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Automated Approach for the Enhancement of Scaffolding Structure Monitoring with Strain Sensor Data

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AUTOMATED APPROACH FOR THE ENHANCEMENT OF SCAFFOLDING STRUCTURE MONITORING WITH STRAIN SENSOR DATA

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ABSTRACT

Construction researchers have made a significant effort to improve the safety of scaffolding structures, as a large proportion of workers are involved in construction activities requiring scaffolds. However, most past studies focused on design and planning aspects of scaffolds. While limited studies investigated scaffolding safety during construction, they are limited to simple cases only with limited failure modes and simple scaffolds. In response to this limitation, this study aims to develop an automated scaffold monitoring approach capable of monitoring large scaffolds. Accordingly, this study developed an automated scaffold safety monitoring framework that leverages sensor data collected from a scaffold, scaffold modeling techniques, and a machine-learning approach. The proposed framework is based on the capability of the machine-learning approach to identify patterns, which in this study are the patterns of the scaffold structural response based on different loads acting on it. Due to the cost and safety issues related to testing an actual scaffold with varying load applications, the scaffold monitoring framework was experimentally tested under a controlled laboratory setting with a single-bay two-story scaffold with four safety cases. After the field trial, this approach was applied on a four-bay and three-story scaffold involving 1,411 safety cases through computational exploration. During this process, this study integrated a divide-and-conquer strategy with machine-learning models to improve the performance of large-scale classification. The results show that the proposed scaffold monitoring approach is capable of large-scale classification of scaffold safety status. Therefore, this approach can be reliably applied to monitor similar scaffolds on construction sites. Further, this approach is replicable to solve other classification problems. In addition, this study is expected to encourage the use of sensing technologies and data analysis techniques to develop automated monitoring approaches.

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CHAPTER 1: INTRODUCTION

1.1. Construction Safety Overview

The construction industry is one of the major contributors to the U.S. economy (Data USA, 2022). At the same time, it is one of the most hazardous sectors among all industries in the U.S. (OSHA, 2019b). This sector employed an estimated 7.49 million workers in 2019 (Data USA, 2022). In 2019 alone, the Associated General Contractors (2020) reported an increase in construction employment by 151,000 (i.e., approximately 2% of the 2018 record). Given the size of the construction workforce and the associated risks in the construction industry, workers' safety and well-being have always been the utmost priority in this sector (Wu et al., 2015). Accordingly, several safety measures have been adopted to ensure their safety on construction sites. The construction industry specifically follows the Occupational Safety and Health Administration (OSHA) recommended solutions (OSHA, 2019b) to prevent different types of accidents. However, preventive measures to ensure accident-proof construction sites are not limited to these recommended solutions.

Despite efforts and precautions to avoid construction accidents, numerous fatalities are reported yearly. For example, in 2020, the private construction industry accounted for 1,008 worker fatalities, i.e., approximately 21% of 4,764 total worker fatalities in all industries (BLS, 2021). Figure 1 summarizes the total number of construction fatalities recorded from 2011 to 2020 (BLS, 2019, 2021).

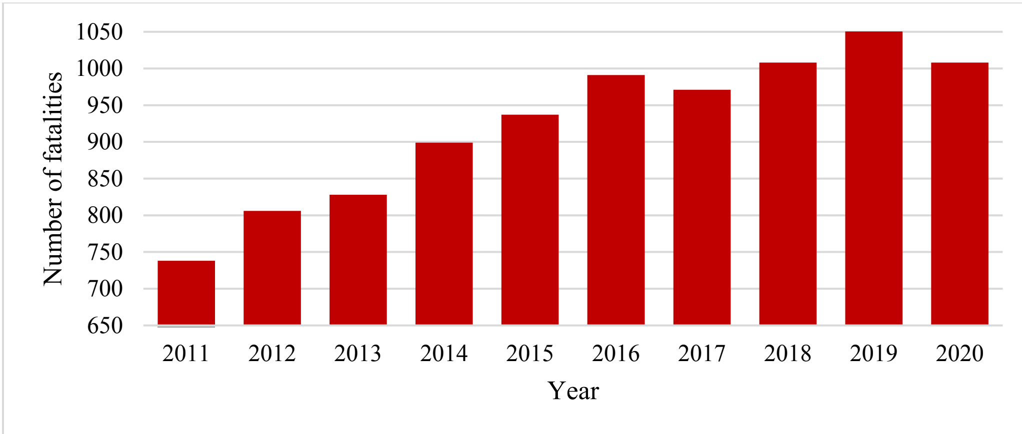


Figure 1. Construction Fatalities in the United States, 2011-2020 (BLS, 2019, 2021)

The upward trend in reported fatalities, as shown in Figure 1, indicates that the general safety measures adopted on construction sites are insufficient to ensure workers' safety. The following sections will discuss the general safety measures taken in the construction industry, followed by a discussion on potential solutions to the conventional safety measure limitations.

1.2. General Construction Safety Measures

All construction sites have manual safety inspections by qualified safety professionals before starting any construction activities as a standard safety measure. In addition, proper use of personal protective equipment (PPE) and regular safety training helps maintain safe work practices. Besides, additional passive and active safety measures are employed as necessary safety prevention measures. These measures help to minimize pre-identified potential hazards during construction activities. For example, passive measures, such as guardrails (S. Zhang et al., 2015), are used in pre-identified fall-prone areas, and warning signs are used to warn workers to be extra cautious to avoid potential risks. However, there are situations when working nearby/around hazard-prone areas is unavoidable. In such cases, these passive measures have limited roles in preventing potential hazards, and more active safety measures play a proactive role in maintaining worker safety. For example, safety harnesses are used to protect workers who work at the edges of fall-prone areas. However, despite the proactive role of such active safety measures in construction hazard mitigation, their application is limited in safety management systems currently used in the construction industry. As a result, these measures are limited to minimizing known hazards and cannot account for several other safety issues that arise at construction sites.

Construction sites have a dynamic nature and a multitude of interactions, leading to continuous changes in site conditions (Park et al., 2016). Such nature of construction leads to different unsafe work conditions, and it is challenging to detect those conditions. As such, it is crucial to monitor construction sites continuously throughout the construction period so that potential hazards unidentified during the planning and earlier inspections can be detected. However, the limited number of personnel dedicated to safety inspections for specific construction sites prevents continuous safety monitoring. Further, the subjective nature of manual safety assessment prevents construction superintendents from detecting all potential work hazards (Carter & Smith, 2006; Perlman et al., 2014; Sacks et al., 2009). Due to these reasons, many unsafe conditions remain undetected and fatal accidents occur. Thus, to eliminate such limitations with the existing safety assessment approach, it is essential to reinforce current safety management systems with active monitoring mechanisms that enable continuous site monitoring to detect potential hazards.

1.3. Real-Time Monitoring of Construction Sites

The need for continuous monitoring of site conditions has attracted researchers to explore different sensing technologies for their possible applications in the active monitoring of construction sites (Chen et al. 2017; Jebelli et al. 2014; Jin et al., 2020; Li, 2020; Liu et al., 2020; Marks & Teizer, 2012; Pradhan et al., 2009; Teizer et al., 2010; Won et al., 2020). The continuous research on sensing technologies, and the following applications, have spread across various aspects of construction and resulted in new tools to ensure and improve safety planning and management on construction sites. Specifically, researchers have focused on developing different real-time monitoring systems, which continuously collect site data in real-time and process those data to detect potential safety issues. In other words, automated approaches convert sensor-collected data into useful information, which in the case of construction safety is whether the data indicate safe or unsafe conditions. On detection of potential safety issues, responsible site personnel are promptly warned to take preventive measures. As such, adopting these new sensing technologies can significantly help enhance safety monitoring.

For the real-time monitoring of construction sites, researchers have explored different technology-based solutions to prevent construction hazards. One of the most frequently studied topics is the prevention of proximity-based hazards. Researchers have explored different types of proximity-based sensing technologies that can be used to track workers and pieces of equipment. Some examples of such sensing technologies are Bluetooth low energy (BLE) sensors (Park et al., 2018; Park et al., 2017; Zhuang, 2020); radio frequency identification (RFID) (Jin et al., 2020; Li, 2020; Marks & Teizer, 2012; Pradhan et al., 2009; Teizer et al., 2010; Won et al., 2020); global positioning systems (GPS) (Wang & Razavi, 2016); inertial measurement units (IMU) (D. Liu et al., 2020; Wang & Razavi, 2016); unmanned aerial vehicles (UAV) (Kim et al., 2019); and ultra-wideband (UWB) (Carbonari et al., 2011; Jo et al., 2019). Besides these proximity-based sensors, motion sensors are commonly used technology for the real-time identification of construction hazards based on workers' motion data (Chen et al. 2017; Jebelli et al. 2014; Kim et al. 2016a; Liu et al. 2012; Yang et al. 2014, 2016, 2017). Other studies include the prevention of fall hazards using infrared and ultrasonic sensors (Lee et al., 2009) and IMU sensors (Yang et al., 2015). Further, some researchers have implemented image processing to detect potential hazards, such as unsafe worker behavior (Fang, Li, Luo, Ding, Luo, et al., 2018; Han & Lee, 2013; Khan et al., 2021), and hazardous work conditions (Seo et al., 2015) in real-time.

Moreover, there has been significant progress in the development and use of wearables, using different sensing technologies, to address various worker-related safety issues. Some examples include IMU-based wearable systems for determining worker fatigue (Sedighi Maman et al., 2017); monitoring body postures to mitigate work-related musculoskeletal disorders (Cho et al., 2018; Nath et al., 2017, 2018; Valero et al., 2017; Vignais et al., 2017; Yan et al., 2017; Yang et al., 2020); and detecting fall hazards (Yang et al., 2016). Researchers have also used wearable systems based on in-built smartphone sensors to identify different worker activities (Akhavian & Behzadan 2016; Zhang et al. 2018). Several studies include the use of wristband-type wearable biosensors for monitoring a worker's stress level (Jebelli et al., 2019), as well as their physical demands (Hwang et al., 2016; Hwang & Lee, 2017) during different site activities; the use of wearable insole pressure sensors to prevent fall hazards (Antwi-Afari, Li, Seo, et al., 2018b), detect unsafe work postures (Antwi-Afari, Li, Yu, et al., 2018), and detect unsafe work conditions (Antwi-Afari et al., 2020). Further, researchers have also used wearable systems based on vibration motors to communicate potential hazard information to workers (Sakhakarmi

& Park, 2019; Sakhakarmi et al., 2021; Sakhakarmi & Park, 2022).Thus, it is evident from these studies that a wide variety of sensing technologies have been introduced in construction research to address different safety issues.

Besides the role of sensing technologies in developing real-time construction monitoring, different data analytics techniques (adapted to analyze the sensor collected data) are also crucial for developing such automated monitoring approaches. Advanced supervised machine-learning (ML) methods among such data analytics tools have been popular among construction researchers to analyze different types of data to develop automated systems. Such data analysis techniques implemented in various construction safety-related studies include support vector machine (SVM) classifiers (Akhavian & Behzadan, 2016; Cheng et al., 2017; Golparvar-Fard et al., 2013; Khosrowpour et al., 2014; Yang et al., 2017), long short-term memory (LSTM) models (Cai et al., 2019; Ding et al., 2018; Yang et al., 2020), computer vision-based convolution neural network (CNN) models (Fang, Li, Luo, Ding, Luo, et al., 2018; Fang, Ding, Luo, et al., 2018; Khan et al., 2021; Kolar et al., 2018; Nath et al., 2020), and neural network (NN) models (Akhavian & Behzadan, 2016; Ayhan & Tokdemir, 2020). The analysis of sensor data, images, and videos with these advanced data analysis techniques has enabled the precise monitoring of construction sites, enhancing construction safety management.

These technology-based studies, along with advanced data analysis techniques, demonstrate notable progress in the development of automated approaches for enhancing construction safety by addressing different safety issues related to falls, proximity hazards, worker stress, etc. As such, these studies highlight the existence of many components related to construction safety and propose solutions for different issues, demonstrating that a single technology cannot solve all these issues. Based on this background, this dissertation focuses on contributing to the safety domain of construction research by developing an automated approach to prevent scaffolding safety hazards, to which researchers have paid insufficient attention in developing active accident prevention research.

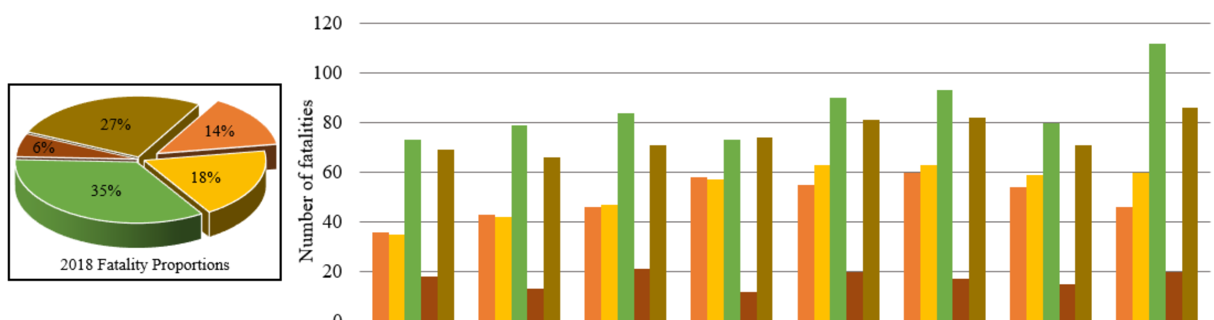
1.4. Scaffolding Structure Safety

Scaffolds are temporary structures that are widely used on most construction sites to facilitate construction activities at elevated positions above the ground, by supporting workers and construction materials. These scaffolds may be supported or suspended, depending on their use (OSHA, 2018). It is estimated that approximately 65% of all construction workers are involved in construction activities requiring the use of scaffolds (OSHA, 2019a). This statistic highlights scaffolding structure safety as one of the essential components of construction safety. Thus, for the safe use of scaffolds, OSHA standard 1926.451 (OSHA, 1996) enforces detailed general requirements for scaffolding structures and required safety measures.

Besides, OSHA scaffolding standards (OSHA, 2002) require a competent person to inspect scaffolding structures for any visible defects before starting each work shift and after the occurrence of any event that could impact the structural integrity of scaffold structures. Following the inspection, the competent person must take corrective measures if needed. Further, OSHA requires that a competent person train the site personnel involved in "erecting, disassembling, moving, operating, repairing, maintaining, or inspecting scaffolds to recognize associated work hazards" (OSHA, 2002). As such, a competent person "must be fully knowledgeable about erecting, disassembling, moving, operating, repairing, maintaining, and inspecting the scaffold" (OSHA, 2020). Given such requirements, construction sites employ a competent person as part of efforts to ensure scaffold safety.

The OSHA requirement of visual inspection before each work shift and after any event impacting their structural integrity suggests that the scaffold inspections are not conducted during ongoing construction activities. It should be noted that such active construction periods are the prime time for changes occurring in scaffold loading conditions and causing unsafe conditions. In addition, it is difficult for the safety inspectors to identify unsafe conditions resulting from changed load conditions, solely depending on visual inspections. Further, although the requirements set by OSHA necessitate a competent person to be trained to fulfill their responsibilities, OSHA has not defined any specific training requirements for a 'scaffold-competent' person. Therefore, most 'competent persons' are not adequately trained to identify unsafe scaffolding structures on construction sites (Halperin & McCann, 2004). Several studies (Abas et al., 2020; Abbaszadeh et al., 2021; Hoła et al., 2018; Sanni-Anibire et al., 2020; Whitaker et al., 2003) have identified the lack of proper supervision and insufficient training of workers erecting scaffolds being major causes for several scaffold related accidents. Further, scaffolding regulation violations are among the top 10 most frequently cited OSHA standards violations (OSHA, 2022), which demonstrates that the existing method of scaffold inspection by a 'competent person' is insufficient and unreliable. As a result, many scaffold-related safety hazards occur on construction sites.

According to the U.S. Bureau of Labor Statistics (2020), 46 out of the 61 scaffold-related fatalities in 2018 were in the private construction industry. Figure 2 shows the construction worker fatalities related to scaffolding structures, as well as the other four major causes of construction fatalities—i.e., fall, struck by object or equipment, caught-in/between, and electrocution—from 2011 to 2018 (U.S. Bureau of Labor Statistics, 2020). This comparison shows that scaffold-related fatalities constitute a major proportion of construction fatalities: 14% in 2018 among the five causes listed in Figure 2.



	2011	2012	2013	2014	2015	2016	2017	2018
Scaffold related	36	43	46	58	55	60	54	46
Fall through surface or existing opening	35	42	47	57	63	63	59	60
Struck by object or equipment	73	79	84	73	90	93	80	112
Caught-In/Between	18	13	21	12	20	17	15	20
Electrocution	69	66	71	74	81	82	71	86

Figure 2. Comparison of Scaffold-related Fatalities with Other Construction Fatality Causes (U.S. Bureau of Labor Statistics, 2020)

The recorded fatalities show that additional measures are required to ensure the safe use of scaffolding structures and safeguard workers from potential hazards. Although the need to improve worker safety conditions has attracted researchers to work on different automated approaches to safety inspection in order to strengthen construction safety management, there have been a limited number of studies related to enhancing the safety of scaffolding structures. These studies are discussed in the following chapter. Most of these studies (Benjaoran & Bhokha, 2010; Collins et al., 2014; Feng & Lu, 2017; Kim, Cho, & Kwak, 2016; Kim, Cho, & Zhang, 2016) focus on identifying potential safety issues during the planning stage so that required preventive measures can be applied during the construction phase. A small portion of past scaffold safety studies (Jung et al., 2018; Xue et al., 2012; Yuan et al., 2016) focus on real-time scaffold monitoring during the construction phase; however, these studies are limited to analyzing small structures to detect a limited number of failure modes. As such, developing a more reliable means of scaffold monitoring is necessary. Therefore, this dissertation focuses on overcoming the limitations of prior scaffold safety monitoring studies by developing an automated scaffold assessment approach to enhance the current state of scaffold monitoring.

CHAPTER 2: LITERATURE REVIEW

The introduction shows that the most prevalent safety inspection methods are insufficient to address all potential safety issues on construction sites. This situation dictates the necessity of additional measures to enhance overall safety management on construction sites. As such, construction researchers have spent a significant amount of time on developing different approaches to address various scaffold-related safety issues. Thus, this section will review studies focused on enhancing scaffold safety. Further, this section will review studies that have implemented different ML approaches, as ML is a crucial component of this study's proposed methodology.

2.1. Scaffolding Safety Monitoring

The involvement of a large proportion of construction workers in activities requiring scaffolds (OSHA, 2019a) has led many construction researchers to conduct studies to ensure safe working conditions on scaffolds. The review of such studies show that researchers have attempted to prevent potential scaffold-related accident in two ways: (a) safe planning/designing of scaffolding structures during planning (i.e., pre-construction), or (b) applying automated approaches to detect potential hazards during construction. The following sub-sections discuss these studies in detail.

2.1.1 Measures During Pre-Construction

There are several studies (Benjaoran & Bhokha, 2010; Collins et al., 2014; Feng & Lu, 2017; Kim, Cho, & Kwak, 2016; Kim, Cho, & Zhang, 2016) that focused on preventing safety issues by identifying potentially unsafe scenarios during the planning stage by utilizing building information modeling (BIM). With these approaches, any unsafe conditions detected from the model are presented to the site personnel before starting construction activities, and required preventive measures are adopted during planning and construction. Benjaoran & Bhokha (2010) proposed a rule-based safety management system to automate the detection of construction activities above ground level (i.e., at elevated locations) from a 4D CAD model. The rule-based system updates the construction schedule by incorporating required preventive measures depending on the type of detected activity. For instance, if the system detects activities requiring scaffolds, a scaffolding inspection activity is added to the construction schedule before starting any of those activities. A detailed construction schedule allows the site engineers to pre-plan required safety measures and protect workers from potential safety issues.

Further, there are other studies that have attempted to enhance scaffolding structure safety by accounting for additional measures, along with the construction schedule. Collins et al. (2014) specifically integrated the construction schedule and risk factors involved in activities requiring scaffolding structures on a BIM model to identify potential hazards. Similarly, other studies (Kim, Cho, & Kwak, 2016; Kim, Cho, & Zhang, 2016) incorporated scaffolding structures' plans and detailed construction crew work plans on a schedule-BIM integrated model. The researchers incorporated an optimization engine on the integrated 4D-BIM to select a scaffolding plan with the fewest safety hazards out of different alternatives based on the detailed work plans and construction sequence. Such scaffold plans enable site personnel to clearly visualize construction sequences and potential safety issues during the planning stage.

In a different study, Feng & Lu (2017) developed a scaffolding system planning model on BIM that automatically developed scaffolding systems following relevant scaffolding regulations, user requirements, and site conditions. Further, their model allowed for potential hazard scenario simulation, which assisted in improving scaffold safety management. Although such integration of different resources in BIM has made considerable progress in safely planning scaffolding activities and timely detection of safety issues during the planning phase, these approaches do not address hazardous scenarios resulting from the continuous changes that occur on scaffolds during the construction stage.

To incorporate the scaffold safety issues that arise during the construction stage, Kim & Teizer (2014) proposed an automated approach of designing and planning scaffolding structures following the sequence of site activities to construct different structural units on construction sites. For this purpose, the researchers used BIM and the approach of designing and planning scaffolds based on the actual work sequence, incorporating the dynamic nature of construction sites. Such site-specific planning and scaffolding structure design result in safer scaffolds as compared to utilizing generic scaffolds (Halperin & McCann, 2004). Further, researchers have attempted to design structurally safe scaffolds with different approaches, such as a finite element method (FEM) modeling of steel scaffolding systems by considering geometric and material parameters (Chandrangsu & Rasmussen, 2011) to represent actual scaffold behavior. However, these approaches of designing structurally safe scaffolds do not include proactive monitoring to prevent potential safety hazards during construction.

2.1.2. Automated Monitoring During Construction

To address the limitations of studies that focused on scaffold safety during the pre-construction phase, researchers have developed several automated approaches that are capable of accounting for safety issues due to dynamic construction conditions (i.e., continuous changes on construction sites). Xue et al. (2012) presented one such early effort of real-time scaffold monitoring by using radio frequency identification (RFID) technology and wireless local area network (WLAN), together with a scaffold safety-management system. This system collects real-time information about scaffolds, such as scaffold building status, daily use, and removal. It then compares those site statuses with standard regulations to identify potential safety issues. Although the proposed framework could detect potential hazards along with the risk level and warn the concerned site personnel, this study was limited to concept demonstration without actual field testing.

For the real-time assessment of temporary structure safety conditions, Jung (2014) explored the capability of a computer vision technique to detect potential structural failures of temporary structures by processing video images. Later, the researcher extended the computer vision-based automated approach to identify potential failures by processing chronological images (Jung et al., 2018). These approaches are based on analyzing sequences of images and video images captured from cameras installed at construction sites. Any changes detected in the physical form of the temporary structure during the analysis help identify potential failures. These studies demonstrated that the computer vision-based approach is capable of detecting very small changes in the structure. However, these studies with computer vision techniques rely on the observed deformation of structural members for potential failure detection. As such, this approach is only applicable when all structural members are visible for the image/video analysis, which is practical in the case of the small structures considered in the presented study; however, all structural members may not be visible in the case of actual scaffolds due to visual limitations in construction sites from moving workers, pieces of equipment, as well as construction materials.

Similarly, a recent study by Khan et al. (2021) utilized a computer-vision-based approach to analyze the safety conditions of mobile scaffolds. However, the approach is limited to mobile scaffolds and is more focused on automated detection of workers' safe and unsafe behavior on scaffolds with or without outriggers rather than the safety of scaffolds based on their structural condition. Further, the study suffered from limited data availability for training deep learning algorithms leading to low performance of their proposed approach on test data. A similar study by Lee & Han (2021) focused on preventing fall hazards in scaffolds due to workers' behavior. The authors used a convolutional neural network to analyze scaffold accelerations resulting from worker movement. For data collection purposes, the authors installed 3-axis accelerometers on the scaffold.

Another attempt to automate scaffold safety monitoring includes a cyber-physical system proposed by Yuan et al. (2016). Their system integrated a physical structure with a virtual temporary structure to analyze the structural safety condition of the physical structure. The researchers used a single bay scaffolding structure of dimensions 1.524 m × 1.524 m × 2.134 m. The structure was equipped with four different types of sensors to record load, strain, acceleration, and displacement corresponding to different load conditions. These measurements from the structure were automatically transmitted to the virtual structure, and a structural performance analysis was performed to identify the safety condition for different loadings. In addition, the system had a mobile application-based warning system to warn concerned site personnel of any potential hazard. Despite the high potential of this approach to give reliable results in scaffold safety analysis, this study is limited to detecting failures due to the base settlement of a small scaffold. Furthermore, the requirement of installing four different types of sensors makes this approach economically unfeasible for monitoring temporary structures.

Some other studies are specific to monitoring temporary structures used to support concrete works, which use multi-bay and multi-story scaffold falsework. For example, Huang et al. (2000) proposed an approach to detect the buckling failure of a scaffold supporting concrete works. The researchers used strain gauges and linear variable differential transformers to measure axial member forces and scaffold column displacement. Then, potential buckling failures were detected by comparing the measured strain and lateral displacement values with the allowable threshold values. In a similar study, Su et al. (2018) proposed an internet of things (IoT) based warning system composed of three different types of wireless sensors to measure displacement, axial forces, and scaffold tilting. However, these studies (Huang et al., 2000; Su et al., 2018) are limited to detecting the buckling failure of scaffolds used as false support during concrete works. Further, using multiple sensors to detect only buckling failure makes these approaches expensive. As such, these methods are not feasible for general scaffold safety monitoring.

2.2. Application of Data Analytics in Construction Safety Studies

Previous studies have used different sensing technologies based on sensor data acquired in their respective studies, demonstrating that data analytics is an integral component in data-based studies. Proper data analytics integration improves the performance of automated monitoring approaches. Advancements in data analytics have made it possible to analyze data in a fraction of seconds, which plays a vital role in the development of real-time safety management systems. Accordingly, construction researchers have adopted different predictive data analytics approaches, together with different sensing technologies, in various construction safety-related studies. For instance, Yang et al. (2016, 2014) used support vector machine (SVM) classifiers for near-miss fall detection of ironworkers, using motion data from a wearable system. Such near-miss fall detection helps prevent potential falls by adopting fall prevention measures in fall-prone areas. Similarly, other researchers explored the capability of SVM to identify worker postures during different activities by using data acquired from IMU sensors (Chen et al., 2017), and to monitor different site activities for construction equipment by analyzing audio signals from different pieces of equipment (Cheng et al., 2017). In a different study, Akhavian & Behzadan (2016) compared the performance of different ML algorithms (i.e., neural network (NN), decision tree, K-nearest neighbor (KNN), logistic regression, and SVM) in classifying workers' activities by analyzing smartphone-based sensor data, and concluded that NN models have the best performance. Further, Yang et al. (2020) used long short-term memory (LSTM) models to analyze IMU sensor data to detect potential work-related musculoskeletal disorders. These studies demonstrate the application of different predictive ML techniques for analyzing sensor data.

Besides, several studies are based on analyzing images or visual data. Nath et al. (2020) used a deep-learning-based convolution neural network (CNN) with computer vision technology to detect personal protective equipment usage by construction workers. Similarly, Ding et al. (2018) used CNN to detect unsafe worker ladder-climbing behavior on construction sites. A similar approach was used in a different study (Fang, Li, Luo, Ding, Rose, et al., 2018) to identify uncertified workers performing specialty trades on construction sites, in order to prevent safety hazards. Fang et al. (2018) used CNN for the real-time detection of workers and equipment on construction sites to assist in planning activities and improve safety. Similarly, other studies have implemented the computer vision technique to address different safety issues (Seo et al., 2015). Fang et al. (2018) proposed the automated detection of construction workers not using hardhats from a far-field surveillance video using the Faster R-CNN method to facilitate the safety inspection process. Son et al. (2019) applied the same method on image sequences to detect construction worker locations and postures under different working backgrounds for safety management and productivity analysis. Further, researchers have also used CNN to detect safety guardrails to prevent fall hazards (Kolar et al., 2018). Besides CNN, researchers have also used LSTM networks to analyze video sequences for recognizing different site activities during site monitoring (Cai et al., 2019). Such capability of analyzing construction site visuals and images to detect unsafe conditions assists safety managers in enhancing the safety management process without actually visiting the site.

These studies demonstrate that data analytics has a crucial role in developing real-time safety monitoring approaches. However, several researchers have indicated the relatively small data sizes used in past studies as a limitation associated with the reliability of adopting such approaches on actual construction sites (Kim et al., 2016; Liu et al., 2012b; Yang et al., 2017). As such, data availability is a major factor that determines the effectiveness and reliability of implementing such real-time approaches.

2.3. Knowledge Gap and Potential Problems

The review of past scaffolding safety studies shows that very few automated approaches attempted to address safety issues during construction. These visual and sensor-based studies overcome the limitations of BIM-based studies that focus on the safety of scaffolds during the planning stage. However, the visual-based approaches suffer from visual limitations in construction sites due to blockage from workers, equipment, and construction materials. Thus, visual disturbances are a strong limitation of computer vision-based approaches as construction sites are full of equipment, materials, and other elements that can be an obstacle to the view of the cameras. To overcome this, it requires installing a large number of video cameras to collect different views of the scaffold to cover the entire scaffold. However, installing an excessive number of cameras makes this approach expensive. In addition, any worker or equipment activity will still block some view of the scaffold, limiting the scaffold monitoring to fully visible scenarios only. Furthermore, visually detected failure cases mean that the structure may have undergone significant deformation and already failed. Therefore, visual-based monitoring is limited in this regard.

Compared to the visual-based approaches, the sensor-based approaches do not suffer from visual limitations, and sensors can detect information that cannot be visually seen. Thus, sensor-based methods address the limitations of visual-based monitoring. Despite this, the sensor-based scaffold safety studies are limited to identifying a limited number of failure modes like base settlement and buckling, and for such detection, past studies relied on data from multiple types of sensors, requiring a different kind of analysis for each data type. However, real scaffolding structures suffer from different failure modes, and the complexity of scaffold failure modes increases as the size of the structure increases. In large scaffolds, the potential failure of local members adds to the total number of failure modes, and local failures can potentially cause critical structural issues. Thus, identifying local member failures becomes more crucial for determining the potential failure of the overall scaffold system, so that proper precautionary measures can be taken in time. However, past scaffold safety studies have given insufficient attention to detecting different scaffold failure modes and have been limited with small prototype scaffolds only.

Given such limitations with past studies, employing these monitoring techniques for actual scaffold monitoring is potentially unreliable. To address these limitations, there is a need of an approach that is quick and reliable in scaffold monitoring without conventional structural analysis and an approach beyond threshold comparison for identifying multiple modes of failure. Further, the approach should be expandable to scaffolds with multiple bays and multiple story rather than simple cases. Therefore, this dissertation focuses on developing such an automated monitoring approach that is expandable to incorporate more scaffold failure modes, as necessary.

CHAPTER 3: RESEARCH OBJECTIVES AND SCOPE

3.1. Goal and Research Questions

The overall goal of this research is to improve the safety of workers involved in construction activities requiring scaffolding structures. For this purpose, this study aims to develop an automated scaffold monitoring approach to enhance the current safety monitoring through an integrated system development and testing. The integrated system development leverages sensor data collected from scaffolds and data analysis techniques to predict the scaffold safety status. Further, the testing ensures that the system can monitor scaffolds. This system development focuses on monitoring multiple failure modes and its expandability to multi-bay and multi-story scaffolds rather than simple cases. To create this new methodology of assessing scaffolding structures, this research will specifically answer the following research questions:

- How can we automate the scaffold monitoring process during construction? What are the essential components in such an automated process that is quick in reliably identifying failure modes and is expandable in nature?
- What analysis technique can realize the automation of the scaffolding structure monitoring to identify multiple failure modes?
- How can we improve the performance of automated monitoring of multi-bay and multi-story scaffold?

3.2. Research Objectives

This study has the following specific objectives for the development of an automated scaffold monitoring approach:

1. Develop a framework for the automated safety assessment of scaffolding structures;
2. Test the safety assessment framework for monitoring scaffolding structures; and
3. Investigate the performance of proposed framework on multi-bay and multi-story scaffolding structure.

3.2.1. Objective 1: Development of Automated Scaffold Monitoring Framework

As this research intends to automate the safety monitoring of scaffolding structures, it is essential to develop a theoretical framework that illustrates a clear concept of the proposed approach, and such a framework will be the basis for conducting this study. As such, the first objective of this study is to develop a theoretical framework for automated scaffolding structure monitoring that overcomes various challenges from representing a scaffold in a digital model, real-time data collection, and to consolidating all data resources for safety monitoring. Chapter 4 explicitly discusses the study specifics to this objective. This study will specifically identify essential components for the automation process and integrate those components to form a framework for automated monitoring.

3.2.2. Objective 2: Testing the Safety Monitoring Framework

While developing a new approach for the first time, it is essential to ensure that the theoretical framework is capable of delivering expected results – being able to conduct automated scaffold monitoring with respect to structural integrity. Such confirmation is possible only with actual testing. Thus, to achieve the desired research goal, this study's second objective is to test the proposed approach framework through a prototype study, which is explicitly discussed in Chapter 5. This study ensures that the proposed method can deliver expected results and demonstrates the real-time monitoring capability of the proposed system. However, actual testing on scaffolds involves several safety issues due to human involvement and the need for various types of load applications. As such, the prototype study involves a small single-bay two-story scaffold to limit potential safety issues in a controlled environment.

The studies corresponding to objectives 1 and 2 will collectively answer the first two research questions: "*How can we automate the scaffold monitoring process during construction? What are the essential components in such an automated process that is quick in reliably identifying failure modes and is expandable in nature?*" and *"What analysis technique can realize the automation of the scaffolding structure monitoring to identify multiple failure modes?"*.

3.2.3. Objective 3: Monitoring of Multi-bay and Multi-story Scaffold

The field testing in Objective 2 is an important step toward developing an automated monitoring system; however, another important aspect for this automated approach is its operation in variable scaffold configurations. As noted in Objective 2, the testing has been conducted on a small set of scaffold due to safety reasons, which in fact is sufficient to demonstrate the functionality of the proposed framework in an actual setting for the similar type of scaffolds. With the valid framework of the proposed approach, the research under this objective explores a considerably larger scaffold and its complicated parametric characteristics for broader applicability. Specifically, a four-bay and three-story scaffold is used to allow this research to investigate a more structurally complex model that involves considerably more failure modes.

Chapter 6 exclusively discusses this study. This study will specifically focus on factors impacting the performance of the proposed approach and improving its performance. This study will answer the last research question: *"How can we improve the performance of automated monitoring of multi-bay and multi-story scaffold?"*

3.3. Research Scope

This study focuses on the safety monitoring of supported steel scaffolds through integrated system development, testing the system on a heavy-duty single-bay two-story scaffold, and finally, the computational exploration of the system to monitor a four-bay three-story scaffold. The key of this research is the scaffold monitoring framework, which is based on the analysis of strain values resulting from scaffold loading conditions on vertical scaffold members. Accordingly, strain sensors are used to get the strain measurements from the scaffold members. However, it should be noted that strain sensor development is not within the scope of this study, and this study used a set of strain sensors which has their specification suited for the prototype testing.

As discussed, this research will be conducted in three steps, each corresponding to one of the objectives in a sequential order, as shown in Figure 3. The first step would be to establish a framework for automated monitoring, which corresponds to the first objective of this dissertation. Then, after the development of the framework, a proof-of-concept study will be conducted to demonstrate that the proposed approach is capable of automated monitoring. This proof-of-concept study corresponds to the second research objective. Due to the cost and safety issues with testing an actual scaffold, this prototype testing involves a small test scaffold of single-bay and two-story. Finally, the last step will include investigating a four-bay and three-story scaffold. This step corresponds to the third research objective. It should be noted that the study corresponding to the third objective comprises only computational exploration, given that the automated framework has been tested from modeling to real-time data collection to real-time testing.

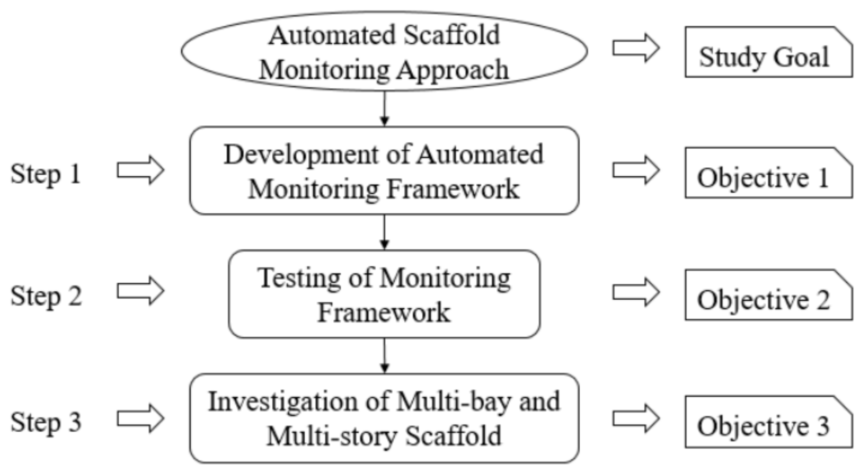


Figure 3. Research Steps

As a foundational methodological development, this study uses scaffold structural failure cases related to external loading factors, such as overloading, uneven base settlement, and overturning, for the scaffold safety analysis. However, failure cases resulting from the factors like wind, earthquakes, or other impact loads are not accounted for in this study. Further, this research does not consider accidental safety hazards, such as falling from a height or electrocution. Different studies (Hamdan & Awang, 2015; Olanrewaju et al., 2021; Pieńko et al.,

2018) have identified unsafe worker behavior, inaccurate assembly of scaffolds, etc. as other causes of scaffolding-related hazards. Such scaffold hazards are also not accounted for in this study. It is important to note that the three types of failure categories (i.e., overloading, uneven base settlement, and overturning) are expandable while considering the local level failure modes and combination of different number of local members failing at a time.

CHAPTER 4: THEORETICAL FRAMEWORK FOR AUTOMATED SCAFFOLD MONITORING

4.1. Overview

An automated scaffold monitoring requires accounting for the structural characteristics of a scaffold, measurements of the scaffold's responses to forces, and translation of measured data to predict safety conditions. This links data from physical systems to digital information extracted after data processing. To encapsulate all these processes, this research creates a general framework for real-time scaffold monitoring for the first time in scaffolding safety research. In doing so, we identify the essential components for automated scaffold monitoring for framework development. Then, those identified components are integrated to form the framework, as shown in Figure 4.

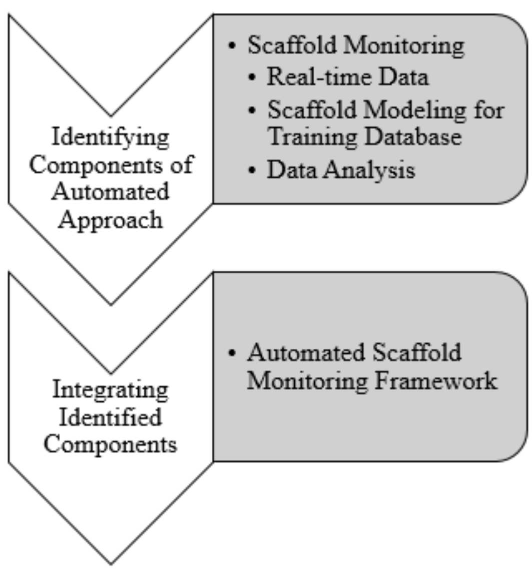


Figure 4. Methodology for Scaffold Monitoring Framework Development

4.2. Essential Components for Automated Scaffold Monitoring

The basic principle behind the automated monitoring approach is to analyze the quantifiable real-time data collected from the site to detect hazardous scenarios, without conventional structural analysis. The challenge with the conventional structural analysis in real-time application pertains to the requirement of a structural computer model and various follow-up analysis with application of a combinations of loads that represent the real-world situation occurring on the scaffolding structure. In an effort to minimize this process for construction real-time applications, this study eliminates the conventional analysis and creates a real-time monitoring framework. For reliable scaffold monitoring, it is required that such real-time data closely represent the safety condition of the actual scaffold. Further, the framework should employ an advanced data analysis technique for analyzing real-time data.

In scientific studies, pattern recognition with ML algorithms has been extensively used as a powerful and quick tool to analyze real-time data and develop automated systems. As this study attempts to analyze the site collected data from scaffolds without applying conventional structural analysis, it is pertinent to use such ML algorithms for developing the scaffold monitoring approach. However, it should be noted that the use of ML techniques requires a large database for training ML algorithms (Golparvar-Fard et al., 2013; Khan et al., 2021), and the reliability of using ML techniques depends on the availability of sufficient representative data. Therefore, before the implementation of the ML technique, an additional step in the framework will be the preparation of a database for training ML algorithms.

However, using a real scaffold to obtain a large number of strain measurement values corresponding to multiple complex loading conditions is not feasible and highly impractical due to the risks involved. Further, the costs associated with building and lab testing such structures make this approach to preparing a strain database very expensive. Furthermore, repeating the same complex and expensive process for various scaffold configurations would further reject the practicality of this database preparation. To circumvent these practicality and feasibility issues, a computer-simulated approach for data generation would be a reasonable approach. A computer-simulated approach should prepare a database that accurately emulates actual data from an actual scaffold. Accordingly, a model representation technique is an essential component of the proposed framework.

With real-time data and a modeling technique, this research applies ML to development of a training database and follow-up data analysis to predict its safety condition. The following sections discuss each of these components in detail.

4.2.1. Real-time Data

An automated safety monitoring system analyzes real-time data to determine site safety status. Thus, it is essential to identify proper data types that are capable of reflecting the structural safety status of scaffolding structures and then make necessary arrangements (i.e., installation of appropriate sensing system) to collect such data. These two steps form an integral part for developing the framework for scaffold monitoring and can be achieved by answering the question: *What kind of data can reliably measure scaffold safety conditions?* As this study focuses on failure modes caused by external loading conditions, this question can be answered with the knowledge of load transfer path on scaffolding structures.

In framed structures like scaffolds, the load transfer path follows floor-beam-column-foundation (ground) (Lechner, 2009). Figure 5 shows an example of a framed structure. On applying loads, the load transfers from the flooring to secondary beams, secondary beams to beams along the perimeter, beams to columns, and columns to the foundation, as shown in Figure 6. This load transfer sequence shows that vertical columns are the major structural components responsible for supporting all compressive loads above it and transferring those loads to the foundation (i.e., these vertical column members directly transfer all structural load to the ground).

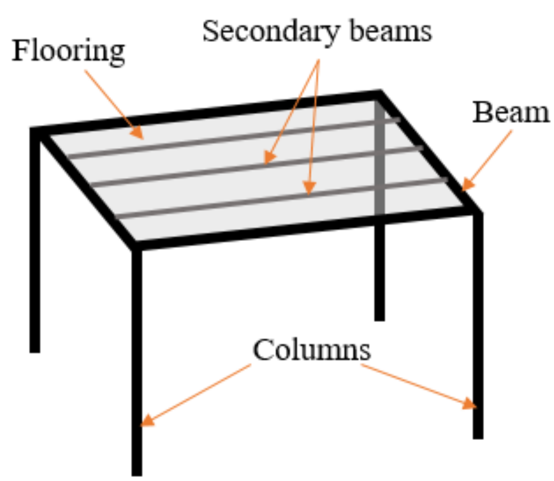
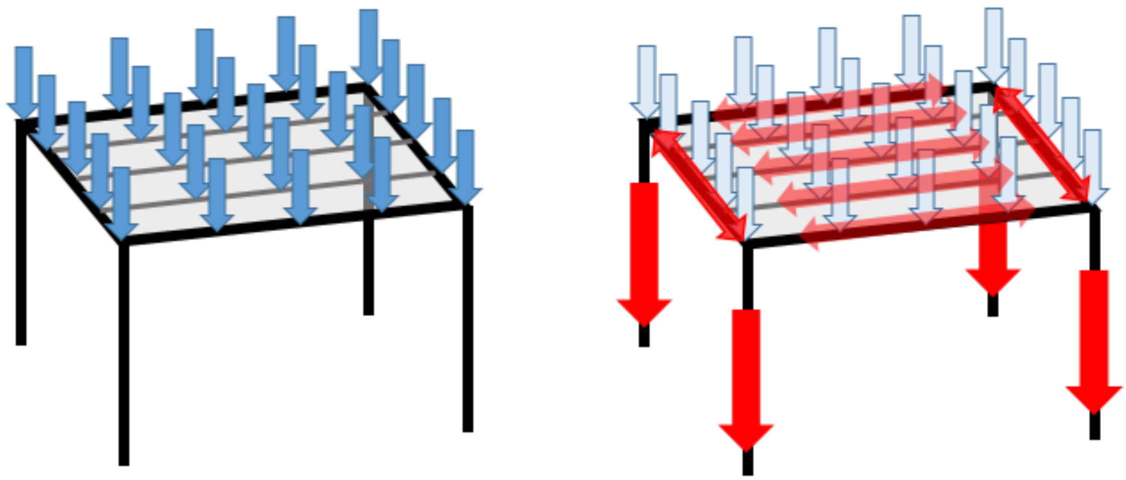


Figure 5. Framed Scaffolding Structure



a. Framed Structure - Loaded b. Framed Structure - Load Transfer

Figure 6. Load Transfer in a Framed Structure

When loads are uniformly distributed over a symmetric structural frame, as shown in Figure 6(b), loads on the structure are evenly distributed on each column, resulting in axial compressive stresses in these members. Such stresses cause the deformation of materials, which is measured in terms of strain (Ɛ)—the strain level changes with the change in loading conditions. Accordingly, different loading conditions cause a redistribution of load on columns. When a column fails on excessive loading, the load redistribution results in high stresses on the remaining columns, which could ultimately cause structural failure. Given the role of column elements, examining all columns in the structure helps determine the robustness of a structure against failure, which past scaffold safety studies did not take into account. Therefore, this study utilizes the scaffold column strain values to measure the scaffold's safety condition.

For the measurement of strain value, it is required to equip the vertical scaffold members with strain-measuring sensors. Thus, this study developed a strain-measuring sensor capable of transmitting the measured values wirelessly. The sensor used commercially available strain gages (350 Ω and gage factor 2.18), a Wi-Fi-compatible Arduino Yun board (converts analog signals from strain gages to digital signals), and an interface shield to connect the strain gage and Arduino Yun. The specifications of the sensor are: operates at 5 Volts; strain gage measurements range of ± 1,000 με with a resolution of 2 με (meaning that the smallest change that the sensor would detect is 2 με); measurement accuracy of 1.44 με; and a sampling rate of 1 hertz. The strain gage board is used to regulate the measured voltage difference. The sensor is illustrated in Figure 7. These sensors will be installed on the vertical members (i.e., columns) of scaffolding structures, and real-time data collected by these sensors will be used to predict the scaffold safety status.

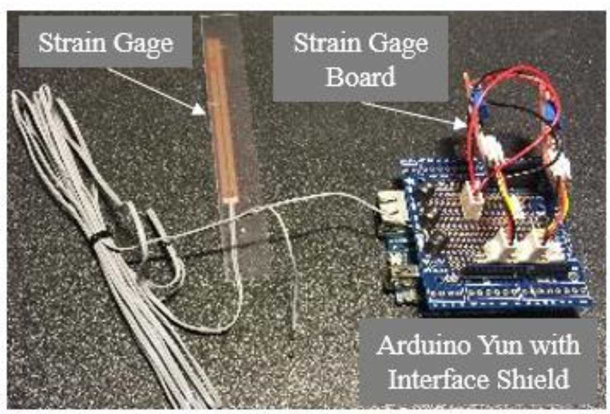


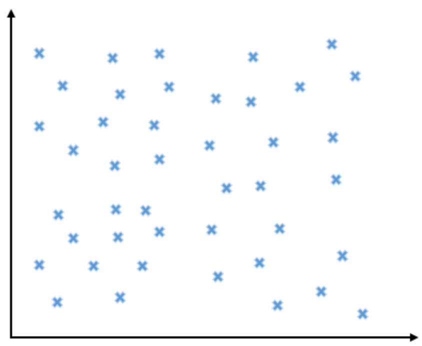
Figure 7. Strain-Measuring Sensor

Here, it should be noted that the impact of external environmental conditions, such as humidity and temperature, on the performance of this strain sensor has not been accounted for in this study.

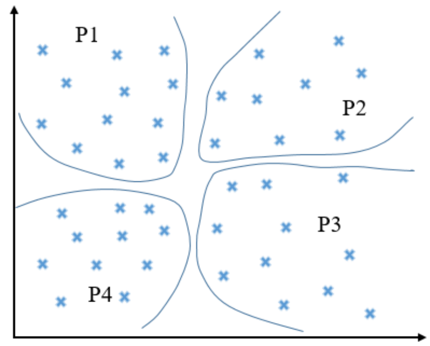
4.2.2. Machine-Learning Algorithms

The proposed scaffold monitoring system in this study is based on analyzing real-time data to determine scaffold safety status. When different forces are applied on scaffold members, the scaffolding structure has different structural responses depending on the nature of applied forces, meaning that the scaffold members have different strain patterns. With the supervised ML approach, the computer can be trained to identify such strain patterns. Thus, a supervised ML algorithm is another key component to the automated approach. The ML approach is based on the idea that systems can learn from training data, identify patterns, and make decisions on new data with minimal human intervention (Brownlee, 2016).

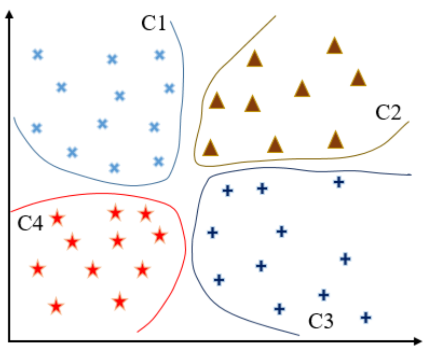
Figure 8 shows a graphical representation of how different strain patterns (i.e., P1, P2, P3, and P4 in Figure 8(b)) corresponding to four different scaffold conditions are classified into different groups by an ML algorithm. Once the algorithms are trained to recognize different strain patterns, these algorithms can be used to predict the scaffold's condition (i.e., C1, C2, C3, and C4 in Figure 8(c)) based on new strain measurement values. Therefore, this component leverages the outputs from the first two components for real-time scaffold safety condition prediction in the following two steps:



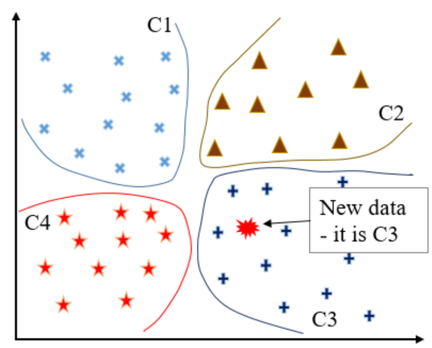
a. Plot of Random Strain Values



b. Classification of Different Strain Patterns



c. Training Classifiers to Learn Different Patterns



d. Trained Classifiers Predicting Class for New Data

Figure 8. Graphical Representation of Strain Pattern Classification using Supervised ML

4.2.2.1. Training ML Algorithms

The first step in the ML component is to train the algorithm to learn different strain patterns corresponding to each scaffold condition (refer to Figure 8). Thus, this step utilizes a training database (discussed in the following section 4.2.3) to obtain parameters of the trained ML model for real-time monitoring.

4.2.3.2. Real-time Scaffold Safety Prediction

The real-time scaffold safety prediction is the final step in this framework. The real-time data recorded by the wifi-enabled strain-measuring sensors will be directly transmitted to a computing processor where the trained ML models predict the real scaffold condition upon real-time data feed.

4.2.3. Scaffold Modeling for Training Database

As discussed earlier, a large training database of representative datasets is required to train ML algorithms to identify strain patterns corresponding to different scaffold safety conditions. Therefore, such database preparation is an essential step for ML implementation. As mentioned earlier, this study uses a scaffold model to prepare such a database that contains data corresponding to scaffold conditions that the ML algorithm is expected to identify. As such, a scaffold modeling technique is required to generate a scaffold model that closely represents the actual scaffold and the potential scaffold failure cases have to be identified before training database preparation. Different steps involved in this component are explained in the following sub-sections:

4.2.3.1. Scaffold Modeling and Validation

The scaffold modeling is an integral component of the training database preparation. This study used a software called COMSOL Multiphysics (*COMSOL Multiphysics Reference Guide*, 2012) to develop a finite element model (FEM) of the test scaffold. The beam-column elements and shell elements were used to model the scaffold frame and planks, respectively. The scaffold modeling technique (Cho et al., 2018) adopted in this study is based on synchronizing the strain behavior of the test scaffold with the scaffold model. Such synchronization assists in developing a scaffold model resembling a real scaffold's structural behavior. For this purpose, this modeling technique follows the following two steps:

1. Transformation of scaffold boundary conditions in the scaffold model;
2. Model-updating process based on material and geometric parameters.

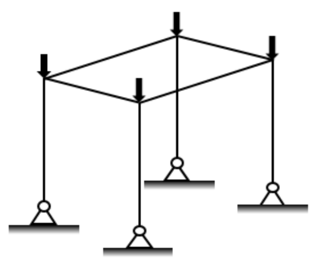
Transformation of Scaffold Boundary Conditions

In construction sites, it is a common practice that the scaffolds rest on stable base plates and are not fixed/attached to the foundations (Pieńko et al., 2018). However, such a boundary condition is considered a free-boundary condition and is regarded as unstable during structural analysis, as it is different from conventional boundaries such as hinges and fixed boundaries. Thus, for the structural analysis purpose, the actual scaffold boundary conditions are transformed to present more realistic conditions between the scaffold model columns and foundation.

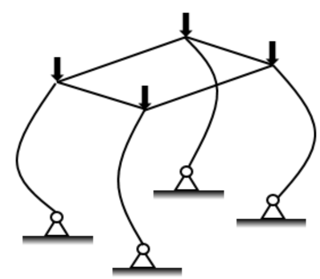
Initially, all boundary conditions are assigned pin connections. Light loads (vertical or lateral) on the scaffold result in a safe condition, as shown in Figure 9(a), and excessive loads on the scaffold cause overloading condition, as shown in Figure 9(b). Therefore, the scaffold has pin connections for such safe and overloading conditions. However, lateral forces or overturning moments result in slippage (sideways movement) or settlement of the structure, depending on the relationship between the applied forces and reaction forces. Accordingly, the boundary conditions are transformed based on the following two conditions:

i. Lateral Load Causing Slippage: Lateral forces (F_x or F_y) > Reaction force of the wooden foundation (μF_z), as shown in Figure 9(c). Under this condition, the pin connection is transformed into a roller boundary with a lateral reaction of μF_z, where μ is a friction coefficient.

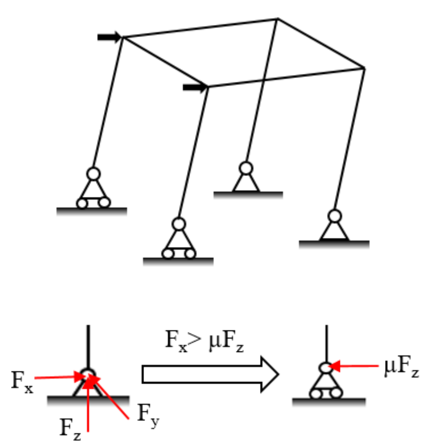
ii. Uneven Settlement Case: When the reaction force along the z-axis, i.e., $F_z < 0$, either the specific column is under the uneven settlement, or the structure is bound to overturn. In such a condition, the associated column is not able to support the load. Therefore, the boundary condition of such a column is transformed into a free condition, as shown in Figure 9(d).



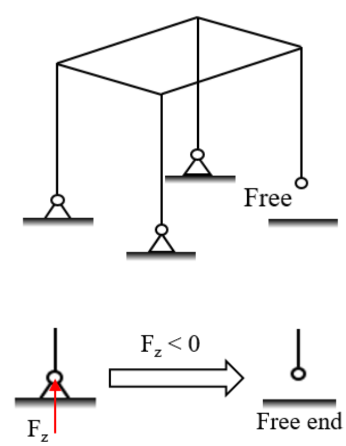
a. Light load resulting in safe case



b. Excessive load causing overloading



c. Lateral load causing slippage



d. Uneven settlement case

Figure 9. Boundary Condition Transformation

Model Parameter Updating Process

The second step in the scaffold modeling technique involves updating the FEM model material and geometric parameters. This process eliminates the discrepancy between numerical analysis and experimental measurements, which arise due to the use of nominal parameter values (such as material properties and geometric dimensions) during FEM modeling. Therefore, with the model-updating process, the scaffold modeling technique will result in a minimum difference in the element-wise strain values, between the test scaffold and the scaffold model, for the given loading condition (L). The following optimization function represents this process:

$$\text{Minimize}\|\text{Strain}_{\text{Test Scaffold}}(L) - \text{Strain}_{\text{Scaffold Model}}(L,X)\| \text{ for all strain measurements} \qquad \text{Eq. 1}$$

$$\text{Subject to } X_L \leq X \leq X_U$$

where X is the model-updating parameter, which is a 2D array consisting of Young's Modulus (*E*) and the thickness of the circular steel section (*t*), i.e., X = [*E*, *t*]; X_L and X_U are the lower and upper limits of the parameter.

As discussed earlier, the boundary conditions are transformed in the FEM model before the model-updating process. Then, the model-updating process is implemented, which involves installing wireless strain sensors on the test scaffold vertical members and transmitting the measured strain values to the FEM model. The FEM model optimizes material and geometric parameters based on the measured strain values to match the FEM model strain response with the measured values. The scaffold model developed with this approach will be validated using a real scaffold to ensure that the model has similar strain behavior to the real scaffold. Finally, this model will be used to generate computer-simulated data that has a near-real representation of data from an actual scaffold.

4.2.3.2. Scaffold Safety Condition Classification

After developing the scaffold model, the next step is to classify potential scaffold safety conditions. For this purpose, the scaffold's safety condition is categorized into safe and unsafe cases. Further, as stated in the scope of this study, the unsafe cases are categorized based on the mode of failure due to external loading conditions. For example, excessive load on the scaffold causes overloading failure, while excessive lateral forces in any direction cause lateral movement of scaffolds, resulting in overturning failure. Similarly, unsettled ground conditions or combinations of ground conditions and applied loads cause uneven settlement of scaffold members. Thus, this study categorized unsafe cases into overloading, uneven base settlement, and overturning failure modes. Therefore, this study has the following four classifications of the scaffold safety conditions:

i. Safe Condition
ii. Overloading Condition
iii. Uneven base Settlement Condition
iv. Overturning Condition

While accounting for refined failure modes of scaffolding structures, the three unsafe conditions may be further classified into different sub-cases. For example, considering the overloading of a single column at a time gives the number of sub-cases for overloading equal to the number of columns on the scaffold. Similarly, the uneven base settlement condition has the number of sub-cases equal to the number of scaffold columns. In the case of overturning conditions, the sub-cases depend on the direction of sideways movement. Furthermore, the consideration of a combination of different member failure cases (in the case of overloading and overturning failures) ensures the inclusion of more potential failure cases.

Although the refined classification of failure modes results in numerous scaffold failure modes, the prototype testing with a real scaffold involved in this study does not account for such failures. Instead, it considers the global failure modes, i.e., overloading, uneven base settlement, and overturning conditions. This is mainly because such prototype testing is limited in terms of the scale of testing and the failure modes, we can test due to the safety issues as it involves human and actual testing with real structures. Further, such testing is expensive too. Therefore, the prototype testing takes into account a limited number of failure cases that can be easily tested in a controlled laboratory setting. However, this study will further investigate a larger system in which various refined failure modes will be considered after validating the approach with prototype testing.

4.2.3.3. Database Preparation

The last step in this component is to prepare a training database, and it is necessary to ensure that this database contains strain datasets for all scaffold safety conditions identified in the previous section. For this purpose, the scaffold model obtained from *Section 4.2.2.1.* is simulated to represent different scaffold safety conditions by applying random combinations of gravity and lateral point loads on the scaffold model. Then, the corresponding scaffold member strain values are recorded to generate the database. The random loads applied to the scaffold model follow ASCE Standard 7-16 (ASCE, 2017). Table 1 summarizes the ranges of gravity and lateral forces applied to the model. This database preparation process overcomes the risks and complications as well as the additional expenses involved in field testing on a real scaffold with complex load applications.

Table 1. Load Ranges Applied to Scaffold Model

Scaffold Safety Conditions	**Gravity Loads (N/m^2)**	**Lateral Loads (N)**
Safe	-1400 to 0	±100 to ±500
Overloading	-1400 to -2000	±100 to ±500
Uneven Settlement	-1400 to 0	±100 to ±500
Overturning	-1400 to 0	±8000 to ±15000

4.3. Framework for Automated Scaffold Monitoring

The earlier discussions in this chapter highlight that the proposed framework's major components are real-time data, scaffold modeling technique for training database, and machine learning approaches. The real-time data is obtained from the strain-measuring sensors installed on scaffolding structures. This data is analyzed with machine-learning approaches for monitoring the scaffold safety. For such ML analysis, the required training database is built based on FEM analysis of a scaffold structural model that is generated through a scaffold modeling technique capable of developing models with near-real representation of real scaffolds. This database consists of near-real strain values for different loading conditions/failure cases specific to the scaffolding structure of interest. With the availability of this training database, ML algorithms are trained to identify different safety conditions. These two steps—preparation of training database from scaffold model and training ML algorithms—are background activities, meaning they occur off-site before installing scaffolds in construction sites. The trained ML algorithms are used in construction sites to analyze real-time data. Figure 10 shows the integrated framework for the automated monitoring of scaffolding structures with these components, and it enlists the corresponding steps in each component.

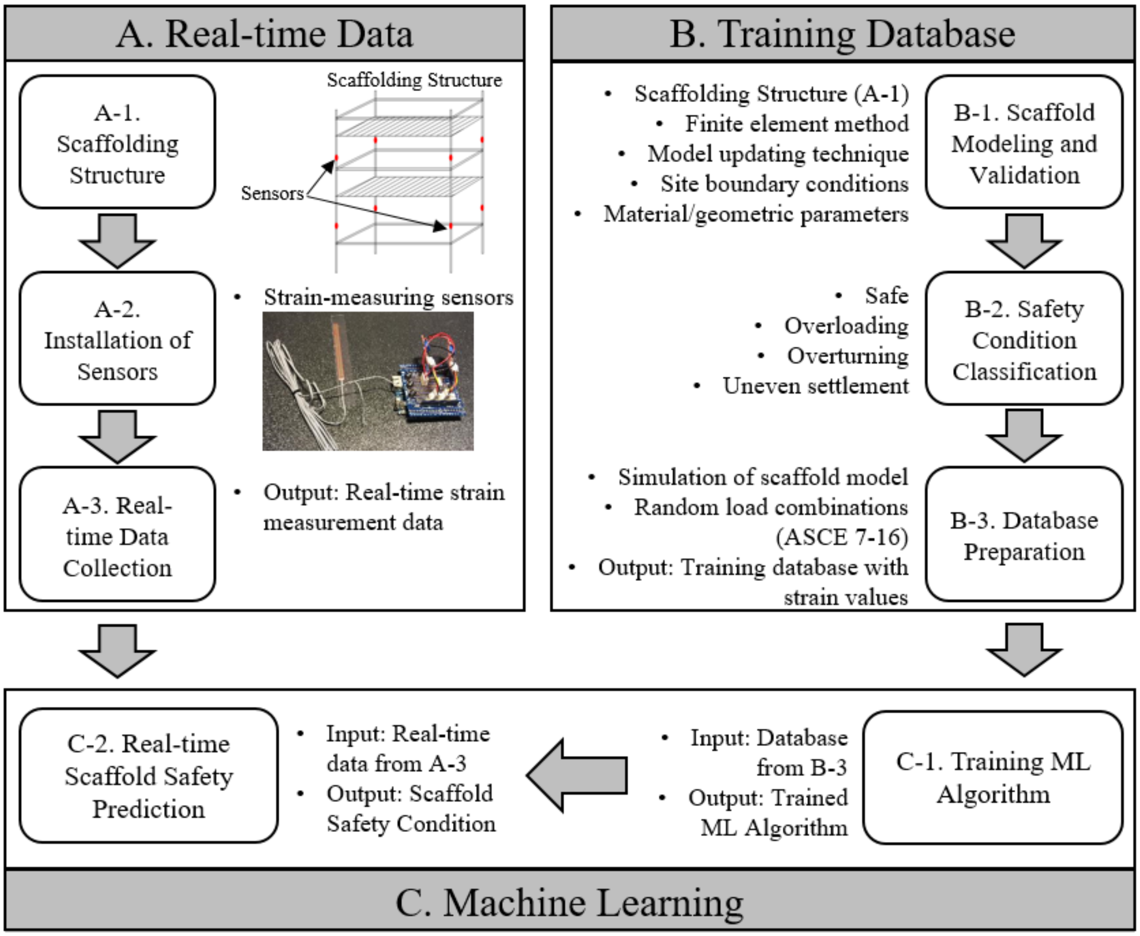


Figure 10. Automated Scaffold Monitoring Framework

It should be noted that the reliability of this automated scaffold monitoring framework lies in the reliability of the scaffold model developed for the training database preparation. Therefore, before the implementation of this framework, the scaffold modeling technique must be validated. Such validation will ensure that the proposed approach can be implemented for real-time monitoring. The validation will employ a real scaffold of single-bay and two-story.

4.4. Chapter Summary

This chapter exclusively focused on achieving the first objective of this dissertation, i.e., to develop a theoretical framework for the automated safety assessment of scaffolding structures and serves as the foundation for this dissertation. Specifically, the researcher identified the following key components for the foundational development of the automated monitoring system.

- Real-time data
- Scaffold modeling technique for training database
- ML algorithm

Based on the literature, the researcher identified scaffold strain measurements as an important parameter for evaluating scaffolding systems. As such, this study will use scaffold member strain values as the parameter to determine scaffold safety status. Thus, the proposed system will use strain-measuring sensors with Wi-Fi compatibility on the scaffold vertical members for strain measurement. The Wi-Fi compatibility enables real-time data collection. The proposed framework uses ML to quickly analyze the collected data to identify the scaffold safety status. The ML application involves training ML algorithms to identify different strain patterns and then using the trained ML algorithm to predict the strain patterns for new incoming data (i.e., the real-time data).

A training database is required for training ML algorithms. Therefore, the researcher uses a computer simulation-based approach to build a training database in the proposed framework. This approach involves 1) computer modeling of the scaffold, 2) scaffold safety condition classification, and 3) training database preparation. First, a FEM-based scaffold model resembling the structural behavior of the scaffold model to be monitored is built by transforming scaffold site boundary conditions and material/geometric parameters. Second, four scaffold safety conditions (safe, overloading, overturning, and uneven base settlement) are classified based on failure modes due to external loading conditions. Third, given the availability of the scaffold model and the safety condition classifications, the training database is prepared by simulating different safety conditions on the scaffold model with random load combinations, as stated in Table 1. This approach to database preparation eliminates the physical load application on scaffolds (which is an unsafe, expensive, and time-consuming process) to generate required strain data corresponding to different scaffold conditions.

This chapter well-integrated the three key components and developed an automated scaffold monitoring framework, which is the foundation for this Ph.D. dissertation research.

CHAPTER 5: TESTING THE SCAFFOLD SAFETY ASSESSMENT FRAMEWORK

5.1. Overview

This chapter focuses on testing the scaffold safety assessment framework proposed in Chapter 4. For this purpose, a proof-of-concept study is performed for the real-time scaffold safety assessment based on analyzing real-time strain measurements from scaffold columns. Note that this validation concerns the framework validation due another set of investigation for more complex system capability in the following chapter. The framework validation is to demonstrate the feasibility of the real-time scaffolding safety assessment approach and its integrated system and data flow from model-based database construction, real-time sensing, and ML prediction.

The validation of such an approach requires human involvement and complex load applications on real scaffolds for data acquisition; however, such involvement of humans and complex load applications make the prototype study very risky and expensive. Thus, the prototype testing is conducted in a controlled setting on a small scale, which is sufficient to demonstrate the mentioned system feasibility.

5.2. Essential Components of the Validation Study

The prototype study (Cho, Park, et al., 2018) comprises two components: a) Learning Component and b) Prediction Component. Figure 11 shows these components, along with the associated steps.

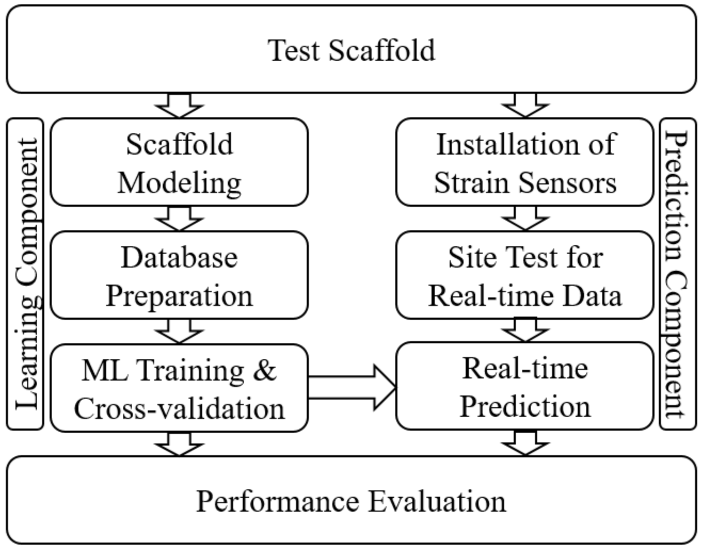


Figure 11. Outline for Proof-of-Concept Study

The learning component involves scaffold modeling, database preparation, and ML training & cross-validation. The final output of the learning component is the ML model that has learned the strain data characteristics corresponding to different scaffold safety cases. In this study, the ML model resulting in 95% cross-validation accuracy are selected for real-time prediction.

Similarly, the prediction component involves the installation of strain sensors on the test scaffold, site testing for real-time data collection, and then real-time predictions using the trained ML model obtained from the learning component. The performance of the system for each of these components is evaluated using different performance metrics. The following subsections discuss each of these steps in detail.

5.2.1. Learning Component

The main purpose of the learning component is to obtain the trained ML model that can categorize scaffold safety conditions (i.e., safe, overloading, overturning, and uneven settlement) based on scaffold member strain values. Thus, this component involves the preparation of a training database consisting of strain values corresponding to all safety conditions and then training ML model to learn the strain values specific to each safety case. A scaffold model corresponding to the test scaffold is initially developed, following the approach discussed in *Section 4.2*. This approach ensures that the model has a structural response similar to the test scaffold. This model is used to generate the strain measurement database required for the training and cross-validation of ML model.

After the scaffold model development, the next step is to prepare the training database. For this purpose, the scaffold model is analyzed with various loading cases to simulate safe, overloading, uneven settlement, and overturning scenarios. The loadings applied to the scaffold model during the analysis follow ASCE 6-17 (ASCE, 2017), as discussed in *Section 4.2* of Chapter 4. Finally, the training database is prepared with the recorded strain values of the scaffold vertical members for each loading case. For each safety condition, 350 strain datasets are recorded. So, the database has a total of 1,400 strain datasets (i.e., 350 datasets × 4 conditions).

As this study (specific to objective 2) focuses on determining the feasibility of applying ML for scaffold failure detection, a relatively simple ML technique, Support Vector Machine (SVM), is selected for ML training and cross-validation. This technique has been successfully implemented in past studies (Bornn et al., 2009; Gui et al., 2017; J. Zhang et al., 2006) for structural health monitoring. SVM is a binary classifier (i.e., classification as either 1 or 0).

However, the scaffolding safety classification is a multi-class classification (not a binary problem). For such multi-class problems, SVM can be implemented in two ways: 1) one-versus-all and 2) one-versus-one classification.

The one-versus-all approach requires training models for each class (i.e., four in our case). Given that four classifiers are available, each classifier positively classifies data from a particular class (i.e., classified as 1) and data from other classes are treated as negative (i.e., classified as 0). For instance, the classifier trained to identify 'safe' class will only positively identify safe strain data, while data from other classes are identified as zero. For the four scaffold safety cases, there would be four classifiers: 1) safe classifier (i.e., safe vs overloading + uneven settlement + overturning), 2) overloading classifier (i.e., overloading vs safe + uneven settlement + overturning), 3) uneven settlement classifier (i.e., uneven settlement vs safe + overloading + overturning), and 4) overturning classifier (i.e., overturning vs safe + overloading + uneven settlement).

However, the one-versus-one approach in multi-class classification performs a binary classification of a class with each of the other classes. For the four classes in this study, there would be six classifiers: 1) safe vs overloading, 2) safe vs uneven settlement, 3) safe vs overturning, 4) overloading vs uneven settlement, 5) overloading vs overturning, and 6) uneven settlement vs overturning.

This study specifically employed the one-versus-all SVM algorithm. This one-versus-all specification of the SVM algorithm treats the prediction of every class as a binary classification problem. As such, four different SVM classifiers will be trained to identify each of the four safety cases. The training will use 80% of the datasets on the training database, and the remaining datasets will be used to cross-validate the trained classifiers. The training and cross-validation steps will be repeated with different SVM parameters until 95% accuracy is achieved in the cross-validation stage. Then, the researcher will select those parameters corresponding to 95% cross-validation accuracy for further use in real-time prediction.

Here, it should be noted that no other ML techniques are evaluated for this validation study, as this study focuses on assessing the feasibility of ML techniques for predicting scaffold safety conditions.

5.2.2. Prediction Component

The prediction component involves the prediction of scaffolding safety conditions by analyzing the real-time data acquired from the test scaffold with the trained classifiers obtained from the training component. For this purpose, strain sensors (as discussed in *Section 4.3.1.* of Chapter 4) are installed on the test scaffold vertical members. As the test scaffold has four vertical members, four corresponding sensors will be installed on the scaffold. Then, different load combinations are applied on the test scaffold to simulate each unsafe condition. For each condition, 50 tests will be conducted to evaluate the real-time safety condition prediction capability of SVM classifiers that are trained with a computer-simulated database (i.e., SVM classifiers obtained from the learning component). Finally, the trained SVM classifiers will predict the scaffold safety condition for each test. At this point, the actual safety condition, as well as the predicted safety condition, will be saved for performance evaluation.

Successful prediction of scaffold safety conditions by analyzing the real-time data with this ML approach shows that given the availability of a training database, ML algorithms can be trained to determine the safety condition of new scaffolds. Further, ML algorithms can be trained to identify additional (new) failure modes if training datasets for such failure modes are available from the computer simulation. Besides, such a monitoring approach requires minimal to no site data collection prior to system deployment.

5.2.3. Performance Evaluation

The predicted safety condition of the scaffold is compared with the actual scaffold condition to evaluate the performance of the proposed approach. Such comparison will identify incorrect classifications and the misclassification rates can be analyzed. Further, accuracy, precision, recall, and F1-score values will be used for the performance evaluation. The accuracy is the measure of correct classifications, precision is the measure of positive identifications that are actually correct, recall is the measure of actual positives that are identified correctly, and F1-score is the harmonic mean of recall and precision. These metrics are computed using the following equations:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad \text{Eq. 2}$$

$$Precision = \frac{TP}{TP + FP} \quad \text{Eq. 3}$$

$$Recall = \frac{TP}{TP + FN} \quad \text{Eq. 4}$$

$$F1 - score = \frac{2 * Recall * Precision}{Recall + Precision} \quad \text{Eq. 5}$$

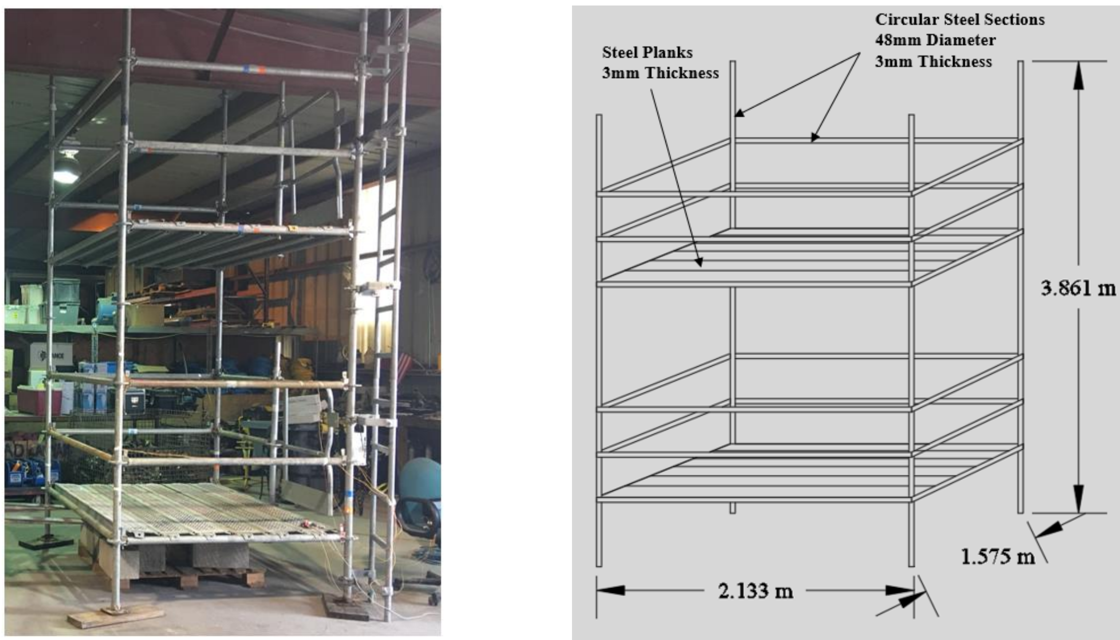
Where, true positives (TP) are the instances in which the scaffold safety cases are correctly predicted as true, false positives (FP) are the instances in which the scaffold safety cases are incorrectly predicted as true, true negatives (TN) are the instances in which the scaffold safety cases are correctly predicted as false, and false negatives (FN) are the instances in which the scaffold safety cases are incorrectly predicted as false.

5.3. Validation Study and Results

This section discusses in detail the prototype study (Cho, Park, et al., 2018) conducted in this study. Initially, information on the test scaffold is provided. Then, the following section will validate the scaffold modeling technique discussed in *Section 4.2.2.1*. This validation focuses explicitly on the capability of the proposed scaffold modeling technique to produce a model with a near-real representation of the actual scaffold for different load cases. Following the scaffold modeling technique validation, a follow-up study is conducted to demonstrate that the scaffold model has similar structural responses to the actual scaffold for different scenarios corresponding to scaffolding safety conditions discussed in *Section 4.2.2.2*. Finally, the prototype study concludes with the validation of the proposed automated scaffold monitoring approach. The following subsections discuss these steps in detail and their corresponding results.

5.3.1. Test Scaffold

This study used a prototype test scaffold of single-bay and two-story for laboratory testing. The test scaffold is a heavy-duty, ring-lock type scaffold constructed using 48 mm diameter circular pipe sections of 3 mm thickness and 3 mm thick steel planks, as shown in Figure 12(a). The scaffold frame consists of four vertical members and 24 side frames, with the overall scaffold dimensions of 2.133 m (length) × 1.575 m (width) × 3.861 m (height) (i.e., 7 ft (length) × 5.16 ft (width) × 12.67 ft (height)), as shown in Figure 12(b). On each floor, steel planks with the dimensions 2.133 m × 0.254 m (i.e., 7 ft × 0.83 ft) are used as flooring. The scaffold rests on wooden plates during the laboratory testing, as shown in Figure 12(a).



a. Actual Scaffold Model

b. Scaffold Dimensions

Figure 12. Test Scaffold: Single-bay, two-story

For the real-time strain data, the strain gages (discussed in *Section 4.2.1.*) were installed on four columns of the test scaffold. Figure 13 shows the test scaffold with four columns resting on wooden foundation. Four strain gages connected with wireless unit are installed at locations marked with red circles.

Figure 13. Test Scaffold with Strain Sensors Installed

5.3.2. Scaffold Modeling Technique Validation

The earlier chapter presented a detailed discussion of the scaffold modeling technique, which involved two major steps: 1) scaffold boundary condition transformation and 2) updating scaffold material and geometric parameters. This section of the prototype study validates the modeling technique (Cho, Sakhakarmi, et al., 2018) for the single-bay two-story test scaffold discussed in *Section 5.3.1.*

It is a common practice that scaffolds are not fixed or attached to the foundations. Considering this, the laboratory testing used wooden foundations for the test scaffold. However, such a boundary condition is considered a free boundary and causes instability during structural analysis. Thus, the transformable boundary conditions were initially assigned to present more realistic conditions between the scaffold columns (i.e., vertical members) and foundations of the scaffold model, as discussed in *Section 4.2.1.2*. For the model updating process (Eq. 1), the initial model-updating parameter (X_0), i.e., nominal parameters, was set with the nominal Young's Modulus value of 200×10^9 Pa for steel and thickness of the circular pipe section (i.e., 3 mm). Then, the parameters' lower and upper limits (i.e., X_L and X_U, respectively) were set as ±15% of X_0. Thus,

$$X_0 = [200\times10^9 \text{ Pa}, 3 \text{ mm}]$$

$$X_L = [170\times10^9 \text{ Pa}, 2.55 \text{ mm}]$$

$$X_U = [230\times10^9 \text{ Pa}, 3.45 \text{ mm}]$$

For the validation of the scaffold modeling technique, four wireless strain sensors were installed on the test scaffold vertical members. The data collected from these sensors were synchronized with the FEM model.

Based on the OSHA scaffold specification (OSHA, 2012), the maximum weight exerted on a heavy-duty scaffolding should not exceed 75 lbs/ft^2. Thus, the maximum loading capacity for the test scaffold, which has a span size of 7 ft in width and 5.16 ft in depth, is calculated as follows:

$$Load_{max} = 7ft \times 5.16ft \times \frac{75lb}{ft^2} = 2709\ lb = 1229\ kgf$$

Although the maximum loading capacity of the test scaffold is determined to be 1229 kgf, due to safety reasons, the loading on the test scaffold was limited to 400 kgf during the testing. Therefore, this study specifically used loading ranging from 100 kgf to 400 kgf, with an interval of 100 kgf (i.e., four different loading cases: 100 kgf, 200 kgf, 300 kgf, and 400 kgf). Accordingly, the experimental strain values were recorded for each loading case.

Tables 2 and 3 summarize the strain measurement values corresponding to the four applied load cases for the test scaffold and the initial model with nominal parameters.

Table 2. Strain Values for Test Scaffold

Column No.	Strain Values for Different Loadings (με)			
	100 kgf	200 kgf	300 kgf	400 kgf
1	-7.051	-13.418	-19.784	-26.149
2	-7.051	-13.415	-19.780	-26.142
3	-7.051	-13.417	-19.783	-26.147
4	-7.050	-13.415	-19.781	-26.144
Average	-7.051	-13.416	-19.782	-26.145

Table 3. Strain Values for Initial Model with Nominal Parameters

Column No.	Strain Values for Different Loadings (με)			
	100 kgf	200 kgf	300 kgf	400 kgf
1	-5.601	-11.198	-16.795	-22.390
2	-5.601	-11.196	-16.791	-22.385
3	-5.602	-11.198	-16.794	-22.389
4	-5.601	-11.196	-16.792	-22.386
Average	-5.601	-11.197	-16.793	-22.387

The FEM model was simulated for each load case to match the analytical strain values with the recorded values. Finally, the optimized value for X is obtained as:

$$X = [198.12\times10^{9}\ \text{Pa},\ 2.612\ \text{mm}]$$

Table 4 summarizes the strain measurement values corresponding to the four applied load cases for the final updated scaffold model. The comparison of strain values for the test scaffold and initial model with nominal parameters shows a drastic difference in the strain values, while the updated scaffold model has similar strain values to the test scaffold.

Table 4. Strain Values for Updated Scaffold Model

Column	Strain Values for Different Loadings (μƐ)			
No.	100 kgf	200 kgf	300 kgf	400 kgf
1	-7.012	-13.042	-20.028	-26.048
2	-7.001	-13.022	-19.997	-26.007
3	-7.003	-13.005	-19.971	-25.974
4	-6.998	-12.979	-19.931	-25.919
Average	-7.004	-13.012	-19.982	-25.987

Figure 14 shows the comparison of the averages of four strain values for the four different loading cases during the scaffold modeling validation. The x-axis represents the applied loads, and the y-axis represents the average strain values of the four scaffold vertical members. This plot shows that the updated model has similar behavior to the test scaffold (i.e., represented by the experimental values), while the initial values (i.e., values with nominal parameters) are higher than the experimental values. Thus, these results indicate that the scaffold modeling technique used in this study is suitable for developing scaffold models with structural behavior similar to actual scaffolds.

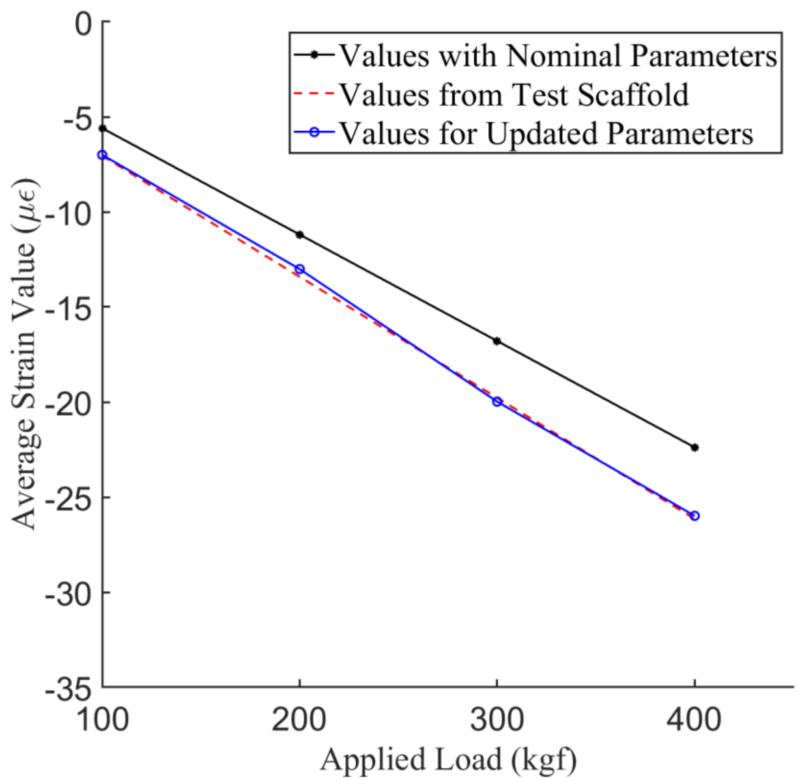


Figure 14. Scaffold Model Average Strain Data Comparison

Follow-up Study to Test Different Safety Cases

This follow-up study conducted additional tests to determine structural responses for different safety cases that this study intends to identify. These tests intend to confirm that the updated model and the actual scaffold have similar structural responses for scenarios corresponding to different safety cases.

A total load of 400 kgf was applied on the test scaffold and the updated scaffold model to evaluate the overloading case. In addition, a forklift was used to simulate uneven settlement and overturning cases by lifting one or two scaffold vertical members. The lift height was limited to 2 inches (approx. 5.1 cm) for safety reasons. To simulate an uneven settlement case, one of the scaffold columns (Column 1) was lifted by a forklift. Similarly, the forklift lifted two scaffold columns (Columns 1 and 4) to simulate an overturning case. The strain values recorded for these three unsafe scenarios from the field test and computer simulation are summarized in Table 5.

Table 5. Experimental Validation Results for Unsafe Scaffold Scenarios

Column No.	Strain Values for Different Safety Cases (μƐ)					
	Overloading		Uneven Settlement		Overturning	
	Actual Scaffold	Updated Model	Actual Scaffold	Updated Model	Actual Scaffold	Updated Model
1	-25.458	-25.141	0.013	0.000	0.001	0.000
2	-25.193	-25.095	-7.082	-7.004	-12.25	-12.02
3	-26.057	-25.889	-8.041	-8.599	-13.04	-12.02
4	-25.319	-25.512	-8.071	-7.004	-0.004	0.000

The strain measurement values summarized in Table 5 show that the strain values from the scaffold model simulations are similar to the field measured values obtained from the real scaffold. Further, the scaffold has distinct strain measurement values for the three cases tested in this study. For the overloading case, both the field test and computer simulation resulted in nearly -25 $\mu\varepsilon$ strain values on all four scaffold vertical members. In the case of uneven settlement and overturning, lifted vertical members had zero strain values, while the other members had greater strain values, as those members were responsible for supporting more loads. These strain pattern results for different failure cases indicated that the proposed approach of detecting scaffold safety conditions through analyzing the strain values could be performed reliably for the considered safety cases with supervised learning techniques.

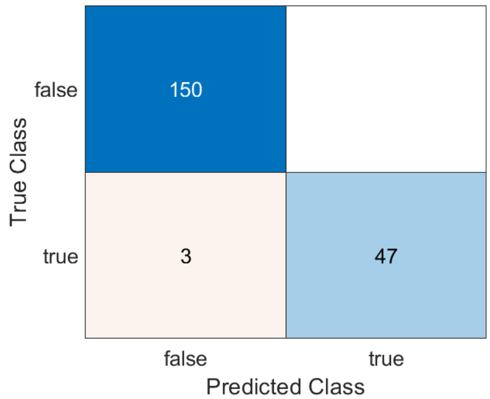
5.3.3. Validation of Automated Scaffold Monitoring Approach

This section presents the validation of the automated monitoring with the proposed methodology (Cho, Park, et al., 2018). Initially, the training database was prepared based on the approach discussed in the earlier chapter. For this purpose, three hundred fifty strain datasets were generated for each scaffold safety condition under consideration. Therefore, the database comprised a total of 1,400 strain datasets. Table 6 shows the sample strain dataset generated from simulation with random loadings (within the load ranges stated in Table 1).

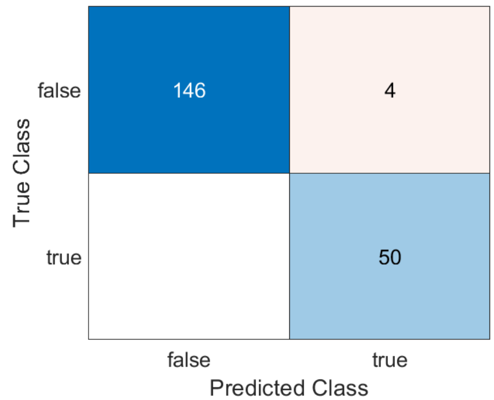
Table 6. Sample Training Database Simulated from Scaffold Model

Scaffold Safety Condition	Strain Values for Different Safety Cases (με)			
	Column 1	Column 2	Column 3	Column 4
Safe	-42.467	-50.411	-38.189	-55.168
	-54.682	-57.021	-29.960	-28.032
	-29.242	-62.386	-49.877	-19.155
	-19.098	-45.165	-39.281	-30.280
	-64.160	-47.289	-54.281	-61.448
Overloading	-75.474	-85.553	-86.016	-75.422
	-31.110	-69.452	-48.278	-49.118
	-80.273	-56.823	-40.069	-62.375
	-53.500	-71.368	-56.696	-58.558
	-54.103	-40.506	-73.353	-45.803
Uneven Settlement	11.295	-7.244	-19.247	-0.026
	-6.278	-12.071	0.466	15.755
	2.282	-6.857	-24.256	-4.818
	-24.755	-8.964	8.771	-3.331
	0.543	11.878	-14.471	-11.775
Overturning	13.437	3.317	-12.116	3.433
	-1.866	-22.338	-13.961	7.771
	-5.247	-22.375	-10.982	3.523
	3.761	18.358	10.926	-8.545
	-19.661	-19.049	5.932	0.939

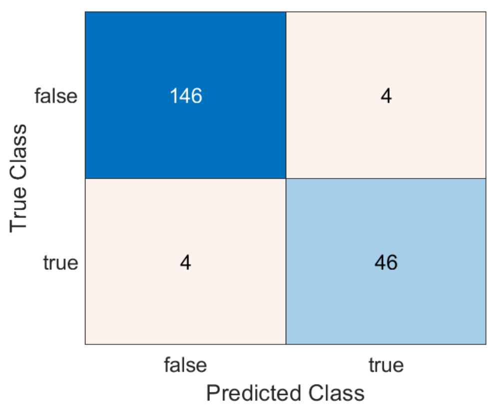
This training database was used to train and cross-validate ML classification models. Those ML models were later used to classify safety conditions for data obtained from strain sensors on the test scaffold under different loading conditions. 300 out of 350 data for each case was used for training purposes. The remaining data were used as cross-validation set to determine the trained model accuracy. This study used the one-versus-all SVM classification method to validate the proposed safety classification approach. As discussed earlier, this classification method treats the problem as a four-class classification. Figure 15 shows the classification result for each classifier.



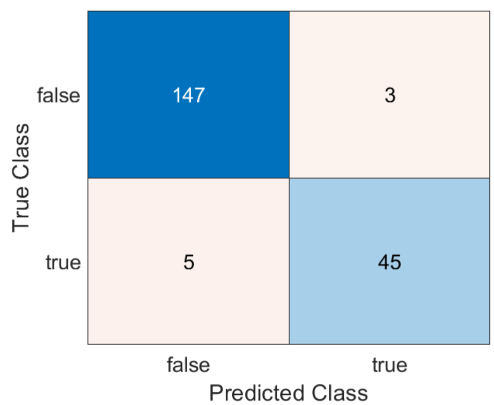
a. Safe Classifier



b. Overloading Classifier



c. Uneven Settlement Classifier



d. Overturning Classifier

Figure 15. Confusion Matrix for Four Classifiers

The classification results show that 47 of 50 safe cases were correctly classified as safe. Similarly, 4 and 5 instances of uneven settlement and overturning cases were misclassified, while none of the non-safe cases were classified as safe. It should be noted that none of the unsafe cases were misclassified as safe, while each of the three unsafe cases had misclassifications. Each overloading and uneven settlement cases had four incorrect classifications, and the overturning case had three misclassifications.

Table 7 enlists the performance metrics for all classifiers. The safe case had the highest 98.5% accuracy, while the accuracy for overloading, uneven settlement, and overturning were 98%, 96%, and 96%, respectively. The recall values for safe, overloading, uneven settlement, and overturning cases were 1.000, 0.926, 0.918, and 0.938, respectively. The precision values were 0.940, 1.000, 0.918, and 0.900 respectively. Similarly, the F1-Scores were 0.969, 0.962, 0.918, and 0.918 respectively. The average prediction accuracy for the simulated training database was 97.13%, which shows that the trained parameters can process strain data to predict the scaffold safety condition.

Table 7. Performance Metrics for SVM Classifiers

	TP	FP	TN	FN	Accuracy	Recall	Precision	F1-score
Safe	47	3	150	0	98.5	1.000	0.940	0.969
Overloading	50	0	146	4	98	0.926	1.000	0.962
Uneven Settlement	45	4	145	4	96	0.918	0.918	0.918
Overturning	45	5	147	3	96	0.938	0.900	0.918

For the validation purpose, the tests were conducted on the prototype scaffold to simulate three failure modes and 50 sets of strain measurements were collected for each failure condition. These measurements were directly fed into the trained SVM classifiers obtained from the simulated training database to predict the scaffold safety condition. Tables 8 and 9 summarize the classification results.

Table 8. Summary of Real-time Data Prediction

Actual Input Cases	SVM Classified Cases			
	Safe	Overloading	Uneven Settlement	Overturning
Overloading	0	50	0	0
Uneven Settlement	0	0	47	4
Overturning	0	0	2	45

Table 9. Binary Classification Results of Real-time Data Prediction

		Actual Input Cases					
		Overloading		Uneven Settlement		Overturning	
SVM Classified Cases	Safe	TN(50)	FN(0)	TN(50)	FN(0)	TN(50)	FN(0)
	Overloading	TP(50)	FP(0)	TN(50)	FN(0)	TN(50)	FN(0)
	Uneven Settlement	TN(50)	FN(0)	TP(47)	FP(3)	TN(48)	FN(2)
	Overturning	TN(50)	FN(0)	TN(46)	FN(4)	TP(45)	FP(5)
Accuracy		100.0%		96.5%		96.5%	
Recall		1.000		0.922		0.957	
Precision		1.000		0.940		0.950	
F1-score		1.000		0.931		0.953	

The classification results show that the trained SVM classifiers could correctly predict all overloading cases. At the same time, there were 4 and 2 incorrect predictions in the case of uneven settlement and overturning cases. The accuracies for each of these cases were 100%, 96.5%, and 96.5%, respectively (i.e., the average accuracy of 96.67%). The recall, precision, and F1-score values were one each for the overloading case; 0.922, 0.940, and 0.931, respectively, for the uneven settlement case; and 0.957, 0.950, and 0.953, respectively, for the overturning case.

5.4. Chapter Summary

This chapter exclusively validated the scaffold modeling technique and the scaffold monitoring system (i.e., the second objective of this study) through a proof-of-concept study. The study results show that the simulated scaffold strain values corresponding to different safety conditions are representative of actual scaffold data. As such, these simulated data can be reliably used to generate ML classifiers (demonstrated by the higher prediction accuracy of the SVM classifier generated through simulated data). Such capability of simulated data enables the development of monitoring systems for any supported scaffolding structures as used in this study, given that a corresponding structural model (FEM) is available to prepare the required training database.

Further, the scaffold model constructed based on the proposed scaffold modeling technique ensures that the FEM model closely represents a real structure, preventing the need for unsafe and expensive field testing for database preparation. Furthermore, given that the scaffold modeling and database preparation can be done offsite, the scaffold installing companies can readily install the scaffold monitoring system on scaffolds at a small cost. Additionally, this database preparation approach overcomes the impact of data size limitation on ML utilization in developing automated monitoring systems as this approach enables the preparation of the required database through computer simulation. Therefore, this prototype study results present a major breakthrough in developing a real-time scaffold monitoring system.

CHAPTER 6: AUTOMATED SCAFFOLD MONITORING FOR SCAFFOLDS WITH MULTIPLE BAYS AND MULTIPLE STORY

6.1. Overview

The prototype study presented in the earlier chapter, Chapter 5, demonstrated the feasibility of the proposed automated scaffold monitoring approach based on real-time strain measurement values for a simple scaffold with an SVM algorithm. However, the type of the scaffold used in the prototype study was limited for safety reasons. Scaffolds with a similar size are commonly used for minor construction activities, while many other construction sites use larger scaffolds, i.e., scaffolds with multiple bays and multiple stories. Large scaffolds involve many different failure modes compared to those in the prototype study. As the complexity of the structure increases (in terms of size), the potential number of failure modes increases significantly. As this may introduce difficulty in ML prediction, another level of investigation focusing on algorithmic perspectives and predictive performance is necessary.

As an example of an increase in modes of failure, overloading on a single structure member could cause part of the bays to fail, which may progressively lead to the collapse of the scaffold. In such a case, early detection of that specific scaffold member with overloading could prevent the collapse with necessary precautionary measures. Similarly, the collapse could result from the failure of a combination of members. Further, this example of the overloading failure case explains that such a failure could be due to a single structural member failure or failure of multiple scaffold members. As such, each of the failure modes discussed earlier (i.e., overloading, uneven base settlement, overturning) would have many categories within each mode. Such categories provide more refined information on the potential failure case such as the member that is potentially overloaded (instead of simply identifying that the scaffold is overloaded). The ability to identify refined details on the failure modes would be more beneficial for timely undertaking proper precautionary measures to prevent catastrophic events. Therefore, the detection of such refined failure modes becomes critical in order to prevent construction site hazards.

The increased number of failure cases while accounting for refined failures adds complexity to the data analysis process due to having a large number of safety classifications and large data size. However, considering such refined failure cases has not received sufficient attention from researchers. Further, the large number of classification cases is one of the problems with large-scale classification (Kugler, 2006), which can be solved with enough number of features (i.e., the number of strain measurements in a dataset in this study) and data size (i.e., the number of datasets). However, this study has the challenge to classify a large number of safety cases with a limited number of strain features based on the number of sensors installed on the vertical scaffold members. Therefore, this part of the dissertation study intends to investigate the monitoring of a multi-bay and multi-story scaffolding structure by considering such refined failure cases and create methodological advancement in the data analysis process to overcome the challenges with large-scale classification. For this purpose, this study will employ a new scaffold model with the same material and support parameters as the test scaffold used in *Sections 4.2 and 4.3*.

6.1.1. Scaffold Model

This study is based on a four-bay and three-story scaffold model, as shown in Figure 16. The scaffolding structure is designed following the OSHA specification (OSHA, 2012). Each bay of the scaffold measured 64 inch (L) x 84 inch (W) x 76 inch (H). Thus, the overall dimension for the four-bay three-story scaffold was 256 inch (L) x 84 inch (W) x 228 inch (H).

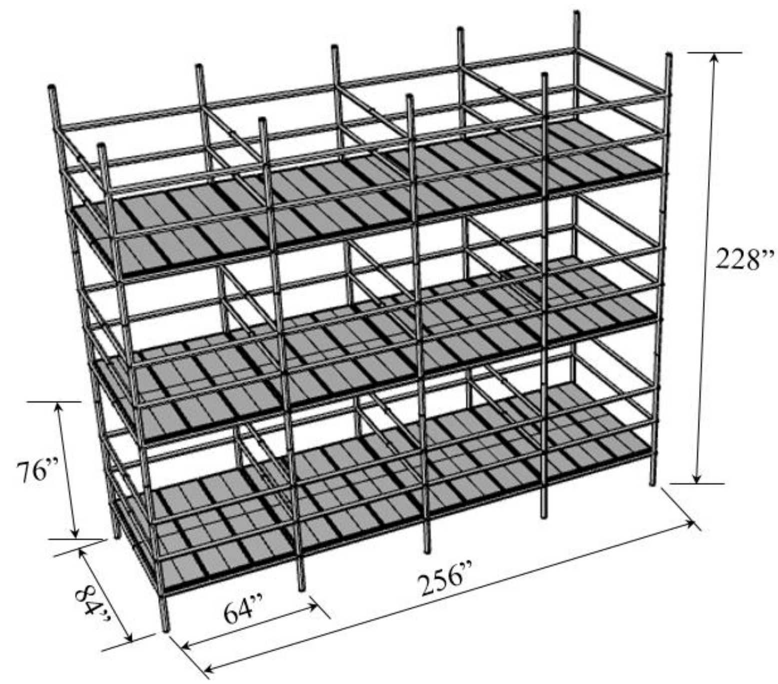


Figure 16. Four-bay, Three-story Scaffold

For this scaffold, 20 sensor data extraction points are considered (i.e., one point on the vertical members between each story), as marked by red circles in Figure 17. The dashed red circles represent data extraction points on hidden vertical members. Here, it should be noted that it is not practical to install many sensors on temporary structures like scaffolds. Thus, although more sensors would consequently result in better scaffolding structure monitoring, the number of data extraction points is limited due to practical concerns.

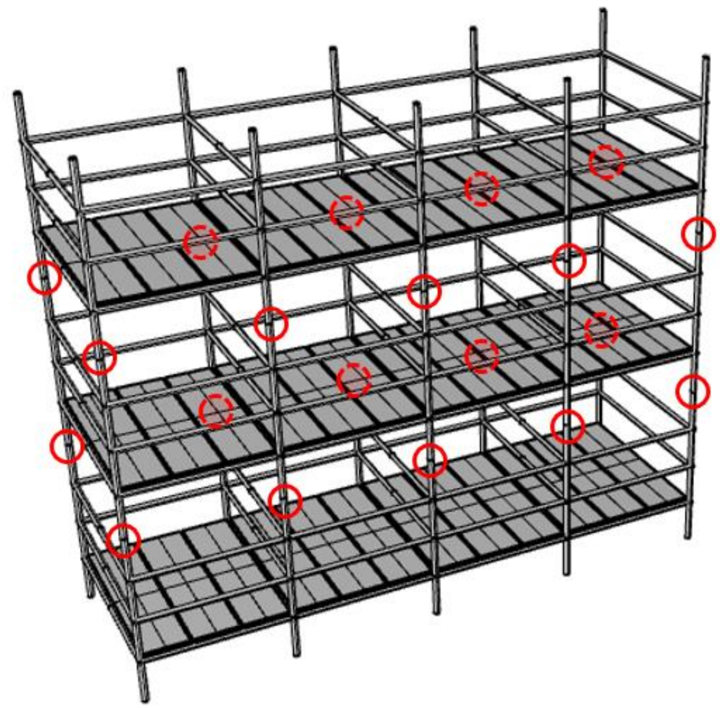


Figure 17. Scaffold Model Sensor Data Extraction Points

6.1.2. Scaffold Safety Condition Classification and Database Preparation

As discussed earlier, this study considers refined failure modes for the three unsafe conditions (i.e., overloading, uneven base settlement, and overturning cases) to incorporate a wide range of potential failure modes. These unsafe conditions are further categorized into more specific unsafe conditions based on the potential failures caused by a single scaffold structural member or a combination of members.

Specifically, the overturning condition results from the sidewise scaffold movement. Thus, this failure mode is sub-categorized based on the sidewise scaffold movement in X and Y directions (i.e., longitudinal and transverse directions of the scaffold). In the case of overloading and uneven base settlement, the classification is based on the potential failure of a member or a combination of a different number of scaffold members due to external loadings. For instance, overloading failure at any time could result due to excessive weight on any of the columns or a combination of columns varying from two to "n" (say, the scaffold has "n" number of columns). Accordingly, 1,411 safety conditions (i.e., one safe and 1,410 unsafe conditions) were categorized for the scaffold (Figure 18) in this study. Figure 18 shows the classification chart of scaffold safety conditions with all sub-categories.

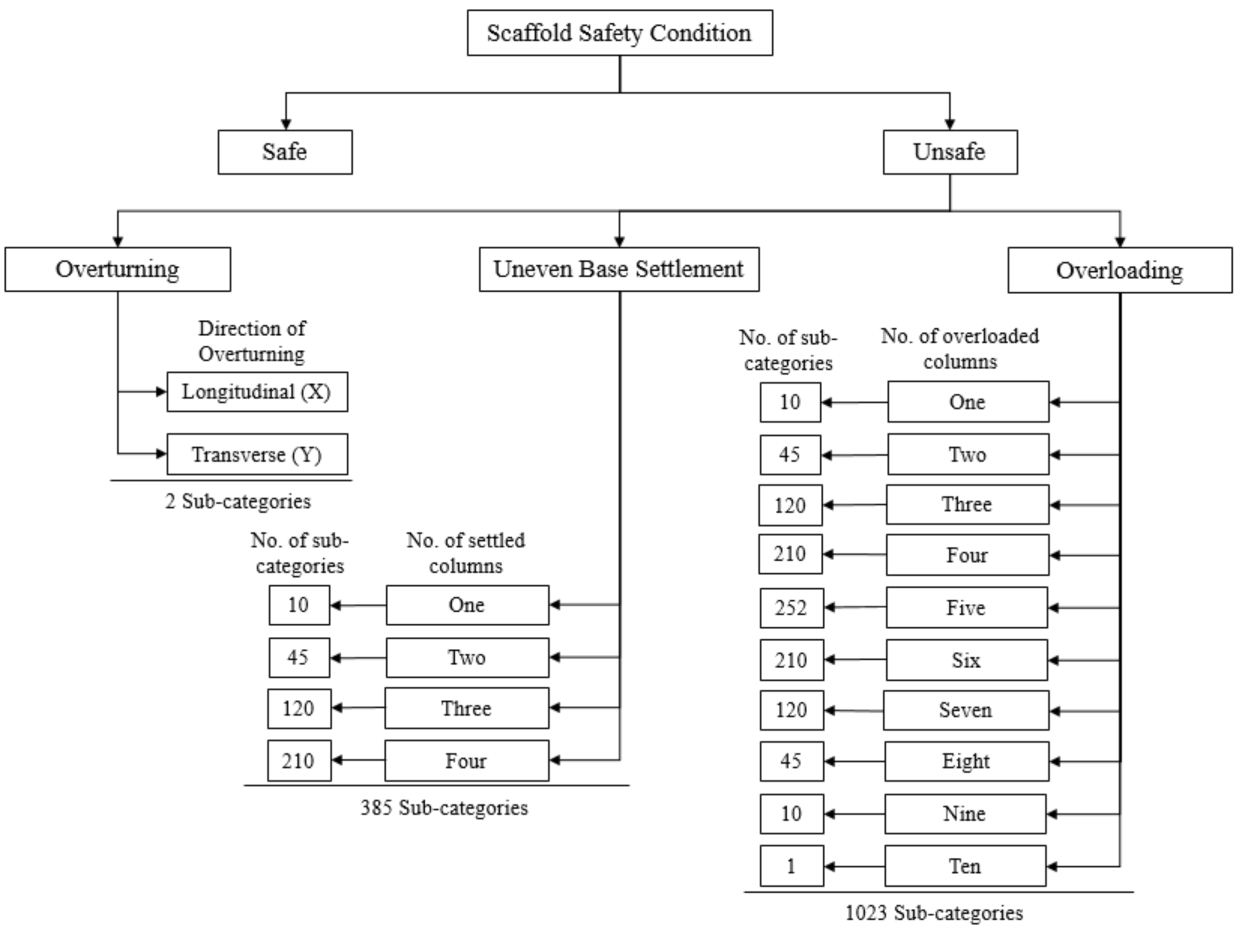


Figure 18. Classification of Scaffold Safety Conditions

The earlier prototype study demonstrated the feasibility of the automated scaffolding safety monitoring framework that integrates real-time data, scaffolding modeling, and ML training and prediction. The initial prototype demonstration proved the feasibility of the approach, and this implies that data availability is no longer a limitation for conducting such research on scaffolds of any size (i.e., multiple bays and multiple stories). Given this, the data required for this study (i.e., database corresponding to the specific scaffolding structure) is obtained by simulating specific potential failure modes on the scaffold FEM model, as discussed earlier. The researcher applied this computer simulation approach to build a database with a thousand datasets for each safety condition, i.e., the database had 1,411,000 datasets with 20 strain features each. This database was used for training ML models in this study. Table 10 shows a sample set from the database. Similarly, a new database with a hundred datasets for each safety condition (i.e., a database with 141,100 datasets) was built for testing the trained ML models with new datasets.

Table 10. A Sample Set from Strain Database

Data-sets	Strain Values (με) at Data Extraction Points 1 to 10									
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
1	-10.5	-19.9	-17.2	-4.5	-7.8	-11.8	-21.5	-22.2	-10.2	-7.7
2	0.9	0.7	-14.3	-0.1	-8.1	-18.2	-90.7	-7.3	-52.1	-4.0
3	2.7	6.9	-5.4	-5.7	0.1	-14.7	-62.1	-9.5	-23.3	-7.1
4	0.2	10.2	-13.2	-0.3	0.2	-15.2	-25.4	-6.3	-10.6	-16.3
5	4.1	7.4	10.9	-3.6	-9.0	1.0	-118.1	4.3	-5.5	-4.0
6	0.0	6.1	-10.0	-5.1	-9.8	-55.7	4.9	-65.1	-9.4	-2.1
7	0.9	5.1	-52.0	-7.0	-11.3	-12.3	5.7	-15.0	-7.7	-7.6
8	-2.2	-1.5	-89.4	-22.4	-43.0	-10.0	-100.1	-104.9	-48.4	-6.9
9	-61.4	-63.5	-93.4	-54.5	-9.1	-39.7	-90.4	-90.1	-14.1	-21.5
10	-102.9	-13.1	-101.1	-99.1	-104.4	-31.8	-95.5	-89.8	-92.5	-62.7
Data-sets	**Strain Values (με) at Data Extraction Points 11 to 20**									
	11	**12**	**13**	**14**	**15**	**16**	**17**	**18**	**19**	**20**
1	-3.3	-12.6	-7.8	-1.8	-5.5	-3.6	-9.2	-10.8	-6.0	-1.5
2	0.5	-0.3	-0.2	-0.3	-3.2	-0.5	-29.2	-1.4	-6.4	-3.5
3	0.7	-0.8	-0.1	-9.7	0.0	-4.9	-12.5	-1.3	-4.7	-16.6
4	2.2	-1.1	-0.2	-4.4	0.1	-6.8	-18.3	-0.5	-2.2	-10.0
5	0.5	-3.1	0.6	-13.4	-5.0	0.5	-10.9	12.3	-0.1	-1.5
6	0.2	3.2	-21.9	-0.2	-4.9	-4.6	4.0	-10.8	-1.9	-8.3
7	0.4	6.5	-4.4	-2.1	-5.0	-25.0	3.2	-20.9	-1.1	-8.4
8	-1.3	-1.1	-7.6	-20.3	-38.4	-8.5	-29.3	-8.7	-35.1	-5.6
9	-46.4	-54.3	-18.1	-28.9	-5.4	-25.5	-1.5	-37.8	-9.0	-12.8
10	-4.0	-8.0	-10.8	-36.3	-22.0	-16.8	-30.4	-35.7	-54.7	-44.3

Following these two-database preparation, ML models are employed to classify specific failure modes by analyzing the scaffold member strain values. The following section will discuss in detail the research methodology.

6.2. Research Approach

Depending on the complexity of new scaffolding structures (e.g., a large scaffold compared to the one used in prototype testing), the performance of such automated monitoring approaches may be impacted by different parameters related to input data and data analysis techniques employed. For example, the larger the number of datasets available for training ML models, the better would be the performance of the ML model. Thus, it is helpful to investigate the impact of the dataset size on the classification performance. Such an investigation would provide insights on understanding the appropriate size of datasets required for optimum performance of the automated scaffold monitoring approach.

Similarly, an ML model performing well for one type of dataset may have a different performance level in another type of dataset (e.g., small-scale classification versus large-scale classification, and image datasets versus numerical datasets). Thus, it is also important to investigate the performance of different ML techniques on the scaffold datasets and focus on improving the classification performance for the large-scale classification of failure modes.

To address these two issues, this study is divided into two parts. The first part of the study investigates the impact of dataset size and different ML techniques on the classification performance for the four-bay three-story scaffold. Thus, this investigation is performed through a comparative ML application, i.e., a repeated ML training and testing process with different ML models with respective parameters and varying input dataset sizes. This study will specifically assist in identifying ML models and their parameters suitable for the scaffold strain datasets and understanding the appropriate size of datasets required for satisfactory performance of the automated scaffold monitoring approach. Then, the next part of the study focuses on a technique to improve the classification performance for large-scale classification of failure modes. The methodologies used in these studies and their respective results are discussed in detail in the following sections.

6.3. Part One: Comparative ML Analysis

The following sections discuss the research methodology adopted for the comparative ML application, followed by an analysis and results.

6.3.1. Research Methodology for Comparative ML Application

This part of the study intends to investigate the impact of dataset size and different ML classification models on safety prediction accuracy with repeated application of ML training and testing processes for different ML models with different input data sizes. While reviewing different construction-related studies conducted with ML application, it was observed that SVM (Akhavian & Behzadan, 2015; Antwis-Afari, Li, Seo, et al., 2018a; Baker et al., 2020; Cheng et al., 2017; Hassan & Le, 2021; M. K. Kim et al., 2021; K. C. Lam & Yu, 2011; Ka Chi Lam et al., 2009; Qi et al., 2018; Ryu et al., 2019; Seong et al., 2018; Wauters & Vanhoucke, 2016), Neural Network (Akhavian & Behzadan, 2015; Antwi-Afari, Li, Seo, et al., 2018a; Czerniawski & Leite, 2020; Golnaraghi et al., 2019; Ka Chi Lam et al., 2009; Qi et al., 2018; Seong et al., 2018), Random Forest (Antwi-Afari, Li, Seo, et al., 2018a; Hu & Castro-Lacouture, 2019; Z. Liu & Li, 2020; Qi et al., 2018; Tixier et al., 2016; Wauters & Vanhoucke, 2016), Decision Tree (Akhavian & Behzadan, 2015; Antwi-Afari, Li, Seo, et al., 2018a; Asadi et al., 2015; Hassan & Le, 2021; Ryu et al., 2019; Wauters & Vanhoucke, 2016), and Naïve Bayes (Asadi et al., 2015;

Hassan & Le, 2021; Hu & Castro-Lacouture, 2019; Seong et al., 2018) are mostly employed by researchers. Therefore, these ML models (i.e., SVM, Neural Network, Random Forest, Decision Tree, and Naïve Bayes) are used in this investigation. The flowchart shown in Figure 19 illustrates the detailed steps followed in the proposed study.

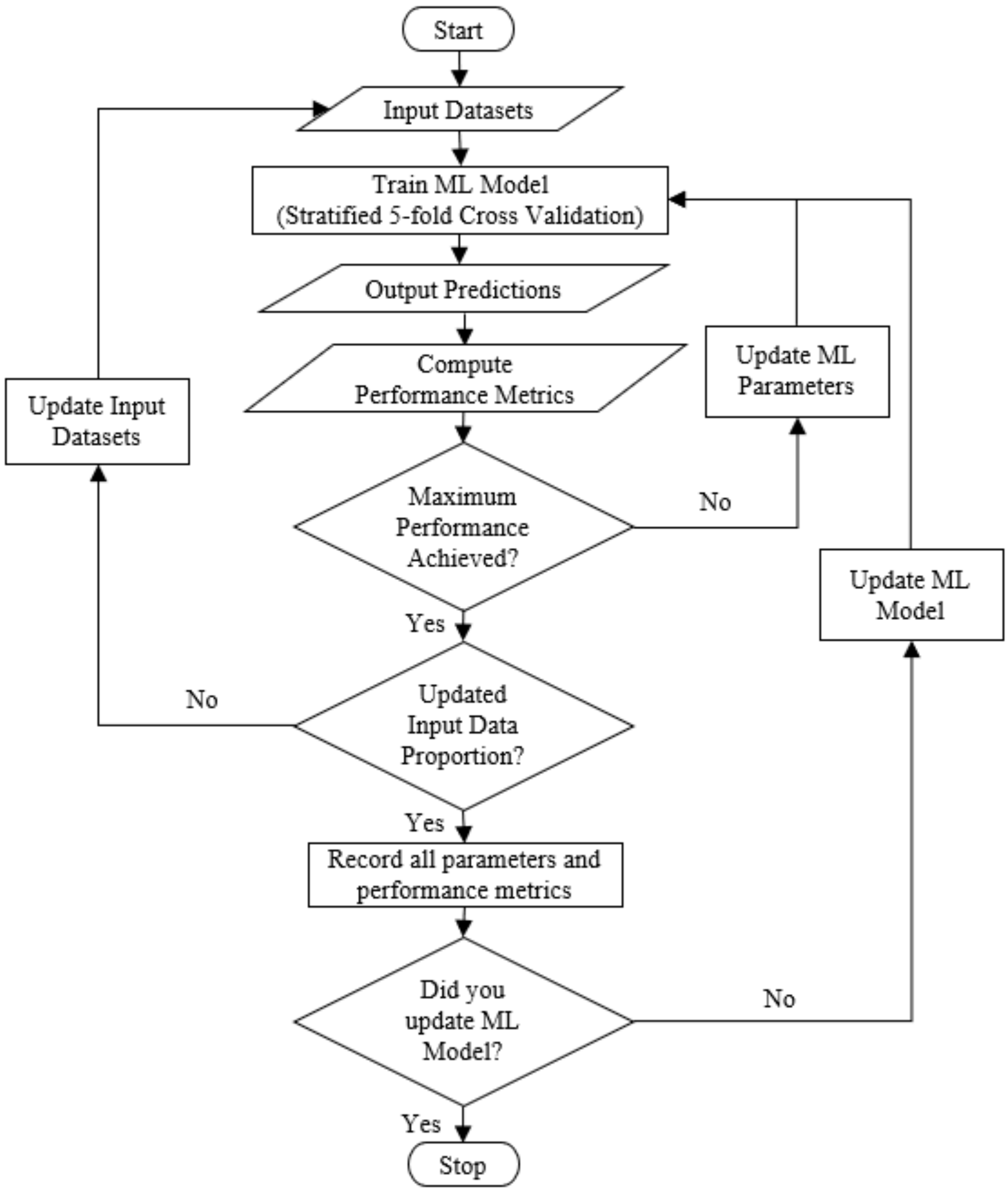


Figure 19. Detailed Flowchart: Comparative ML Analysis

The flowchart shows a process of ML implementation with updated dataset size and ML parameters for different ML models. To ensure better performance of the trained models, a stratified five-fold cross-validation approach (Zeng & Martinez, 2000) was utilized. This approach equally divides the input dataset into five groups. Out of the five groups, four groups (i.e., 80% data) are used for training the ML model and the fifth group (i.e., 20% data) is used for testing. These training and testing processes follow five times such that each group is once used for testing. Then, the testing accuracy is computed as the average of the five accuracies.

Initially, an SVM model will be investigated. During this investigation, the initial input database will include 100 datasets for each safety case. As stated above, the stratified five-fold cross-validation approach is employed for training and testing SVM models. This training and testing processes will be repeated with different SVM kernel parameters (i.e., linear, polynomial, radial basis function, and sigmoid) to determine the SVM parameter that results in the best performance metrics. After identifying the SVM parameters with maximum performance for a specific input data, the input dataset size is updated. Here, the proportion of the input dataset will be increased by 100 each time, i.e., initially, 100 datasets per safety condition, and the new input datasets will comprise 200, 300, 400, 500, 600, 700, 800, 900, and 1000 datasets per safety cases, respectively, for each cycle. It means that this process of identifying the best SVM parameters for respective input datasets will be repeated nine more times (i.e., ten times for each model). After each cycle, the input data size, ML parameters, and performance metrics are recorded and later compared to identify parameters that result in better classification performance.

This entire process shown in Figure 19 is repeated for other four ML models (i.e., Decision Tree, Naïve Bayes, Random Forest and Neural Network) for the same dataset. Following this training and testing processes, the trained models are also used to predict safety cases for the new database of 141,100 datasets. This investigation will ultimately assist in understanding how the ML model performances varies with change in training data size and identifying ML models that better reflect the nature of the data used for scaffold monitoring. Further, it will improve the reliability of incorporating this monitoring system as a part of a construction safety management system.

6.3.2. Analysis and Results

As stated in the methodology, the training process started with SVM model. For the SVM model, different kernel functions (i.e., linear, polynomial, radial basis function (RBF), and sigmoid) were used during training. Table 11 summarizes the average testing accuracies along with the standard deviations for the five accuracies obtained from the five-fold validation with different kernel functions for varying training dataset sizes.

Table 11. Summary of Training Results for Different SVM Models

Dataset Proportion	Linear Kernel		Polynomial Kernel		RBF Kernel		Sigmoid Kernel	
	Average Accuracy	Standard Deviation	Average Accuracy	Standard Deviation	Average Accuracy	Standard Deviation	Average Accuracy	Standard Deviation
10%	64.64%	0.62%	55.41%	0.96%	50.26%	0.51%	5.04%	0.30%
20%	78.13%	0.41%	65.24%	0.49%	64.21%	0.79%	6.12%	0.29%
30%	83.67%	0.21%	70.01%	0.31%	72.20%	0.09%	7.25%	0.13%
40%	86.95%	0.37%	72.42%	0.14%	77.12%	0.38%	7.44%	0.17%
50%	89.27%	0.24%	74.69%	0.17%	80.72%	0.15%	8.52%	0.15%
60%	90.68%	0.17%	76.50%	0.19%	83.18%	0.18%	9.07%	0.10%
70%	92.03%	0.08%	77.51%	0.08%	85.12%	0.17%	9.74%	0.14%
80%	92.85%	0.24%	78.76%	0.19%	86.48%	0.24%	10.12%	0.18%
90%	93.48%	0.15%	79.67%	0.24%	87.61%	0.17%	10.54%	0.11%
100%	94.36%	0.06%	80.51%	0.12%	88.53%	0.23%	10.87%	0.17%

The tabulated results clearly show the impact of data size on the performance of SVM models with different kernel functions. With the increase in data size, the performance improved significantly. Also, the difference in performance of SVM models with different kernel functions is clearly evident from the tabulated results. The results show that the linear kernel function has the best performance for the strain datasets, with maximum accuracy of 94.36% with 100% utilization of input datasets (i.e., 1,000 datasets for each of 1,411 safety cases). Similarly, the radial basis function has the second-best performance and the sigmoid function has the least performance (maximum accuracy being 10.87% for 100% utilization of input datasets) among the four SVM kernel functions. The standard deviations of the five sets of accuracies are below 1% for all kernel functions. These results show that the SVM models require a larger dataset for satisfactory performance of the safety classification.

Similarly, the ML data analysis was repeated for other ML models: Gaussian Naïve Bayes, Decision Tree, Random Forest, and Neural Network. Table 12 summarizes the training results for all these models corresponding to ML parameters with better performance.

Table 12. Summary of Training Results for Different ML Models

Dataset Proportion (%)	SVM Linear		Decision Tree		Gaussian NB		Random Forest		Shallow NN	
	Avg. Acc.*	St. Dev.**	Avg. Acc.*	St. Dev.**	Avg. Acc.*	St. Dev.**	Avg. Acc.*	St. Dev.**	Avg. Acc.*	St. Dev.**
10	64.64	0.62	95.39	0.33	66.67	0.66	89.84	0.53	66.12	1.18
20	78.13	0.41	97.36	0.09	83.74	0.55	96.34	0.03	77.87	0.23
30	83.67	0.21	97.90	0.10	90.03	0.12	98.03	0.14	83.11	0.63
40	86.95	0.37	98.18	0.13	93.35	0.10	98.55	0.10	86.06	0.43
50	89.27	0.24	98.37	0.07	94.96	0.22	98.84	0.07	87.96	0.49
60	90.68	0.17	98.54	0.11	96.12	0.13	99.05	0.08	89.02	0.50
70	92.03	0.08	98.57	0.08	96.75	0.20	99.09	0.03	90.21	0.22
80	92.85	0.24	98.67	0.03	97.50	0.07	99.21	0.02	90.84	0.37
90	93.48	0.15	98.79	0.08	97.89	0.07	99.24	0.08	91.76	0.18
100	94.36	0.06	98.82	0.04	98.19	0.09	99.27	0.04	92.31	0.23

*Average Accuracy in %; ** Standard Deviation in %

The tabulated results show a gradual increase in the prediction accuracies with the increase in the dataset size from 100 to 1000 per failure case for all ML models. Among the different models, Decision Tree model has the highest accuracy for the lowest proportion of datasets used (i.e., over 95% accuracy for only 10% input data size). Similarly, Random Forest model has the highest accuracy of approx. 99% for the dataset size as small as 60% (i.e., 600 datasets for each safety condition). The comparatively results show that approximately 50% of the datasets used in this study is sufficient to have prediction accuracy above 95% for Decision Tree, Gaussian Naïve Bayes and Random Forest models, while greater proportion of datasets are required for SVM and Neural Network models. It should be noted that only shallow neural network models (i.e., NN models with only one hidden layer) were used in this study and the results may be further refined with the use of deep neural network algorithms (i.e., NN models with more than one hidden layer) (Sakhakarmi et al., 2020).

For further analysis of the performance of the trained models on new datasets, the Decision Tree and Random Forest models obtained from the above analysis were used to predict safety conditions of the new test database that consists of 100 datasets for each of 1,411 safety cases (i.e., 141,100 datasets in total). Table 13 summarizes the prediction results for selected classification models. This table shows the input dataset proportion during ML model training and respective training accuracy, accuracy for the new test data, total number of incorrect classifications out of 141,100 test datasets, and the number of instances where safe cases were identified as unsafe and unsafe cases were identified as safe.

Table 13. Results for Selected ML Models with Test Database

ML Model	Input Dataset Proportion for Training	Training Accuracy	Test Accuracy	Total Incorrect Classifications	Safe Cases Identified as Unsafe	Unsafe Cases Identified as Safe
Decision Tree	10%	95.39%	95.35%	6,561	15	42
	20%	97.36%	97.42%	3,640	0	9
	40%	98.18%	97.88%	2,981	3	16
	60%	98.54%	98.35%	2,329	0	9
	80%	98.67%	98.34%	2,342	1	15
	100%	98.82%	98.49%	2,123	1	13
Random Forest	10%	89.84%	89.93%	14,207	0	19
	20%	96.34%	96.03%	5,601	0	8
	40%	98.55%	98.47%	2,148	1	13
	60%	99.05%	98.87%	1,590	1	11
	80%	99.21%	99.16%	1,176	1	8
	100%	99.27%	99.18%	1,150	0	7

The tabulated results clearly illustrate a significant improvement in the prediction performance of trained models on the test database as the size of training datasets increases. The prediction results show that the models trained with smaller sizes of training datasets have very high number of incorrect classifications and such incorrect classifications significantly decrease with the increase in training data size. Between Decision Tree and Random Forest models, Random Forest models are better at correctly predicting the safe cases. However, both of these models have incorrect prediction of unsafe cases as safe case.

The results show that the Decision Tree model trained with 10% of the input dataset (i.e., the model with over 95% training accuracy for least amount of input data) resulted in 95.35% accuracy with 6,561 incorrect classifications out of 141,100 test datasets. It was observed that 15 safe categories were classified as unsafe categories and 42 unsafe cases were classified as safe cases. Similarly, the decision tree model trained with 100% of the input datasets resulted in 98.49% accuracy with 2,123 incorrect classifications. Out of 2,123 incorrect classifications, there were 13 unsafe cases that were identified as safe cases, while one safe case was classified as unsafe. It is also an interesting observation that the Decision Tree models trained with 20% and 60% of input data had 100% accuracy in identifying safe cases, i.e., none of the safe cases were incorrectly classified as unsafe; however, both models classified nine unsafe cases as safe.

Similarly, in the case of Random Forest models, the trained model with 20% of the input datasets (i.e., the model with over 95% training accuracy for least amount of input data) had the accuracy of 96.03% with 5,601 incorrect classifications for 141,100 test datasets. Out of the incorrect classifications, there were 8 unsafe cases identified as safe, while none of the safe cases were identified as unsafe. Similarly, the trained model with 60% input dataset resulted in 98.87% accuracy with 1,590 incorrect classifications. It was observed that one safe case was incorrectly identified as unsafe and 11 unsafe cases were identified as safe cases. For the Random Forest model trained with 100% of the input datasets, the accuracy was 99.18% with 1,150 incorrect classifications. Out of the incorrect classifications, there were 7 unsafe cases identified as safe cases, while all safe cases were correctly identified. Also, the Random Forest models trained with 10% and 20% input datasets have correctly classified all safe cases despite having incorrect classification of unsafe cases as safe. These are important observations which show that ML classifications may be reliably performed even with smaller datasets through proper selection of ML model suitable for the particular data set and classes. This knowledge can be suitable adopted for enhancing the performance of large-scale classifications.

6.4. Part Two: Enhancing Large-Scale Classification

The prediction results of ML models on the test database in the earlier section (Table 13) displayed several incorrect identifications of unsafe cases as safe ones. Similarly, there were numerous incorrect classifications within unsafe cases. While training a single ML model to classify such large cases, there is very little flexibility to focus on improving the classification performance of such cases (particularly the ones with a higher number of misclassifications). To address this issue, this study (Sakhakarmi & Park, 2020) focuses explicitly on a divide-and-conquer strategy to enhance the classification performance of a large-scale classification problem applied to the scaffold safety classification (Figure 18) investigated in this dissertation. This strategy solves problems involving large datasets and a large number of classes by employing a hierarchical structure, which has resulted in improving the performance of multi-class classification problems when employed in combination with ML algorithms like SVM and NN (Fritsch & Finke, 1998; Hsieh et al., 2014; Kugler, 2006). Past studies have employed this approach in solving text and speech recognition problems involving thousands of classifications using an extensive training database.

The divide-and-conquer approach involves a) employing a hierarchical structure to break down a large-classification problem into numerous smaller classification problems; b) training ML classifiers for each smaller classification problem; and c) integrating those small classifiers together to handle the original large-scale problem. With the ability to work on multiple smaller problems to solve a large-scale problem, this approach effectively utilizes limited features for the safety category prediction for a small group rather than limited features to classify a large number of safety categories. Therefore, this approach ultimately simplifies the large-scale problem, giving more flexibility to train multiple ML models to classify different classes. The following sections discuss the research methodology adopted in this study, followed by an analysis and results.

6.4.1. Research Methodology for Enhancing Large-Scale Classification

This study involved three major steps: 1) break down the classification problem into multiple sub-problems, 2) pre-train ML models for each sub-problems, and 3) combine pre-trained ML models to form the prediction model for the overall classification problem. These steps are explained in detail in the following sections:

6.4.1.1. Breakdown Scaffold Safety Classification Problems into Sub-problems

The divide-and-conquer approach simplifies a large classification problem into multiple small problems following a hierarchical process. One of the approaches for such a hierarchical classification of problems is to utilize known information on the existing problem (Fritsch & Finke, 1998). Accordingly, this study sub-classified the scaffold safety cases based on the failure modes. Thus, the hierarchical sub-classification followed the classification structure for the scaffold failure mode shown in Figure 18, classifying the safety conditions in four stages. Figure 20 below shows the four stages of safety classifications marked with different color codes.

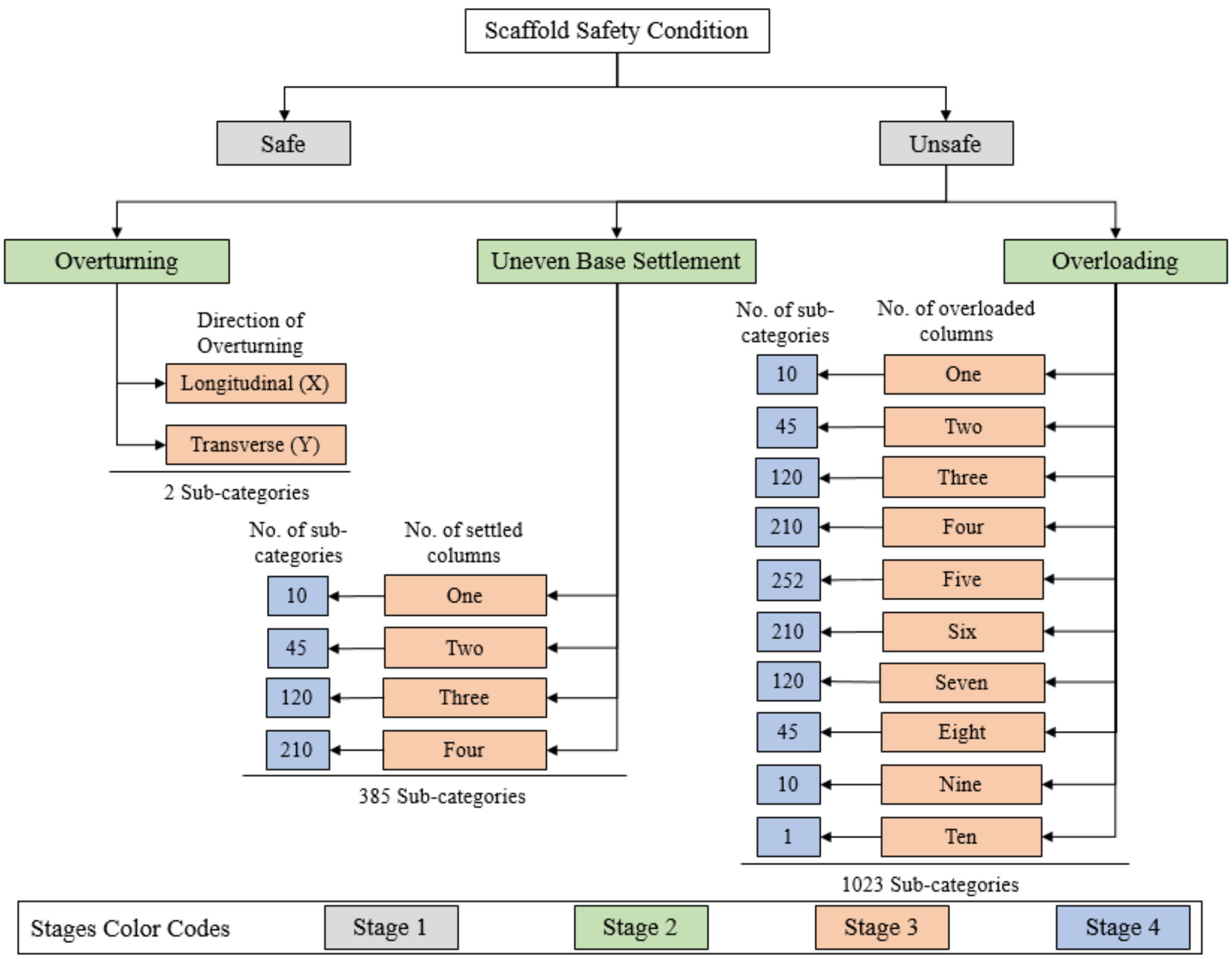


Figure 20. Scaffold Safety Classification Stages

The first stage sub-problem of this overall classification (i.e., Stage 1 marked with grey color in Figure 20) is to identify if the scaffold condition is safe or unsafe. Therefore, safe cases are identified at Stage 1. If the condition is categorized as unsafe, it is further classified into overloading or overturning or uneven base settlement conditions (i.e., Stage 2 marked with green color in Figure 20). Once the unsafe condition is classified as any of those three conditions, the Stage 3 classification marked with orange color identifies the failure modes for overloading and uneven base settlement conditions based on the potential number of member failures (i.e., ten sub-categories of overloading conditions and four sub-categories of uneven base settlement condition), while the overturning condition is classified based on the direction of overturning (i.e., two sub-categories of overturning condition). Finally, the fourth classification stage (i.e., Stage 4 marked with blue color in Figure 20) identifies the combination of a different number of member failures for overloading and uneven base settlement conditions (i.e., 1023 sub-categories of overloading condition and 385 sub-categories of uneven base settlement condition). Therefore, Stage 1 identifies the safe category, which is indexed "1" for classification purposes. Similarly, Stages 3 and 4 identify unsafe categories indexed from "2" to "1411", where Index 2 refers to the overturning failure along the longitudinal direction, and Index 1411 refers to overloading failure due to overload on ten members at a time. Here, it should be noted that the maximum number of classification cases in these classification stages is 252 for the unsafe condition due to overloading on five columns.

6.4.1.2. Pre-train ML Models for Each Sub-classification

Following the classification model discussed in the earlier section, this approach required separate training of one ML model each in Stage 1 (i.e., to identify safe or unsafe) and Stage 2 (i.e., to identify unsafe category: overloading, uneven base settlement, or overturning). Similarly, the remaining two stages required training of three and thirteen ML models to identify sub-categories within each of the three unsafe categories. Thus, there are 18 pre-trained models. The performance of each ML model is evaluated by computing accuracy, precision, recall, and F1-Score values using equations 2, 3, 4, and 5, respectively.

In section 6.3, the author tested shallow NN as one of the ML algorithms, and this algorithm resulted in the lowest performance among the five algorithms (i.e., SVM, Decision Tree, Gaussian NB, Random Forest, and Shallow NN). However, deep NN models, which are more efficient than shallow networks, were not tested in that study. Thus, this study utilizes deep NN models.

A neural network (NN) consists of three different types of layers with different neurons on each layer. Out of these, the first layer is called the input layer, which consists of neurons equal to the number of input features used to train the model. Similarly, the last layer is called the output layer, which consists of neurons equal to the number of output classes in a classification problem. All layers between the input and output layers are called hidden layers. The number of hidden layers and neurons in those layers depends on the complexity of the convergence of input features (*Chapter 6: Multilayer Neural Networks (Sections 6.1-6.3)*, 2008). There is a minimum of one hidden layer in a neural network, and such a neural network with only three layers is called a shallow network (Mhaskar et al., 2017). A network with more than one hidden layer is called a deep neural network.

Figure 21 presents an example of a deep neural network, where the input layer has 20 neurons (representing 20 strain measurement values per dataset), the output layer has 2 neurons (representing 2 classes), the first hidden layer has “m” neurons and the second hidden layer has “n” neurons. All neurons on the consecutive layer are interconnected in NN models. The architecture of NN model depends on the complexity of a problem, and it takes substantial trial-and-error processes with different parameters to identify the optimum number of hidden layers and number of neurons in corresponding layers. Thus, NN architecture design is time-consuming and the most critical task in NN modeling.

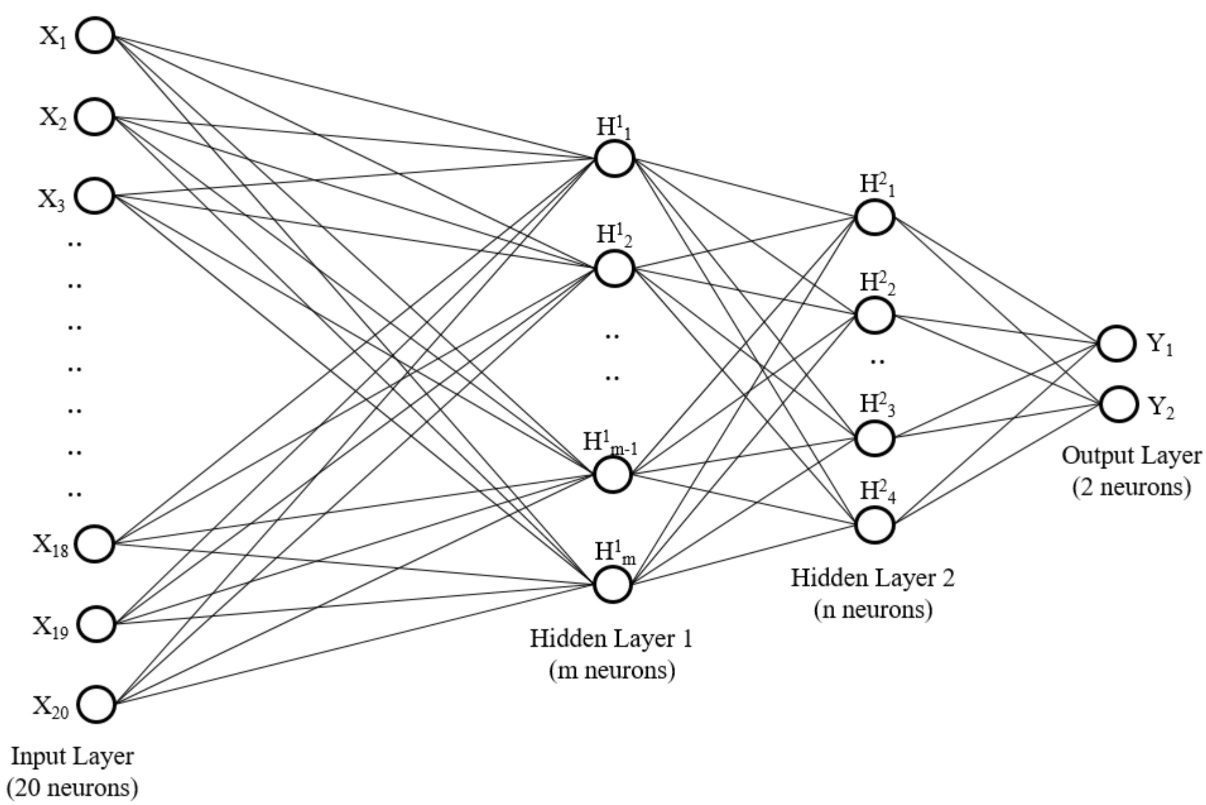


Figure 21. NN Architecture

Each pre-trained model parameters are determined by repeated training and testing with a different number of hidden layers with varying values for nodes to achieve the desired level of performance. During the training process, a stratified five-fold validation approach (Zeng &

Martinez, 2000) was utilized to ensure better performance of the trained models. Similarly, early stopping technique (Brownlee, 2018) was used to prevent the overfitting of trained models. The trained model's performance is measured using the average of five validation accuracies obtained from the stratified five-fold validation approach, along with their standard deviations. The parameters resulting in maximum average validation accuracy and minimum standard deviations are selected for each pre-trained model.

6.4.1.3. Combine Pre-trained ML Models to form the Prediction Model

Once all 18 ML models are trained, these pre-trained models are combined in a sequential order such that the model performs a stepwise analysis of the test datasets. Figure 22 presents the flowchart depicting a stepwise analysis of the input dataset to identify the respective safety condition index. For any input dataset, the prediction model returns the safety index value (i.e., 1 to 1,411) that identifies potential failure modes with the precise location of possible failure points.

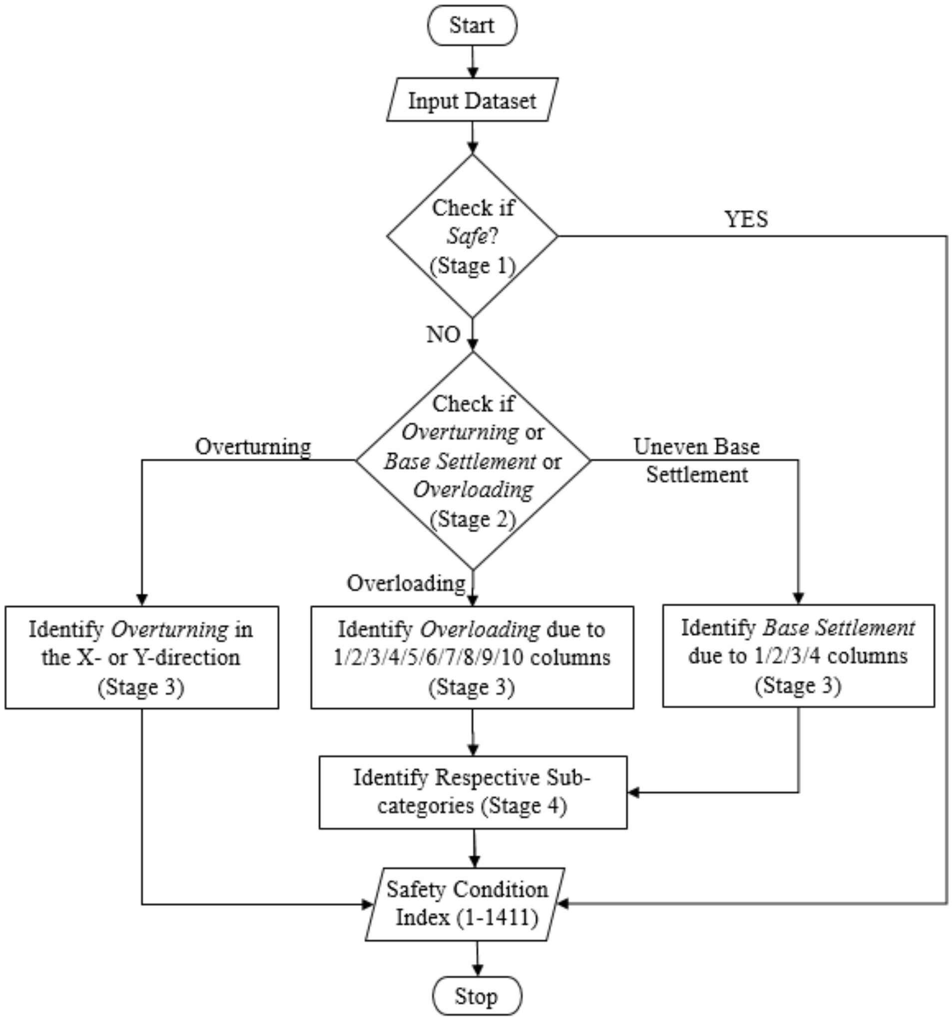


Figure 22. Prediction Model Flowchart

Following the steps shown in the flowchart (Figure 22), the test database was used to test the prediction model. Then the prediction model's performance was evaluated by computing accuracy, precision, recall, and F1-Score values using equations 2, 3, 4, and 5 for each safety index classification.

6.4.2. Analysis and Results

The first NN model in this approach classifies the input datasets into safe or unsafe cases. Thus, to train this model, the safety conditions of the training database was categorized into safe and unsafe categories, i.e., all 1,410 unsafe cases were grouped in a single category. Therefore, the two classes to be classified have input training dataset proportion of 1(safe):1,410(unsafe). This database was used to train the first NN model to identify the input datasets as safe or unsafe cases. Similarly, in the Stage 2 classification, the NN model classifies the input datasets into three classes: overturning, uneven base settlement or overloading. Therefore, the input dataset proportion for these classes is 2(overturning):385(uneven base Settlement):1023(overloading). Similarly, input datasets for each classification model were prepared.

During the pre-training of the first NN model to classify between safe and unsafe cases, it was observed that most of the safe cases were incorrectly classified as unsafe cases. Similar incorrect classifications were observed in the Stage 2 classification as well. On a close observation, it was found that the reason for such incorrect classifications was the imbalanced dataset proportions of the different classes. Given that the proportion of safe to unsafe datasets was 1(safe):1,410(unsafe), the small proportion of safe datasets was insufficient for the ML model to correctly learn the characteristics of safe datasets, resulting in the incorrect classification of safe cases as unsafe. Similarly, the dataset proportion of three unsafe cases in the Stage 2 classification was 2(overturning):385(uneven base settlement):1023(overloading). Thus, these highly imbalanced datasets were the reason for incorrect classification.

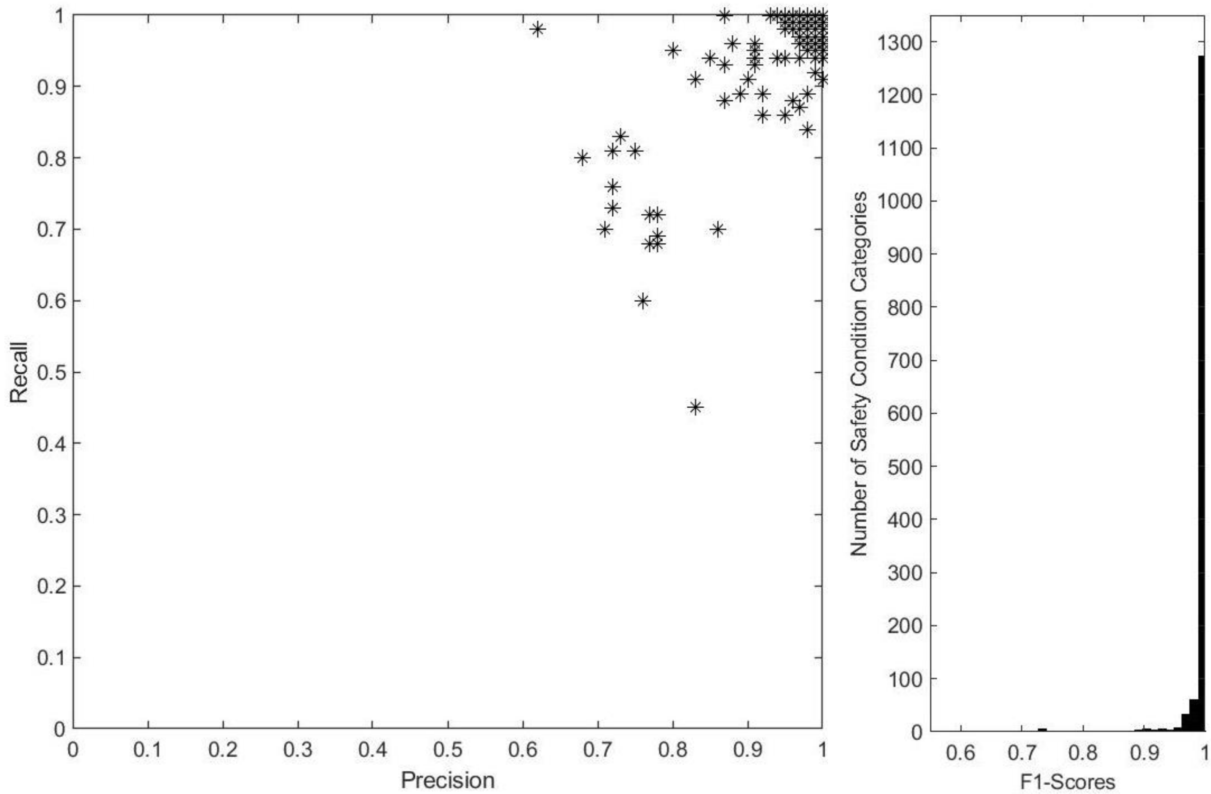
To overcome this issue of incorrect classifications due to imbalanced datasets, Chawla et al. (2002) suggested increasing the number of datasets for the classes with smaller dataset proportions. Following this approach, additional datasets were generated for three sub-categories: Safe, Overturning in X-direction, and Overturning in Y-direction, while the original 1,000 datasets were retained for the other classes. For the safe sub-category, the number of datasets was increased to 60,000. Similarly, the number of datasets was increased to a total of 36,000 for each of the two overturning cases. Therefore, the database size increased to 1,540,000 datasets. With this update, the dataset proportion for safe and unsafe cases changed from 1:1,410 to approximately 1:25 in Stage 1 classification. Similarly, the proportion for overturning, uneven base settlement, and overloading increased from 2:385:1023 to approximately 1:5:14 in Stage 2 classification.

The updated database resulted in a small number of misclassifications and improved the classification accuracy. Table 14 summarizes details on the pre-trained model parameters and the training results.

Table 14. Pre-trained Model Parameters and Results

Model No.	**Stage**	**No. of Sub-Categories**	**No. of Hidden Layers**	**Neurons in each Hidden Layer**	**Stratified Five-Fold Validation Accuracies**	
					Std. Dev. of Accuracies	**Avg. Accuracy**
1	1	2	2	55, 40	±0.00%	99.99%
2	2	3	3	60, 50, 40	±0.00%	97.61%
3	3	2	3	60, 50, 40	±0.00%	100.00%
4	3	4	4	80, 60, 50, 20	±0.03%	99.48%
5	3	10	5	100, 80, 60, 40, 25	±0.21%	99.86%
6	4	10	4	80, 60, 50, 20	±0.07%	99.74%
7	4	45	4	80, 60, 50, 20	±0.04%	99.71%
8	4	120	5	80, 60, 50, 40, 20	±0.17%	97.53%
9	4	210	5	100, 80, 50, 40, 25	±0.04%	97.16%
10	4	10	4	80, 60, 50, 20	±0.06%	99.91%
11	4	45	4	80, 60, 50, 20	±0.01%	99.97%
12	4	120	4	80, 60, 50, 20	±0.00%	99.99%
13	4	210	4	80, 60, 50, 20	±0.04%	99.98%
14	4	252	4	80, 60, 50, 20	±0.10%	99.93%
15	4	210	4	80, 60, 50, 20	±0.04%	99.96%
16	4	120	4	80, 60, 50, 20	±0.02%	99.99%
17	4	45	4	80, 60, 50, 20	±0.02%	99.98%
18	4	10	3	60, 40, 20	±0.02%	99.99%

The 18 pre-trained models with the parameters listed in Table 14 were arranged in a sequential order to get the prediction model. For validating this integrated prediction model, the new test database with hundred datasets for each of 1,411 safety conditions (i.e., a database of 141,100 datasets with 20 strain features each) and the corresponding safety condition index was used. Out of 141,100 datasets, there were 1,049 incorrect classifications, resulting in an accuracy of 99.26%. This result shows a slight improvement from the Random Forest model (i.e., the model trained with 100% input data) results in the earlier section, where the prediction accuracy was 99.18% with 1,150 incorrect classifications out of 141,100 classifications. Figure 23 (a) presents the scatter plot between Recall and Precision values for each safety category. The plot shows that most safety condition categories have Recall and Precision values closer to 1. The minimum values for Precision and Recall were 0.62 and 0.45, respectively. Similarly, Figure 23 (b) presents the histogram of F1-Scores for all safety condition categories. The F1-Scores plot shows that most safety conditions have values closer to 1. The minimum F1-Score value was 0.58. These higher Precision, Recall and F1-Score values for the majority of safety categories indicate good performance of the prediction model.



(a) Precision-Recall Plot (b) F1-Score Plot

Figure 23. Precision, Recall, and F1-Score Results

On closer observation of test results, it was observed that none of the unsafe safety categories were classified as safe. This indicates perfect classification in Stage 1. Further, it was observed that out of 1411 safety categories, 1168 categories had none of the incorrect classifications, i.e., 82.78% of the safety categories resulted in 100% accuracy. Similarly, it was observed that 111 safety categories (i.e., 7.87% of 1,411) had only one incorrect classification. Only 40 safety categories (i.e., 2.83% of 1,411) had over five incorrect classifications. Figure 24 presents incorrect classification information from the test results.

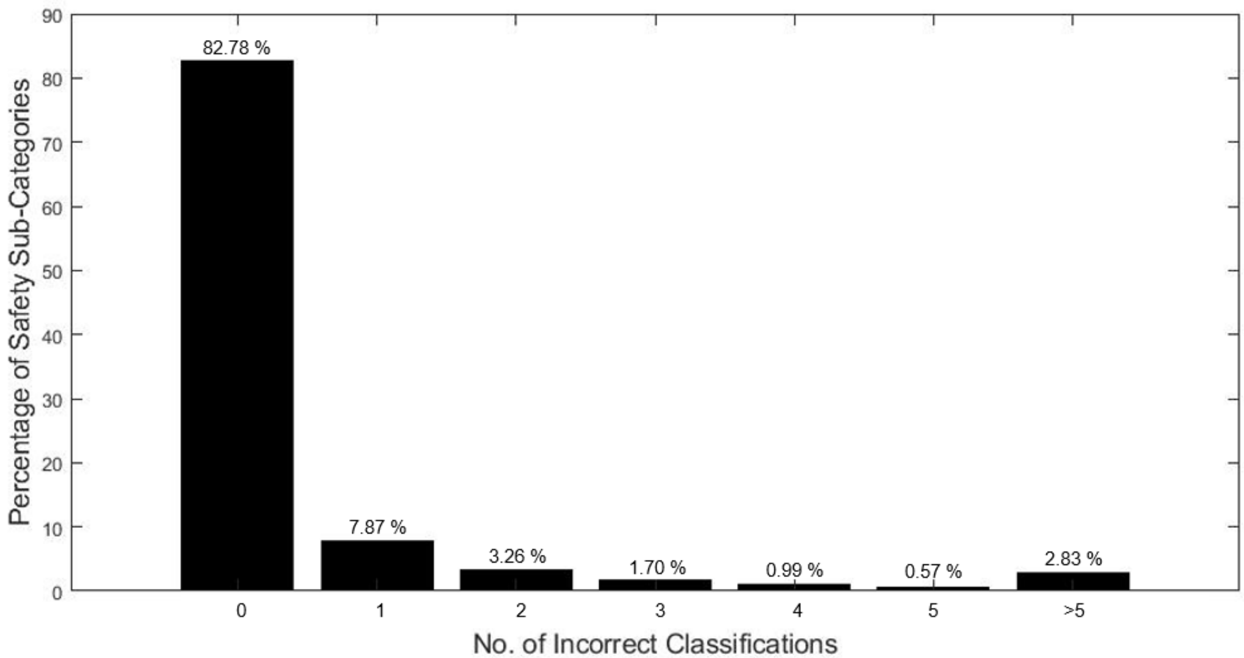


Figure 24. Number of Incorrect Classifications per Safety Sub-Categories

6.5. Chapter Summary

This chapter focused on investigating the performance of the proposed safety assessment approach in predicting refined safety conditions on a multi-bay and multi-story scaffolding structure. For this purpose, this study utilized a four-bay and three-story scaffolding model built following the scaffolding modeling approach validated through a proof-of-concept study in the previous chapter. The scaffold failure modes included refined failure cases resulting from local member failure and combinations of different scaffold members. Accordingly, 1411 safety categories were classified. In addition, the strain database preparation followed the simulation approach validated in the previous chapter.

This study was conducted in two parts. The first part of this study investigated the impact of dataset size and different ML algorithms on the performance of the proposed safety assessment approach on a four-bay three-story scaffold. For this purpose, a comparative ML training and testing process was implemented that tested five different ML models, i.e., SVM, Gaussian Naïve Bayes, Decision Tree, Random Forest, and Shallow Neural Network models, with varying parameters for different input data proportions. This study's purpose was entirely to understand the impact of dataset size and different ML models on the performance of the proposed safety assessment approach. The investigation on the impact of data size and ML models was performed by conducting repeated ML training and testing processes starting with 10% of total datasets for each ML model and then repeating the process for 20%, 30%, 40%, 50%, 60%, 70%, 80%, 90%, and 100% datasets. The results demonstrated that the ML classification performance gradually improved with the increase in dataset proportion for all ML algorithms. Similarly, the five ML algorithms with the selected parameters had slightly different performance levels, with the Random Forest model scoring the highest accuracy. However, these models resulted in incorrect classification of unsafe cases as safe, which is not desirable. Despite this, the results show that the proposed scaffold safety monitoring approach can handle multi-bay and multi-story scaffolds with more safety sub-categories compared to the scaffold used for the approach validation in the previous chapter.

The second part of the study focused on enhancing the performance of larger-scale classification through divide-and-conquer strategy. With this strategy, the large-scale classification problem was divided into 18 small sub-problems following a hierarchical system, and then different ML models were trained for each of those problems. This study specifically used deep neural network models. The application of the divide-and-conquer approach provided the flexibility to focus on small groups of safety cases rather than dealing with all safety cases at the same time. Such flexibility allowed working on specific ML models (here, any of the eighteen pre-trained models) to improve the prediction model performance by performing additional trials with different parameters until the desired performance is achieved for a particular group of safety sub-categories. Further, this approach allowed working on multiple models simultaneously, focusing on different specific groups, which saves training time. Thus, the higher number of incorrect classifications observed in any safety category can be reduced by updating the ML parameters for the safety category-specific pre-trained models without updating parameters for all models. Furthermore, this approach enables the addition of new failure modes to be classified by the prediction model by adding a new model that is trained to identify new failure modes without the need to re-train other ML models. As such, the predication model can be expanded to identify additional failure modes in the future that were not already accounted. Such flexibility allows updating the safety assessment system with less effort if additional failure modes are deemed necessary to be incorporated anytime in the future. Therefore, the divide-and-conquer enhances the performance of large-scale classification and eliminates the challenge of large-scale classification problems. As such, this approach can be replicated to solve other large-scale classification problems.

CHAPTER 7: CONCLUSION AND DISCUSSION

7.1. Research Summary

This study aimed to develop an approach to automate scaffold monitoring by analyzing real-time data from scaffolding structures. For this purpose, this study proposed a scaffold safety monitoring framework based on analyzing scaffold member strain values. This approach uses wireless strain sensors to measure scaffold member strain values that are analyzed to determine the scaffold safety condition by employing supervised ML algorithms. To overcome the limitation of data availability for ML application, the framework also proposed a scaffold modeling technique capable of designing a scaffold model with near-real structural behavior. This model is used to build the database required to train ML algorithms. Further, the researcher conducted a proof-of-concept study with a single-bay two-story scaffold to validate the proposed framework and the scaffold modeling technique.

Besides, this study investigated the proposed monitoring approach's performance on a four-bay and three-story scaffolding structure. With the increase in scaffold size, the structural complexity increases, resulting in a significantly higher number of potential failure modes than the cases accounted for in the test study. The higher number of failure modes results in a larger input data size, impacting the performance of the proposed ML-based safety assessment approach. Thus, the first step of this study investigated the impact of input data size and ML algorithm on the performance of the proposed approach. The second step of the study focused on enhancing the large-scale classification performance.

For this purpose, this study utilized a four-bay and three-story scaffolding structure with 1,411 refined safety modes. These safety modes were classified based on local member failures and combination of different member failures to incorporate a large number of possible failure cases on the scaffold. To determine the impact of data size and different ML models on the classification performance, this study utilized five different ML models, i.e., SVM, Decision Tree, Naïve Bayes, Random Forest, and Shallow Neural Network. Then, all these models were trained with different proportions of data sizes (10%, 20%, 30%,…, 100%), and it was observed that the performance improved with the increase in the input dataset size. Further, the classification accuracy varied for different ML parameters among all tested ML models. This highlights that it is essential to perform multiple trials with different ML parameters for each ML model to identify the model with satisfactory classification performance. Among the tested models, the Random Forest model had the highest accuracy of 99%. These results show that the proposed safety assessment framework can be reliably deployed to monitor multi-bay and multi-story scaffolding structures.

Similarly, the next step in this study focused on a divide-and-conquer approach to enhance the large-scale classification of 1411 safety categories. This approach simplified the large-scale classification problem into 18 smaller problems following a hierarchical system. For each of those smaller problems, separate ML models were trained using deep neural network models, and those pre-trained models were later integrated to form the prediction model. The results from this prediction model demonstrated slight improvement over the results of the Random Forest model from the earlier analysis. Applying this approach for large-scale classification has several benefits, such as, 1) flexibility to work on specific ML models corresponding to the classes with lower prediction performance to improve the overall performance of the predictive model; 2) time saving through concurrent training of multiple ML models; and 3) enables expandability of the predictive model to classify additional failure modes in the future, as necessary.

Implementation of the proposed approach is expected to assist the safety managers in identifying scaffold-related hazardous conditions that are not identified during manual safety inspection. As such, this study is expected to improve the safety assessment of scaffolding structures significantly, ultimately enhancing the safety of construction workers. Further, the expandability of the safety monitoring approach would enable the incorporation of additional safety measures. Furthermore, this study is also expected to encourage construction researchers to use advanced sensing technologies and data analysis techniques for developing automated monitoring approaches.

7.2. Research Contribution

This study has made significant contributions in an attempt to address limitations in past scaffolding structure monitoring studies. The major contribution of this research is the scaffold monitoring framework that utilizes scaffold member strain values as a measure to define the scaffold safety condition. The scaffold member strain values vary depending on the potential scaffold failure mode. As such, the framework is capable of identifying different failure modes with the installation of a single type of sensor, while past studies depended on multiple types of sensors to identify different failure modes. Further, with the approach of classifying refined failure modes based on local member failures and the combination of multiple member failures, this study has incorporated a wide range of potential failure modes. Furthermore, given the availability of a precise scaffold model for training database preparation, the proposed approach can be used to monitor scaffolds with multi-bay and multi-story, and it requires minimal to no site data collection prior to system deployment.

In addition, this study has been able to address the challenge of limited data availability for ML applications in construction research by introducing a scaffold modeling technique for building the required database. Thus, a similar approach may be developed to solve other classification problems.

7.3. Limitations and Future Research

The proposed scaffold monitoring approach focused on identifying potential scaffold failure modes, while the mechanism to alert workers of potential unsafe scenarios was not investigated. Thus, future research should focus on developing a mechanism capable of timely alerting workers of potentially unsafe cases based on the analysis of measured strain values. Further, the system should be able to generate such alerts well in advance so that there is sufficient time for the worker to take preventive actions. In addition, the field test and corresponding computational exploration may be expanded to scaffolds of varying geometric properties (besides the one used in this study) to ensure that this approach performs well for different types of scaffolds.

The proposed approach requires a precise scaffolding structure model to prepare the input database for training ML algorithms. However, detailed designs of scaffolds are rarely created before scaffold erection. Thus, the non-availability of the scaffold model limits the application of this monitoring approach. However, it should be noted that with the wide acceptance of BIM for construction management, it is not common to have temporary structure models available along with the main building models. Further, the additional cost and effort for the installation of sensors may also limit the use of this approach.

Furthermore, this study did not account for the impact of external factors like temperature and humidity on the strain sensor use and measurement accuracies. The system deployment may be limited due to such environmental issues. Thus, it is suggested to conduct a study to identify potential external factors that could limit the field deployment of the proposed scaffold monitoring system. Further, it is also suggested to develop a calibration technique to address environmental issues affecting the system deployment (if any exist). These practical challenges with the strain sensors (e.g., deployment and cloud connection on dynamic construction sites) must be addressed before the proposed approach can be deployed for scaffold monitoring.

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Peer-Reviewed Journal Publications:

1. **Sakhakarmi, S.**, and Park, J. (2022) "Improved Intrusion Accident Management Using Haptic Signals in Roadway Work Zone." Journal of Safety Research, https://doi.org/10.1016/j.jsr.2021.12.015. (JCR Impact Factor: 3.487)
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Dissertation Title:

"Automated Approach for the Enhancement of Scaffolding Structure Monitoring with Strain Sensor Data"

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