

Article

Simplified Scan-vs-BIM Frameworks for Automated Structural Inspection of Steel Structures

Bohee Kim ^{1,*}, Inho Jo ^{1,*} , Namhyuk Ham ^{2,*}  and Jae-jun Kim ¹ ¹ Department of Architectural Engineering, Hanyang University, Seoul 04763, Republic of Korea; jjkim@hanyang.ac.kr (J.-j.K.)² Department of Digital Architecture and Urban Engineering, Hanyang Cyber University, Seoul 04763, Republic of Korea

* Correspondence: odd.innocent@gmail.com (I.J.); nhham@hycu.ac.kr (N.H.)

Abstract: This paper presents a deep learning-based Scan-vs-BIM methodology for evaluating structural integrity through the extraction of features from As-Built scan and As-Planned Building Information Modeling (BIM) comparison data. Traditional Scan-vs-BIM frameworks often rely on Scan-to-BIM processes to generate point cloud-based mesh models for comparison, which significantly impairs computational efficiency. In contrast, the proposed streamlined Scan-vs-BIM framework incorporates a deep neural network (DNN) model consisting of two neural networks: one for structural integrity assessment and another for error type analysis. The model evaluates the structural integrity of individual components in a sequential manner, repeating the process across all elements to comprehensively assess the entire structure. Rather than converting point cloud data into mesh models for comparison, this approach directly measures the spatial discrepancies between the As-Built point cloud and As-Planned BIM, analyzing the distribution tendencies of these distance values. Experimental validation on actual steel structures demonstrated that the proposed method effectively predicts structural integrity, providing significant improvements in both accuracy and computational performance.

Keywords: scan-vs-BIM; steel structure; deep learning; deep neural network (DNN); integrity evaluation; 3D scanning



Citation: Kim, B.; Jo, I.; Ham, N.; Kim, J.-j. Simplified Scan-vs-BIM Frameworks for Automated Structural Inspection of Steel Structures. *Appl. Sci.* **2024**, *14*, 11383. <https://doi.org/10.3390/app142311383>

Academic Editor: Raffaele Zinno

Received: 30 October 2024

Revised: 27 November 2024

Accepted: 2 December 2024

Published: 6 December 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

Integrity evaluation is fundamental for assessing the production quality and safety performance of construction projects, particularly in areas such as new construction, facility management, safety inspections, remodeling, and repairs [1]. Traditionally, integrity evaluation within the construction industry has been a manual process, reliant on the subjective judgment, observation, and expertise of skilled workers, which often results in incomplete and inaccurate reporting [2]. To mitigate these issues, recent research has focused on developing more efficient integrity evaluation methodologies through the application of information and communication technologies (ICTs) to transcend manual limitations [3].

Laser scanning has emerged as a widely adopted method for data collection in integrity evaluations for construction projects [4]. Typically, it is employed to reconstruct As-Built data, which is then used in “As-Planned vs. As-Built” comparison procedures [5]. Point cloud-based As-Built verification methods, in general, depend on manually designed models of real-world structures [6]. Consequently, there is an increasing demand for tools capable of automating the processing of As-Built data and enhancing “As-Planned vs. As-Built” comparison efficiency. In response, recent research efforts have concentrated on automating construction progress monitoring, leading to rapid advancements in associated theories and technologies [7].

A recent study has demonstrated that the “Scan-vs-BIM” framework, which compares As-Built scan data with As-Planned Building Information Modeling (BIM) models,

performs effectively in terms of geometric comparison [8]. Both As-Built scan data and As-Planned BIM models used in the Scan-vs-BIM framework continue to evolve, while the associated input costs decrease [9]. These processes facilitate the assessment of the As-Built status of construction projects in a detailed, timely, and semantically accurate manner [10]. Furthermore, converting As-Built scan-based point cloud data into mesh models using the Scan-to-BIM framework, followed by comparison with As-Planned BIM models, has significantly improved the accuracy and automation of “As-Planned vs. As-Built” comparisons [11].

However, conventional Scan-to-BIM processes within the Scan-vs-BIM framework are associated with several challenges: (1) individual structural integrity evaluation is restricted, resulting in diminished reliability of structural models, and (2) the efficiency of the process is hindered by the slow speed and significant memory requirements associated with the creation of point cloud-based mesh models and the automatic determination of structural error types [12]. Additionally, comparing As-Planned BIM models with As-Built point clouds within the Scan-vs-BIM framework requires converting both data types into a unified format (mesh models), thereby reducing the overall efficiency of the framework [13]. Therefore, a solution that can directly compare these data types in their original states would greatly enhance the integrity evaluation process and address the shortcomings of the current framework.

Recently, the application of deep learning to the construction industry has gained considerable traction, yielding substantial improvements over traditional frameworks [14]. Deep learning has been increasingly applied to address complex challenges in the construction industry, offering improvements in both speed and accuracy over traditional methods. Akinosho et al. highlighted that deep learning models automate complex tasks such as structural health monitoring, construction site safety assessment, building occupancy modeling, and energy demand prediction [15]. Their analysis shows that deep learning automates complex tasks and efficiently processes large datasets, reducing the need for manual intervention and speeding up data processing. The model’s ability to learn complex patterns and representations from data improves accuracy, providing better predictive performance than traditional methods. However, challenges such as data availability, the “black box” nature of deep learning models, and the need for specialized expertise remain. Addressing these challenges is crucial for the wider adoption of deep learning in the construction industry. Consequently, applying deep learning to the Scan-vs-BIM framework presents a promising opportunity to overcome the limitations inherent in conventional approaches. The aim of this study is to develop a novel deep learning-based Scan-vs-BIM framework that directly compares As-Built scan data with As-Planned BIM models without the need for mesh conversion, thereby improving computational efficiency and accuracy in structural integrity evaluation. Specifically, we propose the distance deep neural network (Distance-DNN) model, which evaluates structural integrity by analyzing the distribution tendencies of distance values between the As-Built point cloud and the As-Planned BIM model.

The remainder of this paper is organized as follows: Section 2 presents a literature review related to Scan-vs-BIM and deep learning. Section 3 describes the methodology and framework of the Distance-DNN-based Scan-vs-BIM process. A review of the model training process and the training results of Distance-DNN are presented in Section 4. Section 5 discusses the evaluation of Distance-DNN after applying it to an actual steel structure case. Finally, Section 6 summarizes the conclusions of the study.

2. Literature Review

2.1. Scan-vs-BIM in Construction

Within the architectural, engineering, and construction (AEC) industry, traditional integrity evaluation methodologies are predominantly manual-based. These approaches rely heavily on subjective estimation, observational skills, and the expertise of professional workers, rendering them prone to incomplete and inaccurate reporting [2]. Such reliance

on human judgment introduces variability and inconsistencies in the assessment process. To address these limitations, substantial research efforts are underway to develop efficient and objective integrity assessment methods. Among these, three-dimensional (3D) laser scanning has been proposed as a powerful tool for integrity evaluation due to its ability to accurately capture the As-Built state in three dimensions [5].

The 3D laser scanning technique is one of the major computer vision technologies that has been used since the 1990s [16]. It has the advantage of providing fast, accurate, comprehensive, and detailed 3D data about the scanned scene. It can capture a scene accurately in millimeters, and the captured information is saved as a 3D point cloud model that is typically called an As-Built scene. The collected 3D point cloud can be used to create an As-Built 3D Computer-Aided Design (CAD) model that can be applied to building design, reconstruction projects, tracking of project progress, and quality control [9]. Despite its numerous advantages, 3D laser scanning is not without its limitations. One of the primary challenges associated with this technology is the time required to perform each scan, particularly in complex environments where multiple scans from different vantage points are needed to achieve adequate resolution and minimize physical obstructions between the scanner and the target object [17].

The variability inherent in construction environments, coupled with the ambiguity surrounding the standards for optimal scanning results, poses significant challenges for practitioners seeking to adopt 3D laser scanning as a standard evaluation practice. In recognition of these challenges, the US General Services Administration (GSA) has developed guidelines for procuring and evaluating 3D imaging services, with the objective of clearly defining acceptable margins of error for 3D scan data [18]. The GSA's deliverable selection matrix, illustrated in Table 1, classifies the Level of Detail (LOD) into four levels. At Level 1, the tolerance for the collected data is ± 51 mm, whereas at Level 4—the most detailed level—the permissible tolerance is reduced to ± 3 mm. These classifications serve as benchmarks for establishing acceptable error ranges and ensuring consistency in the quality of 3D scan data used for construction integrity evaluations.

Table 1. Point cloud quality definition introduced by GSA.

Level of Detail (LOD)	Tolerance (mm)	Resolution (mm)
Level 1	± 51	152×152
Level 2	± 13	25×25
Level 3	± 6	13×13
Level 4	± 3	13×13

Three-dimensional laser scanning has become an essential tool for a range of construction activities, including surveying, earthmoving, monitoring concrete casting progress, highway alignment, paving operations, and construction quality control [4]. It has emerged as a highly prevalent data collection technique for integrity evaluation and is extensively utilized in the reconstruction of As-Built data and in performing “As-Planned–As-Built Comparisons” [5]. This technology offers a detailed and accurate representation of physical environments, thereby facilitating more reliable evaluations of construction processes and outcomes.

Bosché and Haas [19] proposed a method for automated detection, recognition, and identification of objects in laser-scanned point cloud data by leveraging prior information from 3D CAD/BIM models. This concept was defined as “Scan-vs-BIM”. The data used for detection are the range point clouds obtained from laser scans, representing the As-Built environment of construction sites. The prior information consists of the detailed 3D CAD models of the objects as designed (As-Planned). Their approach involves aligning the As-Planned 3D models with the As-Built point cloud data to identify and retrieve structural components within the scanned environment. This method was validated through laboratory experiments, demonstrating efficient and robust retrieval of 3D CAD objects from point cloud data. Additionally, they showcased how the approach could

facilitate automated construction progress assessment by comparing the planned models with the actual construction status [8]. Nguyen and Choi [20] proposed a 3D laser scan collection methodology for data acquisition for on-site dimensional inspection of piping systems in industrial plants. They proposed a Scan-vs-BIM framework with Random Sample Consensus (RANSAC) that performs a comparison function between the collected As-Built 3D point cloud and As-Planned 3D CAD.

Kim et al. [21] proposed the basic principle of project progress evaluation by applying the Scan-vs-BIM concept through 3D point cloud data and 4D parameters of BIM. As-built point cloud and As-Planned BIM comparison improves the efficiency and productivity of construction project management. They found that the Scan-vs-BIM framework could monitor the overall project status, including productivity analysis, progress, and quality verification, and easily identify issues and predictable engineering tasks. Li et al. [22] conducted a study to secure an accurate precast concrete model by applying the Scan-vs-BIM methodology in a Virtual Trial Assembly (VTA) environment. They developed an automated modeling approach to obtain As-Built point cloud models. The traditional Scan-vs-BIM method involves constructing a mesh by projecting to the unit plane (xy, yz, and xz planes). Maalek [23] developed an algorithm to increase the accuracy of point cloud processing and improved the accuracy of the Scan-vs-BIM framework by assessing the pipe axis plane of the As-Built point cloud data itself and projecting it there to implement a mesh.

In conclusion, 3D laser scanning and the Scan-vs-BIM framework have demonstrated significant promise in enhancing construction project management, structural integrity assessment, and quality control. The integration of these technologies into the construction industry facilitates the transition from manual, labor-intensive evaluation methods to automated, data-driven approaches. However, the approach of the Scan-vs-BIM framework is still difficult to scale for real-time analysis. The reason is that the traditional framework comparing the As-Built scan and As-Planned BIM takes a long time to apply in real time and uses a lot of memory due to data transformation. Therefore, the existing methods for Scan-vs-BIM need to be improved to be suitable for real-time analysis [11].

2.2. Deep Learning in Construction

Deep learning is a subordinate concept of machine learning in which a computer learns patterns from previous experiences. The complex structure of large datasets is obtained using a backpropagation algorithm that represents how the machine changes the hidden parameters used to compute each layer's representation from the previous layer's representation [24]. Artificial neural networks (i.e., the basic network concept in deep learning) use machine learning algorithms to imitate biological neural networks [25]. In general, a deep learning model consists of an input layer, a hidden layer, and an output layer. A deep neural network (DNN) literally means a deep learning model with multiple layers of "deep" hidden layers [26].

Deep learning has improved productivity and efficiency in a variety of industries owing to the automation of previously manual and time-consuming tasks [27]. Currently, research studies aiming to improve the traditional diagnostic framework by applying deep learning in the construction field are increasing. Traditional frameworks have been improved by applying deep learning to equipment tracking, crack detection, construction work management, sewage assessment, and 3D point cloud enhancement [14]. As a result of previous studies, the framework applied with deep learning could guarantee faster speed and accuracy compared to traditional methodologies.

For instance, Koo et al. [28] explored the use of 3D geometric deep neural networks, specifically multi-view CNN (MVCNN) and PointNet, to automate the classification of BIM element subtypes, such as doors and walls, in Industry Foundation Class (IFC) models. Their approach addressed the limitations of the manual specification of semantics, which is prone to errors and omissions. The MVCNN model achieved superior prediction performance, confirming that deep neural networks can effectively detect subtle differences in local geometries, enhancing the accuracy and efficiency of BIM element classification.

Zhou et al. [29] proposed an end-to-end vision measurement framework for structural health monitoring (SHM) using a novel deep neural network tracker called Siamese Single Decoder Network (SiamSDN). This framework does not require manual feature extraction or predefined motion areas; instead, it identifies the tracking object solely from the first frame. In their experiments involving a shaking table test and UAV-based field tests, the SiamSDN tracker improved displacement measuring accuracy by 66.16% and 57.54%, respectively, compared to traditional feature point matching approaches, demonstrating precise frequency characteristic acquisition.

Hu et al. [30] introduced a powerful deep learning-based 3D reconstruction method for cable-stayed bridges. Their framework uses both multi-view images and photogrammetric point clouds as inputs to an encoder–decoder network that models high-level structural relations and low-level 3D geometric shapes. The method successfully reconstructed bridge models with structural components and their relationships, achieving an average F1 score of 99.01%, a Chamfer distance of 0.0259, and a mesh-to-cloud distance of 1.78 m. This performance surpasses that of manual reconstruction approaches in spatial accuracy, highlighting the method's robustness to noise and partial scans.

Wang et al. [31] presented a novel fused BIM reconstruction approach for mechanical, electrical, and plumbing (MEP) scenes by leveraging semantic information from images and precise geometry from 3D LiDAR point clouds. They fine-tuned a state-of-the-art deep learning model for the semantic segmentation of MEP components and developed an instance-aware component extraction algorithm for LiDAR point clouds. Their method demonstrated higher accuracy and efficiency compared to previous BIM reconstruction methods, effectively handling complex MEP environments.

Perez-Perez et al. [32] proposed Scan2BIM-NET, an end-to-end deep learning method for semantic segmentation of structural, architectural, and mechanical components in point cloud data. Their approach classifies elements such as beams, ceilings, columns, floors, pipes, and walls using two convolutional neural networks and one recurrent neural network. Tested on 83 rooms from real-world industrial and commercial buildings, the method achieved an average accuracy of 86.13%, significantly improving the accuracy of semantic segmentation in the Scan-to-BIM process, particularly in under-ceiling areas with closely spaced mechanical and structural elements.

Smith and Sarlo [33] developed an alternative segmentation method tailored specifically to large-scale steel buildings. Instead of processing 3D point cloud data directly, they utilized image processing techniques on 2D “slices” of the point cloud. By extracting centroids of structural cross-sections using 2D convolution and projecting them back into 3D space, they constructed a 1D beamline model, including connections. This method proved robust against variations in framing systems, clutter, and point cloud sparsity, effectively handling complex geometries that traditional 3D point cloud segmentation methods struggle with.

These studies demonstrate the effectiveness of deep learning in improving various traditional frameworks within the construction industry by enhancing accuracy, efficiency, and automation. However, applications of deep learning specifically in structural integrity verification, particularly within the Scan-vs-BIM framework, remain limited.

Additionally, recent studies have demonstrated the effectiveness of deep learning in detecting structural changes using camera images [34,35]. While camera images offer high-resolution visual data, they may lack the precise spatial and geometric information necessary for accurate structural integrity assessment. Three-dimensional laser scanning provides detailed dimensional data that capture the exact spatial relationships and dimensions of structural components, which is crucial for quantitative analysis in a Scan-vs-BIM framework. However, integrating image-based methods with laser scanning could be a potential area for future research, combining the strengths of both modalities.

In conclusion, the application of deep learning may improve the traditional Scan-vs-BIM framework. Deep learning can replace the processing method that compares As-Planned BIM and As-Built scan data in a single format in the traditional Scan-vs-BIM

framework. This study collects comparison data by directly comparing two types of data in the original state and proposes a deep learning model that can analyze the features of these comparison data.

3. Methodology

The Distance-DNN-based Scan-vs-BIM framework proposed in this study aims to evaluate the integrity of the target structure based on direct comparison data between the As-Built 3D scan and As-Planned BIM. Evaluating the integrity of individual structural components is crucial for pinpointing specific areas that may require maintenance or repair. This level of granularity enables targeted interventions, reduces overall maintenance costs, and enhances the safety and reliability of the structure [12]. Traditionally, generating BIM models from point cloud data involves a Scan-to-BIM process where the point cloud is manually or semi-manually converted into a mesh model. This involves identifying and modeling structural elements by fitting geometric primitives (nodes, edges, or planes) to the point cloud data.

However, the traditional process that relies on Scan-to-BIM in the Scan-vs-BIM framework causes the following problems: First, individual integrity evaluation of structures is not possible, and there is a lack of reliability in the generated structural models. Second, in the process of creating a point cloud-based mesh model through Scan-to-BIM, it shows slow speed and low efficiency due to large memory allocation. Third, the error type of the structure cannot be automatically determined. The Scan-vs-BIM framework uses As-Planned BIM and As-Built scan data. Comparing these two types of data in one format (mesh) reduces the efficiency of the Scan-vs-BIM framework. However, Distance-DNN, which analyzes the features through a direct comparison of the two types of data in an unmodified state, resolves the shortcomings of the traditional framework and can show strong performance and computational speed.

Figure 1 shows the flowchart of the proposed Distance-DNN-based Scan-vs-BIM framework that performs structural integrity evaluation based on direct comparison data. The proposed framework consists of the following steps: (1) preprocessing, (2) Scan-vs-BIM, and (3) Distance-DNN. The framework evaluates the structural integrity of one single structural object per process and repeats the same process for all structural objects to review the integrity of the entire structure. The piecewise operation improves computational efficiency by breaking down the complex shape into smaller, more manageable sections, allowing for localized computations that require less memory and processing power. While our current implementation executes these operations sequentially, they can be parallelized to further enhance efficiency.

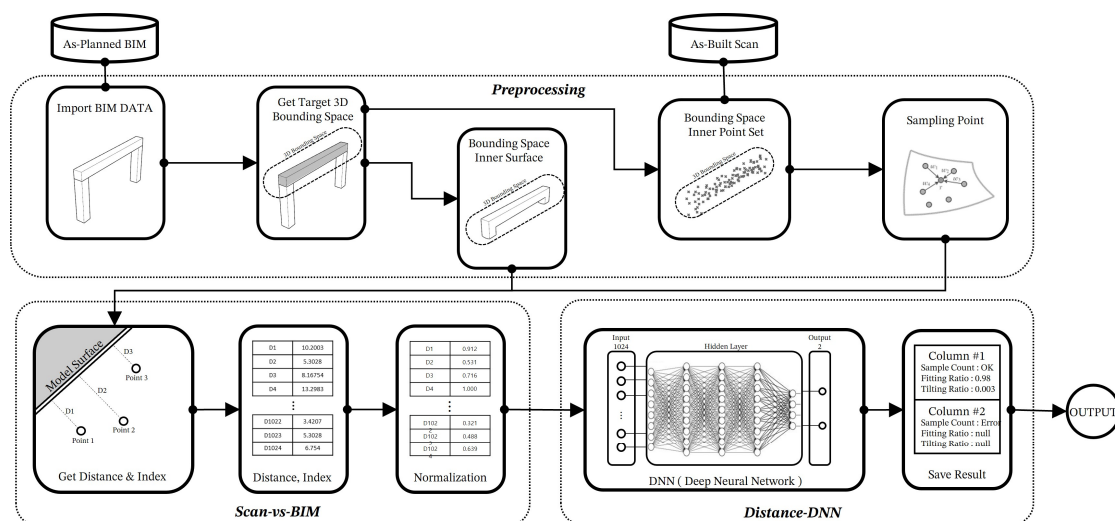


Figure 1. Flowchart of simplified Scan-vs-BIM.

In the preprocessing step, a parameter-based bounding space of a BIM object is created for single-structure evaluation. The bounding space becomes the reference for a single operation. It performs the function of separating the BIM shape model and sampling the points inside the bounding space. In the Scan-vs-BIM process, the geometric relationship data of the point cloud and BIM are collected. The method of constructing and comparing meshes through the Scan-to-BIM process of the traditional Scan-vs-BIM process requires a lot of computation; thus, the processing speed is slow. However, the framework of this study performs integrity evaluation by collecting only distance and index data, which are direct comparison data. In the Distance-DNN process, the tendency of distance and index data to perform a structural integrity evaluation function and a function to predict structural error types is analyzed. A DNN model was constructed to perform two functions.

The proposed framework was implemented using Python programming language (version 3.8) due to its extensive libraries and tools for scientific computing. For the development and training of the Distance-DNN model, we utilized the TensorFlow deep learning library (version 2.4), which provides robust support for constructing and training neural networks. Data preprocessing and manipulation were performed using NumPy (version 1.19) and Pandas (version 1.2) libraries, and visualization of results was achieved using Matplotlib (version 3.3). All computations, including data processing and model training, were conducted on a workstation equipped with an Intel Core i11 CPU, 64 GB of RAM (Intel Corporation, Santa Clara, CA, USA), and an NVIDIA RTX 4080 Ti GPU with 24 GB of VRAM (NVIDIA, Santa Clara, CA, USA). GPU acceleration was applied to improve the training speed of the deep neural network.

3.1. Preprocessing

In the preprocessing stage, data are processed for comparison with point cloud and BIM data. Using only essential data in BIM and point cloud analysis is the most cost-effective and efficient way to manage data. Therefore, the structural integrity of one single structural object is evaluated and the same is repeated for the entire structure to evaluate its integrity. To evaluate the structural integrity of a single structure, it is necessary to collect the As-Planned BIM shape information and As-Built point cloud sampling data located around the target structural object. In the proposed process, the work bounding space is defined based on the parameter values of the target structural object on the BIM model, and the target object shape and point cloud group inside the bounding space are separated. Through the preprocessing step, the processing speed increases, and memory optimization can be achieved by reducing the amount of computations throughout the framework. Even if the structure is not completely collected from the As-Built scan data, structural integrity evaluation is possible even if only a certain number of points required in the process are collected.

3.1.1. Bounding Space of Target Structural Object

When evaluating the integrity of a single structural object in the Scan-vs-BIM framework, the most effective way is to compare only the shape of the target object with the point cloud near the target structural object. The As-Built scan cannot be a standard for work because it consists of point cloud data with scattered points without a fixed index. Therefore, it should be defined based on the target structural object of As-Planned BIM consisting of parameters. The target structural object of the BIM model contains various data, and all of these data are defined as parameters. The structural object's parameters include the "start point" and "end point" of the object, the centerline connecting the two, and the shape of the section. In this study, the work standards were clearly defined by utilizing the characteristics of these BIM parameters. Therefore, in the preprocessing stage, the bounding and work reference bounding spaces are defined based on the parameters of the target structural object on the BIM model. The process of defining the bounding space is shown in Figure 2.

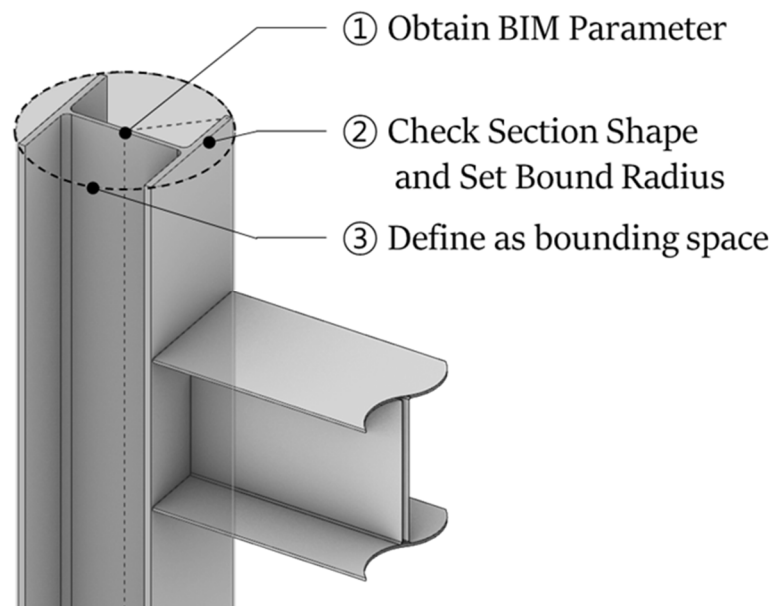


Figure 2. Bounding space of target structural object.

First, the structural parameters are collected from the BIM model, which serves as the basis for the analysis. These parameters include the centerline and cross-section shapes used to construct the bounding space around the object. Second, the radius (R) of the bounding space is set based on the cross-sectional shape. The R value is set in consideration of the error range of the 3D scanner's device and the general range recognized as a structural error. The error range of the 3D scanner's device was defined to be ± 51 mm, which is the level of accuracy of the LOD Level 1 specified by GSA (Table 1). The structural error range was defined to be ± 13 mm according to the Code of Standard Practice of the American Institute of Steel Construction (AISC) [36]. Finally, in order for Distance-DNN to clearly understand structural error types (Deflection, Tilt, Rotation, Error), an additional margin was needed to understand the surrounding environment of the object. Therefore, set the R value of the bounding space to the farthest position from the center reference section (i.e., $+199$ mm). Third, based on the centerline, all ranges within the R value are defined as bounding space. The bounding space created is a virtual 3D range made up of equation values and becomes the reference for all preprocessing operations.

3.1.2. Extraction of Object Shape Inside Bounding Space

This process obtains all shape data inside the bounding space. The shape information includes the shape of the target object and any fragmented shapes cut relative to the outside of the object across the bounding space. The shape was modified based on a virtual space predefined as the bounding space using a Boolean operation. Boolean operations on two solids are based on intersection calculations and surface member classification [37].

The process of extraction of the object shape of an object inside the bounding space using Boolean operations is shown in Figure 3. First, the list of all objects that intersect in the bounding space was classified, and the Boolean operation was cut through based on the outer space (split). Next, the process was used to exclude all shapes outside the bounding space from the selection (remove). Finally, all objects inside and all the split shapes were combined (merge). If the next operation is performed with multiple shapes that are not merged into one, the distance between the point and all shapes that are not merged must be calculated. Since only the minimum value has to be selected among them, the amount of computations increases as much as the number of shapes. This issue adds approximately 0.5 milliseconds to the analysis time of a single structural object, which is negligible compared to the total processing time. In the context of analyzing an entire structure with numerous components, this overhead constitutes less than 5% of the overall

computation time, ensuring that the efficiency of the framework is maintained. However, in the analysis of the entire structure, the computation time is overwhelmingly increased due to this problem. Conversely, using the combined shape eliminates unnecessary calculations and guarantees predictable calculation speed because the distance value to the point needs to be calculated only once in extracting the distance value.

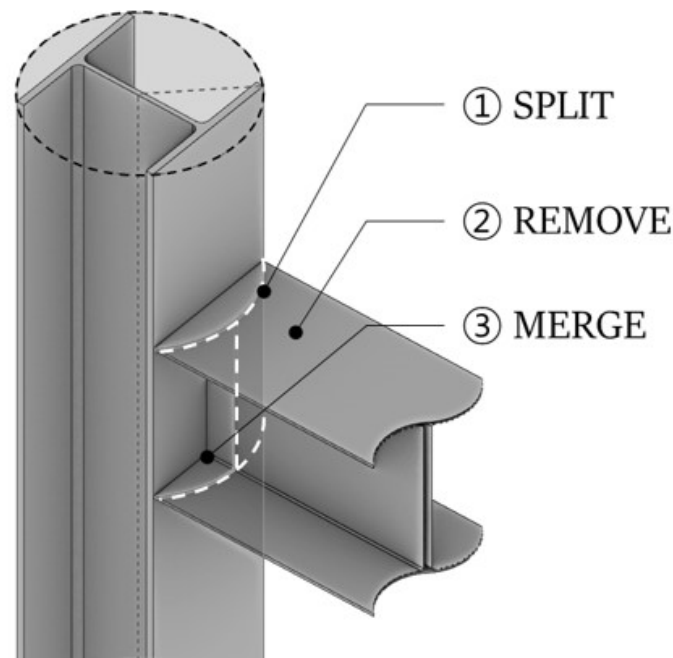


Figure 3. Extraction of object shape inside bounding space.

3.1.3. Extraction of Points Inside Bounding Space

In this process, all points in the bounding space were collected and a sampling process was included for optimization. A geometric formula was applied to distinguish a point inside the bounding space. The mathematics involved in this step are discussed in the equations (Appendix A). Among the parameters of the target structural object, the “start point” and “end point” are defined as p_1 and p_2 , respectively; the target point to be checked whether it is within the bounding space is defined as p_0 . If the calculated shortest distance is smaller than the R value of the bounding space, it is considered an internal point.

The DNN needs to predefine the size of the input layer. Not all points within the bounding space can be used as indicators of analysis. Therefore, it is necessary to predefine the number of points to be input in the DNN-based integrity evaluation. In general, the DNN uses an input size of the form power of 2 [26]. When the points collected on a general structural column are uniformly arranged in the longitudinal direction, 512 points are 8 mm, 1024 points are 5 mm, and 2048 points are arranged at intervals of 2 mm. Structural integrity can be assessed more accurately and in detail by using as many points as possible and arranging them at small intervals. However, if a large number of points are used, the amount of computations of the DNN increases, thus reducing the efficiency of the framework [38]. Therefore, it is necessary to define the number of points according to the appropriate criteria. Considering the mechanical error of the 3D scanner and the variables of the field conditions, it was determined to configure the input data at intervals of 5 mm and sample 1024 points as a reasonable standard for structural integrity evaluation.

The simplest way to sample a point cloud is to randomly select 1024 points. However, random selection has a disadvantage in that the data structure is lost because the selected point is concentrated only on a specific part and cannot maintain the data features of the existing point cloud [39]. Therefore, a theoretical methodology for sampling rather than random selection was presented. Farthest Point Sampling (FPS) is the most used

method [40]. FPS works by starting at a point in the set and iteratively selecting the point farthest from an already selected point [41]. These methods do not minimize geometric errors and subsequent processing of a sampled point cloud is not possible, thus leading to sub-optimal results [42]. In a recent study, SampleNet—a new differential relaxation methodology for sampling from a point cloud that approximates the points sampled as a mixture of points in the point cloud—was proposed. The approximation method of SampleNet consistently acquires good results in classification and geometric reconstruction applications [43]. By applying SampleNet to the proposed process, 1024 points were sampled. Through SampleNet, the features of the point cloud can be clearly maintained, and the framework can output consistent and stable results.

3.2. Scan-vs-BIM

Scan-vs-BIM collects geometric comparison data of point clouds and shapes. The distance between the sampled point cloud and the BIM shape is calculated to build the dataset. The traditional Scan-vs-BIM framework requires high computational performance due to the complex process of converting point cloud data into mesh models and performing detailed geometric comparisons with BIM models. This mesh generation and alignment process can take several hours per project, especially for large and complex datasets, and demands significant memory and processing power. In some cases, the calculations can take several days, depending on the scope of the structure. However, the proposed framework can conduct integrity evaluation using only 3D distance and index data. Index data refer to the normalized positional values of the sampled points along the structural object's length, derived from the BIM model's parameters. Specifically, for each point in the point cloud within the bounding space, we calculate its relative position along the centerline of the structural component. This index value provides a standardized measure of where each point lies along the length of the object. By combining distance data with these index values, the model can understand the spatial distribution of deviations along the component. Based on this method of transforming data structures, the algorithm can simplify the dimensional structure it recognizes, providing fast and predictable computational speed with fewer computational resources than existing frameworks [43].

Figure 4 shows the geometric comparison method of Scan-vs-BIM based on Distance-DNN. First, the shortest distance was calculated in the 3D space of the point cloud data of As-Built scans using coordinates and As-Planned BIM data. The method of calculating the shortest distance between the point cloud data and the BIM shape uses the Closest Point Method (CPM) to find the target point on the shape closest to the origin point [44]. Then, the target-origin distance is calculated through the 3D coordinate system and stored in the 3D distance dataset.

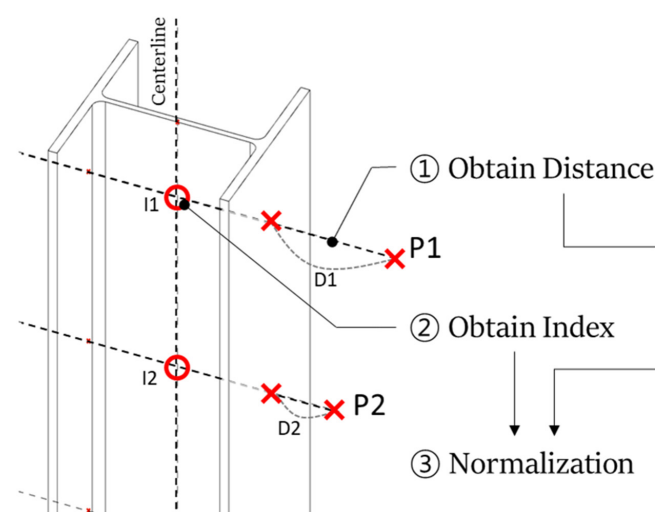


Figure 4. Scan-vs-BIM based on Distance-DNN.

A deep learning model is trained by extracting features from data. If the data input to the model is scattered without criteria, it is difficult to achieve integrity evaluation. In general, features are maintained by adding baseline data [26]. In this study, the parameter index was collected by aligning the relative positions of the points with the model centerline of the BIM parameters. Through the collected index data, the tendency of point cloud and shape comparison data was identified.

Finally, the process performs data normalization. Normalization is an operation in which all data are transformed to the same degree of scale. In this study, data were adjusted based on a predefined error range scale. By adding the 3D scanner's mechanical error range of ± 51 mm and the structure's error range of ± 13 mm, 64 mm was set as the normalization bound. The collected distance values were divided by the normalization bound and converted into float data between 0 and 1. Due to the nature of DNNs, float data between 0 and 1 must be input; thus, data larger than the range value are fixed to 1 (i.e., the maximum value of the input format).

3.3. Distance-DNN

This process analyzes the features of distance and parameter index data collected in the previous process to determine integrity evaluation and structural error types. In this study, a DNN model was built to perform this function. The name of the proposed deep learning model is Distance-DNN. Integrity evaluation can be performed quickly even with an input value of 1024×2 consisting of 1024 distance data points and 1024 parameter data points in the float format between 0 and 1.

Distance-DNN performs structural integrity evaluation and analysis of types of structural errors. Theoretically, a DNN structure cannot simultaneously perform more than one function [26]. Therefore, each network that performs individual tasks must be configured, and the framework unites the individual networks to accomplish their tasks. In this study, an integrated framework divided into a structural integrity evaluation (SIE) network and a structural error type analysis (SETA) network is proposed so that the Distance-DNN can smoothly perform two functions. Here, the SIE network evaluates the structural integrity of the input data, and the SETA network analyzes the types of structural errors.

This full network architecture is visualized in Figure 5, where the SIE and SETA networks are structurally similar. The network sequentially analyzes features as input data (1024×2), which go through a Multi-Layer Perceptron (MLP). The numbers in brackets are the change in layer size. And the global max pooling layer to aggregate information crosses all layers. While both networks share a similar base architecture for feature extraction, the SIE network concludes with a single neuron output layer for regression (integrity rate), using a linear activation function. In contrast, the SETA network ends with a multi-class softmax output layer for the classification of structural error types. Finally, the output score for the specified label is derived through the MLP. The SIE network evaluates only the structural integrity and derives an output score for the "Fitting Rate". The SETA network needs to derive structural error types, and it is necessary to classify them. In this study, four types of structural errors were classified as "Tilt", "Deflection", "Rotation", and "Error"; this was set as the output label of the SETA network. The output classes of the structural error type analysis (SETA) network are defined as follows:

- Tilt: A deviation of the structural component from its intended vertical or horizontal orientation.
- Deflection: A bending or sagging of the component due to load or structural issues.
- Rotation: A rotational displacement around the component's axis.
- Error: Any other form of structural discrepancy not covered by the above categories, such as misalignment or incorrect placement.

The "Error" label includes all error types that are not included in "Tilt", "Deflection", and "Rotation". For example, if the structural object is installed in a different place than the planned location or the intermediate joint member is different, it is included in the "Error" label.

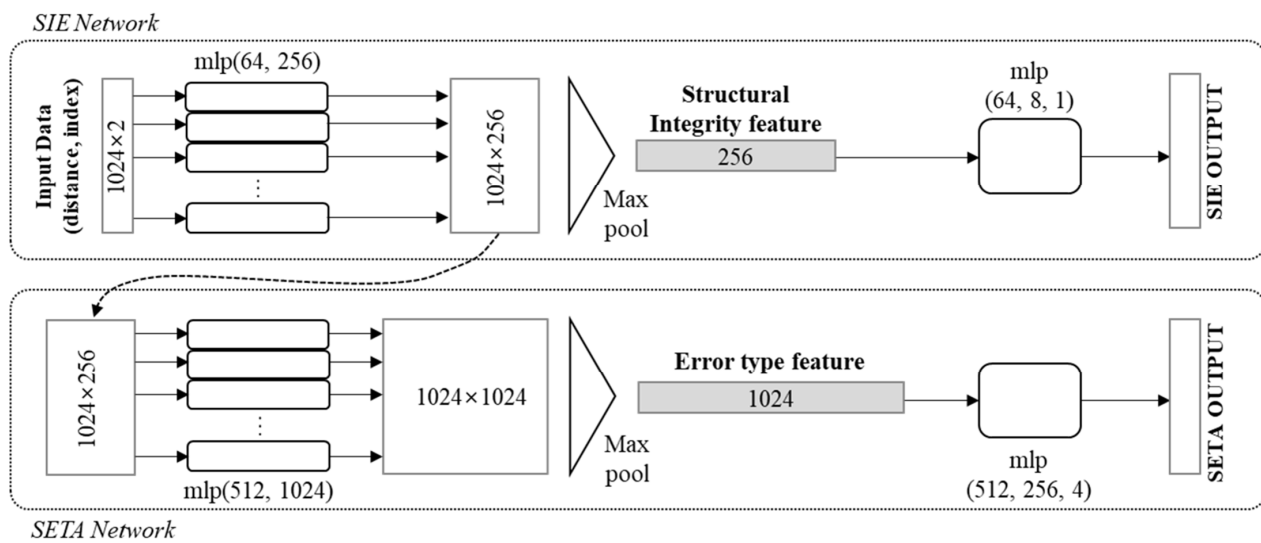


Figure 5. Architecture of SIE and SETA networks.

The order of structural integrity evaluation using Distance-DNN is described as follows: First, through the Scan-vs-BIM process, data consisting of 1024 distance data points and 1024 parameter data points in a float format between 0 and 1 are loaded. The data go through the SIE network, and the output score for “Fitting Rate” is calculated. Afterwards, the output scores for the “Tilt”, “Deflection”, “Rotation”, and “Error” labels are calculated through the SETA network. Performing cross-validation synthesizes the derived structural integrity evaluation score and probability of each type of error and then exports the results. The result is expressed as a percentage for each label, and all structural objects are evaluated.

4. Training of Distance-DNN

Training a DNN model refers to the process of inversely calculating the weights for the connected nodes between layers based on input and output data [26]. Therefore, input and output data to train the Distance-DNN as an algorithm for integrity evaluation are essential. In this study, two types of data were collected for training the Distance-DNN: real project data and virtual data. Real project data were used to train the function of real structural objects. Virtual data were used to train structural error types. The Distance-DNN framework was implemented by training the SIE and SETA networks with the collected data. The performance of Distance-DNN was evaluated in terms of the “accuracy” and “loss” according to the learning results.

4.1. Data Collection

As-Built scan data and As-Planned BIM data of a real project were collected to build training data. The structural object in the BIM model was separated, and only the point cloud around the object was used. The Distance-DNN trained the distance and index data features extracted from the collected real project data. However, the amount of Scan-vs-BIM data collected from real data is not sufficient to train Distance-DNN.

In this study, the training data were obtained by augmentation of data through random point sampling. In general, more than 100,000 point clouds are captured for one structural object [45]. Only 1024 points required by Distance-DNN are randomly sampled, and this is defined as a dataset. Through this method, augmentation was performed from a single structural object’s data to hundreds of datasets. From the above process, a total of 26,500 real project datasets were constructed.

4.2. Virtual Dataset Generation

Distance-DNNs for structural integrity evaluation cannot be trained using only a limited real dataset. Although this was partially resolved through augmentation, there is still a small amount of data. Additionally, there is a limit to collecting data showing structural errors in real projects. A Distance-DNN trained only with data without structural error determines that there is no error even when receiving actual structural error data. Therefore, a dataset with clearly defined structural errors was generated in a 3D virtual space. The dataset is prescriptive for structural errors, and an unambiguous training process of the Distance-DNN on the types of structural errors is enabled.

A flowchart for generating a virtual dataset is illustrated in Figure 6. The process goes through the following steps: First, a 3D model that reflects the original 3D model of the structural object and structural errors is created. Next, the point cloud of the outer error model is acquired using the 3D scanning methodology. Finally, the distance and index data between the structural object model and point cloud are outputted. Through this process, a total of 65,000 virtual datasets were constructed.

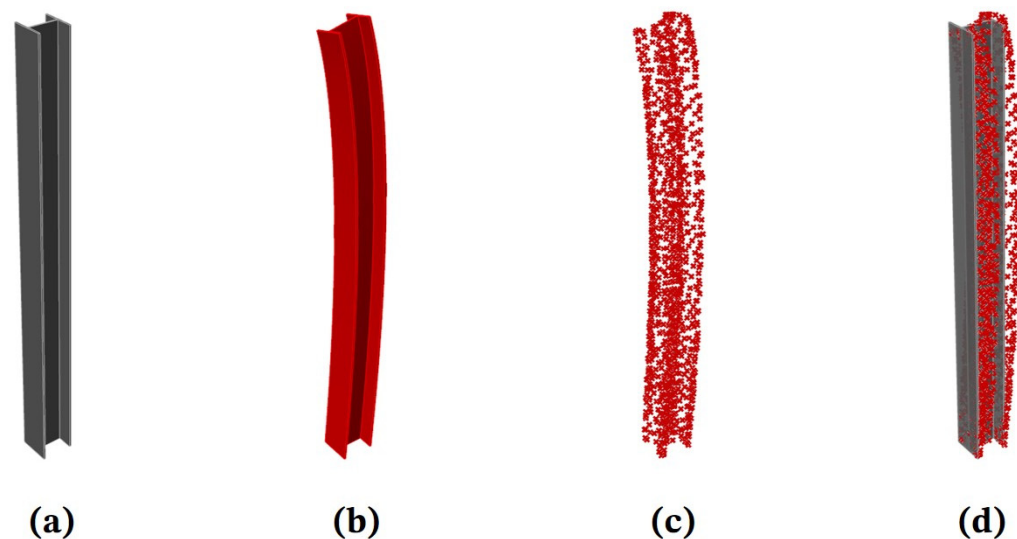


Figure 6. Virtual dataset creation process: (a) normal object model, (b) error object model, (c) error object model point cloud conversion, and (d) normal object and error point cloud overlap.

Figure 7 is a visualization of the created virtual dataset organized by type. The plot below is the result of arranging the distance data based on parameters. The 3D data (x , y , and z) went through dimensionality reduction and resulted in 2D data (distance and index) and 1024 samples were sampled. However, it is still possible to determine the type of structural error. The Distance-DNN also trained these features to derive results.

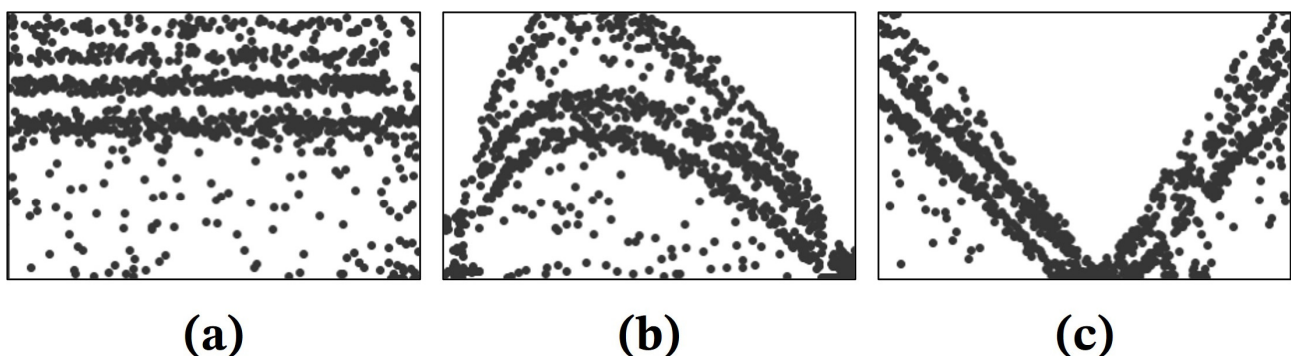


Figure 7. Virtual dataset of 3D model and plot of distance: (a) Error, (b) Bend, and (c) Tilt.

4.3. Training Results

The training results are shown in Table 2. The SIE network performs integrity evaluation with 95.77% accuracy. This proves that the Scan-vs-BIM using Distance-DNN is a very powerful solution in determining whether there is a simple structural error. The loss rate due to estimation error was 0.03, and the error rate for data prediction was low. The SETA network could classify structural error types with 68.97% accuracy. Although it is less accurate than the SIE network, it could guarantee a certain level of reliability in the assessment of the type of structural error. The loss rate is 0.04 and the prediction error rate is as low as that of the SIE network. The Scan-vs-BIM framework of previous studies could only check structural errors, but the Distance-DNN-based Scan-vs-BIM can simultaneously evaluate integrity evaluation and determine error types.

Table 2. Results of SIE and SETA network evaluation.

Training Results	SIE Network	SETA Network
Accuracy rate	0.9577	0.6897
Loss rate	0.03	0.04

5. Evaluation

The Distance-DNN-based Scan-vs-BIM was applied to actual steel structures to conduct structural integrity evaluation experiments. The target steel structure covered an area of 423 m² with a height of 10 m and included 184 structural objects (Figure 8). In the past, it was constructed through As-Planned BIM and used as a factory. Three-dimensional scanning data were collected at the time of completion for the remodeling of the structure, and the point cloud data were collected using a Faro Focus3D X 330 laser scanner (FARO Technologies, Inc., Lake Mary, FL, USA). This scanner has a range of up to 330 m and an accuracy of ± 2 mm. During data acquisition, the scanner was set to a resolution of 1/5 (corresponding to approximately 122,000 points per second) and a quality setting of 4 $\times$ to balance between data density and scanning time. The total number of points acquired was approximately 10 million. Structural deformation of the objects did not occur during the process used. There were differences between the As-Built and As-Planned data due to the addition of pipes and equipment (Figure 8).

The BIM model was created using Autodesk Revit 2022. BIM parameters were accessed programmatically using Dynamo (version 2.17), allowing us to extract information such as nodes, edges, and element geometries. The BIM model was constructed at LOD 200, with structural object details accurately represented.

The experimental results for the SIE and SETA networks are listed in Table 3. The integrity evaluation of structural column objects was conducted based on the Distance-DNN framework. It took 42 ms to evaluate the integrity of all 20 structural column objects. The integrity evaluation rate for one column object was calculated to be 2.1 ms and was faster than the traditional Scan-vs-BIM framework. It also used less computational resources. The network predicted that all columns were, on average, 94.68% accurate. Additionally, as a result of the structural error type analysis, the proportion of the “Error” label was high. This is attributed to the SETA network’s prediction that the probability of “Error” among structural error types is highest because equipment and pipes are added to the target structure. However, since only the point cloud around a single object was included in the calculation process, and the structural object of the target steel structure was not deformed, the SIE network predicted no difference between BIM and scan. From the experiments, it was proved that the SIE and SETA networks could derive accurate results for structural integrity evaluation and show faster operation speed than the traditional Scan-vs-BIM framework.

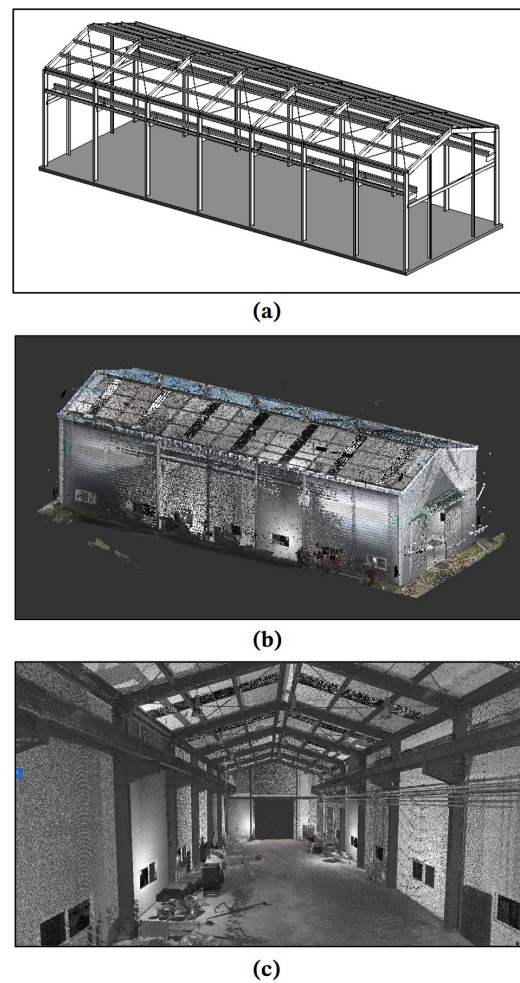


Figure 8. (a) As-Planned BIM structural model, (b) As-Built point cloud, and (c) inside view.

Table 3. Results of structural integrity evaluation of columns through Distance-DNN.

Column	Integrity Rate	Error Rate				
		Tilt	Deflection	Rotation	Error	Total
1	0.97780	0.00067	0.00109	0.00369	0.01675	0.02220
2	0.93720	0.00073	0.00531	0.00810	0.04866	0.06280
3	0.93240	0.00124	0.00662	0.01031	0.04943	0.06760
4	0.93200	0.00162	0.00348	0.01103	0.05187	0.06800
5	0.94890	0.00205	0.00143	0.00703	0.04059	0.05110
6	0.93890	0.00142	0.00212	0.01085	0.04672	0.06110
7	0.93000	0.00240	0.00258	0.01122	0.05379	0.07000
8	0.93720	0.00149	0.00180	0.01085	0.04866	0.06280
9	0.94060	0.00165	0.00352	0.00929	0.04495	0.05940
10	0.96480	0.00062	0.00173	0.00573	0.02712	0.03520
11	0.97180	0.00073	0.00127	0.00469	0.02152	0.02820
12	0.94360	0.00108	0.00316	0.00920	0.04296	0.05640
13	0.94840	0.00109	0.00323	0.00787	0.03942	0.05160
14	0.93850	0.00172	0.00372	0.00937	0.04669	0.06150
15	0.94690	0.00096	0.00267	0.00832	0.04116	0.05310
16	0.94000	0.00106	0.00155	0.01001	0.04738	0.06000
17	0.94710	0.00145	0.00379	0.00671	0.04095	0.05290
18	0.94830	0.00198	0.00163	0.00871	0.03938	0.05170
19	0.94220	0.00099	0.00336	0.01015	0.04330	0.05780
20	0.96860	0.00102	0.00084	0.00457	0.02497	0.03140
Avg.	0.94676	0.00130	0.00274	0.00838	0.04081	0.05324

To validate the computational efficiency of our proposed framework, we conducted experiments comparing the processing times of the traditional Scan-to-BIM method and our method under the same conditions. The traditional method required approximately 8 h to process the entire structural dataset, primarily due to the mesh generation and alignment steps. In contrast, our method completed the same task in approximately 3 min, demonstrating a reduction in processing time by over 95%. This efficiency gain is attributed to the elimination of mesh-related computations and the use of distance and index data, which simplify the evaluation process while maintaining accuracy. Based on this evidence, the Distance-DNN-based framework proved to be a powerful structural integrity evaluation solution, and it was able to improve the traditional Scan-vs-BIM framework.

6. Conclusions

This study presents and evaluates Distance-DNN, a deep learning model developed for structural integrity evaluation by identifying features in As-Built scan data and comparing them with As-Planned BIM data. The Distance-DNN-based Scan-vs-BIM methodology proposed here diverges from traditional Scan-vs-BIM approaches, which typically involve constructing comparative models and processing them through complex transformations. Instead, the proposed framework integrates two distinct neural networks that perform integrity evaluation and error type analysis, offering a comprehensive assessment of structural integrity. Specifically, this study constructed a total of 26,500 real project datasets through augmentation of existing project data and generated an additional 65,000 virtual datasets within a 3D virtual environment featuring clearly defined structural errors. During the training process, the structural integrity evaluation (SIE) network achieved an accuracy of 95.77%, while the structural error type analysis (SETA) network attained an accuracy of 68.97%. The respective loss rates of the two deep neural networks were 0.03 and 0.04, reflecting minimal prediction errors. When applied to an actual steel structure, the trained Distance-DNN demonstrated a verified accuracy of 94.2% in structural integrity evaluation.

Traditional Scan-vs-BIM approaches have posed challenges for real-time analysis due to their substantial computational demands [11]. In contrast, the Distance-DNN-based Scan-vs-BIM framework facilitates analysis by directly comparing As-Built scans with As-Planned models, obviating the need for complex data transformations. Consequently, this approach is computationally efficient, achieving a processing speed of 2.1 milliseconds per object, thereby enabling real-time structural integrity analysis. Additionally, the Distance-DNN framework is highly versatile and capable of evaluating the integrity of an object based on its As-Planned geometry, even in the absence of detailed BIM data. Given its robust computational speed and high accuracy, this framework holds significant potential for application in construction scenarios where structural integrity evaluation is critical.

Despite these promising results, the study has several limitations that warrant further investigation. First, the current framework has been primarily validated on linear structural components, such as columns and beams. While it can generalize across various linear structural members, its applicability to non-linear or complex structural components—such as curved beams, slabs, free-form structures, and elements with variable cross-sections—remains unverified. The framework relies on consistent geometric properties for feature extraction, which may not be present in complex geometries. This limitation suggests that additional research is necessary to adapt the methodology for a broader range of structural elements. Second, the SETA network achieved a lower accuracy of 68.97% compared to the SIE network, indicating limitations in accurately classifying specific types of structural errors. This reduced accuracy could impact the effectiveness of targeted maintenance and repair strategies, as misclassification of error types may lead to inappropriate remedial actions. Enhancing the classification performance of the SETA network is therefore essential for the framework to provide more reliable diagnostic information. Third, although the study utilized a substantial amount of augmented and virtual datasets, the reliance on simulated data may not capture all the nuances of real-world structural variations and environmental factors. Factors such as sensor noise, environ-

mental conditions, and unforeseen structural anomalies present in actual construction sites might affect the model's performance. This potential gap could affect the model's generalizability when deployed in diverse construction scenarios, highlighting the need for more extensive real-world data collection and validation. Lastly, the framework assumes that the As-Planned BIM data are accurate and detailed. In practice, discrepancies in BIM data quality, such as outdated information or modeling errors, could affect the integrity evaluation, leading to potential false positives or negatives. This dependency on the quality of input data necessitates the development of methods to assess and enhance BIM data accuracy before analysis.

To address these limitations, future research efforts for the deep learning-based Scan-vs-BIM framework should prioritize improving the preprocessing algorithms and the accuracy of the error type estimation components. In addition, the focus should be on extending the framework to accommodate these complex geometries to improve its generalizability and practical usefulness in various construction scenarios. In particular, it is essential to improve the robustness, accuracy, and versatility of the Distance-DNN-based Scan-vs-BIM framework. This will contribute to the development of a more comprehensive structural integrity assessment tool that can handle a wide range of structural components and real-world conditions. This will support the goal of promoting safer and more efficient construction practices and performing accurate structural integrity assessments in real time across a variety of construction scenarios, in line with the industry's move towards digitization and advanced analytics. In conclusion, these improvements will enable the reconfiguration and optimization of neural network architectures, which will ultimately contribute to the advancement of real-time analytic capabilities and the overall reliability of the Scan-vs-BIM methodology.

Author Contributions: Conceptualization, I.J. and J.-j.K.; methodology, B.K. and I.J.; software, B.K. and I.J.; validation, B.K., I.J. and N.H.; formal analysis, I.J.; investigation, B.K.; resources, B.K. and N.H.; data curation, B.K. and N.H.; writing—original draft preparation, B.K. and I.J.; writing—review and editing, N.H. and J.-j.K.; visualization, B.K.; supervision, J.-j.K.; project administration, I.J. and N.H.; funding acquisition, B.K. and N.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Inside Point Calculations

Among the parameters of the target structural object, the start point and end point are defined as P_1 and P_2 , respectively. A vector u on a straight line passing through P_1 and P_2 is derived.

$$\vec{u} = \begin{bmatrix} x_2 - x_1 \\ y_2 - y_1 \\ z_2 - z_1 \end{bmatrix}$$

The target point to be checked whether it is within the bounding space is defined as P . The foot of the perpendicular from P to the P_1, P_2 line is defined as P_0 . The value of a vector starting at point P and going to P_0 is prescribed and is organized as follows:

$$|\overrightarrow{PP_0}| = |\overrightarrow{PP_1}| \sin \theta$$

Then, using the cross product calculation of vectors, the following formula is derived. Finally, the minimum distance between the point and the line segment is derived. If the calculated shortest distance is smaller than the R value of the bounding space, it is considered an internal point.

$$\left| \vec{u} \times \overrightarrow{PP_0} \right| = |\vec{u}| |\overrightarrow{PP_1}| \sin \theta$$

$$d = \frac{|\overrightarrow{PP_0}|}{|\vec{u}|} = \frac{|\vec{u}| |\overrightarrow{PP_1}| \sin \theta}{|\vec{u}|} = \frac{|\overrightarrow{PP_1} \times \vec{u}|}{|\vec{u}|}$$

References

- Usmen, M.; Vilnitis, M. Evaluation of safety, quality and productivity in construction. In *IOP Conference Series: Materials Science and Engineering*; IOP Publishing: Bristol, UK, 2015.
- Schaufelberger, J.E.; Holm, L. *Management of Construction Projects: A Constructor's Perspective*; Routledge: London, UK, 2017.
- Bhagat, G.; Jha, K.N. Stage-wise evaluation of integrity risks in public works procurement in India. *Int. J. Constr. Manag.* **2023**, *23*, 2818–2829. [\[CrossRef\]](#)
- Cheok, G.S.; Stone, W.C.; Lipman, R.R.; Witzgall, C. Ladars for construction assessment and update. *Autom. Constr.* **2000**, *9*, 463–477. [\[CrossRef\]](#)
- Rebolj, D.; Pučko, Z.; Babič, N.Č.; Bizjak, M.; Mongus, D. Point cloud quality requirements for Scan-vs-BIM based automated construction progress monitoring. *Autom. Constr.* **2017**, *84*, 323–334. [\[CrossRef\]](#)
- Golparvar-Fard, M.; Peña-Mora, F.; Savarese, S. D4AR—a 4-dimensional augmented reality model for automating construction progress monitoring data collection, processing and communication. *J. Inf. Technol. Constr.* **2009**, *14*, 129–153.
- Yalcinkaya, M.; Singh, V. Patterns and trends in building information modeling (BIM) research: A latent semantic analysis. *Autom. Constr.* **2015**, *59*, 68–80. [\[CrossRef\]](#)
- Zhang, C.; Arditi, D. Automated progress control using laser scanning technology. *Autom. Constr.* **2013**, *36*, 108–116. [\[CrossRef\]](#)
- Bosché, F.; Guillemet, A.; Turkan, Y.; Haas, C.T.; Haas, R. Tracking the built status of MEP works: Assessing the value of a Scan-vs-BIM system. *J. Comput. Civ. Eng.* **2014**, *28*, 05014004. [\[CrossRef\]](#)
- Bosché, F.; Ahmed, M.; Turkan, Y.; Haas, C.T.; Haas, R. The value of integrating Scan-to-BIM and Scan-vs-BIM techniques for construction monitoring using laser scanning and BIM: The case of cylindrical MEP components. *Autom. Constr.* **2015**, *49*, 201–213. [\[CrossRef\]](#)
- Wallbaum, M.; Soman, R.K. Towards real-time Scan-versus-BIM: Methods applications and challenges. In Proceedings of the 2021 European Conference on Computing in Construction, Online, 26–28 July 2021.
- Wang, Q.; Guo, J.; Kim, M.-K. An application oriented scan-to-BIM framework. *Remote Sens.* **2019**, *11*, 365. [\[CrossRef\]](#)
- Zeng, R.; Shi, J.J.; Wang, C.; Lu, T. Integrating as-built BIM model from point cloud data in construction projects. *Eng. Constr. Archit. Manag.* **2024**, *31*, 3557–3574. [\[CrossRef\]](#)
- Khallaf, R.; Khallaf, M. Classification and analysis of deep learning applications in construction: A systematic literature review. *Autom. Constr.* **2021**, *129*, 103760. [\[CrossRef\]](#)
- Akinosho, T.D.; Oyedele, L.O.; Bilal, M.; Ajayi, A.O.; Delgado, M.D.; Akinade, O.O.; Ahmed, A.A. Deep learning in the construction industry: A review of present status and future innovations. *J. Build. Eng.* **2020**, *32*, 101827. [\[CrossRef\]](#)
- Baltsavias, E.P. A comparison between photogrammetry and laser scanning. *ISPRS J. Photogramm. Remote Sens.* **1999**, *54*, 83–94. [\[CrossRef\]](#)
- El-Omari, S.; Moselhi, O. Integrating 3D laser scanning and photogrammetry for progress measurement of construction work. *Autom. Constr.* **2008**, *18*, 1–9. [\[CrossRef\]](#)
- US General Services Administration. *GSA Building Information Modeling Guide Series: 03*; US General Services Administration: Washington, DC, USA, 2009.
- Bosché, F.; Haas, C.T. Automated retrieval of 3D CAD model objects in construction range images. *Autom. Constr.* **2008**, *17*, 499–512. [\[CrossRef\]](#)
- Nguyen, C.H.P.; Choi, Y. Comparison of point cloud data and 3D CAD data for on-site dimensional inspection of industrial plant piping systems. *Autom. Constr.* **2018**, *91*, 44–52. [\[CrossRef\]](#)
- Kim, S.; Kim, S.; Lee, D.-E. 3D point cloud and BIM-based reconstruction for evaluation of project by as-planned and as-built. *Remote Sens.* **2020**, *12*, 1457. [\[CrossRef\]](#)
- Li, D.; Liu, J.; Feng, L.; Zhou, Y.; Qi, H.; Chen, Y.F. Automatic modeling of prefabricated components with laser-scanned data for virtual trial assembly. *Comput.-Aided Civ. Infrastruct. Eng.* **2021**, *36*, 453–471. [\[CrossRef\]](#)
- Maalek, R. Field Information Modeling (FIM)TM: Best Practices Using Point Clouds. *Remote Sens.* **2021**, *13*, 967. [\[CrossRef\]](#)
- LeCun, Y.; Bengio, Y.; Hinton, G. Deep learning. *Nature* **2015**, *521*, 436–444. [\[CrossRef\]](#)

25. Werbos, P. Beyond Regression: New Tools for Prediction and Analysis in the Behavioral Sciences. Ph.D. Thesis, Harvard University, Cambridge, MA, USA, 1974.
26. Goodfellow, I.; Bengio, Y.; Courville, A. *Deep Learning*; MIT Press: Cambridge, MA, USA, 2016.
27. Vargas, R.; Mosavi, A.; Ruiz, R. Deep Learning: A Review. *Preprints* **2018**, 2018100218. [[CrossRef](#)]
28. Koo, B.; Jung, R.; Yu, Y. Automatic classification of wall and door BIM element subtypes using 3D geometric deep neural networks. *Adv. Eng. Inform.* **2021**, *47*, 101200. [[CrossRef](#)]
29. Zhou, Y.; Peng, S.Y.; Yan, L.F.; He, B. A novel DNN tracking algorithm for structural system identification. *Smart Struct. Syst. Int. J.* **2021**, *27*, 803–818.
30. Hu, F.; Zhao, J.; Huang, Y.; Li, H. Structure-aware 3D reconstruction for cable-stayed bridges: A learning-based method. *Comput.-Aided Civ. Infrastruct. Eng.* **2021**, *36*, 89–108. [[CrossRef](#)]
31. Wang, B.; Wang, Q.; Cheng, J.C.; Song, C.; Yin, C. Vision-assisted BIM reconstruction from 3D LiDAR point clouds for MEP scenes. *Autom. Constr.* **2022**, *133*, 103997. [[CrossRef](#)]
32. Perez-Perez, Y.; Golparvar-Fard, M.; El-Rayes, K. Scan2BIM-NET: Deep learning method for segmentation of point clouds for scan-to-BIM. *J. Constr. Eng. Manag.* **2021**, *147*, 04021107. [[CrossRef](#)]
33. Smith, A.; Sarlo, R. Automated extraction of structural beam lines and connections from point clouds of steel buildings. *Comput.-Aided Civ. Infrastruct. Eng.* **2022**, *37*, 110–125. [[CrossRef](#)]
34. Qiu, Q.; Lau, D. Real-time detection of cracks in tiled sidewalks using YOLO-based method applied to unmanned aerial vehicle (UAV) images. *Autom. Constr.* **2023**, *147*, 104745. [[CrossRef](#)]
35. Luan, L.; Zheng, J.; Wang, M.L.; Yang, Y.; Rizzo, P.; Sun, H. Extracting full-field subpixel structural displacements from videos via deep learning. *J. Sound Vib.* **2021**, *505*, 116142. [[CrossRef](#)]
36. American Institute of Steel Construction. *Code of Standard Practice for Steel Buildings and Bridges*; American Institute of Steel Construction: Chicago, IL, USA, 2016.
37. Wang, C.C. Approximate boolean operations on large polyhedral solids with partial mesh reconstruction. *IEEE Trans. Vis. Comput. Graph.* **2010**, *17*, 836–849. [[CrossRef](#)]
38. Gelfand, N.; Ikemoto, L.; Rusinkiewicz, S.; Levoy, M. Geometrically stable sampling for the ICP algorithm. In Proceedings of the Fourth International Conference on 3-D Digital Imaging and Modeling 2003 (3DIM 2003 Proceedings), Banff, AB, Canada, 6–10 October 2003.
39. Quan, S.; Yang, J. Compatibility-guided sampling consensus for 3-D point cloud registration. *IEEE Trans. Geosci. Remote Sens.* **2020**, *58*, 7380–7392. [[CrossRef](#)]
40. Qi, C.R.; Yi, L.; Su, H.; Guibas, L.J. Pointnet++: Deep hierarchical feature learning on point sets in a metric space. In Proceedings of the 31st International Conference on Neural Information Processing Systems (NIPS'17), Long Beach, CA, USA, 4–9 December 2017.
41. Eldar, Y.; Lindenbaum, M.; Porat, M.; Zeevi, Y. The farthest point strategy for progressive image sampling. *IEEE Trans. Image Process.* **1997**, *6*, 1305–1315. [[CrossRef](#)] [[PubMed](#)]
42. Lang, I.; Manor, A.; Avidan, S. Samplenet: Differentiable point cloud sampling. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, Seattle, WA, USA, 13–19 June 2020.
43. Wang, D.; Shen, H.; Truong, Y. Efficient dimension reduction for high-dimensional matrix-valued data. *Neurocomputing* **2016**, *190*, 25–34. [[CrossRef](#)]
44. Ruuth, S.J.; Merriman, B. A simple embedding method for solving partial differential equations on surfaces. *J. Comput. Phys.* **2008**, *227*, 1943–1961. [[CrossRef](#)]
45. Kim, T.H.; Woo, W.; Chung, K. 3D Scanning Data Coordination and As-Built-BIM Construction Process Optimization-Utilization of Point Cloud Data for Structural Analysis. *Archit. Res.* **2019**, *21*, 111–116.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.