

**AUTOMATIC GENERATION OF STRUCTURAL GEOMETRIC
DIGITAL TWINS OF CONCRETE BRIDGES FROM
POINT CLOUDS**

BY

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A Thesis Presented to the
COLLEGE OF GRADUATE AND INTERDISCIPLINARY STUDIES
KING FAHD UNIVERSITY OF PETROLEUM & MINERALS
DHAHRAN, SAUDI ARABIA

In Partial Fulfillment of the
Requirements for the Degree of

MASTER OF SCIENCE

In

CONSTRUCTION ENGINEERING AND MANAGEMENT

DECEMBER 2024

KING FAHD UNIVERSITY OF PETROLEUM & MINERALS

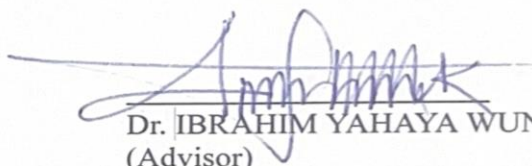
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Dedication

This thesis is dedicated to the cherished memory of my late father, whose wisdom and love continue to guide me, and my late friend, whose kindness and support are forever remembered.

To my beloved mother, for her unwavering belief in me and endless sacrifices; to my wife, whose patience and encouragement have been my greatest strength; and to my family and friends, for their steadfast support and inspiration throughout this journey. This work stands as a testament to the impact of your love and guidance on my life

ACKNOWLEDGMENTS

First, I give all praises to Almighty Allah (God) for granting me the strength, wisdom, and perseverance throughout this journey. Without His guidance and blessings, this achievement would not have been possible.

I am profoundly thankful to my advisor, Dr. Ibrahim Yahaya Wuni, for your invaluable guidance, encouragement, and support during my research. Your expertise and insights have been instrumental in shaping this work. I also extend my sincere appreciation to the members of my committee for their constructive feedback and unwavering commitment to throughout this research journey.

To my beloved wife, I am forever grateful for your patience, encouragement, and unwavering belief in me. Your love and support have been my anchor throughout this journey. To my family, thank you for your endless sacrifices, prayers, and inspiration that have carried me through challenging times.

Lastly, I am deeply thankful to my friends, especially Faisal Lawan Muhammad whose support, camaraderie, and encouragement have made this journey memorable and fulfilling. This work would not have been possible without each of you. Thank you all for being a part of this milestone in my life.

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LIST OF ABBREVIATIONS

DT	Digital Twin
gDT	Geometric Digital Twin
BIM	Building Information Modeling
SHM	Structural Health Monitoring
RC	Reinforced Concrete
CAD	Computer-Aided Design
CNN	Convolutional Neural Networks
ResNet	Residual Neural Networks
RNN	Recurrent Neural Networks
IoT	Internet of Things
RFID	Radio-Frequency Identification
PLY	Polygon File Format
RCP	Representative Concentration Pathways
DS	Design Science
VGG	Visual Geometry Group (referring to a type of deep neural network)
mAP	Mean Average Precision

ABSTRACT

Full Name : [Saidu Abdulai Koroma]
Thesis Title : [An Automatic Generation of Structural Geometric Digital Twin of Concrete Footbridge Using Point Cloud]
Major Field : [Construction Engineering and Management]
Date of Degree : [December 2024]

The growing need for accurate virtual replicas of physical structures has made geometric Digital Twins (gDTs) indispensable tools for enhancing construction planning, structural analysis, and asset management. This research study explores two advanced techniques, including photogrammetry and machine learning and LiDAR scanning, which are integrated into a Building Information Modeling (BIM) workflow to develop a gDT model of a concrete footbridge. The project scope includes assessment of the strategies performance in generating accurate 3D geometric models. Strategy 1 used photogrammetry for image classification and object detection, with a test accuracy of 92.8%, though it suffered from issues such as overfitting and unstable validation metrics. On the other hand, Strategy 2, using the Multi-Scan LiDAR technique, resulted in very accurate 3D models, lowest errors, and solid integration with BIM, which is therefore the most reliable. The results highlight the limitations of photogrammetry-based method while, at the same time, showing the potential of LiDAR scanning for the automatic and precise generation of gDT. It concludes that LiDAR-based solutions offer improved accuracy and scalability and thus provide a starting point for practical applications in complex infrastructure works and support further development in digital twin technology.

ملخص الرسالة

الاسم الكامل: سيدو عبدولاي. كوروما

عنوان الرسالة: إنشاء نموذج رقمي هندسي تلقائي لجسر المشاة الخرساني باستخدام النقاط السحابية

التخصص: الهندسة وإدارة البناء

تاريخ الدرجة العلمية: ديسمبر 2024

الحاجة المتزايدة للنسخ الافتراضية الدقيقة للهياكل الفيزيائية جعلت التوائم الرقمية الهندسية (gDTs) أدوات لا غنى عنها لتحسين التخطيط الإنشائي، وتحليل البنية التحتية، وإدارة الأصول. تستكشف هذه الدراسة البحثية تقنيتين متقدمتين، بما في ذلك التصوير الضوئي وتعلم الآلة ومسح الليدار، والتي تم دمجها في عملية نمذجة المعلومات البنائية (BIM) لتطوير نموذج gDT لجسر مشاة من الخرسانة. يتضمن نطاق المشروع تقييم أداء الاستراتيجيات في توليد نماذج هندسية ثلاثية الأبعاد دقيقة. استخدمت الاستراتيجية الأولى التصوير الضوئي لتصنيف الصور وكشف الكائنات، بدقة اختبار 92.8%، على الرغم من معاناتها من مشاكل مثل الإفراط في التعلم وعدم استقرار معايير التحقق. من ناحية أخرى، أسفرت الاستراتيجية الثانية، باستخدام تقنية ليدار متعددة المسحات، عن نماذج ثلاثية الأبعاد دقيقة جدًا، وأخطاء قليلة، وتكامل قوي مع BIM، وبالتالي هي الأكثر موثوقية. تسلط النتائج الضوء على قيود الطريقة المعتمدة على التصوير الضوئي، بينما تُظهر في الوقت نفسه إمكانيات مسح الليدار للتوليد التلقائي والدقيق لـ gDT. وتخلص الدراسة إلى أن الحلول المستندة إلى ليدار تقدم دقة وقابلية توسعة محسنة وبالتالي توفر نقطة انطلاق للتطبيقات العملية في أعمال البنية التحتية المعقدة وتدعم المزيد من التطور في تكنولوجيا التوائم الرقمية.

Chapter 1: Introduction

1.1 Background

The structural integrity of built assets (e.g., buildings, roads, bridges) have significant impact on the well-being and security of people (Ma *et al.*, 2018). However, the construction industry (CI) faces grave challenges in real-time tracking of these physical assets, especially structural health monitoring of old infrastructure. The process of monitoring structural health involves conducting on-site observations, evaluating the state, managing data, making decisions, planning, and implementing necessary repairs (Agdas *et al.*, 2015).

The current approach to structural health monitoring uses a traditional approach involving visual examination and manual measurement of structural components, which can be laborious and susceptible to inaccuracies (Kim, Wang and Li, 2019). The efficacy of the traditional protocols is contingent upon the proficiency and self-regulation of the individuals responsible for their execution (Tavakolan *et al.*, 2022). Thus, there is an increasing need to automate the structural health monitoring processes. Kim, Wang and Li (2019) highlighted the significance of an autonomous system for proactive and accurate evaluation of structures and monitoring their health cannot be overstated, particularly in light of the considerable number of aging buildings and infrastructure projects.

The rapid wave of digitalization and automation of processes in the construction industry in recent times are providing excellent opportunities and technologies for real-time tracking of old physical asset (Alaloul *et al.*, 2020). One such viable digital solution is the concept of a digital twin. Digital Twin (DT) refers to the process of generating a digital model that replicates the characteristics of a physical asset and adjusts accordingly to variations in its surroundings in order to achieve the

best possible functionality (Osadcha, Jurelionis and Fokaides, 2023). This involves the integration of a virtual entity with a physical object during its entire lifespan (Hosamo and Hosamo, 2022).

DT facilitates the monitoring and control of physical entities via a digital representation, encompassing the ability to observe in real-time and employ simulation-based predictions to anticipate and strategize for future actions (Osadcha *et al.*, 2023). The National Institute of Technology (2021) stated that, for existing infrastructures, the demand for inspection, evaluation, and management has experienced significant growth in recent years, particularly in the context of transport infrastructure. In particular, bridges require rehabilitation and maintenance at certain intervals during their lifespan. According to the National Institute of Technology (2021), approximately 40% of bridges in the United States have surpassed the age of 50, with 13.6% of them exhibiting functional deficiencies. Hosamo and Hosamo (2022) indicated that similar patterns can also be observed globally, encompassing countries such as Australia, the United Kingdom, and various European states, including Norway.

The DT has many applications, including the real-time monitoring of physical structures such as bridges. For example, Fu *et al.* (2022) evaluated the ability to digitally recreate everything in the real world and provide engineers input from the virtual environment. As a result, businesses may now more quickly identify and address physical issues, create and construct better assets, and reap value and benefits than was previously possible (Attaran and Celik, 2023). However, one of the important assets which has received limited application of digital twinning is bridges. Ren, Ding and Li (2019) stated that bridges are crucial infrastructural assets that play a significant role in facilitating socioeconomic activities in a geographical area. One strategy to improve the essential services necessary for society's living circumstances is by digitally enhancing the monitoring of old existing infrastructure assets to ensure their structural health. With the emerging transition of

traditional construction to digital construction, building information modelling (BIM) enables the integration of detailed semantic information into a geometric DT (gDT) modeling approach, which may be utilized throughout the whole lifecycle of a bridge asset to support a number of applications, such as building structural health monitoring and maintenance (Panah and Kioumars, 2021). Therefore, this thesis seeks to investigate how to automatically generate structural gDTs of infrastructure assets such as concrete bridges for a more accurate real-time tracking and structural health monitoring.

1.2 Problem Statement

A representative digital model to provide real-time tracking and structural health monitoring of bridges must be able to capture the various factors that influence the structural efficiency and overall condition of bridges (Hosamo and Hosamo, 2022). Environmental influences, the age of the structure in terms of its lifespan, and maintenance techniques are among the factors that contribute to the overall condition and longevity of a structure (Structural Engineering International, 1996). The maintenance plans are mostly attributed to the established monitoring and inspection systems (Hosamo and Hosamo, 2022). DT offers a more advanced and robust system to monitor the structural health of bridges. The initial and fundamental stage in developing a reliable and precise DT for the purpose of structural health monitoring involves the creation of a virtual geometric representation of the existing asset. This representation is generated within a parametric and updatable platform, commonly referred to as a geometric DT (gDT) (Hosamo and Hosamo, 2022).

Predominantly, efforts to manage these bridges have leveraged building information modelling (BIM). BIM integrates comprehensive semantic data into a gDT modeling framework, which spans the entire lifespan of a structure (Panah and Kioumars, 2021). This approach aids in a multitude

of applications, such as monitoring and maintaining the structural integrity of bridges. To employ BIM as the digital representation for monitoring the structural integrity within the context of the gDT, it is imperative that the model exhibits a high degree of accuracy and encompasses up-to-date information pertaining to the various components of the bridges' structural elements (Lu, Chen, *et al.*, 2020; Volk *et al.*, 2014).

However, the majority of bridges include outdated information regarding their structural components (Volk *et al.*, 2014). This information is typically maintained in the form of 2D drawings, either in physical copies or in electronic formats such as computer-aided design (CAD) (Lu, Chen, *et al.*, 2020; Mirzaei *et al.*, 2020). The existing method for generating as-is BIM for gDT's virtual model involves the manual extraction of data from buildings. The collected data is subsequently utilized to generate or revise BIM in software applications such as Autodesk Revit, which are used for modeling and simulating purposes (Jiang *et al.*, 2021; Wang *et al.*, 2021).

This approach is labor-intensive, time-consuming, and limited in accuracy, primarily due to challenges in accessing structural elements in most physical assets. Therefore, real time automation could save a lot of resources in the operation and maintenance phase of the bridge asset. The automatic generation of gDT of physical asset using point clouds is not entirely new. For example, Lu and Brilakis (2019) used point clouds for automation which generated the DT for an existing reinforced concrete bridge using a slicing-based object matching approach that makes use of four distinct kinds of labeled point clusters. Lu *et al.*(2020) developed a semi-automatic approach to establish a systematic, accurate and convenient digital twinning system based on images and CAD drawings. To automatically retrieve the surface point cloud of the box and slab-beam bridge structural components, Truong-Hong and Lindenbergh (2022) introduced novel methods of conventional neural networks (CNN), residual neural networks (ResNet), and recurrent

neural networks (RNN) are examples of traditional image processing algorithm techniques that Arashpour, Ngo and Li (2021) reviewed. It is shown that these techniques typically require protracted transfer learning to obtain project-specific data from infrastructure assets in order to obtain hints of site scenes with advanced reasoning and inference capabilities. Of these automated techniques, point clouds provides a cost-effective, accurate and efficient method of generating a structural health monitoring system for bridges (Mirzaei, Arashpour, Asadi, Masoumi and Li, 2022).

While the existing applications of point clouds for automatic generation of structural gDT of concrete bridges in the literature have merits, there are contextual challenges in generating gDT of concrete bridges. Such contextual challenges warrant the development of gDT in various contexts to expand the knowledge of how effective point clouds can be leveraged to automatically generate accurate gDT of infrastructure assets such as bridges. In particular, Saudi Arabia is extremely underrepresented in the literature. Therefore, this thesis aims to develop an automatic generation of structural gDT of concrete bridges in Saudi Arabia using point clouds.

1.3 Research Aim and Objectives

The purpose of the research is to develop an automatic generation of structural gDT of existing concrete bridges in Saudi Arabia from point clouds. The thesis derived the following specific objectives:

- (i) To create conditional criteria for determining structural member function and section family type using geometric information.
- (ii) To develop and evaluate semantic database from raw point clouds to produce a digital model and automatically generate a gDT of concrete bridges.

1.4 Research Questions

Given the aim of automatically generating structural gDT of existing concrete from point clouds, the following research questions warrant critical considerations:

- (i) What geometric and non-geometric semantic information can be deduced from point clouds?
- (ii) How can point cloud-based semantic information be efficiently transformed into BIM models in the form of geometric virtual models?
- (iii) What is the accuracy and efficiency of the automated point cloud processing approach in generating the virtual model of structural parts of concrete bridges?

1.5 Contributions of the Study

While there is a surging scientific research interest in the structural monitoring of physical asset in developed countries, little is known about the automatic generation of structural element of DT for RC bridge using point cloud in Saudi Arabia. Therefore, there are three (3) contributions of this study. First, it will provide a tool for management to be able to monitor the structural health of bridges in real-time and to implement timely corrective actions in case they find problems. Second, the thesis will contribute to the body of knowledge of how best to automatically generate structural gDT of infrastructural assets using point cloud. The study would demonstrate this in the context of Saudi Arabia. Finally, the outcome of the study is expected to improve the implementation of digital twin in the construction sector.

1.6. Scope and Limitations of the Thesis

This study is conducted in the context of Saudi Arabia. The use of point clouds for the development of geometric digital twins was, however, a limitation. Because there are many varieties of both bridges and DT used in the construction industry, this was both geometrically focused and narrowly limited to concrete bridges.

There are some noteworthy limitations of the study. The first restriction relates to the number of sensors and infrastructure assets that would be chosen for the investigation. In the absence of resources, the study could not link the structural gDT model and physical asset since cost is a significant factor in DT development. Second, this study could not capture the structural properties, since it does not use linkages like sensors. Future research will address these. Thirdly, the reliance of the study on commercial software for the building of the DT system may limit the system's capacity for replication and customization.

Chapter 2: Literature Review

2.1 Introduction

This chapter offers a summary of relevant research as well as conceptual framework proposals. A brief explanation of the enabling technologies for creating structural geometric digital twins in the construction industry is discussed after the operational description of key concepts (such as: digital twin, geometric digital twin, and point clouds) to ensure that readers have a common understanding of how they are used throughout the thesis. Eventually, the chapter examines and discusses the structural geometric digital twin generation from point cloud. The chapter further concludes with an appraisal of the literature which summarizes the relevant literatures that provide the basis for the thesis research.

2.2 Definitions of Key Concepts

2.2.1 Digital twin

It is evident that the scientific literature defines DT in a variety of ways. Nevertheless, the definitions are developed using the term's actual usage, without taking into account any particular industry. Opoku *et al.* (2021) discussed the uncertainties in the definitions of DT caused by its absence of association with particular sectors in the worldwide industry. However, the idea of DT as a technology should consist of three different components. The following components comprise a system: a physical object, a digital subject, and the information connecting them (Tao *et al.*, 2019; Wagner *et al.*, 2019). Fotland, Haskins and Rølvåg (2020) defined DT as a virtual model of a physical asset that collects real-time data from the object and delivers information that cannot be directly accessed from the hardware itself. Luo *et al.* (2018) defined DT as a comprehensive and highly accurate digital model that combines many domains, such as mechanical, electrical, hydraulic, and control. Manuse and Snizek (2016) provided a definition of DT as a comprehensive

representation of a real or projected objects that is practically generated utilizing a collection of digital data structures ranging From the most microscopic scale of an atom to the greater geometric scale. Gabor *et al.* (2016) described DT as the process of simulating the physical entity itself in order to forecast the future state of the system. In addition, Rosen *et al.* (2015) characterized DT as an accurate representation of the present condition of the process and its interactions with the surrounding environment in the real world. The definitions from later publications clearly demonstrate that, regardless of the industry in which digital transformation is applied, there must be a physical entity, digital object, and information that links them together to enable a two-way dynamic relationship between the virtual model and the real object (Tao *et al.*, 2019). Additionally, the physical component needs to be present for the virtual entity to be recognized as a DT. This differs greatly from digital modeling, which involves the integration of geometric models with engineering tools to facilitate decision making through simulation (Opoku *et al.*, 2023).

2.2.2 Geometric digital twin

The creation of digital documentation, which represents the current status of the construction environment, depends on existing (as-is) BIM data. However, this process can be costly and time-consuming when done manually (Ochmann *et al.*, 2016). Nonetheless, to establish an effective and precise Digital Twin (DT) for structural health monitoring, the initial and fundamental task is to construct a virtual geometric model of the existing asset using a parametric and updatable platform. This model is commonly referred to as a geometric Digital Twin (gDT) (Lu, Chen, *et al.*, 2020; Lu and Brilakis, 2019b). Panah and Kioumars (2021) has been demonstrated BIM to enable the integration of semantically dense data for a gDT modeling method across the whole lifespan of a building, facilitating diverse applications such as maintenance and monitoring of a building's structural health. gDT's virtual model for monitoring structure health will be based on BIM, it is

imperative that the model is precise and includes up-to-date data regarding the building's structural components. Nevertheless, most infrastructure assets possess outdated data regarding their structural components, which is predominantly kept as 2D computer-aided design (CAD) drawings in both digital and physical formats (Lu, Chen, *et al.*, 2020; Volk *et al.*, 2014). The current method for generating an as-is BIM for gDT's virtual model involves manually extracting data from buildings and creating or updating the BIM using modeling and simulation software like Autodesk Revit. This method is time-consuming, labor-intensive, and prone to errors due to difficulties in accessing structural elements in most buildings (Mirzaei *et al.*, 2020; Wang *et al.*, 2021). Saudi Arabia thus needs accurate and effective methods for creating as-is BIM as gDT's virtual model for concrete bridge structural components.

2.2.3 Point cloud

Point clouds include 3D geometric data in the form of geometric or geodetic coordinates (Hamraz *et al.*, 2017; Poullis, 2013). There is a wide range of sources, such as laser scans, photos, and videos, that can yield 3D point cloud data. The techniques used to capture reality and generate 3D point cloud data have advanced and are now readily available, allowing for more accurate and cost-effective collection of point cloud data (Hosamo and Hosamo, 2022). With the advancement of point cloud data collection devices, Hosamo and Hosamo (2022) emphasized that there is an increasing need to gather 3D point cloud data for existing concrete bridges and other infrastructure assets.

The current state of 3D point cloud data for construction applications has been succinctly summarized in several article reviews. These papers specifically address the processing of laser scan or image data for the purpose of generating as-built/as-is BIM models (Hosamo and Hosamo,

2022; Tang *et al.*, 2010). One of these studies, authored by Tang *et al.* (2010) investigated the automatic reconstruction of as-built BIM models using laser-scanned point cloud data.

2.3 Enabling Technologies for Generating Structural Geometric Digital Twin

In recent times, there has been a notable increase in the adoption of advanced technologies in the construction industry. These technologies are used to monitor Internet of Things (IoT) data and manage automated systems. Digital technologies, such as Digital Twin, provide a thorough depiction of bridges and their assets by combining the physical and digital domains (Hosamo and Hosamo, 2022).

Recently, the accuracy and efficiency of creating virtual models of existing facilities in BIM format have been greatly enhanced due to the rapid advancements in surveying and non-contact sensing technology (Jiang *et al.*, 2021). Prominent instances of such devices, namely gDT connection devices, that are capable of obtaining precise data include RFID (radio-frequency identification), 2D and 3D cameras, and laser scanner (Anil *et al.*, 2013; Hua *et al.*, 2022; Iglesias *et al.*, 2018; Kim, Wang, Yoon, *et al.*, 2019; Kwon *et al.*, 2014; Wang, 2008). Laser scanners have demonstrated exceptional precision in capturing data of physical objects in the form of point clouds, specifically known as gDT data (Wang *et al.*, 2020). However, laser scanners are unable to acquire semantic information, such as object class, which is necessary for producing BIMs. To gather and deduce semantic information, gDTs' virtual models and data processing methods are necessary.

2.4 Structural Geometric Digital Twin Generation from Point Cloud

The generation of structural elements for reinforced concrete (RC) bridges using gDT point clouds is typically characterized by a wide range of variations, often accompanied by the presence of outliers. The absence of training data, resulting from the high cost of reality capture, has made it even more difficult to deploy the end-to-end deep learning model in this scenario. Consequently,

only a limited number of studies have successfully conducted precise and dependable detection of reinforced concrete (RC) bridge components (Kim *et al.*, 2020; Yan and Hajjar, 2021). However, Xue, Lu and Chen (2018) showed the use of 2D images to generate semantically complete as-built BIMs. They divided semantic information into two categories: (1) geometric information, which includes member position, section shape, and dimensional tolerance; and (2) non-geometric information, which includes member function (e.g., bearings, beams, girders, bridge deck) and kind (e.g., section family type). Point clouds provide direct geometric data for creating BIMs in the form of gDT's virtual models. Non-geometric information, on the other hand, must be inferred and evaluated based on the available geometric data.

Positional information is included in the initial geometric data required for generating an as-is BIM of structural elements, such as gDT's virtual model. This includes the geometric characteristics of the structural members, such as piers being vertical components, as well as the spatial connections between these members, such as bracings located beneath beams (McCullough, 1992). According to McCullough (1992), segmentation algorithms have been employed to gather locations that possess comparable geometric characteristics of structural components. Conversely, employing different factors like spatial position, points normal vector, and point density within the point clouds, clustering algorithms have been widely used to discover similar patterns inside a point cloud, also known as clusters. (Aldoma *et al.*, 2012; Aljumaily *et al.*, 2017; Czerniawski *et al.*, 2018; Miller *et al.*, 2018; Romero-Jarén and Arranz, 2021). While the majority of prior research has focused on using positional data to identify structural elements, this method is error-prone, sensitive to noise in point cloud datasets, and only classifies point clusters as likely structural elements (McCullough, 1992; Pătrăucean *et al.*, 2015).

Several researches extracted section shape data from point clouds using machine learning approaches, notably Convolutional Neural Networks (CNNs). This information is crucial for generating an accurate virtual model of structural elements for gDT generation (Mirzaei, Arashpour, Asadi, Masoumi and Li, 2022). Machine learning techniques have been utilized in several applications, including the identification of construction waste (Arashpour *et al.*, 2023; Lu *et al.*, 2022; Mirzaei, Arashpour, Asadi, Masoumi, Bai, *et al.*, 2022). However, Convolutional operations of CNN methods cannot be established due to irregularity, disorder, and lack of structure in point cloud data (Bello *et al.*, 2020). Bello *et al.* and Coudron *et al.*, (2020) highlighted that previous studies have utilized deep learning techniques. The first set of techniques involves transforming the point cloud into a structured grid, a process that requires a significant amount of memory and results in a substantial loss of information. The second category of techniques, such as PointNet, employed deep learning directly on point clouds.

PointNet functions as a mechanism for learning local features in order to produce a comprehensive point signature by combining individual point data. PointNet demonstrated exceptional performance on multiple benchmark datasets, surpassing previous records (Mirzaei, Arashpour, Asadi, Masoumi and Li, 2022). Despite admitting the fact from relevant literatures for non-geometric data derived from point clouds, it is equally critical for building the gDT's virtual representation of structural components. The research efforts obtained a high level of accuracy in detection by utilizing well-developed image processing techniques and procedures. However, the effectiveness of these methods is significantly influenced by the presence of several unrelated objects in point clouds. Furthermore, the act of projecting two-dimensional images into a three-dimensional space has a significant impact on the overall performance of these methods (Mirzaei, Arashpour, Asadi, Masoumi and Li, 2022).

2.5 Appraisal of the Literature

Evidently, the scientific literature indicates the presence of the challenges in automatically creating a virtual model of gDT from as-is point clouds for the aim of constructing structural health monitoring. These can be classified into four distinct categories, as indicated by research above: (1) The existing method of manually eliminating noise and occlusions from point cloud data, as well as manually classifying and detecting structural components, is wasteful and unworkable for constructing a virtual model of a gDT. (2) Previous research relied mainly on correct local characteristics in point clouds, but this may not be reliable for real-world point cloud datasets with high levels of noise and occlusions. (3) Previous research has limited applications to specific types of RC concrete bridges or structural section forms, which cannot be generalized to other infrastructure assets or structural member section shapes. (4) There is a need to adopt various technologies, resulting in complex data processing steps (Lu, Chen, *et al.*, 2020). The automated development of gDT's virtual model must be efficient, accurate, and generalizable in order to provide the needed services (Mirzaei, Arashpour, Asadi, Masoumi and Li, 2022; Xue *et al.*, 2018). As a result, there is an urgent need in Saudi Arabia for technologies that can automatically extract semantic information from existing point clouds and convert it into BIMs for RC concrete bridge structural elements.

Chapter 3: Research Methodology

3.1 Introduction

This chapter provides a clear relationship between research design, process, and prototype development, illustrating that methodology is more than just procedures. The first section of the chapter describes the study principles and design that create the formal basis for confirming the design science (DS) research technique. The justifications for the suitability of the DS technique for this investigation are then given. The chapter also describes how point clouds are made, paying special emphasis to the non-geometric data, the technology required, relevant semantic geometric data, and the DT development process. The chapter's end includes an overview of the 3D BIM model, procedures, technologies, and the development of DT.

3.2 Research design

A research design outlines the framework for the methodologies and procedures that are utilized to gather and examine data in order to address research questions (Wuni, 2022). It is necessary to choose appropriate research to gather appropriate data and address the underpinning research questions required to develop an automatic generation of structural gDT of existing concrete bridges in Saudi Arabia from point clouds. This thesis adopted design science (DS) as the research design to offer high-level direction for choosing the most suitable methods and strategies to solve the research problem. The guidelines for implementing the DS approach described in table 3.1:

Table 3.1: Guiding principles for Research in design science

Guiding Principles	Description
Design an artefact, procedure, approach, or model	Research in the field of DS must result in a workable concept, model, technique, or instantiation.

Relevance of the problem	The goal of research in DS is to create technologically sound answers to significant and pertinent issues.
Design assessment	A design artefact's quality, effectiveness, and utility must be thoroughly proven through well-conducted evaluation techniques.
Contributions to research	Clear and verifiable contributions to the design artifact, design foundations, models, and/or design procedures are required for effective DS research.
Rigor of research	Research in DS necessitates the use of exacting techniques in the development and assessment of the research output.
Design as a procedure for searching	Utilizing existing tools to accomplish goals and adhere to regulations in the problematic environment is necessary in the quest for an efficient product.
Sharing research findings	Effective communication of DS research is necessary to both technology- and management-oriented audiences.

Source: Adapted from (Kanjanaabootra, 2016, p. 3)

DS is an appropriate approach for this study because the outcome of this thesis would be practical and produce real-world artifact enhancing structural health monitoring of existing infrastructural asset. The DS interface of construction management research should focus on technological norms produced through practical testing and science underpinning (Voordijk, 2011). Voordijk, (2011) further stated that the core tenet of DS research is that knowledge and comprehension of a design challenge and its resolution are obtained through the creation and utilization of an artifact, and they contend, also through the advancement of solutions, procedures, and models. Therefore, this makes it essential since this thesis is geared towards bringing out DT product.

3.3 Research process

The flowchart below in figure 3.1 offers a more thorough breakdown of the steps followed to an generate a structural gDT of existing concrete bridges in Saudi Arabia from point clouds. Following well-established academic research conventions, the study thoroughly reviewed pertinent literatures to gain insight into the recent progress in the field of DT for structural health monitoring (SHM) and define the boundaries of current knowledge. Based on the current

knowledge of literature review, the first phase of the research process was initiated to identify the research gap from the previous literatures required to automatically generate a structural geometric digital twin (gDT) from point cloud data. Subsequently, the research questions were defined and the aim was broken down into specific complimentary objectives.

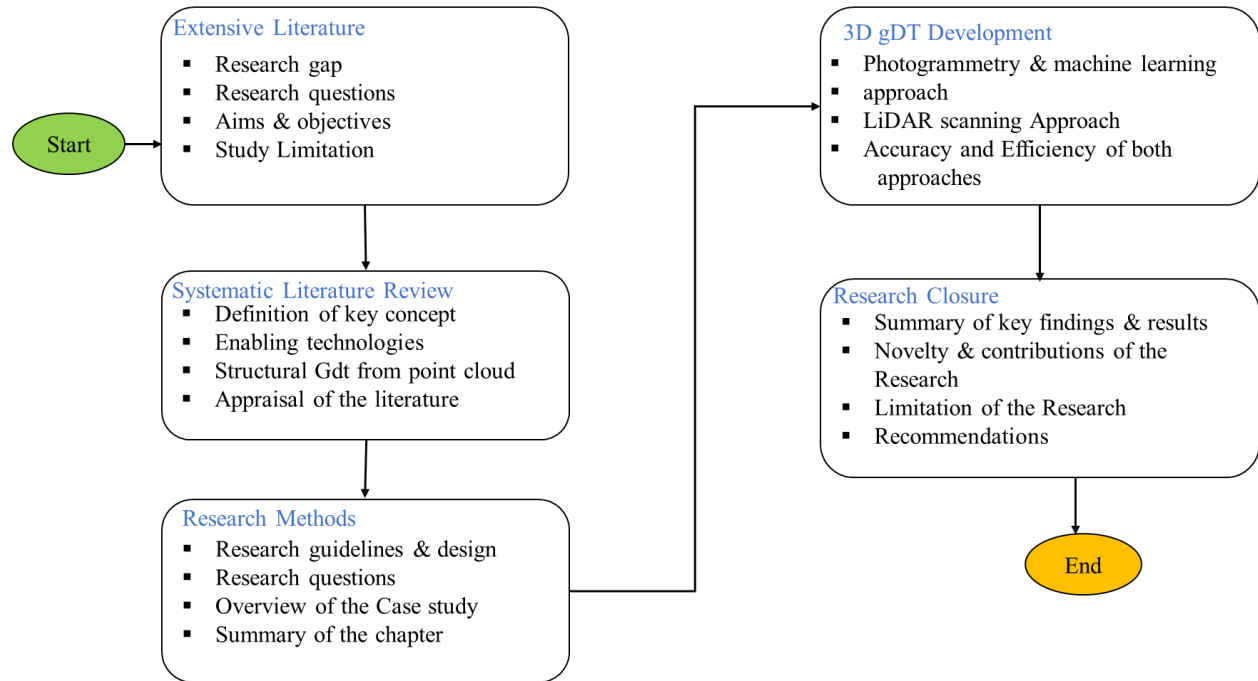


Figure 3.1: A flowchart showing research process of the thesis

Consequently, the second phase of the study, which is actual research, is broken down into two strategies. These strategies include the photogrammetry and Machine Learning approach using various footbridge images and Point cloud LiDAR scan sensor approach. All these strategies have different pathways to achieving the goal of the research findings. The processes involved in achieving these strategies are described in the following subsections.

3.3.1 Strategy 1: Photogrammetry and Machine Learning Approach Using Various Footbridge Images

This section outlines the process for collecting, preprocessing, validating, and delivering structural health monitoring (SHM) data to generate a DT model. With the growing complexity of sensor technologies in creating gDT, photogrammetry is used in such circumstances as a reliable technique. Photogrammetry-based methods are becoming increasingly popular for digital twinning due to their simplicity, portability, and cost-effectiveness in extracting detailed information. For example, Lu *et al.*, (2020) developed a semi-automated method for geometric digital twinning of existing buildings using CAD drawings and images. Similarly, Kim and Son (2011) used 3D photogrammetric data to assess construction progress, and Golparvar-Fard, Peña-Mora and Savarese (2015) introduced an automated approach to track construction progress using daily photographs and BIM. Figure 3.2 depicts the two-step framework for geometric digital twinning using photogrammetry and machine learning (ML), and the various steps are explained below:

Field Data Collection: This step involved searching and capturing raw footbridge photogrammetry data, primarily images, and other related sources. The goal was to collect a comprehensive dataset representing the physical asset with associated structural deficiencies.

- I. **Data Categorization:** The term image categorization refers to the labeling of images into one of a few defined categories of the asset (i.e., footbridge), such as slabs, piers, girders, cracks and spalling. Image categorization is generally not perceived as difficult by humans, as demonstrated by the ineffectiveness of machine learning and other computer programs. This understanding has facilitated the manual treatment and labeling of data into distinct categories. The dataset comprises two thousand three hundred and eighty-five (2,385) images across all categories.

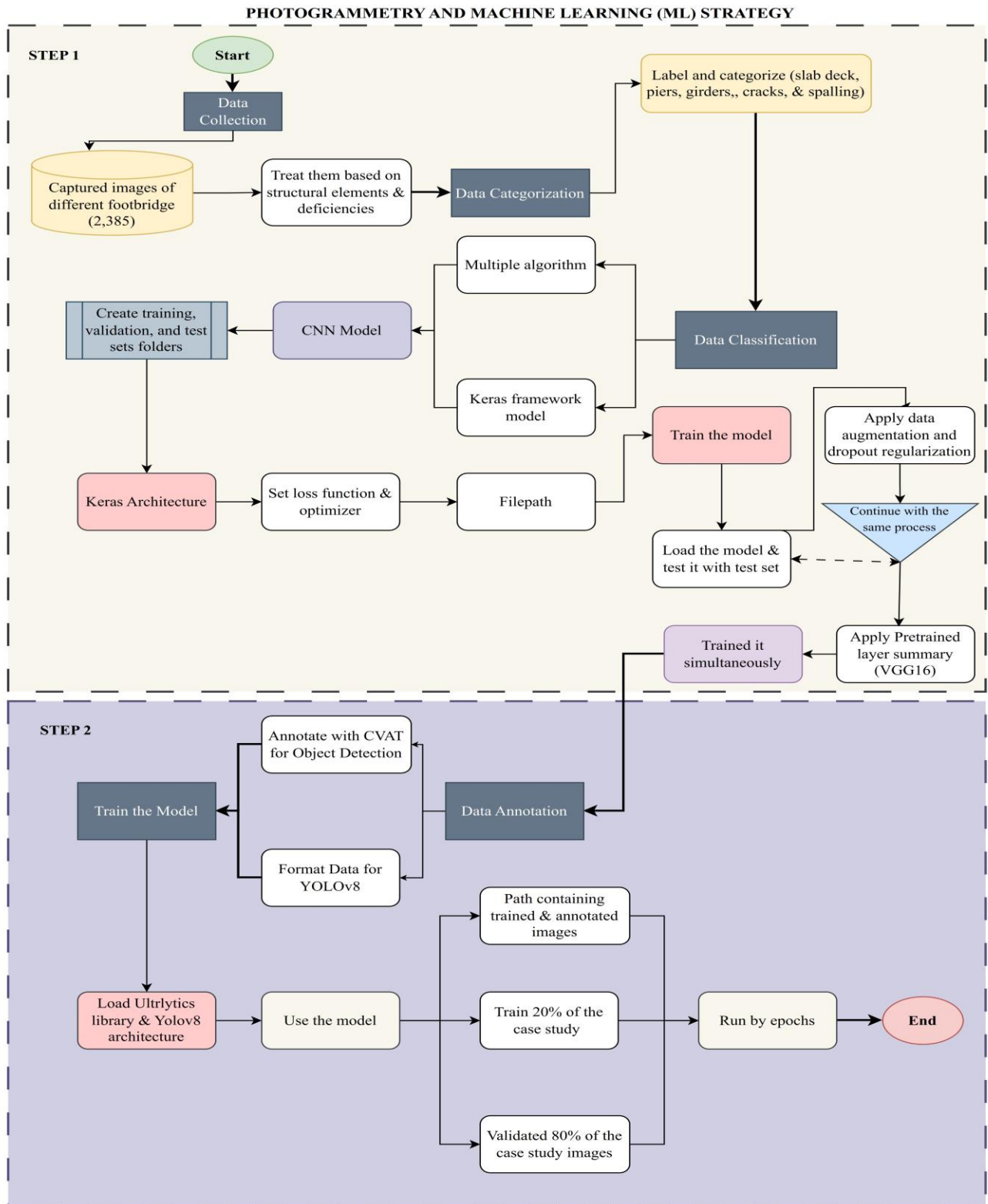


Figure 3.2: Step-by-step process in Strategy 1

II. **Image Classification:** Classifications are systematically divided into groups and categories based on their characteristics. Image classification has emerged to narrow the gap between computer vision and human vision by training computers with data. Image dataset classification is achieved by classifying images into predetermined categories based on the content of the vision. The dataset is then divided into training, validation test and test sets, with 80% of the data used for validation and 20% for training. For example, if 100 images are collected, 80 will be used for validation and 20 for training. The outcome of these tests is tested in the test set.

In deep learning, when training a model, the priority is to increase accuracy and decrease the loss. The accuracy is like having 9 out of 10, which implies good. On the contrary, the distance between the model prediction and the true target is the loss. It is noteworthy to recognize that validation data set is making prediction on an image, if the confirmation check is true means that the loss is less, but if it is false, there is huge loss in number. Hence, the priority is to reduce loss and increase accuracy. This data augmentation process allows for an accuracy test, achieving a model accuracy of approximately 85-95% (Detection *et al.*, 2022).

However, this research used deep learning to classify the image dataset. Since deep learning models have been introduced to permanently decompose information in a homogeneous structure that humans encounter, the Keras architecture framework is used with multiple algorithms, represented as a Convolutional Neural Network (CNN). Sticking this up with CNN to give the pretrain model. The pretrain model is trained with features of dataset to give the predicted/train model in step 2.

- I. **Data Annotation:** In order to annotate the data, the tool used in this research is CVAT. Prudently, this tool is created for object detection computer vision related works. And since this step requires us to perform annotation on the dataset, the rectangle boundary box is utilized.
- II. **Format and Structure the Data:** It is significant to note that any single algorithm in machine learning has a requirement on how to input data into it. In the case of this research, it is of no exception since the data is exported to a specific format called Yolo 1.1. The download dataset has four imbed files including obj-train-date, train text, obj names, and obj. data. Amongst the many things to detect, the first is the class, width, height of the boundary box, that is relative to the entire size of the image. Secondly, create very specific directories containing the data. In this research, both images and labels directories are used. Ultimately, every image in the image dataset created needs to have an annotation file and a file in the label directories, which is called exactly the same but with different extensions. For example, if the images are .jpg, the annotation files are .text. This, apparently, defines the structure for the data required. Finally, the image directory and label directory should contain all images and annotations. However, the labels should also be expressed in the Yolo format like class id, position (xy), width, height, and coordinates.
- III. **Training the Data:** Now that the dataset is formatted and structured, object detection using YoloV8 through python becomes seemingly easy to execute. In training the object detection or a machine learning model, even though there are different environments, the research adopted the local environment. In this environment, the following steps are pursued:

- a. import the ultralytics python library. This library has lots of dependences, and it's crucial for importing Yolo format files.
- b. load a specific Yolo V8 architecture. In this research, YOLOv8 Nano is imported because it is the smallest and the lightest.
- c. type all the detected classes like spalling, cracks, piers, slab deck etc.
- d. there are three arguments in the script including path, train, and val. Path is the absolute path to your directory containing images and labels. The dataset is divided into training and validation. The algorithm runs both training and the validation dataset into epochs.

Since the model shows moderate performance, there is validation loss and overfitting, leading to non-regularization in the in the object detection of the model. This outcome of the model predicted has inability to complete the remaining steps in the automatic generation of the DT model as shown in figure 3.2. Therefore, the research adopted strategy 1 to settle the issue of regularization and overfitting since the pretrained model has a resemblance to the predicted model.

3.3.2 Strategy 2: Point cloud LiDAR scan sensor approach.

This strategy, described in figure 3.3, enables both clients and design-build professionals to complete work efficiently and with near-perfect results. The process is carried out using the SiteScape app with Multi-scan collected. The Multi-Scan process start by capturing individual scan segments with the Sitescape app. The intended scanning area is divided into roughly square sections to ensure complete coverage. This process is conducted stepwise, as presented in Figure 3.3.

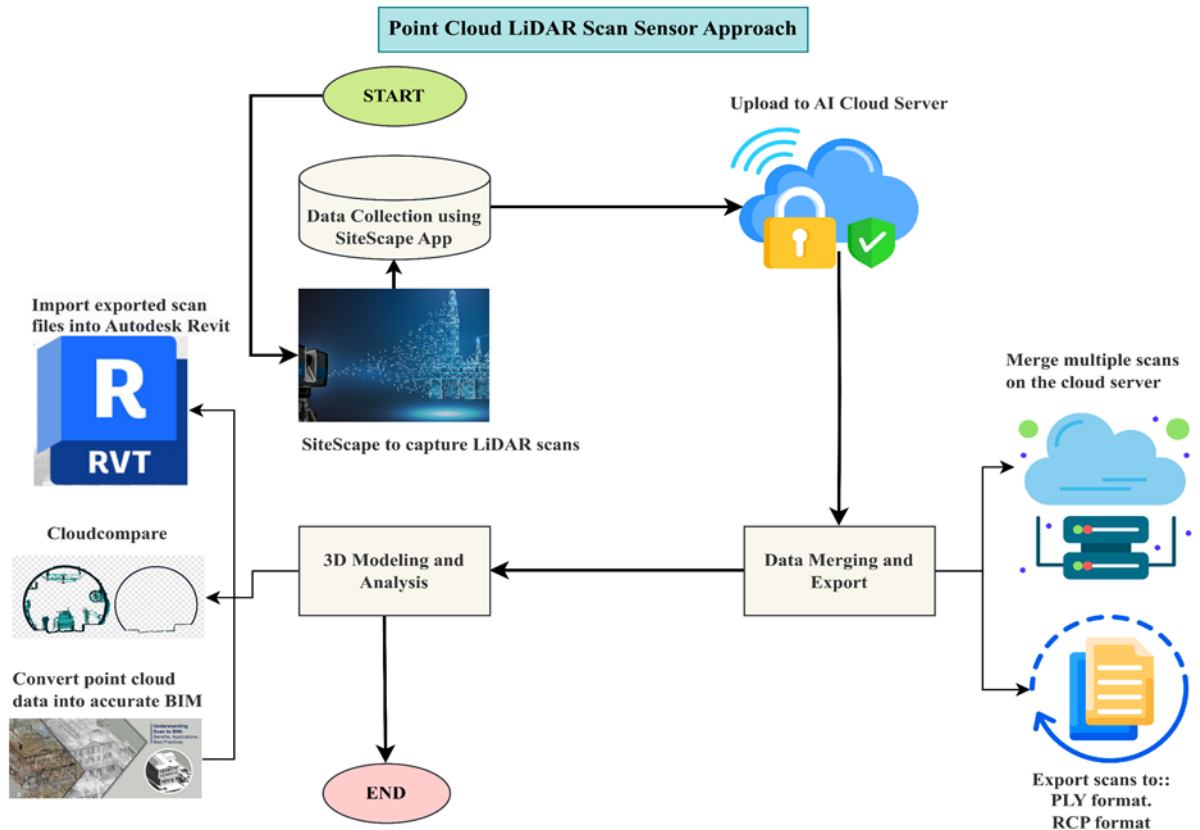


Figure 3.3: Step-by-step process in Strategy 2

- I. **Capturing Segments:** Each scan is initiated by starting the app and continuing until the progress bar is full. The capture button is clicked again to begin the next segment, repeating the process up to ten times.
- II. **Ensuring Overlap:** Overlap between adjacent scan segments is maintained to avoid gaps, which is critical for seamless merging.
- III. **Cloud Syncing:** Once all scan segments are captured, they are synced to the Sitescape Cloud.

The merging process occurs on the Sitescape desktop platform. Each scan segment is aligned manually using a grid and various adjustment tools. The first scan segment is aligned to the grid

as a reference point. Furthermore, additional segments are adjusted using move and rotate tools to ensure proper alignment. The process allows for continuous refinement of previous alignments. Walls across segments are checked for parallel alignment using the grid and outline tool to ensure uniformity. Once all segments are aligned, the merge function combines the segments into a unified model. The model will be exported as either a Polygon file format (PLY) or Representative Concentration Pathways format (RCP). The RCP file make it easy to generate the 3D Model accurately into any parametric software like Revit, whilst the ply format enabled the file to be imported by different software and machine learning algorithms, including Cloudcompare to remove point cloud occlusion and identify geometric structural elements, as well as machine learning algorithms for Lidar object detection, 3D model, and other analysis.

Meanwhile, Table 3.2 outlines the primary tools that were employed in this research to put the proposed BIM-enabled digital twin framework for structural health monitoring (SHM) into implementation. As the next subsections will explain, these tools are composed of both hardware and software, as seen in Table 3.2.

Table 3.2: Tools used in this research

Task	Sub-task	Tool	Description
Development of digital asset	Generation of geometric structural members if the model.	Collected, treated, and levelled data.	To separate the data to different sections of the footbridge into structural elements and structural deficiencies.
Data acquisition, Preprocessing, Validation, and Transmission	Digital signal preprocessing and development.	Python 3	An open-source programming language that is used to develop programs for preprocessing the collected sensor data and performing data validation using the given metrics and ground truth values.
BIM-enabled SHM Digital twin Creation and Visualization	Digital model adoption	Autodesk Revit 2024	A BIM software tool widely used in the architecture, engineering, and construction industries to enable professionals to design, visualize, simulate, and collaborate on building projects.

3.4 Concrete Footbridge DT Model Development (Case Study)

The case study (Figure 3.4) focuses on an existing footbridge at King Fahd University of Petroleum and Minerals (KFUPM) in Saudi Arabia, which connects Buildings 7 and 14. The footbridge was selected due to its frequent use by employees, instructors, and students, and its strategic location facilitating easy access to other academic buildings. The bridge spans approximately 54 meters in length and is 7 meters high, and 3.6-meter-wide oriented in an east-west direction.



Figure 3.4: Case Study of the Research

3.5 Summary of the chapter

This chapter discussed and justified the research design adopted in the thesis. It described the various stages of the research process. It further outlined the strategies adopted in the development and validation of the DT model. Subsequently, the chapter described the procedures involved in each strategy creating point clouds, paying special emphasis to the DT generation process, required tools, and relevant non-geometric information and semantic geometric data. The chapter finished with a summary of the 3D BIM model, techniques, and technologies used.

Chapter 4: Results

4.1 Introduction

This chapter presents the results derived from implementing three distinct strategies for developing a DT model aimed at automatic generation of structural gDT of a footbridge. Systematically, this chapter evaluates the effectiveness and efficiency of each approach, ranging from photogrammetry techniques to advanced LiDAR scanning, especially in capturing, processing, and modeling critical structural data of the footbridge. By leveraging various technologies, including deep learning algorithms, Computer Vision Annotation Tools (CVAT), and BIM software, the research explores how these strategies contribute to accurate geometric modeling and monitoring of structural deficiencies. The analysis focuses on assessing data accuracy, model performance, and the integration capabilities of digital twins within a BIM framework, providing a comprehensive evaluation, that enhances the infrastructure maintenance and decision making of each strategy.

4.2 Strategy 1 – Photogrammetry and Machine Learning (ML) Using Footbridge Images

4.2.1 Result of the Image Classification

After creating the training, validation, and test sets folders to organize the data, the model is the built without utilizing or applying the pretrained and augmentation data techniques. Hence, the architecture model is created with approximately 1 million parameters (weight). This weight stores the information learned by the model. Table 4.1 indicates Keras architecture of the model.

Table 4.1:Keras architecture of the model

Layer (Type)	Output Shape	Param #
Input Layer	(None, 180, 180, 3)	0
Rescaling	(None, 180, 180, 3)	0
Conv2D (conv2d_15)	(None, 178, 178, 32)	896
MaxPooling2D	(None, 89, 89, 32)	0
Conv2D (conv2d_16)	(None, 87, 87, 64)	18496
MaxPooling2D	(None, 43, 43, 64)	0

Conv2D (conv2d_17)	(None, 41, 41, 128)	73856
MaxPooling2D	(None, 20, 20, 128)	0
Conv2D (conv2d_18)	(None, 18, 18, 256)	295168
MaxPooling2D	(None, 9, 9, 256)	0
Conv2D (conv2d_19)	(None, 7, 7, 256)	590080
Flatten	(None, 12544)	0
Dense	(None, 5)	62725

Summary:

- **Total Params:** 1,041,221 (3.97 MB)
- **Trainable Params:** 1,041,221 (3.97 MB)
- **Non-trainable Params:** 0 (0.00 MB)

The next step is by providing a loss function for the model. Loss function is a measurable way to gauge the performance and accuracy of a machine learning model (DataCamp, n.d.). This process involves setting the loss function to calculate the error between the model predictions and the true target values. The model predictions are improved using an optimizer to leverage the backpropagation algorithm to minimize errors. Finally, the training accuracy is evaluated to measure the performance of the model.

The dataset is created and stored on the filepath. This filepath is where the model is stored and the name given to it is “save_best_only”. This saves the highest accuracy from the running epochs.

Figure 4.1 depicts percentage of training and validation accuracy.

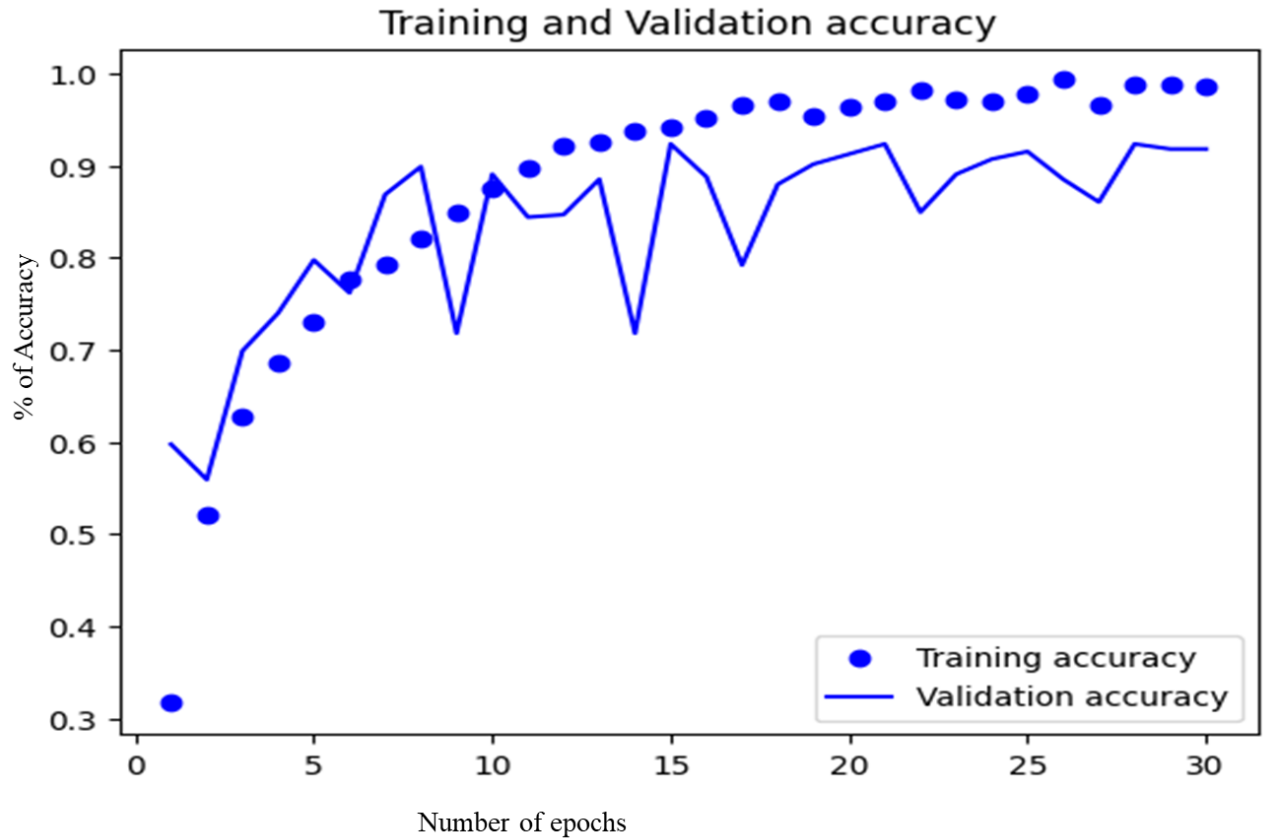


Figure 4.1: Percentage of training and validation accuracy

Figure 4.1 shows the percentage for training and validation accuracy for each epoch. This process the model to update the weight and improve accuracy. The training is done on the training dataset and validation is done on the validation dataset. This is inverse for the training and validation loss in Figure 4.2.

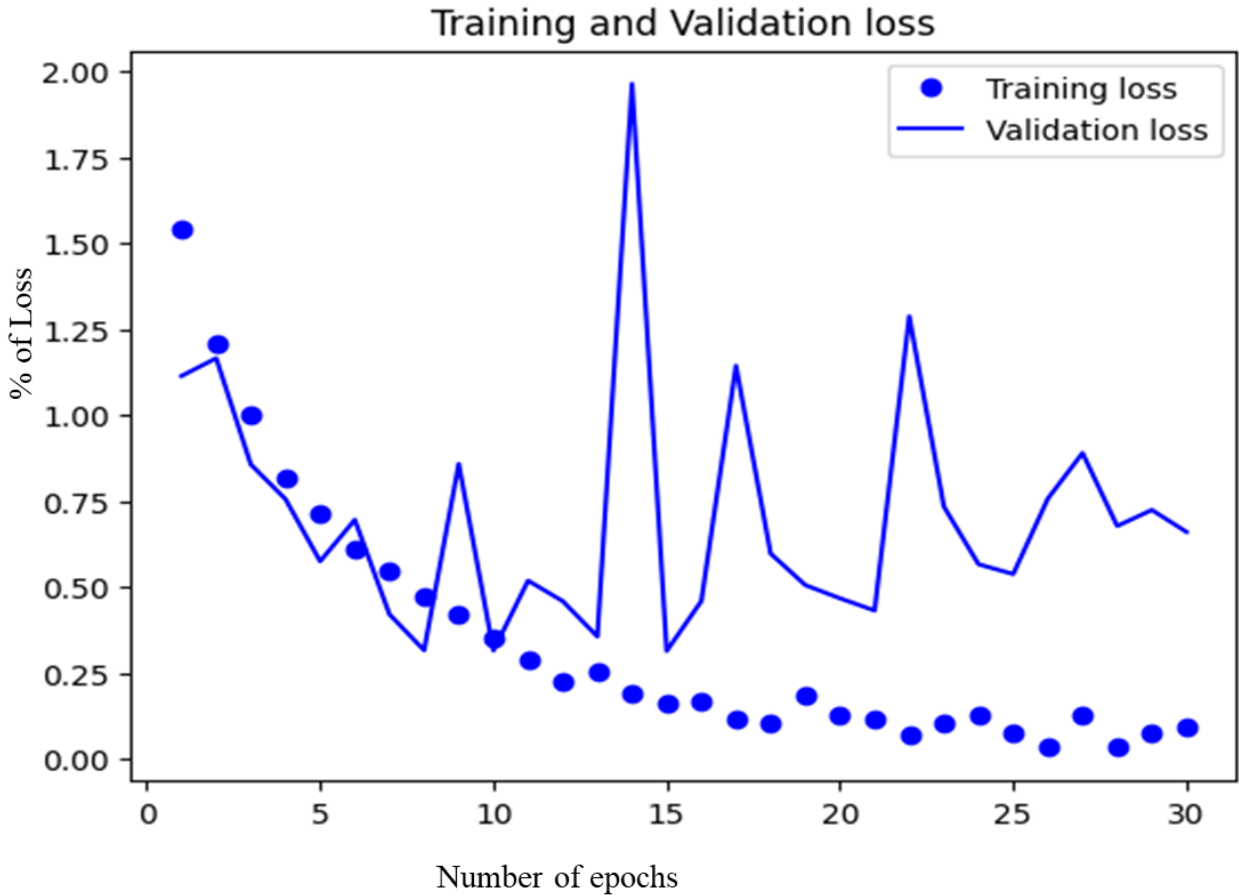


Figure 4.2: Percentage training and validation loss

The ML model, in Figure 4.2, describes training and validation loss over 30 epochs. The model is learning and getting better at using the training data, as evidenced by the training loss gradually declining. Similar downward trends are seen in the validation loss at first, but beginning around epoch 10, there are notable oscillations with abrupt spikes and erratic patterns. These variations point to possible problems in the validation process, such as instability or overfitting. The behavior of the validation loss suggests that more research is necessary, perhaps by adjusting hyperparameters, expanding the size of the validation dataset, or using regularization techniques to enhance generalization, even though the training loss stays constant. Because of this, the model is loaded and tested on the test set, which gives a test accuracy of 0.928 or 92.8%. To avoid overfitting and enhance generalization, the next stage of model development involves introducing

data augmentation and dropout regularization, which purposefully sets some node values in the model to zero. In order to enhance accuracy and generalization and avoid overfitting, data augmentation is carried out by increasing the quantity of training data. The output model of the first step is now loaded and tested to the test set. The result of the analysis is shown in Figures 4.3 and 4.4, respectively.

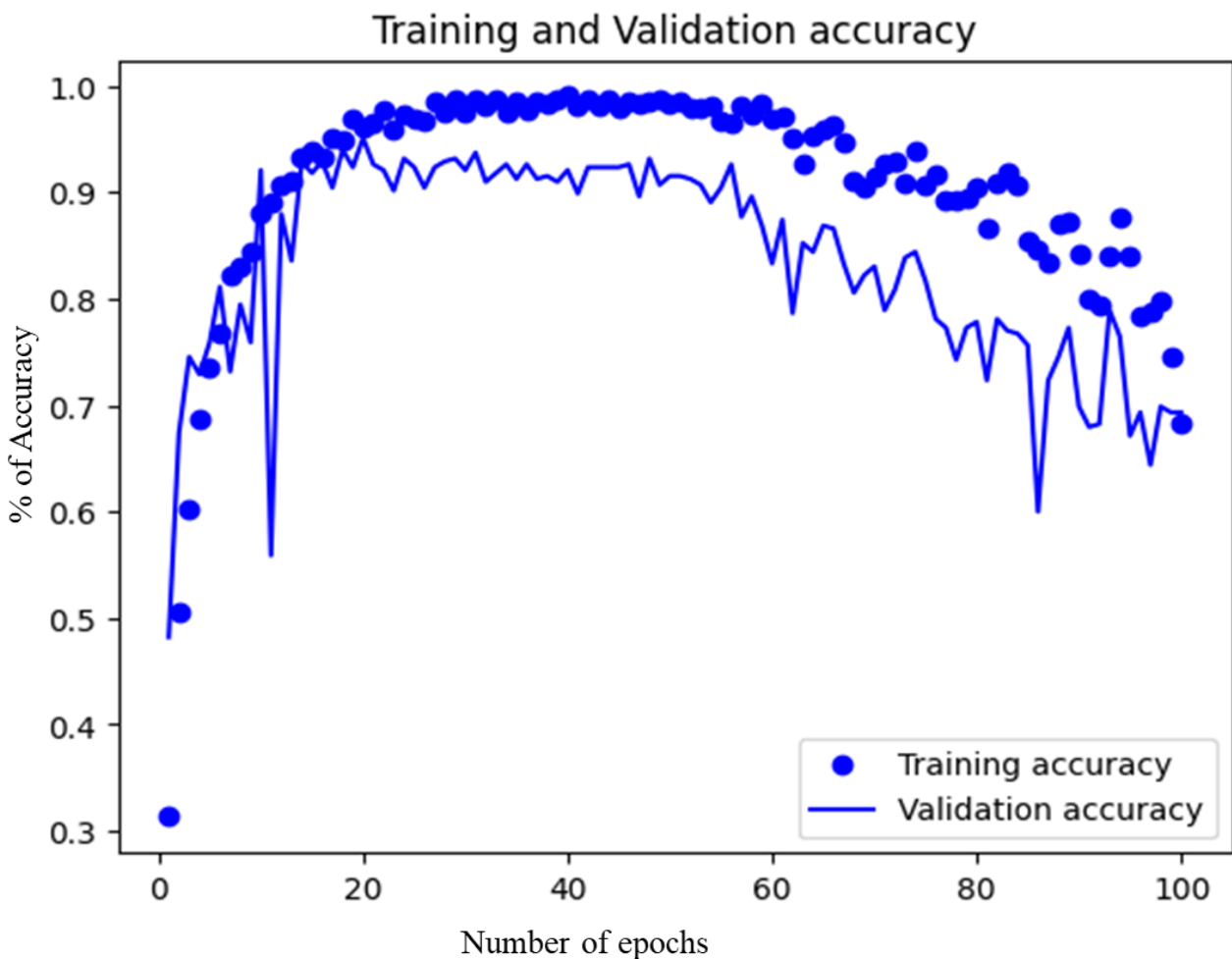


Figure 4.3: Training and validation accuracy of the augmentation process

Figure 4.3 depicts the training and validation accuracy of a machine learning model over 100 epochs. The training accuracy rapidly increases and then stabilizes around 0.95, indicating that the training data is being learned effectively. Validation accuracy improves initially, peaking near

training accuracy before gradually declining and fluctuating in later epochs. This divergence indicates possible overfitting, in which the model performs well on the training data but struggles to generalize consistently to the validation data. To address this, regularization techniques, early stopping, and hyperparameter tuning could help improve generalization and validation accuracy.

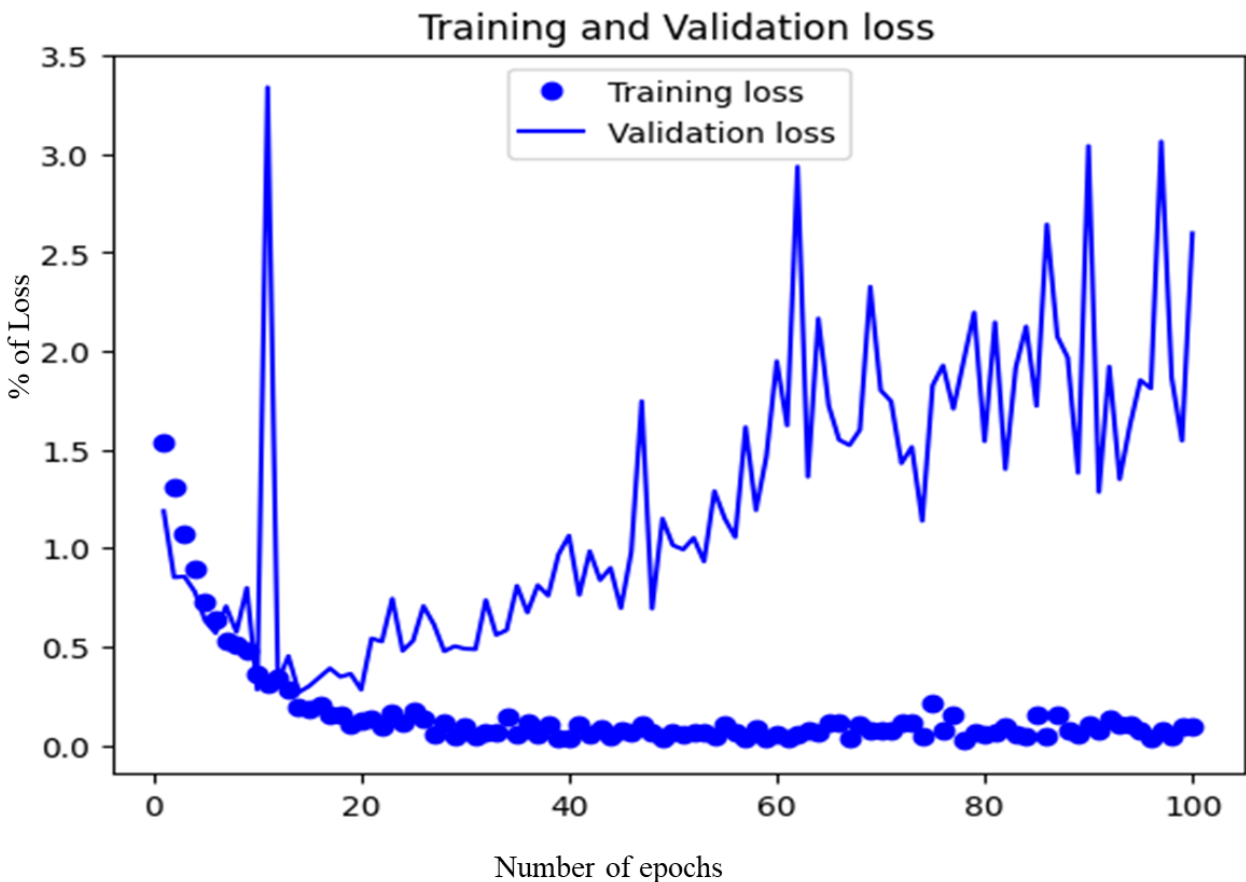


Figure 4.4: Training and validation loss of the augmentation process

On the other hand, Figure 4.4 presents the training and validation losses over 100 epochs. The training loss consistently decreases and stabilizes near zero, indicating that the training data is being learned effectively. In contrast, the validation loss initially decreases before beginning to fluctuate significantly after about 20 epochs, with large spikes and irregular patterns. This suggests that the model is overfitting, as it fails to generalize well to the validation data despite excellent performance on the training set. To address this, techniques such as early stopping, regularization,

and data augmentation may help improve model generalization and reduce variability in validation loss.

Furthermore, the model is loaded to be tested on the test set, indicating the start of the pretrained model. Pretrained models are models that are trained on a large dataset and trained weights, which acts as a filter to extract increasingly meaningful representation out of the data before passed to the model for training, thereby improving prediction accuracy and prevent overfitting. The filter and/or layer used in this research is the pretrained layer summary (VGG16). The VGG16 architecture is shown in Table 4.2.

Table 4.2: VGG 16 architecture

Layer (Type)	Output Shape	Param #
Input Layer	(None, 180, 180, 3)	0
block1_conv1	(None, 180, 180, 64)	1792
block1_conv2	(None, 180, 180, 64)	36928
block1_pool	(None, 90, 90, 64)	0
block2_conv1	(None, 90, 90, 128)	73856
block2_conv2	(None, 90, 90, 128)	147584
block2_pool	(None, 45, 45, 128)	0
block3_conv1	(None, 45, 45, 256)	295168
block3_conv2	(None, 45, 45, 256)	590080
block3_conv3	(None, 45, 45, 256)	590080
block3_pool	(None, 22, 22, 256)	0
block4_conv1	(None, 22, 22, 512)	1180160
block4_conv2	(None, 22, 22, 512)	2359808
block4_conv3	(None, 22, 22, 512)	2359808
block4_pool	(None, 11, 11, 512)	0
block5_conv1	(None, 11, 11, 512)	2359808
block5_conv2	(None, 11, 11, 512)	2359808
block5_conv3	(None, 11, 11, 512)	2359808
block5_pool	(None, 5, 5, 512)	0

Summary

- **Total Parameters:** 14,714,688 (56.13 MB)
- **Trainable Parameters:** 14,714,688 (56.13 MB)
- **Non-trainable Parameters:** 0 (0.00 MB)

This layer extracts important details on training images before passing the model. The outcome of the pretrained model training and validation accuracy loss is shown figure 4.5 and figure 4.6.

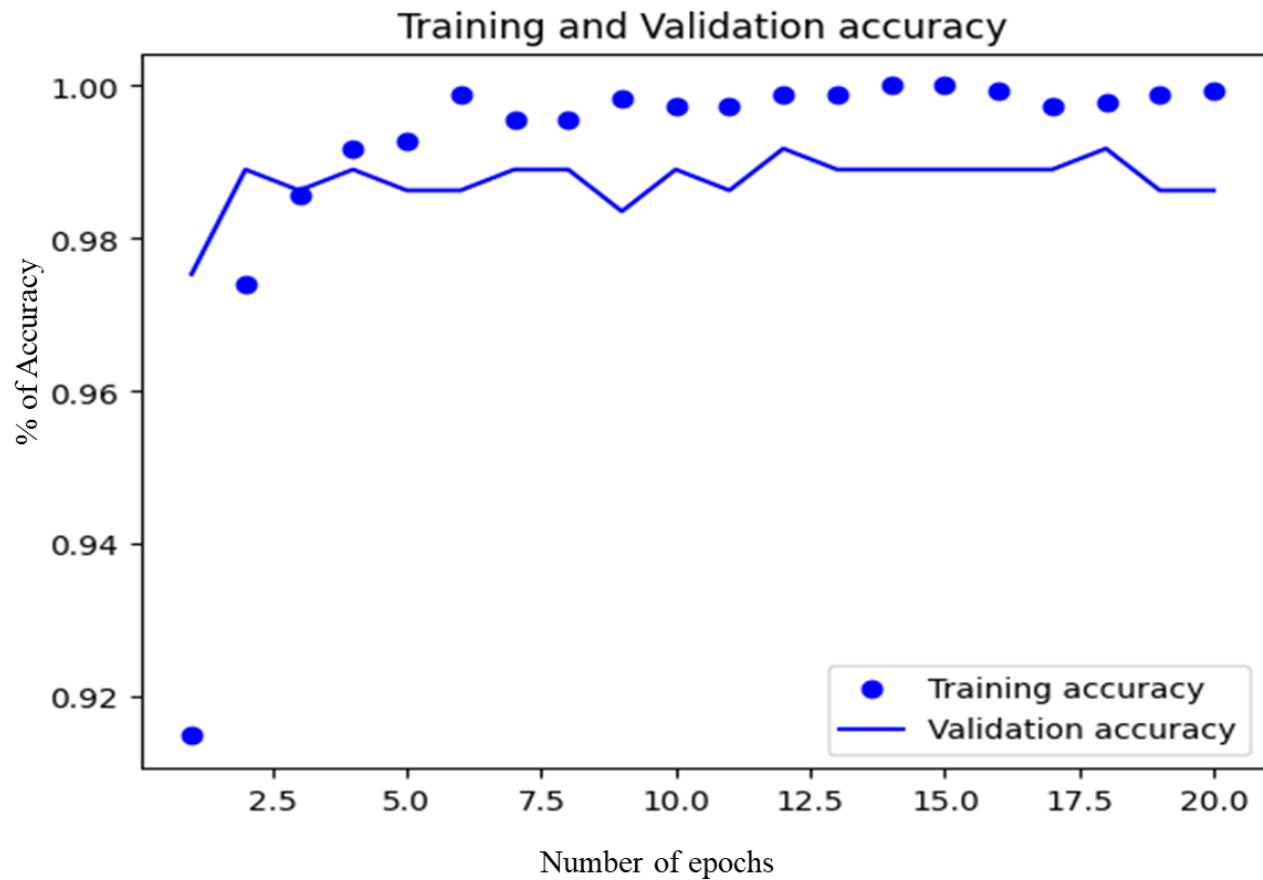


Figure 4.5: Pretrained model training and validation accuracy

Figure 4.5 displays the training and validation accuracy over 20 epochs. Training accuracy rapidly improves and stabilizes near 1.0, indicating effective learning from the training data. Validation accuracy follows a similar pattern, closely matching training accuracy across epochs. This close alignment indicates that the model generalizes well without evidence of overfitting. Both accuracies reach a plateau after approximately 5 epochs, indicating early convergence. The model performs consistently and robustly on both the training and validation datasets.

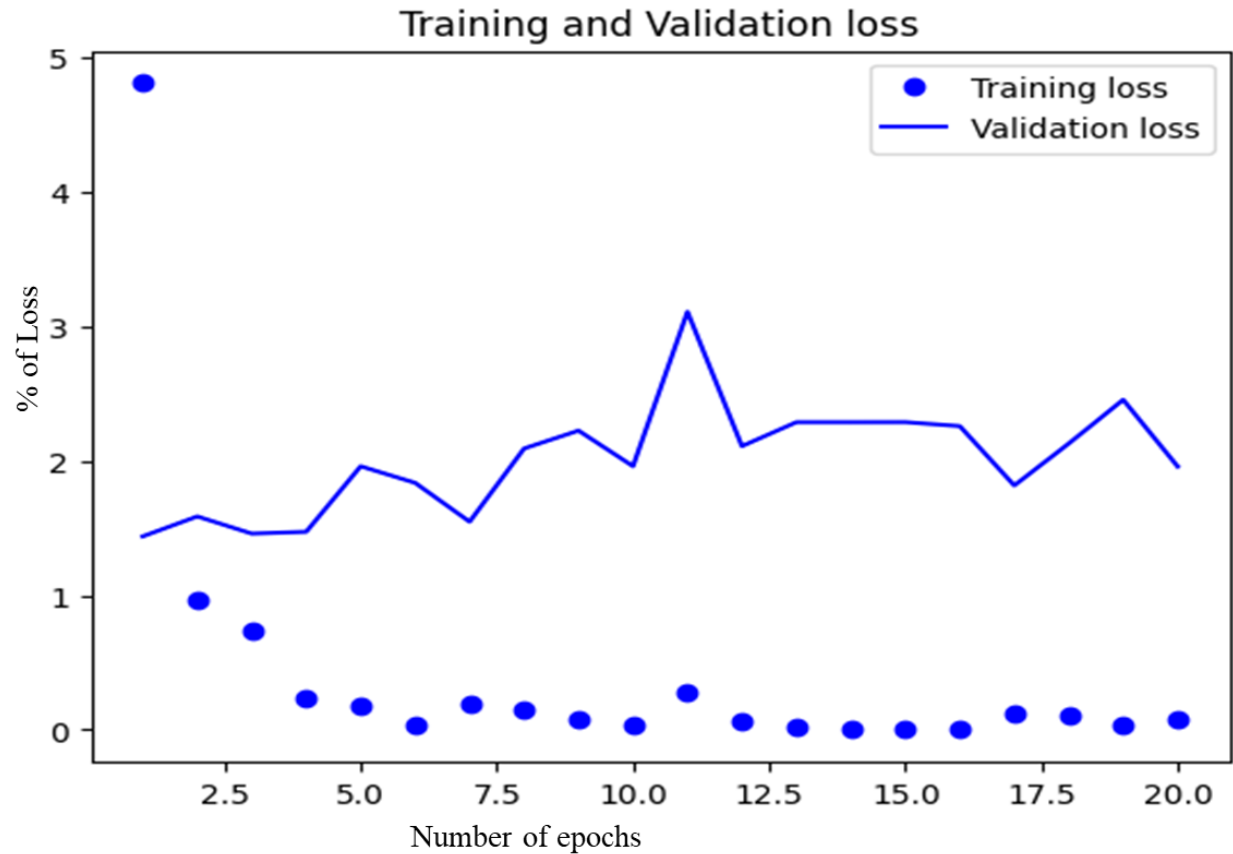


Figure 4.6: Pretrained model training and validation loss

Conversely, Figure 4.6 shows the training and validation loss over 20 epochs. The training loss gradually lowers, eventually nearing zero, suggesting that, from the training data, the model is effectively learning. In contrast, the validation loss varies dramatically, with abrupt peaks and uneven patterns, indicating that the model may fail to generalize to new data. These variations point to probable overfitting or instability in the validation process. To improve generalization and reduce variability, it may be necessary to use regularization techniques, fine-tune hyperparameters, or increase the size and diversity of the validation dataset.

Overall, the graph shows excellent model performance with effective generalization and learning. Moreover, it is noteworthy to recognize that the result of the image classification qualifies the dataset to be used for object detection.

4.3 Object Detection

4.3.1 Results of the Object detection Phase

Figure 4.7 shows the Precision-recall curve of strategy 1 that determines the model performance on the object detected model. The Precision-Recall (PR) curve, in figure 4.8, illustrates the trade-off between precision and recall for the model. The curve for "crack" class achieves a mean Average Precision (mAP) of 0.562, indicating moderate performance in correctly identifying positive samples while minimizing false positives.

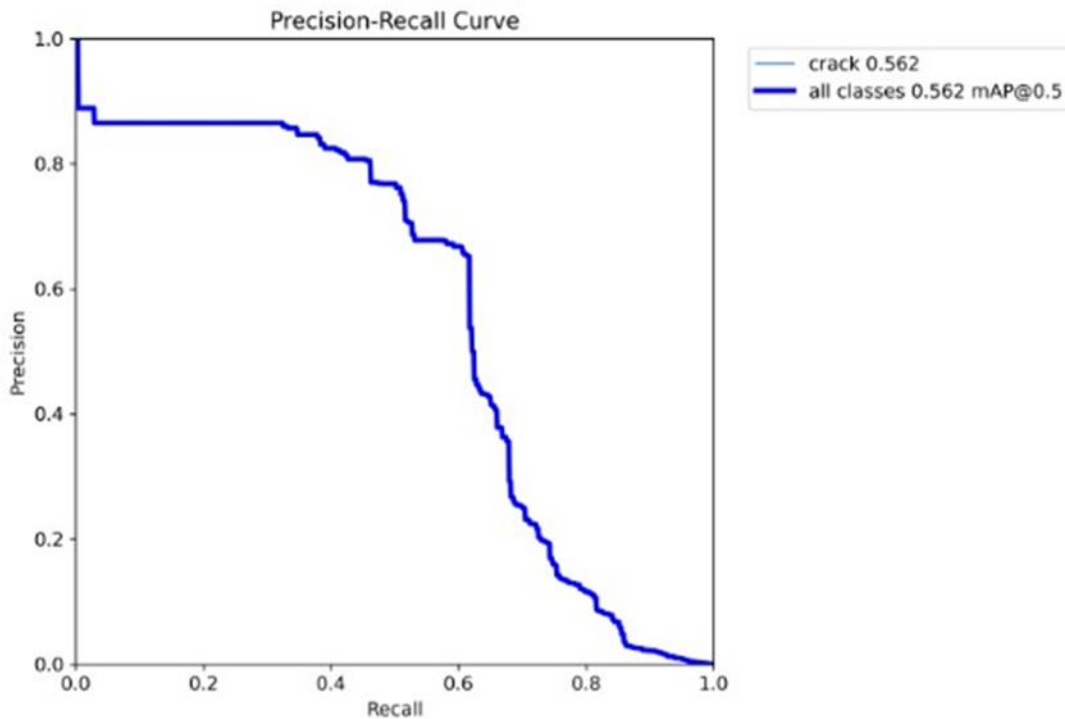


Figure 4.7: Precision-recall curve of strategy 1

As recall increases in figure 4.7, precision decreases, which is expected as the model retrieves more relevant results at the cost of including false positives. The overall mAP@0.5 for all classes is 0.562, reflecting consistent performance across the dataset. While the performance is reasonable, further improvements could be made by refining the model or balancing the dataset. Figure 4.8

illustrates the training and validation performance of a model over 20 epochs, including losses and assessment metrics.

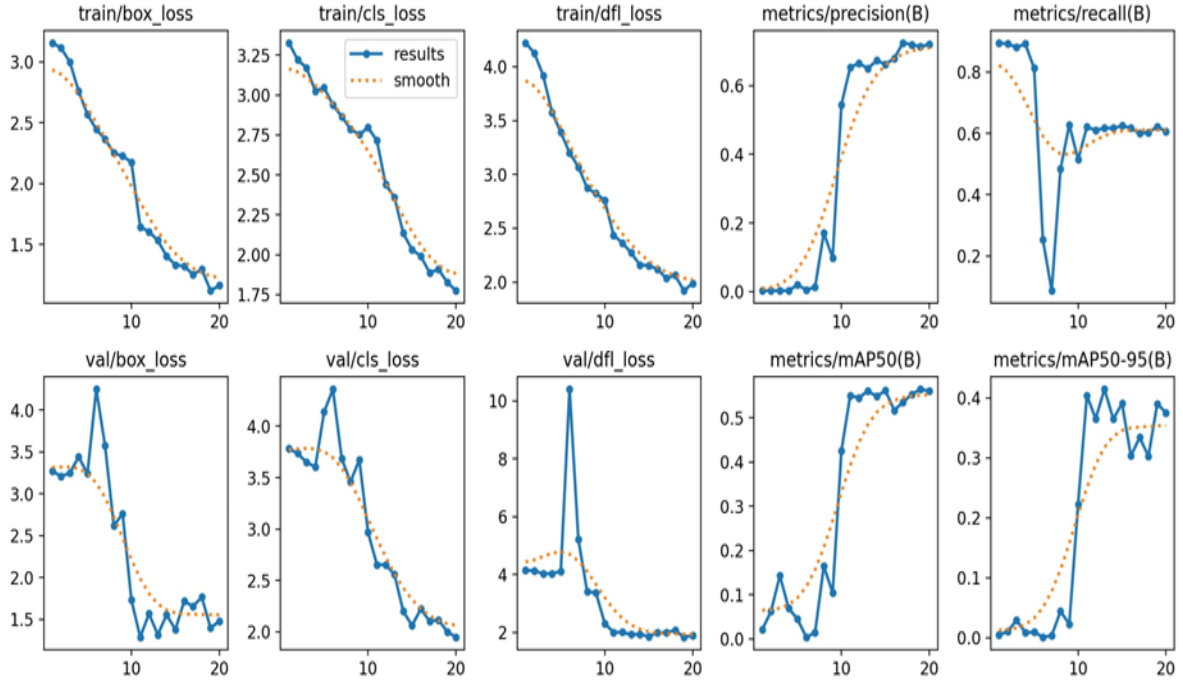


Figure 4.8: Result showing the performance of strategy 1

From Figure 4.8, the box loss, classification loss (cls), and distribution focal loss (dfi) all drop consistently, indicating effective learning on the training data. The validation losses are decreasing, indicating better model performance on unseen data, albeit some differences signal minor instability. Moreover, Precision gradually improves and stabilizes at a high value, whereas recall sway before stabilizing, indicating inconsistency in detecting all positive cases.

Metrics such as mAP50 and mAP50-95 are continually improving, demonstrating increased overall model accuracy and generalization.

Overall, the model signifies good learning capabilities with improving metrics, but slight shifts in validation losses and recall suggest opportunities for modification, such as fine-tuning hyperparameters or enhancing the dataset.

The reason for the moderate performance in strategy 1 is because, in machine learning, the algorithms are incapable of generalizing object detected in the dataset since there is no resemblance in the targeted data. Due to this dataset that has resulted to the performance in Strategy 1, the research tried to opt for another approach. This approach leads to the second strategy.

4.4 Strategy 2 – Point cloud LiDAR scan sensor approach.

This strategy uses the Sitescape application to perform a Multi-Scan LiDAR process, which allows for the creation of a single, accurate 3D model by combining multiple scan segments. The process entails taking ten separate scans, ensuring overlap between adjacent segments, and combining them in a desktop environment. This detailed workflow is intended to improve scanning accuracy and streamline merging, making it ideal for complex environments requiring precise data collection.

Furthermore, the merged scan appears in the scan list after it has been processed, which can take several minutes or more depending on the data complexity. When the process is completed, users are notified by email. The end result is a highly accurate 3D point cloud that can be exported in PLY or RCP formats, making it suitable for further analysis or integration with other software. In this research, Revit 2024 version is used to generate the 3D point cloud automatically to DT 3D model. The model generated is thus is seen in the Figure 4.9

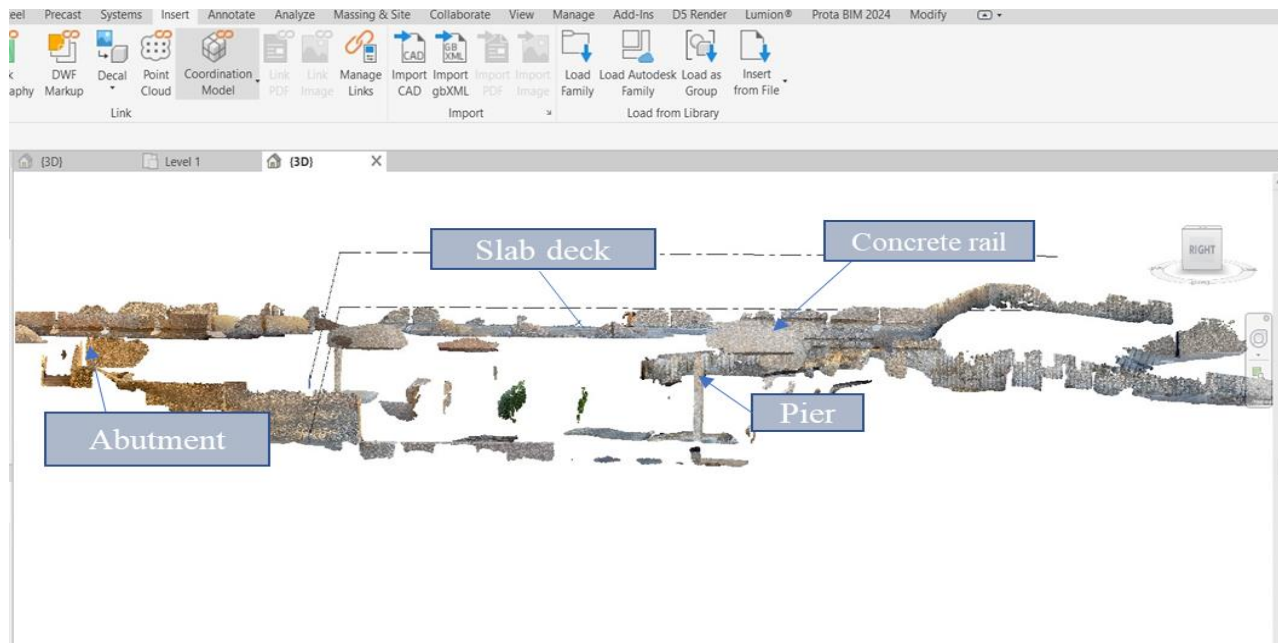


Figure 4.9: Showing a 3D Point Cloud Development

Figure 4.9 depicts a 3D point cloud model created using a multi-scan LiDAR process. The model depicts a spatially accurate reconstruction of a scanned environment, including visible details such as walls, structures, and possibly vegetation. The model is displayed as a point cloud, with each point representing a precise spatial coordinate obtained during the scanning process.

The point cloud contains detailed representations of the scanned area, including visible walls and features. However, some gaps or areas with fewer points may indicate insufficient data collection or limited resolution in specific sections. The sections of the walls and structures appear mostly straight and parallel, indicating good alignment during the merging process. This indicates a well-executed multi-scan process for creating a 3D point cloud. This 3D point cloud is suitable for architectural analysis, construction planning, and virtual walkthroughs.

Ensuring practical application of the 3D Point Cloud to create the 3D model, Revit 2024 is used as a parametric BIM software. The Structural geometric features of the software are used, aiming

to come out with a clear representation of the concrete footbridge due to the tracing of the 3D Point Cloud. The result of this applicability is shown in the figure 4.10.

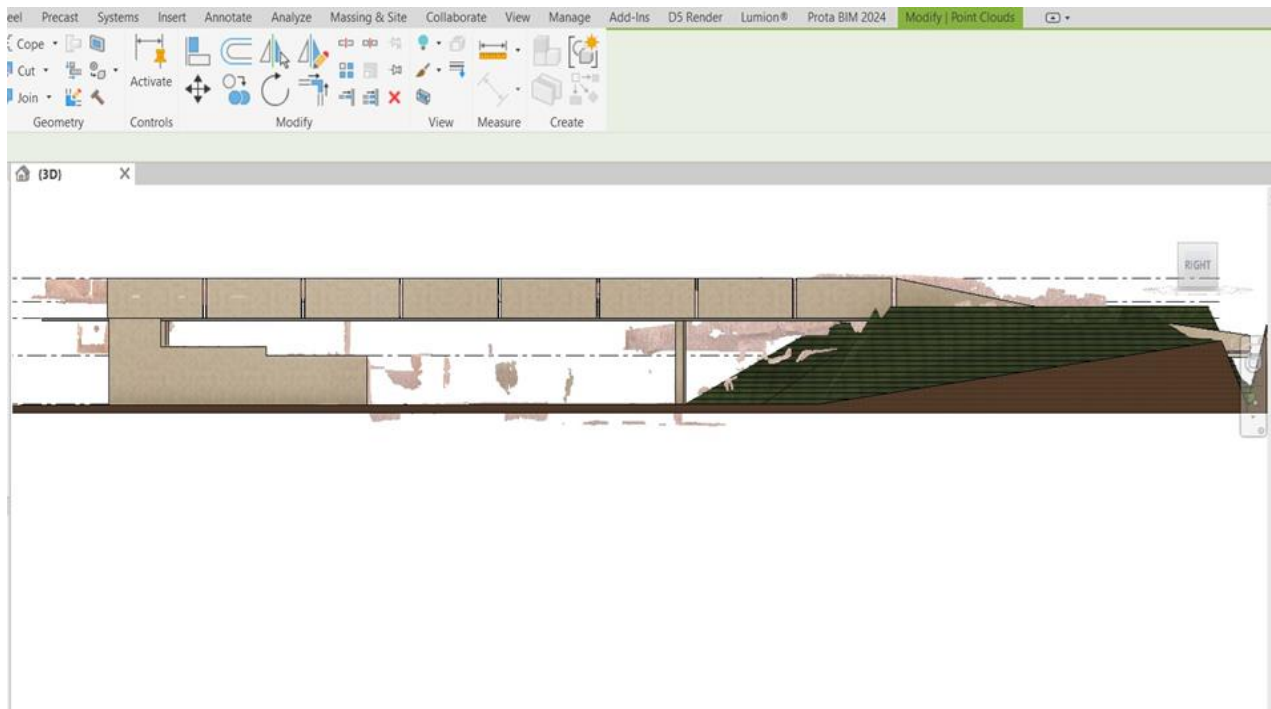


Figure 4.10: Showing the 3D Model Development

Figure 4.10 shows a cross-sectional view of a 3D model created with Point Cloud data and additional design elements. The model incorporates structural components, landscaping, and terrain details, demonstrating a combination of reality capture and virtual reconstruction. The cross-sectional representation reveals details about the structural layout, terrain gradients, and potential design interventions. However, the integration of Point Cloud data into the model demonstrates precise alignment, ensuring that the captured reality matches the designed elements. This strategy not only ensures design accuracy but also makes it easier to analyze and make decisions for construction or planning.

4.4.1 Comparison Between Physical and Virtual Measurement

This analysis shows, in Figure 4.11, the percentage error measurement between the physical asset (Concrete Footbridge) and the digital model. The difference in measurement determine the level of accuracy of the automatic generated DT model.

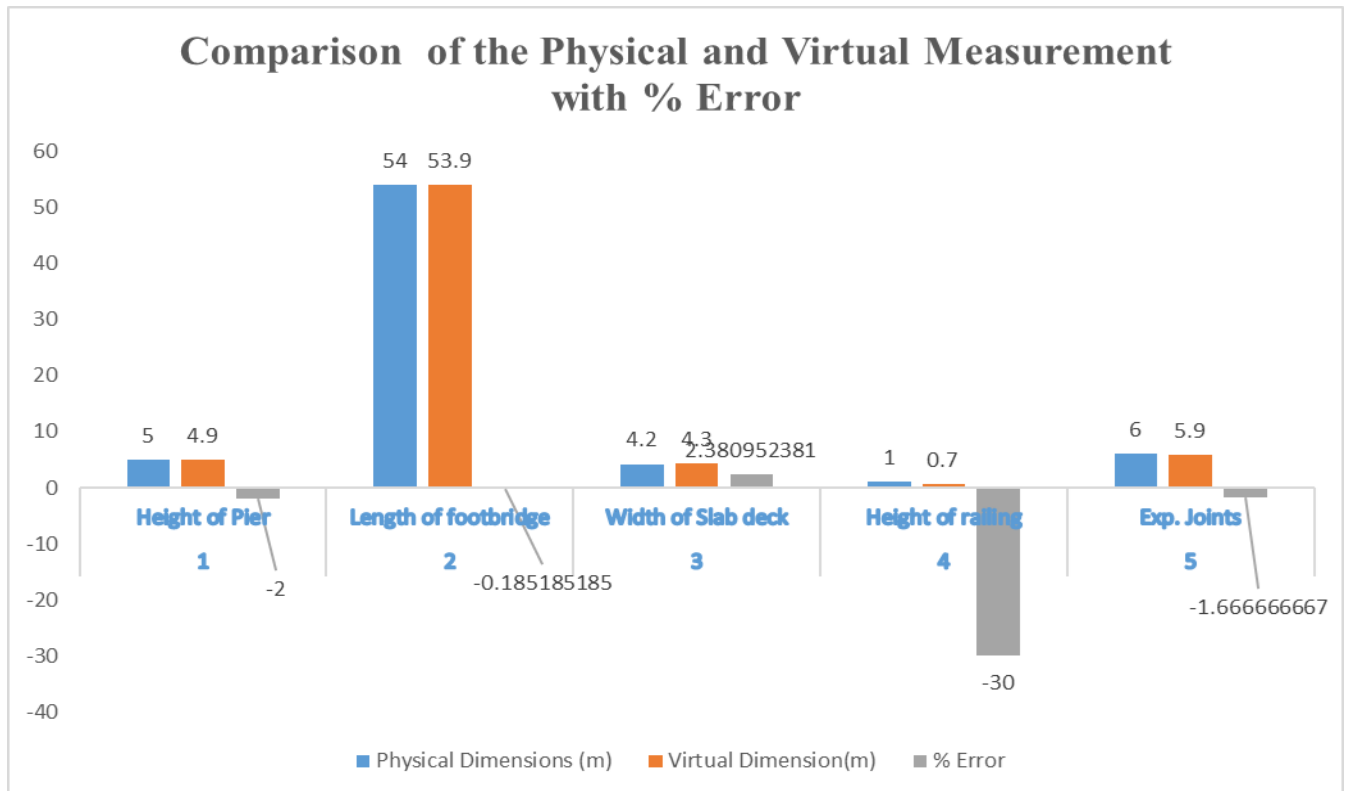


Figure 4.11: Showing the % of Error between the Virtual and Physical Measurement

Figure 4.11 evaluates structural elements by comparing physical dimensions with virtual dimensions. And from the figure, the percentage of error is relatively low, indicating a high degree of accuracy in the virtual modeling process. This result is useful for quality control and validation of design accuracy. This information is useful for high-level decision making, validation, and inspection of assets located in an environment difficult to access.

Chapter 5: Conclusion, Contributions and Recommendations

5.1 Introduction

This chapter presents the summary of key findings on the three methods adopted, including photogrammetry, machine learning, and LiDAR scanning implemented within a BIM framework. It further summarizes the findings of the objectives outlined in the research study, providing clarity and completeness of the research work. The chapter further details the novelty, theoretical contribution, practical relevance, and policy implications of the research. Subsequently, limitations and recommendations of the research are documented. The recommendations enable the implementation of gDT development for further research with accurate, effective, and efficient practical applicability in the construction sector.

5.2 Summary of Key Findings

This research has evaluated the enabling technologies and two different approaches to the development of a gDT model of a concrete footbridge. Each approach is based on the most advanced technologies, such as photogrammetry with machine learning, and LiDAR scanning, integrated into BIM framework. The summary of the outcome of these strategies include:

- I. Based on recent peer-reviewed literature and projections, Key technologies featured include laser scanning, building information modeling (BIM), cloud services, machine learning, and IoT, among others. Laser scanning and BIM dominate the discussions, reflecting their established roles in accurate data capture and modeling. Emerging trends point towards increased reliance on machine learning and cloud technologies, indicating a shift towards more automated, scalable solutions for managing and processing gDT data. The data suggests a growing integration of advanced computational technologies with

traditional methods to enhance the efficacy and application of digital twins in construction and infrastructure projects.

- II. **Strategy 1** used photogrammetry with 2,385 images of footbridges and showed moderate success in image classification and object detection. However, the model faced overfitting and instability in validation accuracy and loss, hence requiring further improvements in data quality and model tuning. This achieved a test accuracy of 92.8%, although it was not robust in generalization and poorer overall performance, and therefore had limited practical applicability for multi-class object detection.
- III. **Strategy 2** used the multi-scan LiDAR method, which succeeded in capturing and merging point clouds to build up an accurate 3D geometric model through the use of Revit 2024. Integration with BIM ensured all data from LiDAR corresponded exactly with physical to virtual, with a minimal percentage of error and high-quality structural analysis. Therefore, this is the method that could hold the most potential in practical applications pertaining to architectural analysis, construction planning, and asset inspection.

The research concludes that photogrammetry techniques, as represented by strategies 1, provide the results at a medium level, while the challenges to achieve the required precision and generalization for complex structural modeling are substantial. In contrast, Strategy 2 (LiDAR-based approach) offers better accuracy and reliability, leading to the most effective solution for developing DT models in challenging environments.

5.3 Conclusions

Objective 1: To create conditional criteria for determining structural member function and section family type using geometric information.

As a result, this thesis developed the conditional criteria required for defining structural member function and section family type using geometric information collected from point cloud data.

The review emphasized that geometric characteristics such as member position, section shape, and spatial connections serve as foundational criteria for identifying structural components like piers, beams, and bracings. Techniques such as segmentation and clustering algorithms were highlighted as effective tools for classifying geometric features, despite challenges like noise sensitivity and potential misclassification in point cloud datasets. Furthermore, the integration of advanced methods, including Convolutional Neural Networks (CNNs) and Machine learning demonstrated the potential for accurately inferring both geometric and non-geometric information essential for creating semantically complete as-is BIM models. These criteria provide a structured framework for systematically associating geometric data with specific structural member functions and section family types, enabling more precise and automated generation of structural geometric digital twins (gDTs).

Objective 2: To develop and evaluate semantic database from raw point clouds to produce a digital model and automatically generate a gDT of concrete bridges.

This research evaluated three advanced approaches to develop and assess the potential of a semantic database for generating a geometric digital twin (gDT) model of a concrete footbridge. Strategy 1 utilized photogrammetry to classify images and detect objects, achieving moderate success with a test accuracy of 95%. However, overfitting, unstable validation metrics, and limited robustness hindered its practical applicability. In contrast, Strategy 2, using the multi-scan LiDAR method integrated into a BIM framework, demonstrated the highest potential. It successfully captured and merged point clouds into a precise 3D geometric model with minimal error, ensuring accurate alignment between the physical and virtual models. This approach not only provided a

high-quality structural analysis but also showcased its practicality for applications in construction planning and asset inspection. The findings underscore the importance of integrating robust technologies like LiDAR with semantic processing for automated and reliable gDT generation.

5.4 Novelty and Contributions of the Research

5.4.1 Novelty of the Thesis

This research introduces a novel approach to developing a digital twin (gDT) model for a concrete footbridge by comparing two advanced strategies using photogrammetry and machine learning, and LiDAR scanning, all integrated within a BIM framework. It highlights the strengths and limitations of each method, with photogrammetry and machine learning showing moderate success but facing challenges like overfitting and unstable validation, while LiDAR scanning demonstrated superior accuracy and reliability when paired with BIM, achieving precise 3D models with minimal error. This study offers valuable insights into refining these technologies for practical applications in construction, structural analysis, and asset management.

5.4.2 Theoretical implications

This research makes a significant theoretical contribution by advancing the understanding of how to integrate photogrammetry and machine learning, and LiDAR scanning within a BIM framework for digital twin development. It provides a detailed evaluation of each method's performance, highlighting the need for improved data quality, model optimization, and validation stability in photogrammetry-based approach. The study also underscores the transformative potential of LiDAR-BIM integration in achieving highly accurate and reliable digital representations. These findings pave the way for future research on optimizing digital twin technologies for applications in construction, structural analysis, and asset management.

5.4.3 Practical contribution

This research offers valuable practical and industrial contributions by demonstrating the applicability of advanced technologies like photogrammetry with machine learning, and LiDAR scanning integrated with BIM for digital twin development. It provides actionable insights into the limitations and potential of each approach, emphasizing the effectiveness of LiDAR-BIM integration in creating precise and reliable 3D models. These findings can directly benefit industries by improving construction planning, structural analysis, and asset management processes, enabling more efficient and accurate decision-making in real-world projects.

5.4.4 Policy significance

This research has clear policy relevance by demonstrating how advanced technologies like LiDAR scanning and BIM integration can set new standards for digital twin development in construction and infrastructure management. It highlights the importance of adopting accurate and reliable methods to ensure better structural analysis, construction planning, and asset inspection. These findings can inform policies aimed at promoting the use of cutting-edge digital tools in the construction industry, improving efficiency, safety, and sustainability in infrastructure projects.

5.5 Limitations of the Research

The research faced several constraints and drawbacks that hindered the initial plan of developing a real-time monitoring of structural geometric digital twin:

- A key limitation of the study was the difficulty of having the sensors, due to lack of financial resources, to effectively monitor the structural health of the footbridge.
- The unavailability of laser scanners equipment coupled with the restriction of drone technology to gather quality and balance dataset was crucial in the photogrammetry-based approaches, which resulted in poor performance in multi-class object detection and low precision-recall

metrics. Issues with overfitting and unstable validation metrics in these approaches highlighted the need for better model optimization and parameter tuning to achieve consistent results. The goal of real-time monitoring was further challenged by computational and integration complexities, particularly in photogrammetry methods, which made them less practical for dynamic applications. While LiDAR scanning demonstrated high accuracy and reliability, the photogrammetry strategies showed limited applicability, underscoring the need to address their inherent limitations to improve their utility in future digital twin development.

5.6 Recommendations

First, quality and diversity of datasets should be enhanced, especially for photogrammetry-based strategy. It is necessary to create a balanced dataset with diverse images taken under different conditions for better object detection, classification, and generalization, enhancing dataset quality and diversity is essential, particularly for photogrammetry-based strategy. This involves curating balanced datasets with diverse images captured under varying conditions to improve object detection, classification, and generalization.

Second, the model architecture should be optimized by incorporating advanced frameworks such as VGG16 or ResNet for enhanced feature extraction and classification accuracy. Fine-tuning hyperparameters and employing regularization techniques are also crucial for mitigating overfitting and improving model stability, optimizing model architectures by incorporating advanced frameworks like VGG16 or ResNet can significantly enhance feature extraction and classification accuracy. Fine-tuning hyperparameters and regularization techniques are also crucial for mitigating overfitting and improving model stability.

Third, it is recommended to leverage LiDAR technology, especially through the adoption of Multi-Scan LiDAR for projects requiring high-precision and complex modeling. Integration of LiDAR data with BIM frameworks provides accurate digital representation and efficient structural analysis. A hybrid approach combining photogrammetry and LiDAR techniques is suggested to capitalize on the strengths of both methods, especially in projects with diverse data capture and modeling requirements. Leveraging LiDAR technology is another critical recommendation, especially through adopting Multi-Scan LiDAR for high-precision and complex modeling projects. Integrating LiDAR data with BIM frameworks ensures accurate digital representations and efficient structural analysis. A hybrid approach that combines photogrammetry and LiDAR techniques is suggested to capitalize on the strengths of both methods, particularly in projects with diverse data capture and modeling requirements.

Fourth, advanced metrics such as mAP50-95, F1 score, and cross-validation should be used to rigorously evaluate the model performance for robustness. Comparing results across multiple datasets and validation schemes can further enhance reliability. Exploring automation and scalability is equally important; automating the integration of point cloud data with BIM can streamline scalable DT model generation, simplifying workflows for data preprocessing, merging, and analysis.

Finally, the expansion of practical applications of DT models is encouraged. The extension of these models to infrastructure maintenance, disaster management, and accessibility planning in remote or hazardous environments will extend their application beyond traditional construction projects. These recommendations aim to improve the accuracy, efficiency, and versatility of DT model development and implementation.

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- A trained Civil Engineer with a Master's in Construction Engineering and Management and over 4 years of relevant experience.
- A highly motivated and dedicated student seeking a PhD scholarship in the field of Construction Engineering and Management (CEM).
- A professional member of relevant bodies in my field, including Sierra Leone Institution of Engineers (SLIE) and the Project Management Institute (PMI).
- A multi-disciplinary professional capable of working with multidisciplinary and multicultural teams.
- A problem-solver with strong quantitative and qualitative analytical skills relevant to buildings, civil engineering, and infrastructure projects.
- Knowledgeable of the Sierra Leonean context and cultural dynamics associated with civil and infrastructure works.

Education

- **MSc Construction Engineering and Management** [09.2022 –2024]
King Fahd University of petroleum and Minerals, Dharan, Saudi Arabia
Dissertation title: Automatic Generation of Structural Geometric Digital Twin of Concrete Bridges from Point Clouds.
- **BEng (Honors) in Civil Engineering** (First Class Honors) [2018 – 2021]
Fourah Bay College, University of Sierra Leone, Sierra Leone
Capstone project: Developing a Resilient and Sustainable Urban Mobility Plan (Case Study: Jui-Hastings Community)
- **BSc (Honors) in Physics** (Second-Class upper Honors) [2013– 2017]
Fourah Bay College, University of Sierra Leone, Sierra Leone
Capstone project: Investigating the Potential Users of Ensemble Forecasts by Using the INSTAT Model (Case Study: Freetown, Sierra Leone).

Professional Experience

• **Technical Supervising Engineer** [01.2023 – 02.2024]
European Union, Freetown, Sierra Leone

- Collaborated with project teams to support the planning, execution, and monitoring of construction projects.
- Provided technical oversight and compliance monitoring for all its works project for the Karene District Council office.
- Assisted in conducting site inspections, ensuring adherence to safety regulations, and quality control.
- Prepared project reports, progress updates, and contributed to project documentation.
- Issued provisional and Final certificate of works.
- Monitored standard environmental protection concerns throughout project implementation.

• **Project Manager** [02.2022 – Date]
Creative Building with Construction Solutions & General services, Freetown, Sierra Leone.

- Collaborated with project team to plan, schedule, and execute construction projects, ensuring adherence to quality and safety standards.
- Assisted in the design and analysis of infrastructure projects, including buildings, roads and bridges.
- Collaborated with team members and stakeholders to ensure project objectives were met.
- Assisted in coordinating construction activities, including procurement, resource allocation, and sub-contracted work.
- Monitored project progress, identified risk, and implemented effective mitigation strategies to ensure timely completion.
- Guided and helped in preparing bids and contract documents for construction projects.

• **Site Engineer** [03.2020 – 12.2021]
Environmental Services Solution Consultancy, Freetown, Sierra Leone

- Helped in the analysis and design of structural elements of the proposed facilities.
- Supervised, monitored, and control the implementation of public works at Port Loko District, including schools, market centre, and Hand dug wells.
- Prepared bid document and Bill of Quantity take-offs (Estimate).
- Helped in Collaboration and coordination of project works within project team members.
- Provided high level report to the project manager (PM) on the status of the project.
- Provided mentorship on the new technical resource.

• **Team Lead (State Volunteer work)** [06.2020 – 07.2020]
Office of Presidential Infrastructure Initiatives, Freetown, Sierra Leone

- Managed manual survey to determine the traffic volume count in the Jui-Hastings corridor to ensure representative data are obtained during the survey process.
- Provided survey forms for the enumerators when needed and on time to collect data required.
- Ensured that the placement of enumerators is safe.
- Proffered solutions that will match-up to unexpected weather change.
- Prepared daily report on the traffic conditions and all obstructions within the Jui-Hastings Corridor.

Scientific Publication

1. Yamin J.M, and Koroma S.A. (2023). Critical Factors Influencing the Adoption of Built Operate Transfer (BOT) System in The Gulf Areas: A Comprehensive Review, 5th Conference on Sustainability in Civil Engineering (CSCE'23). *Construction Engineering and Management, KFUPM, KSA* (Published)

Skills

- Construction planning and scheduling tool (e.g. Primavera, MS project, Power BI)
- Microsoft Suite (MS Word, MS Excel, MS Visio Drawing & MS PowerPoint)
- Building information modelling (e.g., AutoCAD, Revit, Navis work, Python, Synchro, Lumion, Sketchup, Prota-structure, Teckla Structure, Plan swift, and Civil 3D)
- Geographic Information Systems (e.g., ArcGIS)

Additional Skills

- Design, Construction and Project Management
- Community stakeholders' engagement and consultation.

Core Competencies

- Strong analytical and problem-solving abilities
- Excellent communication and interpersonal skills
- Teamwork and collaboration
- Time management and organizational skills
- Fuzzy Synthetic evaluation (FSE)

- Analytical Hierarchy Process (AHP)

Countries of Work Experience

- Sierra Leone and Saudi Arabia.

Academic and Practical knowledge courses

- Structural Design
- Materials and Construction Technology
- Project Management
- Construction Management and Building Economics
- Computer Aided Design -AutoCAD and Revit

Languages

- [For each language indicate proficiency: good, fair, or poor in speaking, reading and writing]

Language	Speaking	Reading	Writing
English	Good	Good	Good
Arabic	Fair	Fair	Fair
Temne	Good	Fair	Fair
Krio	Good	Good	Fair

References

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Certification

I, the undersigned, certify that to the best of my knowledge and belief, this CV correctly describes me, my qualifications, and my experiences. I understand that any willful misstatement described herein may lead to my disqualification or dismissal, if engaged.



Date: 23 12 2024