one of which is to ensure safe working environments. In other words, the safety of construction sites needs to be maintained [5,9], especially for mega building construction projects.

In fact, numerous approaches have been proposed to avoid the fall type of accidents for construction safety, which can be simply divided into the active and passive systems [7,9]. The former, such as personal fall protection (PFP), uses an extra harness to actively protect a construction worker from falling, which is primarily utilized in outdoor spaces such as roofs and may significantly reduce the construction worker's mobility [7]. The latter, such as guardrails, floor covers, and sensors with warning mechanisms, strives to avoid a construction worker from approaching floor openings or restricted areas and usually requires much time to set up the system [9]. For instance, when one part or material of guardrails is missing, it may take a few days to a week to get the guardrails installed [5]. Once the line of sight in construction sites is poor, the probability of having falls or related accidents is high [5,9]. For sensor-based fall prevention systems, each construction worker has to carry the sensor(s), and all sensor-generated data need to be well collected [10]. However, such assumptions seem to be unrealistic since construction sites are complex and dynamic in nature [11,12], and the quality of the sensory data collected varies significantly due to versatile field communication and/or sensors calibration problems. Thus, additional time is required for re-collecting or re-processing the data. Hence, the warnings made by such systems are often not immediate, significantly reducing their usefulness [13,14].

Therefore, the research area of this manuscript is concentrated on the construction safety fall situations in mega building construction projects. Specifically, this research aims at developing a passive, indoor safety warning system, based on Wi-Fi-generated channel state information (CSI), for falls or related accidents. Once a construction worker approaches any of indoor restricted areas such as floor openings, an alarm will be triggered to remind him or her. Use of CSI requires the installation of a regular wireless access point (WAP) at one end of an indoor space, as well as the installation of another special wireless network interface card (NIC) at the other end of the space [15]. A customized software program is also needed so as to collect and analyze the received Wi-Fi CSI data set. Nevertheless, no sensor needs to be carried by human beings. By analyzing CSI data, the literature shows that people's standing position, facing orientation, squatting or bending over, walking gait, etc., can be detected or recognized if appropriate algorithms are employed [16–18]. In recent years, as deep learning technology has become more and more mature, deep learning algorithms have gradually become one of the most promising methods to analyze applications such as CSI with a large amount of data [19–24]. Further, the current deep learning technology has proved that as long as the size of the CSI data set collected is adequate, even if the data set contains erroneous values or does not cover the full range of data, meaningful results will still be produced [22,23,25–27]. In addition to the CSI-related hardware and software issues, the deployment time of such an indoor safety warning system, including the hardware installation time and the data collection and analysis time, cannot be long. Only when the aforementioned requirements are met, field safety managers can quickly implement the proposed approach to each of the indoor spaces that requires attention to construction safety for mega building construction projects. To this end, the manuscript is structured as follows: Section 2 introduces related literature. Section 3 describes the proposed approach, including deep learning algorithms used and the collection and analysis of the Wi-Fi-generated CSI data. Section 4 discusses the verification and validation of the proposed approach, followed by research conclusions and future work.

2. Related Work

2.1. Mega Building Construction Projects and Construction Safety

Today, new skyscrapers or high-rise buildings are still needed in many of the developed or developing countries since the population of urban areas in these countries has continued to increase [3]. In addition, since existing, old buildings in urban communities are usually difficult to achieve the goal of energy conservation and carbon reduction, from the government's perspective large-scale renovation for such buildings must be carried out in order to realize the ambition of the SDGs [4]. In such a construction or renovation site, thousands of construction workers may all work for the same mega building construction project [2,4,6,8]. Investigation on construction safety for this type of projects has become an imperative. Otherwise there would be more fatal accidents since the durations of such projects are longer with more participants [9].

In fact, the literature shows that the construction industry is the industry most prone to fatal accidents [14,28–31]. In the UK, the construction industry accounts for one-third of all occupational fatalities [9]. In the United States, the construction industry has a maximum of 26 deaths per 100,000 people per year from 2010 to 2012, accounting for between 17% and 20% of all fatal occupational injuries [5]. A recent report shows that in China an average of 725 people died each year due to construction-related accidents [28].

A UK research report shows that in the construction industry, 11% of fatal accidents occurred at the beginning of the project, 58% occurred in the middle of the project, 9% occurred at the later stage of the project, 7% occurred at the end of the project, and 15% occurred after the end of the project, which includes subsequent decoration works [9]. The same report shows that 4% of fatal accidents in the construction industry occurred in design and engineering firms, 25% in the contractors or subcontractors for civil or infrastructure construction, 49% in the contractors or subcontractors for office buildings construction, and 22% in the contractors or subcontractors for residential buildings construction [9]. From the aforementioned statistics, it can be seen that building construction sites are the largest accident place [5,30]. Additionally, more accidents indeed occur after the superstructure of a building has been completed, which can be proved by the fact that most of the accidents happen in the middle or late stages of the project [9]. During this period of time, many construction workers are engaged in various indoor jobs [9]. There may be several hazards on such an indoor construction site, such as unfinished doors, windows, elevators, stairs, etc., but after all, it is still an indoor environment with basic space configuration and power supply services [9]. Safety-related equipment or devices should be able to be installed or deployed here. Nevertheless, few past studies have used the characteristics of indoor construction sites to explore how to improve construction safety.

The fall type of accidents, which can be defined as people falling from height or struck by falling object, has been identified as the most frequent accidents happened in the construction industry worldwide [2]. In China, falls from a high place are the dominant type of construction accident, accounting for 51.7% of all accidents [32]. Previous studies indicated that the management of indoor workers' positions is often utilized to achieve indoor safety monitoring (i.e., to manage workers' positions and to keep them out of danger areas so as to prevent falls) [33–36]. Researchers have enumerated the factors leading to falls, which include but are not limited to, failure of safety net systems, floor openings not covered, personal factors such as bad temper and misbehavior of workers, no safety checks, no safety signs, no on site monitoring systems of workers, no location tracking of workers, poor quality of PPE used, failure to provide PPE, negligence in using safety belts in heights, bad work conditions such as poor housekeeping, hot and rainy weather, dusty and noisy conditions, fire hazards, low knowledge and skill level of workers, strong winds when working at height, etc. [1,2,7–9]. Other researchers investigated the risks associated with falls for high-rise buildings construction and classified such risks into five types: (1) environmental risk; (2) financial risk; (3) political risk; (4) social risk; and (5) technical risk [8].

In the United States, the Occupational Safety and Health Administration (OSHA) defines a floor opening as an opening measuring 0.305 m (1 ft.) or more in its least dimension in any floor or roof through which persons may fall [14]. In addition to a floor opening, an indoor construction site may have a restricted area containing hazardous materials or objects that may lead to accidents, such as high-voltage or electro-inductive devices, toxic chemicals, etc. [5]. Such hazards could cause injuries as minor as a sprain or strain to as serious as broken bones or even result in death [5]. Other researchers indicated that the construction worker who has an accident is usually not performing the scheduled work, but just roaming the construction site (i.e., distracted), at which time the accident typically occurs [9].

As for the fall prevention techniques, numerous methods have been proposed in the literature, and some of them are listed as follows [7,10]: (1) fall hazard identification using Building Information Modeling (BIM) tools; (2) fall hazard identification using video camera techniques; and (3) real-time tracking systems for construction workers using various sensors, wireless sensor networks, or radio frequency identification (RFID)-based sensors. Other researchers have argued that the use of safety meetings, safety inspections, safety incentives and penalties, strict organization safety policy and legislation, and improved safety training and awareness could all help reduce the fall type of accidents [3]. Overall, the attitude of construction workers towards safety is the key to the prevention of falls [29,31]. The hope of using these technologies is to remind them who are facing danger at the right time, at the right place, but after the reminder, they still need to take action before the accident can be truly avoided [5,9,28].

2.2. CSI

CSI can be defined as a matrix of complex values representing the amplitude attenuation and phase shift of wireless signals, which are transmitted between a WAP and a NIC in the Wi-Fi environment following the IEEE 802.11n standard [37–48]. In fact, CSI can be regarded as a time series of Wi-Fi signal measurements, which captures how wireless signals travel through a confined space with surrounding static or dynamic objects in time, frequency, and spatial domains [20]. Literature shows that CSI is mainly utilized for wireless sensing purposes, and each entry of a CSI matrix consists of two parts, one is a floating-point number of the real part, and the other is a floating-point number of the imaginary part [37]. Many CSI-related studies deal with amplitude variations in the time domain, which have different patterns for each distinct object detected and can be used for human presence detection and activity or gesture recognition if appropriate algorithms are employed [49–52]. Some studies are concentrated on CSI phase shifts in the spatial and frequency domains (i.e., transmit/receive antennas and carrier frequencies), which are related to signal transmission delay and direction [21]. In sum, CSI phase shifts information is more difficult to be used to detect objects compared to CSI amplitude variations information [21].

In fact, CSI is introduced to evaluate the communication link state [19]. In other words, the quality of the wireless channel can be estimated by the CSI matrix, and the communication rate can be adjusted accordingly [19]. In the IEEE 802.11n standard, CSI is measured and parsed from the physical layer using orthogonal frequency division multiplexing (OFDM) technology [20]. In mathematical form, CSI can be expressed as Equation (1) below [20]:

$$Y = H \times X + N \tag{1}$$

where H is the CSI matrix; Y and X are the received and transmitted signal vectors respectively; and N refers to an additive noise vector [17,49]. In practice the most commonly used NIC for CSI measurements is Intel 5300 [53,54], which was also employed in this research. Other NICs that can be used for CSI-related experiments are Atheros 9390 and ESP32 [15,16]. The Intel 5300 NIC can report CSI for 30 groups of subcarriers, spread evenly among the 56 subcarriers in a 20 MHz channel or the 114 subcarriers in a 40 MHz channel [15]. Figure 1 shows the real Intel 5300 NIC configuration with three antennas, and any IEEE 802.11n-based WAP can be used together with this NIC for CSI measurements. Figure 2 shows the detailed CSI data format, and each entry in the CSI matrix can be expressed as Equation (2) below [17,49]:

$$H_{r,s,k,t} = A + i\,B \tag{2}$$

where r represents each receiving antenna, s represents each transmitting antenna, k represents each subcarrier group, t represents each time point, A represents the real part number, and iB represents the imaginary number [17,20,49]. Figure 3 shows sample portion of CSI data. Theoretically, in each OFDM subcarrier with a certain frequency, the CSI matrix, $H_{r,s,k,t}$, is a complex value that can be used to represent the amplitude and phase, as listed in Equation (3) below [17,20,49]:

$$H_{r,s,k,t} = |H|e^{i\ X} \quad (3)$$

where $|H|$ represents the amplitude and X represents the phase [17,20,49]. By applying Euler's formula, Equation (3) can be transformed into Equation (4), and the amplitude and phase can be obtained by using Equations (5) and (6), respectively, as listed below:

$$H_{r,s,k,t} = |H|(cosX + i\ sinX) \quad (4)$$

$$\text{Amplitude } |H| = \sqrt{A^2 + B^2} \quad (5)$$

$$\text{Phase Radian } X = \tan^{-1}(B/A) \quad (6)$$

Figure 1. Intel 5300 NIC with three antennas.

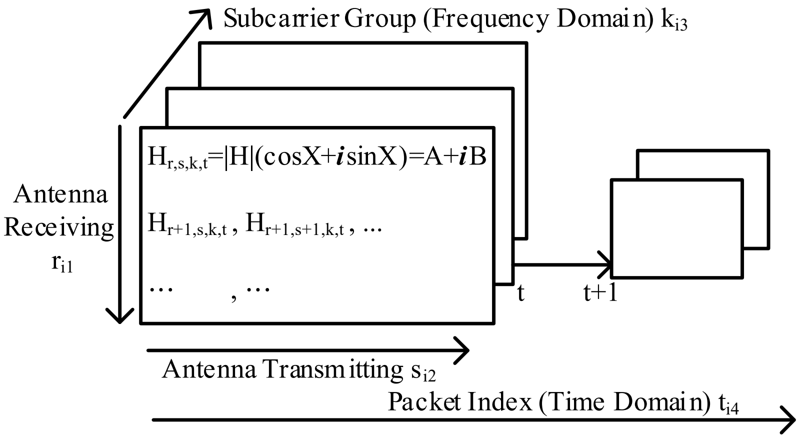
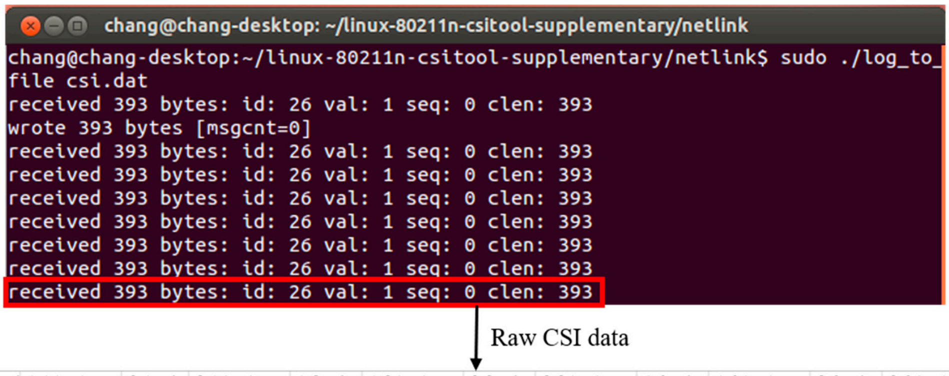


Figure 2. A CSI Matrix with four dimensions: r_{i1}, $i1$ = 1 to # of the receiving antennas; s_{i2}, $i2$ = 1 to # of the transmitting antennas; k_{i3}, $i3$ = 1 to 30 (total groups); t_{i4}, $i4$ = 1 to infinite (current time to future time).



T1R1_real	T1R1_imaginary	T2R1_real	T2R1_imaginary	T1R2_real	T1R2_imaginary	T2R2_real	T2R2_imaginary	T1R3_real	T1R3_imaginary	T2R3_real	T2R3_imaginary
4.98165	4.428133	-2.214067	-1.107033	1.107033	1.66055	-0.553517	-8.30275	12.730883	-13.837916	-3.874617	0.553517
6.08868	-6.088683	-1.107033	2.214067	2.767583	-1.66055	-11.070333	-1.107033	-17.159016	-17.712533	1.107033	4.428133
-6.08868	-7.195717	2.214067	2.214067	-2.767583	-2.214067	-2.214067	12.730883	-20.480116	18.26605	4.98165	-1.107033
-7.19572	5.535167	2.214067	-2.214067	-2.767583	2.767583	11.62385	3.3211	16.051983	21.58715	-1.107033	-4.428133
3.87462	7.195717	-2.214067	-2.214067	2.767583	2.214067	5.535167	-11.070333	22.694183	-13.2844	-4.98165	0.553517
7.19572	-2.767583	-2.214067	1.66055	2.214067	-2.767583	-9.9633	-7.749233	-8.30275	-24.354733	-1.107033	4.98165
-0.55352	-7.195717	1.107033	2.214067	-2.767583	-2.767583	-9.9633	7.749233	-25.461766	3.3211	5.535167	1.66055
-6.6422	-1.107033	2.214067	-0.553517	-2.767583	2.214067	4.98165	11.070333	-3.3211	23.801216	1.107033	-3.874617

Figure 3. Sample portion of CSI data.

Traditionally, the values of the receive signal strength indicator (RSSI) available in all Wi-Fi environments have been investigated extensively in the literature for localization purposes [15,37]. In fact, RSSI can be regarded as the total power combined value of all signals received at the listener, while CSI is the signal measurement value from a pair of antennas at a specific frequency [15,37]. Researchers have confirmed that compared with CSI, RSSI is not a stable value [15,37]. This is due to the fact that wireless signals often travel via both direct paths and indirect paths, such as reflection and scattering paths [15,37]. Hence, multiple aliased signals are superposed at the receiver as the RSSI value, which may not decrease monotonically with the propagation distance, leading to larger localization errors [15,37]. Nevertheless, CSI measures propagating wireless signals for each antenna pair of transmitter and receiver at each subcarrier frequency in order to provide amplitude and phase distortions [15,37]. In this way, CSI variations in the time domain have different patterns for different humans or objects, which have been recognized as a better guide when calculating distances or detecting objects [15,37].

3. Approach

3.1. Feasibility Analysis of Using Deep Learning for CSI Sensing

This section first discusses the feasibility of applying deep learning methods to CSI sensing from the literature, then explores the problems that deep learning may face in construction sites. Finally, construction safety experts were consulted to define the requirements that deep learning-based CSI sensing must fulfill, in hopes of designing a feasible CSI sensing method for construction safety.

In the literature, dozens of analysis methods have been proposed for CSI sensing, and researchers have classified such methods into three types: (1) pattern-based recognition; (2) model-based recognition; and (3) deep learning-based recognition [20]. The first type leverages pattern recognition methods, which includes machine learning algorithms, in order to find distinct patterns to identify human behavior or moving objects [20]. The second type utilizes a mathematical or physical model capable of describing simplified human behavior or moving objects and then finds the unique relationship between CSI signal variation and the model output [20]. Nevertheless, the major problem of the two types of methods is that the prediction accuracy is not high, or the prediction stability is not enough, so these methods are often only applicable to specific data sets. Once the field environment sensed is slightly changed, such as adding a new object, either the entire analysis process must be performed again, or unreasonable constraints must be imposed, so as to obtain satisfactory prediction results.

Recently, since the use of the CSI technique can generate a large number of data sets without difficulty, and since the type of deep learning methods is particularly suitable for processing big data, using deep learning for CSI sensing has gradually become evident. In other similar fields involving a large amount of data, such as image recognition, as long as the quality of the data sets collected is good, deep learning has been regarded as one of the most effective methods for such prediction tasks. However, since almost all image recognition methods cannot operate in poor light conditions, and there is a concern of destroying personal privacy in collecting images [16], image-based methods may not be appropriate for construction safety applications. CSI sensing using deep learning, on the other hand, does not have the aforementioned issues. It can be expected that applying deep learning in CSI sensing will soon become the preferred method as deep learning does for image recognition.

In addition, researchers have conducted several experiments to sort out the factors that should be considered when analyzing Wi-Fi signals. The following lists such factors that are related to construction safety in indoor spaces and may deserve further investigations for this research:

- Past research has pointed out that Wi-Fi signals are attenuated differently when passing through walls of different materials [55]. However, inside an indoor space, as long as the interior partition pertains to the lightweight wall type, the indoor Wi-Fi signal will not suffer a lot of attenuation [55].
- Based on the IEEE 802.11n standard, Wi-Fi environments can have the 2.4 GHz or 5 GHz frequency bands. If the indoor space is small (i.e., less than 100 m^2), and there are no obstacles in the middle, using 5 GHz will have better CSI sensing results than using 2.4 GHz [49]. This is due to the fact that the amplitude variability at 5 GHz is smaller than at 2.4 GHz resulting in less data noise [49]. However, in real-world indoor environments, since the 2.4 GHz frequency band has stronger signal penetration ability than 5 GHz, and the 2.4 GHz transmission distance is longer, it is recommended to use 2.4 GHz for CSI sensing [49].
- Based on the IEEE 802.11n standard, 14 channels are designated in the 2.4 GHz range, spaced 5 MHz apart from each other. For the United States and some other countries, there are 11 channels open for use in the 2.4 GHz frequency band. With today's internet trend, even a new building may have nearby existing Wi-Fi signals. When CSI sensing is performed, it is better to use the least loaded channel in order to have more well distinguished results [49].
- With the use of IEEE 802.11n, there is the possibility of using signal bandwidths of either 20 MHz or 40 MHz. Theoretically, a higher bandwidth corresponds to a higher data throughput; however, it reduces the number of channels that can be used [49]. When CSI sensing is performed, there is no discernible difference between using the 40 MHz bandwidth or the 20 MHz bandwidth [49].
- For the WAP, theoretically the higher the number of antennas, the better. If a person is not on the sight line, it is almost impossible to detect any activities and movements in the one-transmission-antenna-and-one-receiving-antenna configuration [49]. Since the Intel 5300 NIC already provides three antennas, in this research it is assumed that there are two antennas installed in the WAP utilized.

After understanding the technical limitations and suggested ways of using CSI sensing for construction safety, the research team then consulted with 12 construction safety experts and asked the experts to assist in determining the most common indoor space size that needs to be monitored in a typical construction site for this research. The experts also helped determine how much time and money he or she is willing to spend to set up such a CSI sensing approach. As indicated previously, it is impossible to use CSI sensing to monitor an excessively large indoor space. If the experts can know the most common indoor space size that needs to be monitored, including the number of restricted areas such as floor openings, and the time and money that can be paid, these conditions should be regarded as the development goal of the CSI sensing approach.

The research team invited 12 construction safety experts with more than 20 years of experience, some with MRT station building construction experience, and some with military engineering experience. The research team first explained the research background and methods, and then asked experts to select the most suitable option from each of the following questions:

1. According to your experience, please select the most common one from the following space size and number of restricted areas (such as floor openings). The proposed approach will be deployed to monitor the position of construction workers to avoid incidents such as falls. Please choose the smallest space with the least restricted area which needs to be monitored, since larger spaces or more restricted areas can be monitored by deploying more than two sets of the proposed approach:
   - Approximate 10 m^2 with 5 restricted areas;
   - Approximate 50 m^2 with 5 restricted areas;
   - Approximate 50 m^2 with 10 restricted areas;
   - Approximate 100 m^2 with 5 restricted areas;
   - Approximate 100 m^2 with 10 restricted areas;
   - Approximate 100 m^2 with 15 restricted areas.
2. Any system that can sense a construction worker's location needs to be calibrated. Assume that the CSI sensing approach proposed in this study can be calibrated only once a day as long as the construction site does not change significantly. Based on your experience, how much time are you or safety managers willing to spend each day performing the setting up and calibrating work?
   - Approximate 10 min;
   - Approximate 15 min;
   - Approximate 20 min;
   - Approximate 30 min.
3. Based on your experience, how much are you or safety managers willing to spend to install such a real-time construction worker location monitoring system?
   - Approximate USD 500;
   - Approximate USD 1000;
   - As long as the price and performance are reasonable, since construction safety is priceless, such purchases should be mandatory.

For the first question, 10 of the 12 experts chose the "Approximate 50 m^2 with 5 restricted areas" option. The experts said that even if the space is small, there are still safety risks; however, it does not seem to be of much significance to monitor the whereabouts of construction workers for the 10 m^2 space case. As for the 50 m^2 space case, there are usually less than five restricted areas. The research team told the experts that fewer restricted areas should only affect the data collection and computer calculation time. In theory, the deep learning model will become simpler due to this change, and the rest of the system will behave as usual.

For the second question, half of the experts chose 10 min and the other half chose 15 min. The experts said they can understand that the computer system needs to be calibrated, but since the schedule of a construction project is always quite tight, too much set-up time may make the system less practical.

As for the third question, the research team told the experts that this system is estimated to be approximately USD 1000, and if it is built in large quantities, it should be able to reach below USD 500. However, all of the experts chose the third option. The experts said that since this system is not expensive, as long as the system is useful, construction safety is the most important goal to be fulfilled.

The experts also expressed that although it is riskier for construction workers to be outdoors, as long as they strictly wear PPE and safety managers can frequently check, field accidents can be avoided. From the perspective of the project duration, construction workers spend more than two-thirds of their time indoors. Thus, various accidents are more likely to occur here, especially when the lighting condition is not good. Furthermore, indoor construction sites have the potential to cause the fall type of accidents, which may vary from day to day. This is due to the fact that the construction project schedule is always tight, and there may be limited resources such as floor covers, so construction workers only use temporary fences to protect themselves. However, when there is insufficient light during construction in the evening or at night, accidents may occur. If the proposed system can reset the latest restricted area every day, and can operate in a dark environment, it should be more in line with the actual needs of construction safety management.

3.2. System Architecture and Data Collection

The goal of the proposed system is to apply CSI sensing to identification of construction workers' positions and to prevent them from entering the indoor restricted areas. According to the previous experts' suggestions, this system should be more suitable for an indoor space with the size about 50 m^2. If the space size is much less than 50 m^2, use of CSI sensing is not recommended. If the space size exceeds 100 m^2, it is recommended to virtually cut into several compartments with an area of about 50–100 m^2, and then use the proposed approach one by one. Additionally, only 10–15 min of system installation and deep learning training time should be available every day for one construction site. If there is no major change in the construction site within a day, when construction workers approach any of the restricted area, the system should issue a warning to avoid accidents. Finally, the system cost should be less than USD 1000 and use of CSI sensing should detect the position of a construction worker at night. Nevertheless, since the final two requirements are already met by the existing CSI technique, the other requirements will be discussed further in the following paragraphs.

Figure 4 shows the architecture and plane view of the proposed system for an indoor space, whose size can be about 50–100 m^2. There is a WAP device at one end of the indoor space, which is connected to two WAP antennas. The other end of the indoor space has three antennas connected to the Intel 5300 NIC, which is linked to a computer program, called CSI-DL Analyzer, for data collection and analysis work with TensorFlow 2.10 installed. The optimal configuration of such a room is to virtually cut the space into five lanes, each with a width of about 2 m with just one antenna in either end, as shown by the dotted, virtual line in Figure 4. Additionally, there is at most one restricted area in each lane, but there can be any other common objects on the entire indoor space. Indeed, the shape of the indoor space is preferably a rectangle or a square. If it is an irregular shape, it is recommended to virtually cut the space into several quadrilaterals, and then deploy the system one by one to help detect the positions of construction workers.

Regarding the data collection or training data preparation work, CSI-DL Analyzer is currently not connected to Internet to avoid processing unnecessary network packets. CSI-DL Analyzer will transmit network packets to the WAP device by using the "ping" command at a frequency of 50 times per second to 1 time per second, and the default is 2 times per second. Since the WAP will respond, CSI-DL Analyzer will receive the response packets to create the CSI-CSV data file. The format of this CSV file is simple, and one CSI tuple (one row in a CSV file) consists of 13 columns. The first 12 columns contain 12 floating point numbers, and the 13th column is the location label. It should be noted that since one network packet corresponds to 30 subcarrier groups, the location labels of the 30 CSI tuples are all the same. During the analysis, only one location label will be matched with the 12 columns of the 30 CSI tuples. Also note that although the CSV file does not have any timestamp column, each tuple is in fact recorded according to the order in which the CSI network packet is sent. In addition, since one CSI tuple contains twelve floating-point numbers, each group of two numbers can form a CSI record. The first floating-point number of a CSI record represents the value of the real part of the CSI, and the second floating-point number represents the value of the imaginary part of the CSI, which can be inputted into Equations (4) and (5) to obtain the amplitude and phase value.

Hence, at a specific time point one CSI tuple for a certain subcarrier group in fact contains six CSI records. This is due to the fact that the system has two WAP-end antennas and three NIC-end antennas, by arranging and combining all of the antennas data, there will be six CSI records, each of which corresponds to the transmission of the network packet between a certain WAP-end antenna and a certain NIC-end antenna.

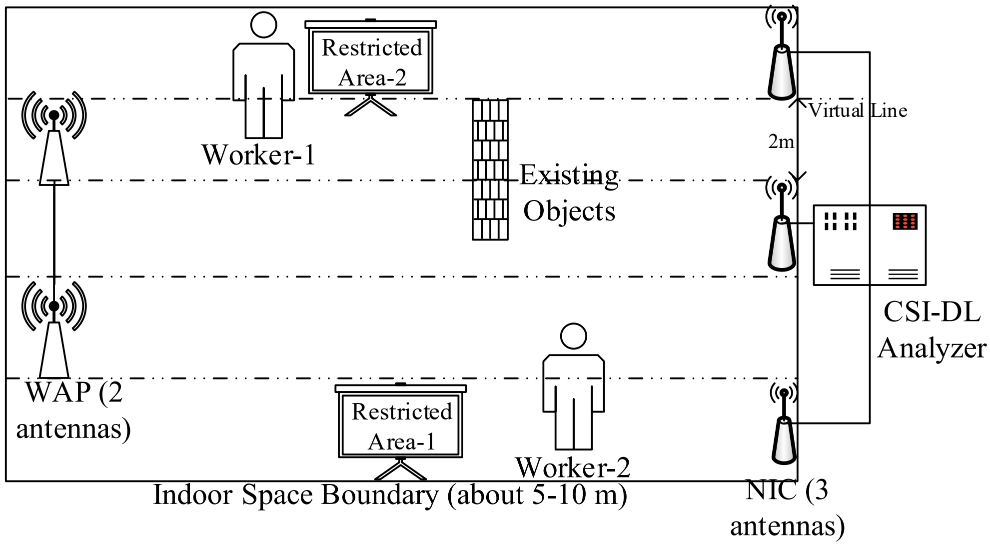


Figure 4. The architecture and plane view of the deep learning-based CSI sensing system in an indoor space.

Moreover, it is the Intel 5300 NIC driver that generates such CSI-CSV data files. In the data collection process, a construction worker will be asked to carefully detour around a certain restricted area (assume its name is "A") at his normal walking speed for one minute. During the one-minute period, a label called "Restricted Area A" will be placed in the 13th location column of the CSV file. Then, repeat these steps until all of the restricted areas have been visited and their location labels are generated. In addition, the same construction worker will be asked to walk in any of the safe indoor places for two to five minutes, which implies that they must stay away from all of the restricted areas. Finally, the "safe" location label will be created to associate with the related CSI tuples. It should be also noted that since a restricted area requires one minute of CSI walking data, it is recommended to generate the same number of minutes of CSI walking data for the safe location. Additionally, the total data collection time should be less than or equal to 10 min. Therefore, if the data collection work is carried out in 10 min, and if two network packets are received per second, there are 36,000 CSI tuples ($10 \times 60 \times 2 \times 30$), with the CSV file size about 4 MB.

3.3. Design of Deep Learning Model

First, after collecting the CSI-CSV file for one indoor space for 10 min, the file was directly inputted into the deep learning convolutional neural networks (CNN) method. The location label of each CSI network packet served as the class attribute, and the first 12 columns of each CSI tuple were converted into the amplitude and phase values, serving as 360 independent variables (i.e., each CSI network packet involving 30 subcarrier groups), each corresponding to one CSI tuple, each with 12 amplitude and phase values. Based on this data set, the training process took about 4 min. However, although sometimes the CNN accuracy was more than 80%, the model stability was not good. For example, if the CSI-CSV file of another room with similar conditions was selected for training, or if the positions of some existing objects of the same indoor space were changed, the accuracy of the CNN model varied significantly.

In addition, on construction sites, a construction worker is constantly on the move, and when she/he approaches a restricted area, s/he is likely to be in a safe area one step ahead and a restricted area next. Therefore, it may be necessary to consider two consecutive CSI tuples on the time axis during analysis. In practice, two consecutive CSI tuples on the CSV file are likely to be two data of different CSI subcarrier groups at the same time point. Thus, starting from the first CSI tuple, each 60 tuples of CSI data will be used to form a new group, which implies that all of the CSI data pertaining to the first two time points are in the first new group. The 61st-120th CSI tuples of the original CSV file will be used to form the second new group to represent the third and fourth time points, and so on.

In deep learning fields, recurrent neural network (RNN), long short-term memory (LSTM), and gated recurrent unit (GRU) algorithms are particularly suitable for analyzing data with sequential properties, such as time series data, and human language and speech. RNN can be described as the first-generation sequential data analysis algorithm, but it is less able to handle long-term patterns. LSTM can handle patterns for a long time or across different time intervals, but the analysis speed is slow and the memory usage is large. GRU can be described as the third-generation improved algorithm, which has gradually gained attention. In fact, these algorithms are different from conventional approaches in the sense that they do not use principle component analysis (PCA) or related ways to extract important features and can analyze data sets directly to obtain interesting patterns [21]. Therefore, based on the data pre-processing steps mentioned in the previous paragraph, since every 60 CSI tuples form a new group, each new group of data can be described as the objects in the construction site presenting CSI data every second. The order between the new groups can represent certain human activities or gestures. In addition, the CSI technique inevitably still has problems such as noise and disconnection when network packets are not received correctly. If GRU is selected as the main algorithm for detailed sequence analysis, the Conv1D algorithm, similar to CNN, can be used as either the coarse classifier or the filter for noise data removal before the GRU algorithm can process the remaining data set. In this way, good results may be obtained, as shown in the yellow part on the left of Figure 5, which is also a common strategy to combine CNN and RNN-like algorithms.

Nevertheless, if only the steps in the yellow part of Figure 5 are used, the actual prediction results are still unsatisfactory, and the accuracy of the model is around 85%, but the stability is much improved. The accuracy of the model prediction is not high, probably since the positions of the five antennas are not carefully considered. As shown in Figure 4, if the object in the construction site is on the left side of Figure 4, the signal received by the two antennas on the left side should have a greater influence. If the object is on the right side of Figure 4, the signal received by the three antennas on the right side should have a greater influence. Therefore, in order to consider the pairing of these antennas, the research team proposed a deep learning architecture as shown in Figures 5 and 6. Firstly, the input data is duplicated into three parts. Each part is described as follows:

- The first part contains the original structure, that is, a CSI tuple contains six CSI records, each CSI record representing a WAP and NIC antennas combination.
- In the second part, the input data is further divided into three partitions, each partition corresponding to one antenna at the NIC side (totally three antennas), plus two antennas at the WAP side. Thus, in each partition, a new CSI tuple contains two CSI records.
- In the third part, the input data is further divided into two partitions, each partition corresponding to one antenna at the WAP side (totally two antennas), plus three antennas at the NIC side. Thus, in each partition, a new CSI tuple contains three CSI records.

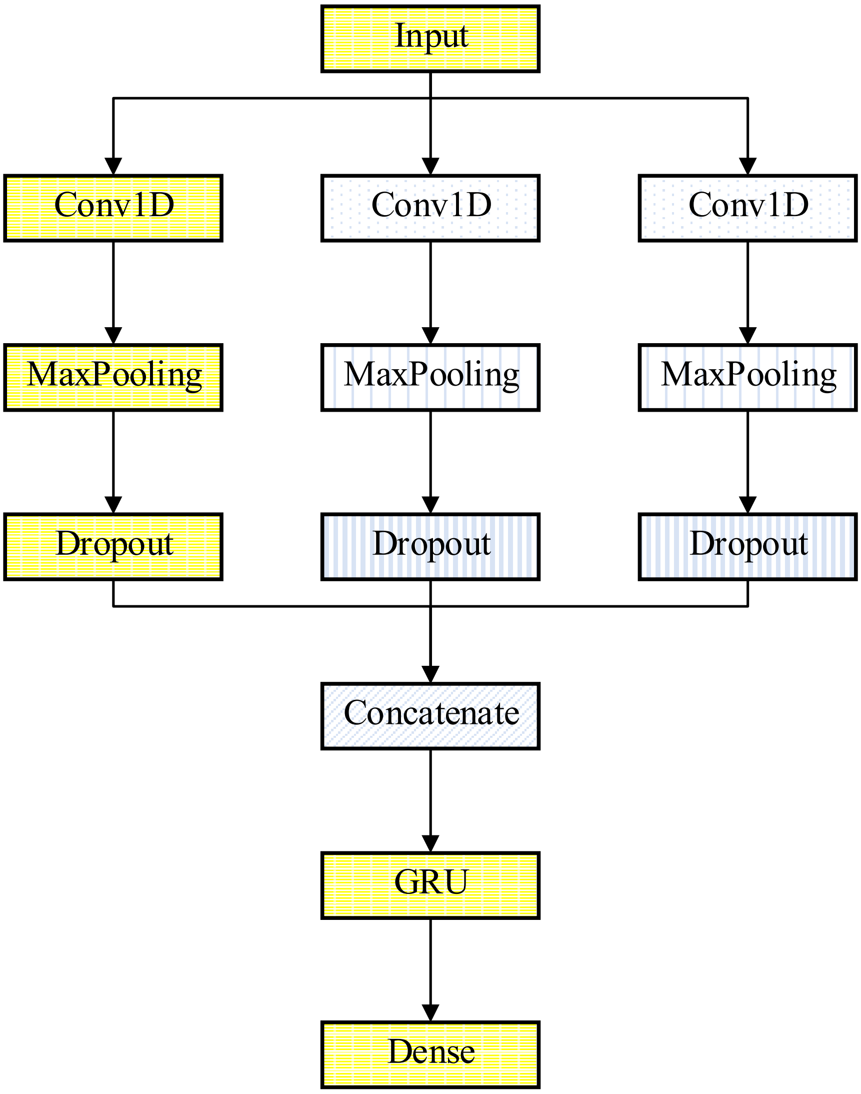


Figure 5. The architecture of the proposed deep learning model for CSI sensing.

As shown in Figure 6, after Conv1D, MaxPooling and Dropbox have been performed, respectively, each part of the CSI data will supposedly contain preliminary classification results without noise values. The Concatenate class is utilized to combine the three parts into one part again. It is also worth mentioning that each CSI tuple in the three parts or in the combined part actually represents the same time point if these parts come from the same input data. Since algorithms such as CNN are not designed to deal with sequential relationships, such relationships between different time points are left to be analyzed by GRU. Finally, GRU will clarify the sequential relationships, and Dense will help determine the position label for each CSI network packet received.

In the training and testing stages, the K-fold Cross-Validation method has been utilized. First, the data set is divided into k equal parts. The k-1 parts are used for training and the remaining one part is used for testing. Finally, the process is repeated k times, as shown in Figure 7, and the error can be obtained using Equation (7) below:

$$\mathrm{Error} = \frac{1}{5}\left(\sum_{i=1}^{5} \mathrm{Error}_i\right) \tag{7}$$

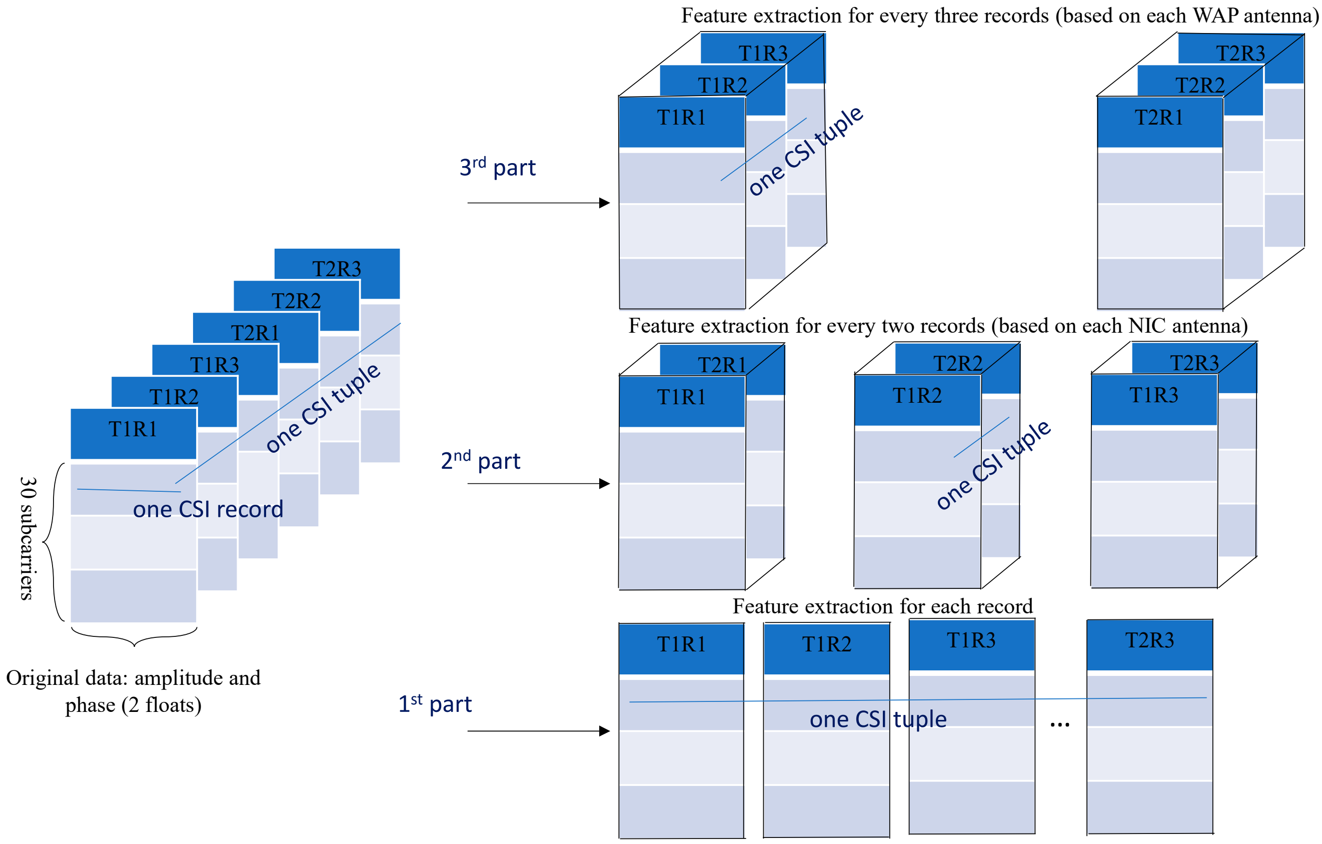


Figure 6. Schematic view of how a CSI tuple processed parallel to the three parts.

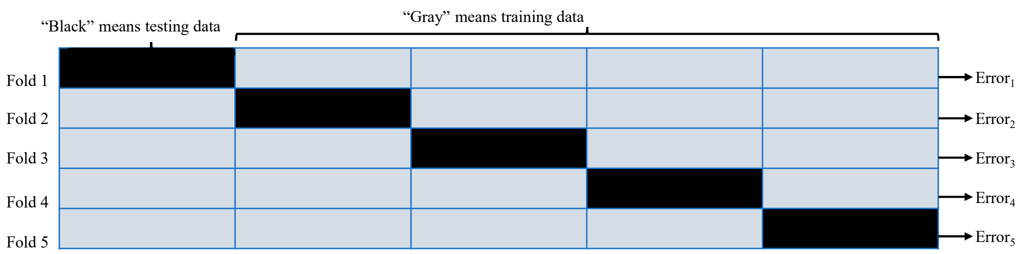


Figure 7. K-fold Cross-Validation, k = 5.

4. Evaluation and Discussion

4.1. Verification of the Proposed Approach

In order to verify the developed system, the research team selected two construction sites: one is at the basement floor of a 26-story building in a certain place in New Taipei City, and the other is at the second floor of a train station renovation project in a certain place in Taoyuan City. The area of each test site is about 70 m^2 and 80 m^2, respectively, and the shapes are shown in Figure 8, with five restricted areas marked in red font. For the New Taipei City site, the data collection work was performed during the day, and six construction workers were performing various tasks on site. For the Taoyuan City site, the data collection work was performed in the evening, and two construction workers were on site to clean up.

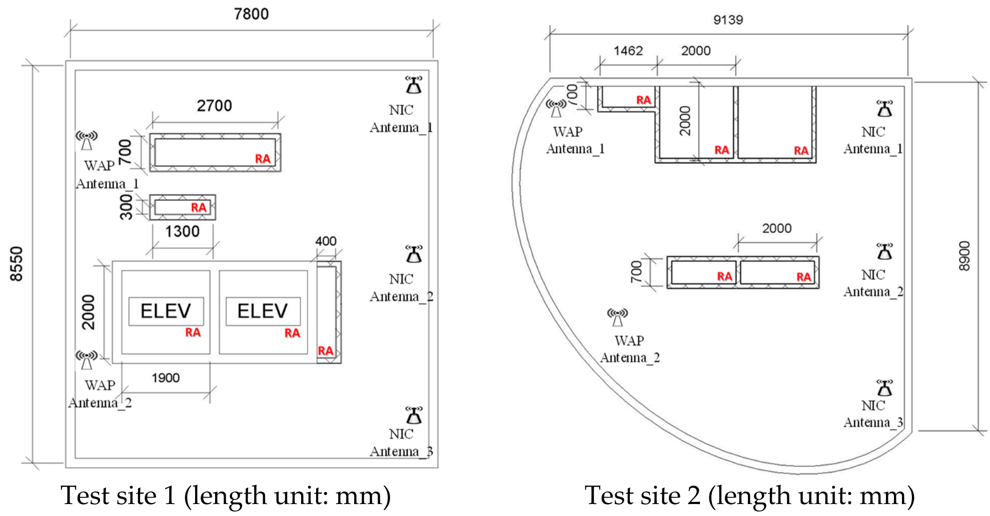


Figure 8. Plane configuration of the two sites.

The research team spent approximately 20 min collecting CSI data at each test site, spending one minute walking around each restricted area for the first five minutes. Next, the same person walked around the safe area of the site for the next five minutes, and the research team asked field construction workers not to approach the restricted areas during the data collection periods. Thus, a total of 10 min of CSI data was used to form the first data set. Then, the research team moved some objects at random to change the scene of the site a little. Finally, the research team repeated all of the activities in the first 10 min to create the second data set. Therefore, each test site had two data sets, each with 10 min of CSI data. Certainly, the first data set of each test site was used for model training and the second was used for model testing.

Figure 9 shows the training results of the deep learning model for the first indoor test space. As the epoch parameter increases, the model accuracy can finally reach 96%. Figure 10 shows that the model loss value for the first indoor space decreases as the epoch parameter increases. It should be noted that for this test, the CSI-DL Analyzer was equipped with an Intel i7-10870H CPU with 16G of memory. In addition, the research team prepared another laptop with the same specifications, but with a NVIDIA RTX-3060 (6G) GPU. The model training time was 421 s without GPU, and only 56 s with GPU.

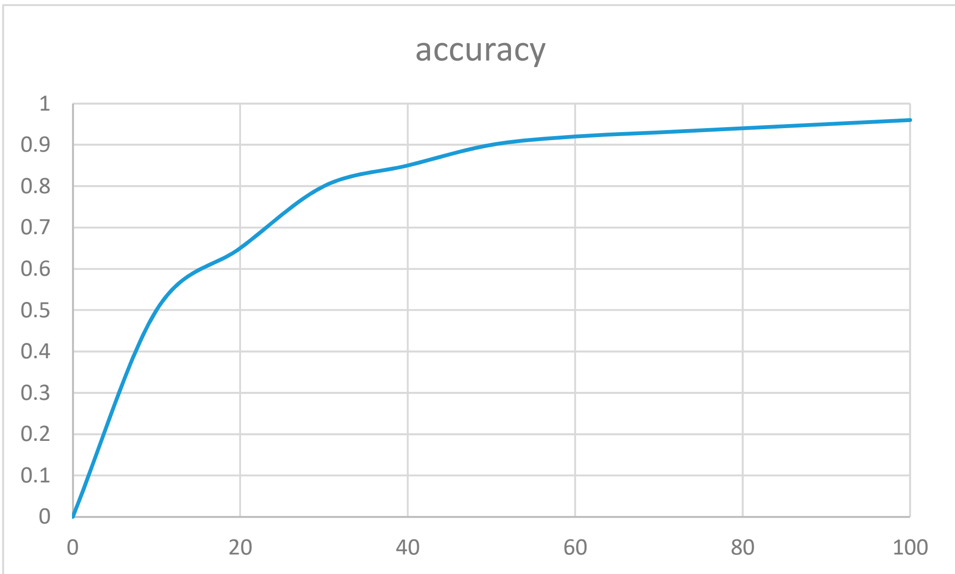


Figure 9. The accuracy growth curve at different epochs.

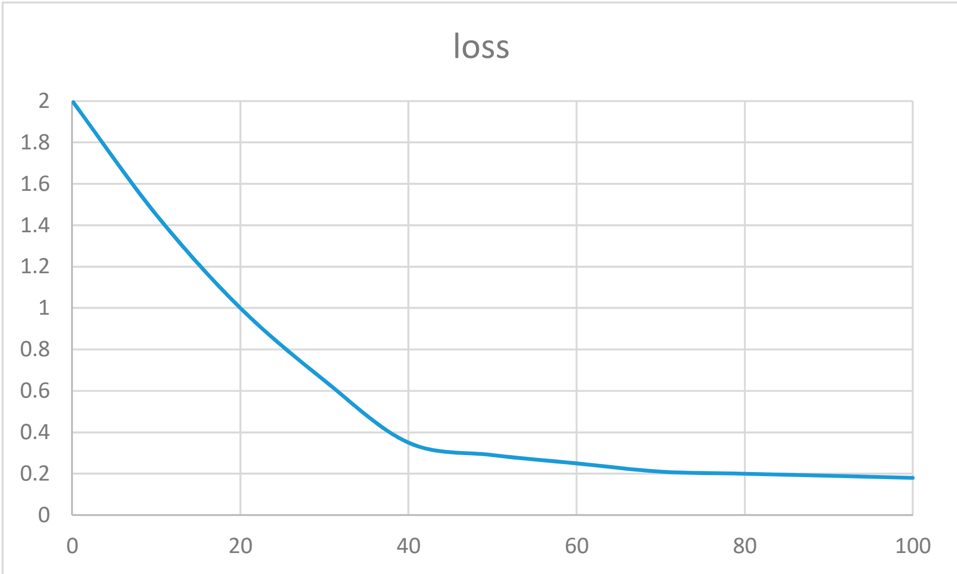


Figure 10. The decrease curve of loss value under different epochs.

Table 1 shows the testing results of the first test site using non-training data (i.e., the second data set). Table 2 shows the testing results of the second test site using non-training data (i.e., the second data set). The accuracy of both tests is above 94%. When a CSI network packet is collected and predicted using CSI-DL Analyzer, the time required is less than one second.

Table 1. The confusion matrix for the first test site using the second data set (accuracy = 95.7%).

Predicted Label / Actual Label	R.A.1	R.A.2	R.A.3	R.A.4	R.A.5	Safe
R.A.1	62	1	0	1	0	2
R.A.2	0	58	1	0	1	1
R.A.3	1	0	60	1	0	2
R.A.4	1	1	1	61	1	3
R.A.5	0	0	1	1	57	1
Safe	1	0	0	3	1	280

Note: R.A is the abbreviation of the restricted area.

Table 2. The confusion matrix for the second test site using the second data set (accuracy = 94.5%).

Predicted Label / Actual Label	R.A.1	R.A.2	R.A.3	R.A.4	R.A.5	Safe
R.A.1	66	1	0	1	1	2
R.A.2	0	55	1	1	0	1
R.A.3	0	0	50	2	1	2
R.A.4	1	1	1	61	1	3
R.A.5	1	0	1	3	65	1
Safe	2	3	1	1	1	290

Note: R.A is the abbreviation of the restricted area.

4.2. Discussion and Future Work

The research team then explained the results of the two test sites to the 12 experts. Except for the system deployment time, the experts agreed that the current system achieved the goal set when the system was developed. Other suggestions were summarized as follows:

- Concerning the effectiveness of the system, the experts appreciated that the prediction accuracy of the model can reach more than 94%, and less than one second of prediction time is needed. The experts believed that construction workers will be warned once they approach any of the restricted areas.
- Concerning the efficiency of the system, the experts indicated that currently it takes about 12 min to set up CSI-DL Analyzer and the antennas as well as to collect required CSI data. But with model training, it may take up to eight minutes. The research team suggested four solutions to the reduction of such system deployment time: (1) the first solution is to use GPU to accelerate the model training time. For example, in the first test site the model training time can be less than one minute if GPU is employed, so the entire system deployment time is only 13 min. However, this approach is costly and requires the purchase of GPUs in each CSI-DL Analyzer; (2) the second solution is to transmit the data to the cloud through the network, execute it in the cloud server with GPU, and then transmit the trained model back, which is worthy of follow-up research; (3) the third solution is to reduce the time of walking in the safe area, which is equivalent to shortening the data collection time. However, the research team has encountered fewer safe area labels, which increase the number of misjudgments, so it is debatable whether to do so; and (4) the final solution is to apply the transfer learning method to each new data set collected. Theoretically, compared to the original training data set, only about 20% of the CSI data for the new site would be needed so that the deep learning model based on the existing construction site can learn to recognize the new scene, which is worthy of further research.
- Some of the experts worried that an indoor space on a construction site can be very large and that multiple CSI-DL Analyzers must be deployed in order to monitor all personnel movements, which will increase the project's time and cost. The experts also suggested that since such an indoor space may not have partition walls at the beginning, as the construction progresses, multiple small spaces will suddenly form. The experts hoped that the CSI-DL Analyzer can still detect any movements in each of the small rooms through the partition walls. The research team responded that currently omnidirectional antennas are used in the CSI-DL Analyzer, but considering the actual needs, directional antennas should be used instead. The reason is that in an omnidirectional antenna each signal can be transmitted to any point in the 3D space. For such an antenna, not only its transmission distance is not long, but the ability to penetrate a wall is not good. Nevertheless, since the omnidirectional antennas of CSI-DL Analyzer are deployed on the edges of the walls at both ends of an indoor space, these antennas do not need to send or receive the signals from the other side of the two walls. Instead, they need to transmit or receive the signals wandering in the indoor space, thus making directional antennas more suitable. In general, a directional antenna signal has better ability to pass through walls and a longer transmission distance. The research team will use directional antennas in the future to explore how the CSI-DL Analyzer can be used in a large indoor space, which can include partition walls for internal small spaces.
- Finally, the experts indicated that since the CSI-DL Analyzer can detect human activities, although it was originally set to detect falls, it should also be able to detect other types of construction safety accidents. In indoor spaces, another common types of accidents are electric shocks and construction machine failures. To avoid the electric shock type of accidents, it is necessary to also establish a restricted area and prohibit construction workers from entering. This should be similar to prevention of the fall type of accidents, but there may be strong electromagnetic waves in the vicinity of an electric shock accident, which may affect the capability of the CSI-DL Analyzer. As

for the construction machine failure type of accidents, it may be necessary to establish different failure modes to predict and avoid, depending on the machine types. The research team stated that CSI sensing under strong interference of electromagnetic waves, similar to CSI sensing in large indoor spaces, requires the enhanced version of Wi-Fi device and antennas. The research team will study this topic in depth and present it in the next version of CSI-Dl Analyzer. As for the type of construction machine failures, the research team believed that the key is to predict whether a machine is about to have problems, which can be determined by the appearance or geometry change of the machine, such as stackers. Hence, in the future, before using these machines every day, the CSI-DL Analyzer will first detect whether the machines are abnormal or check them regularly.

Overall, the experts appreciated the CSI-DL Analyzer's centimeter-level detection capabilities. The fact that construction workers do not need to carry any sensors to be detected is novel. Thus, the experts believed that this is very suitable for the working environment of construction sites. In addition, the CSI-DL Analyzer's capability to operate in dark environments is also a very interesting feature from the experts' perspective. For some important construction sites or facilities, the safety management and control issues are important. The experts believed that the CSI-DL Analyzer may be used in these sites and look forward to its next version. Finally, in the part of shortening the deployment time of the CSI-DL Analyzer, whether using transfer learning or cloud computing, the core technology may be use of advanced database technology to store and manage CSI data. Since the building-related data such as spatial layout and materials information can be extracted from BIM tools [56,57], further elaborations on BIM and advanced database technology for CSI sensing may be highly needed.

5. Conclusions

Construction safety has always been an uncompromising goal. With the trend of sustainable development, there have been more and more mega building construction projects and large renovation projects for old buildings around the world. Construction workers in these projects indeed spend most of their time performing various tasks in the indoor environment. However, such a working environment usually does not have adequate safety protection measures. Thus, the CSI-DL Analyzer proposed in this research was designed to immediately alert a construction worker once he or she approaches any of the restricted areas in an indoor space. CSI-DL Analyzer can be quickly deployed in a designated space to collect data and to perform model training. Inside the CSI-DL Analyzer, a customized deep learning model architecture was developed, and CNN and GRU methods were mixed to accommodate CSI data. The data from two real-world test sites were collected, and the prediction accuracy of the model can reach more than 94%. The experts indicated that since the CSI-DL Analyzer can monitor the personnel mobility effectively, even in a dark environment, and since construction workers do not need to carry any sensors, the CSI-DL Analyzer certainly can help avoid the occurrence of falling accidents.

There are still several challenges that need to be addressed in future work of the CSI-Dl Analyzer, such as the detection of other types of safety accidents and the development of a planning tool for the CSI-DL Analyzer deployment. In fact, use of BIM tools for such spatial planning can be regarded as a recent trend [58–60]. Another feasible suggestion is to reduce the cost of the CSI-DL Analyzer or to shorten its deployment time, which can expand the application scope of the CSI-DL Analyzer and reduce the number of construction safety incidents.

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