INTERNATIONAL JOURNAL OF INTEGRATED ENGINEERING
ISSN: 2229-838X e-ISSN: 2600-7916

IJIE

Vol. 17 No. 7 (2025) 312-325
https://publisher.uthm.edu.my/ojs/index.php/ijie

Exploring The Application of Deep Learning in Enhancing The QLASSIC: A Review

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DOI: https://doi.org/10.30880/ijie.2025.17.07.029

Article Info

Received: 19 February 2025
Accepted: 4 July 2025
Available online: 31 December 2025

Keywords

QLASSIC, deep learning, defect detection

Abstract

As society evolves, there is a growing demand for high-quality living spaces. However, defects in new housing have become a growing concern for homeowners. To address this, the Construction Industry Development Board Malaysia (CIDB) introduced the Quality Assessment System in Construction (QLASSIC), quantifying construction quality. Meanwhile, deep learning has emerged as a highly accurate method for defect detection, surpassing traditional techniques and gaining widespread use in various industrial applications. This paper searches and analyses the keywords of 181 articles using the Google Scholar database. It first explores housing quality assessment practices from various countries as the research background. Then it centres on reviewing the current QLASSIC practices. Since QLASSIC evaluates construction quality largely through visual defects (comprising approximately 70% of its criteria), the potential application of deep learning, which has attracted significant interest, is also being discussed. Towards the end of this review paper, future research directions are also suggested.

1. Introduction

The housing construction industry in Malaysia is progressing towards higher quality standards [1]. To enhance the execution levels of construction projects and the quality of the homes delivered, many construction companies have implemented various Quality Management Systems (QMS) in their project management practices, including ISO 9001and Total Quality Management (TQM) [2], [3]. However, quality issues in newly constructed homes continue to present significant challenges. According to the new house owners' satisfaction survey, 63% of consumers expressed dissatisfaction with the condition of their newly purchased homes, primarily due to various defects adversely affecting overall quality [4]. Data from the Construction Industry Development Board Malaysia (CIDB) Construction Law Report confirms the existence of quality defects in residential projects, with an increasing trend observed year on year [5]. In response to these challenges, CIDB has established a standardised system known as the Quality Assessment System in Construction (QLASSIC), designed to evaluate and quantify the quality of construction projects [6].

The primary advantage of QLASSIC lies in the standardisation of construction quality, ensuring consistency and transparency in project evaluations [7]. Contractors and developers adhering to the QLASSIC standard can adopt higher workmanship standards, thereby enhancing their reputation within the construction industry.

Projects that achieve high QLASSIC ratings typically exhibit fewer defects upon completion, allowing owners to experience reduced construction flaws and improved building performance, which in turn leads to higher satisfaction levels [8]. Furthermore, the widespread application of QLASSIC has elevated the image of Malaysia's domestic and international construction industry, positioning it as a vital tool for benchmarking against global best practices.

Traditional machine vision defect detection methods require specialised manual design and extraction of image features; meanwhile, deep learning methods can automatically extract features and have strong target recognition capabilities. Therefore, researchers have attempted to apply deep learning technology to defect detection, achieving an accuracy that exceeds that of traditional methods. In addition, deep learning has demonstrated significant potential for building defect detection [9], [10]. Its automation capabilities significantly enhance the efficiency and accuracy of defect identification, reducing the time required for manual inspections and mitigating safety risks. The compelling feature extraction and multi-defect recognition capabilities of deep learning enable precise localisation of subtle defects, such as cracks, leaks, and corrosion, thereby significantly improving detection accuracy [11]. Moreover, deep learning supports data-driven decision-making by analysing historical data and predicting building materials' lifespan and defect trends, which facilitates proactive maintenance, reduces labour costs, and extends the longevity of structures [9]. When integrated with augmented reality (AR) and virtual reality (VR) technologies, deep learning not only provides real-time visualisation of inspection results but also serves as a training tool for industry professionals, enhancing their detection skills [12]. Importantly, deep learning models possess self-optimising capabilities, allowing for the integration of data from various sensors, further enhancing the comprehensiveness and accuracy of defect detection [13]. In summary, deep learning offers substantial value in enhancing the safety and durability of buildings, and its applications are expected to continue evolving and expanding as technology advances. It is worth noting that the scope will focus on residential developments in Pahang, primarily targeting the assessment and detection of craft quality using the visual method outlined in the CIS 7 quality standard. And the limitation lies in the assessment of hollowing and functionality issues, which require specialised tools or methods.

2. Methodology

This paper searched the Google Scholar database for 18 papers using the keywords "QLASSIC" and "deep learning" over the past 5 years. However, it was found that the literature combining the two is a research gap, as evidenced by browsing abstracts and conducting qualitative analysis using a keyword method. Therefore, it used the snowball method to recombine keywords. Through the keywords "housing quality assessment" and "QLASSIC", 132 papers were identified, and 11 types of housing quality assessment systems were categorised by analysing the abstracts and keywords. Additionally, the keywords "deep learning in the construction industry" and "QLASSIC" were used to search for 31 papers, and three application types of deep learning in the construction industry were summarised through theme analysis. Based on the above analysis, it is found that the application of deep learning in QLASSIC detection is feasible.

3. Overview of the QLASSIC System

Since introducing the BS 5750 quality system standard in the UK, the construction industry has adhered to the concept of quality assurance certification for 45 years, since 1979. The adoption of the international standard ISO 9000 in construction began in 1987 [14]. However, despite the rapid growth of the construction industry, quality issues continue to be a significant bottleneck hindering urban development. To address construction quality problems, regulatory authorities in various countries have implemented relevant policies and regulations based on the ISO 9000 quality system standard [15], [16]. The quality supervision models and evaluation systems employed differ across countries and regions.

Table 1 *Summary of assessment systems*

System names	Countries	Dates of creation	Assessment contents
QUALITEL [17]	France	1974	Noise assessment, thermal durability assessment, and sanitary facility assessment for housing
Construction Quality Assessment System (CONQUAS) [18]	Singapore	1989	Construction quality throughout the building lifecycle and contractor performance

System names	Countries	Dates of creation	Assessment contents
Building Research Establishment Environmental Assessment Method (BREEAM) [19]	UK	1990	Environmental assessment and resource consumption of all buildings
Performance Assessment Scoring System (PASS) [20]	China Hong Kong	1991	Construction quality throughout the building lifecycle
Building Environmental Assessment Method (BEAM Plus) [21]	China Hong Kong	1996	Evaluation of environmental performance levels and technological innovations of buildings from a sustainability perspective
Leadership in Energy and Environmental Design (LEED) [22]	USA	1998	Assessment of environmental performance levels of buildings from a sustainability perspective
National Australian Built Environment Rating System (NABERS) [23]	Australian	1999	Assessment of environmental performance levels of buildings from a sustainability perspective
Comprehensive Assessment System for Built Environment Efficiency (CASBEE) [24]	Japan	2002	Environmental assessment, performance evaluation, and renovation
Portuguese acronym of Leverag (Líder A) [25]	Portugal	2005	Assessment of environmental performance levels of buildings from a sustainability perspective
Quality Assessment System in Construction (QLASSIC) [26]	Malaysia	2006	Quality of workmanship in buildings
GB50375 [27]	China Mainland	2006	Construction quality throughout the building lifecycle

Table 2 *Weight allocation according to QLASSIC in residential buildings*

Components	Category A Landed housing			Category B Stratified housing		
CIS7 versions	2006	2014	2021	2006	2014	2021
Structural works	25	15	0	30	20	0
Architectural works	60	70	85	50	60	83
M&E works	5	5	2	10	10	3
External works	10	10	13	10	10	14
Total score	100	100	100	100	100	100

Table 3 *Weight allocation according to QLASSIC in non-residential buildings*

Components	Category C Public building			Category D Special Public building		
CIS7 versions	2006	2014	2021	2006	2014	2021
Structural works	30	20	0	30	20	0
Architectural works	45	55	82	35	50	80
M&E works	15	15	4	25	20	5
External works	10	10	14	10	10	15
Total score	100	100	100	100	100	100

As shown in Table 2 and Table 3, the relative weightings of the various components remained largely stable between CIS 7:2006 and CIS 7:2014. However, significant changes were introduced in CIS 7:2021, which eliminated the assessment of structural works, increased the emphasis on architectural works, substantially reduced the proportion allocated to M&E works, and slightly adjusted the weighting for external works.

Generally, the QLASSIC assessment process is characterised by its meticulous and precise nature. To begin with, the building developer, contractor, or project owner submits an assessment application to CIDB. Upon approval, CIDB dispatches qualified assessors to the site, who determine the sampling quantity and specify the actual evaluation locations based on the construction drawings. The sample criteria outlined in the CIS 7 guide the specific sampling locations and quantities. Following the sampling plan and under the QLASSIC assessment standard, assessors conduct on-site inspections of structural engineering, building engineering, mechanical and electrical services, and external works, using professional tools and assessment forms. To encourage contractors to "get it right the first time and every time," QLASSIC scoring is applied exclusively to the initial inspection of the works. Upon completion of the on-site inspection, the assessors calculate the final score based on the proportion of compliant samples and their respective weightings, after which CIDB issues a project-based assessment report [30].

Numerous studies have investigated the effectiveness of QLASSIC in enhancing building quality in Malaysia [29], [33], [34]. Findings indicate that projects adhering to the QLASSIC standard generally exhibit a significant reduction in defects compared to those without [33]. Furthermore, buildings assessed under the QLASSIC framework demonstrate superior performance in terms of durability and maintenance costs. Although implementing QLASSIC has brought significant benefits to the Malaysian construction industry, it still faces several challenges. The successful implementation of QLASSIC requires that construction firms and workers understand the assessment standards. However, the presence of a large number of non-skilled workers in the Malaysian construction sector complicates the training process. Furthermore, some contractors, particularly smaller ones, resist adopting QLASSIC standards due to a lack of resources or technical expertise. These challenges need to be addressed to promote the implementation rate of QLASSIC, which is typically present in Malaysia's housing projects.

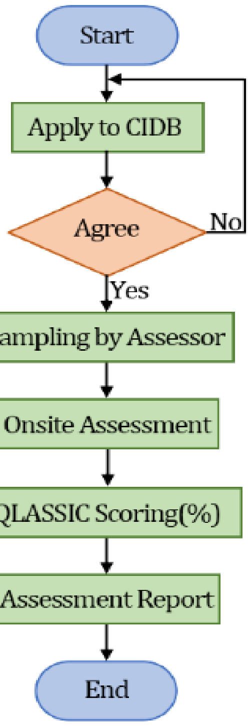

Fig. 1 *QLASSIC assessment process*

4. Deep Learning Fundamentals

Deep learning, a significant branch of machine learning, mimics the structure and function of the human brain's neural networks [35]. By learning from vast amounts of data, computers can automatically extract features and perform intelligent processes, such as classification and recognition. The remarkable performance of deep learning has propelled the third wave of artificial intelligence, with the majority of leading applications now utilising deep learning methodologies [36]-[38].

The concept of deep learning originates from the study of artificial neural networks. It can be regarded as an advancement built upon traditional neural network architectures, effectively synonymous with neural networks [39]. Consequently, many deep learning algorithms incorporate the term "neural network," exemplified by architectures such as Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), and Generative Adversarial Network (GAN) [40].

CNN excels in image processing by preserving image features through convolutional layers, followed by dimensionality reduction via pooling layers [41], [42]. The processed data from these layers is input into fully connected layers to produce the desired output. CNN efficiently reduces the dimensionality of large image datasets without compromising results, while retaining the features of images in a manner consistent with human visual processing principles, thereby adhering to the principles of image processing. They are commonly employed in applications such as image classification and retrieval, object detection, segmentation, facial recognition, and product quality control [43]-[47].

RNN is an algorithm specifically designed to effectively handle sequential data, representing an advancement over traditional neural networks [48], [49]. RNN incorporates the output from the previous time step into the hidden layer of the next time step, facilitating joint training. Due to their inherent memory capability, parameter sharing, and Turing completeness, RNN is highly efficient at learning the nonlinear characteristics of sequences. Consequently, they are frequently employed in applications such as text generation, speech recognition, machine translation, image captioning, and video tagging [50]-[54].

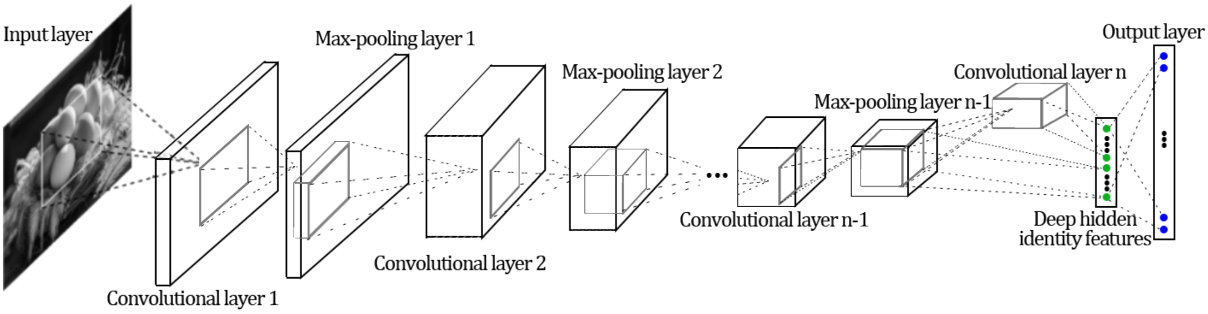

Fig. 2 *CNN structure*

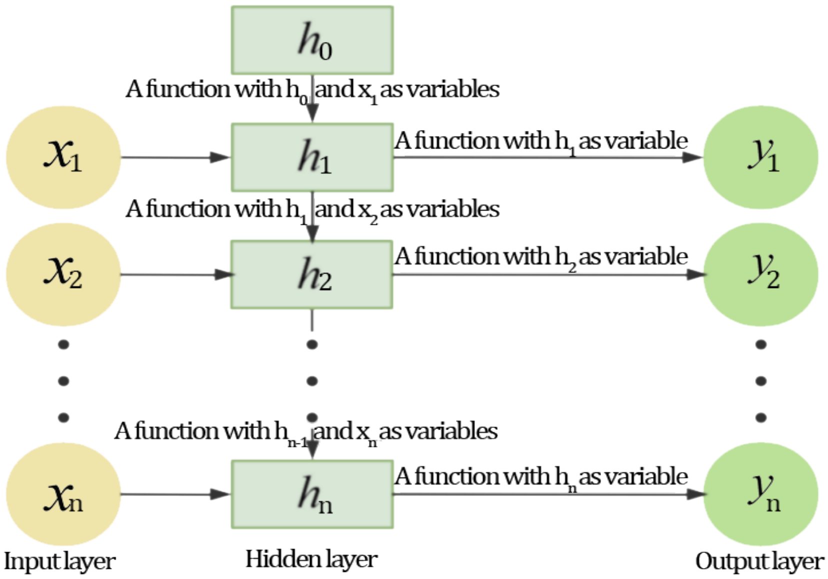

Fig. 3 *RNN structure*

GAN has emerged as a highly popular unsupervised learning algorithm in recent years, capable of automatically annotating training datasets while continuously optimising the process [55]-[57]. This approach is both highly efficient and cost-effective. In GAN, the discriminator is initially fixed, and the generator produces data that serves as the training set for the generator itself, intending to deceive the discriminator. Once the generator is able to fool the discriminator successfully, further training of the generator becomes redundant. At this stage, the generator is fixed, and the discriminator is trained using both real data and data generated by the generator until it can accurately distinguish between all fake images and real ones. Theoretically, GAN can train any type of generator network, leading to a significant increase in research interest in GAN. They are commonly utilised in scenarios such as generating image datasets, producing photographs and cartoon characters, and generating images from text, semantics, and other visual inputs [58]-[62].

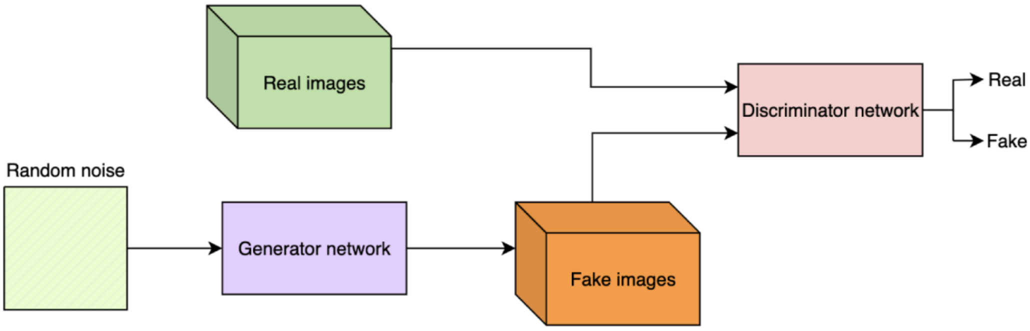

Fig. 4 *GAN structure*

In contrast to traditional machine learning algorithms, deep learning excels in feature extraction by relying on automatic processes rather than manual intervention. The results demonstrate its remarkable performance and strong learning capabilities, supported by a variety of frameworks such as TensorFlow and PyTorch [63]-[65]. Deep learning architectures, characterised by numerous layers and extensive breadth, theoretically possess the ability to approximate any function, thereby enabling the resolution of highly complex problems. However, deep learning is highly dependent on the availability of data; the larger the dataset, the better the performance tends to be. Currently, in specific tasks such as image recognition, facial recognition, and natural language processing (NLP), deep learning has surpassed human performance in some instances. This highlights the transformative potential of deep learning methodologies across various domains, including defect recognition and classification.

5. Application of Deep Learning in The Construction Industry

Deep learning has become the method of choice in image analysis due to its exceptional performance in feature extraction and object recognition in images and videos [66]. The general workflow of deep learning encompasses the collection of datasets, dataset preprocessing, design and training of neural networks, model evaluation and selection of the optimal function.

In recent years, deep learning has increasingly become a key tool in driving innovation and improving efficiency within civil engineering [67]-[69]. Specifically, its applications have demonstrated strong potential and broad prospects in critical research areas, including structural damage detection, monitoring construction worker safety, and predicting building energy demand.

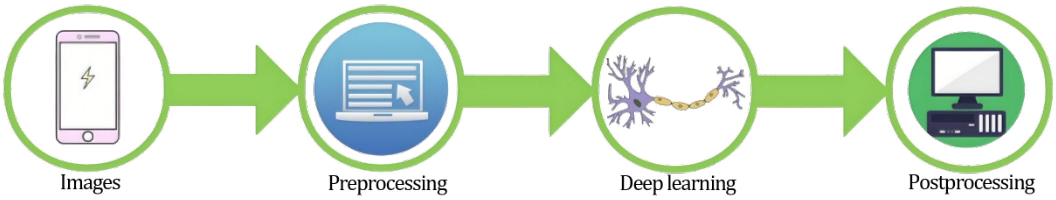

Fig. 5 *Deep learning process*

5.1 Structural Damage Detection and Prediction

Structural damage detection has long been a central research focus in civil engineering [9]. For instance, Nex et al.. [70] demonstrated that CNNs outperform traditional image analysis approaches in detecting visible structural damage. Zhong et al. [71] utilised CNNs to automatically classify building quality issues, improving the efficiency of complaint management by classifying the textual contents of Building Quality Complaint (BQC) documents. Yu et al.. [72] proposed a novel deep CNN-based method that can automatically identify and locate damage in building structures equipped with intelligent control systems, starting from raw signals or low-level features.

Crack detection is an essential component of the maintenance and assessment process for concrete structures. Deep learning algorithms have been widely applied to automatically detect concrete cracks, spalling, and cracks in asphalt pavement. For example, Li & Zhao [73] modified the AlexNet architecture to design a CNN capable of detecting cracks in real concrete surface images. In the study by Liu et al. [74], an improved pixel-level Mask R-CNN detection model was proposed to automatically detect vertical cracks in asphalt pavement base layers detected by Ground Penetrating Radar (GPR). Fei et al.. [75] introduced an efficient deep network called CrackNet-V, which is used for pixel-level crack detection in 3D asphalt pavement images.

Additionally, Structural Health Monitoring (SHM) has garnered considerable research interest. For example, Oh et al. [76] demonstrated the effectiveness of CNN-based methods for predicting the seismic response of building structures through numerical studies on the ASCE benchmark model and experimental research on reinforced concrete frame structures. Liao et al. [77] proposed a shear wall design method based on GANs, which learns from existing shear wall design documents and intelligently conducts seismic design quickly. Fan et al. [78] introduced a powerful deep learning model, SegGAN, a segment-based Conditional GAN, for reconstructing structural responses under extreme loading conditions, such as seismic loads.

5.2 Construction Worker Safety Monitoring

The labour-intensive nature of the construction industry exposes workers to high safety risks [79]. Workers are often subjected to heavy physical loads, and accidents, particularly falls, are common during high-altitude work. As a result, effectively monitoring the safety of construction workers, particularly their physical load and fatigue levels, has become a critical research focus. For example, Yang et al. [80] combined wearable sensors with a variant of RNNs to track lower-body movements of workers during physical load tasks. Yu et al. [81] combined CNNs with fatigue models and biomechanical analysis to automatically detect the fatigue levels of construction workers. Nath et al. [82] utilised CNNs to automatically detect the use of personal protective equipment by construction workers from images, ensuring that workers consistently adhere to safety regulations during their work.

5.3 Building Energy Demand Forecasting

The continuous growth in global building energy demand, coupled with the pressures of the energy crisis and environmental impact, has led to an increasing need for reliable energy demand forecasting models. Somu et al. [83] proposed a deep learning-based energy consumption prediction model, CNN-LSTM, which operates on energy consumption data recorded at predefined intervals and is capable of learning the spatiotemporal dependencies in energy consumption data. Kim & Cho [84] introduced a CNN-LSTM neural network that extracts spatial and temporal features to effectively predict residential energy consumption. In the research by Tian et al. [85], a GAN-based approach for parallel forecasting of energy consumption in buildings was proposed. This approach generates parallel data from a small amount of original data sequences using GANs, creating a hybrid dataset of original and synthetic data for building energy consumption time series forecasting.

In summary, integrating deep learning into the construction industry has not only enhanced the level of intelligence but also played a crucial role in improving safety, reducing energy consumption, and optimising resource allocation. These advancements have propelled the construction industry toward a more sustainable and green future [86]-[88].

6. Specific Applications of Deep Learning in Defect Detection

The QLASSIC assessment is fundamentally based on defect groups, with approximately 70% of the evaluation focusing on visual assessments. If homeowners can visually identify defects, it is indicative of underlying issues with workmanship. However, relying solely on visual inspection is insufficient for a comprehensive and accurate assessment of workmanship quality. In such instances, homeowners may require simple tools to facilitate further detection and evaluation, including cameras, markers, tapping rods, and measuring tapes. These tools help homeowners systematically record and inspect potential issues.

For more complex and detailed inspections, professional tools such as L-squares, steel wedges, gauges, and angle finders are necessary [30]. Due to their intricate operation, these tools are typically employed exclusively by trained inspection personnel to ensure the accuracy and reliability of the assessment results. Integrating deep learning technologies into this evaluation process can enhance the detection and analysis of defects, thereby improving overall assessment efficacy.

Table 4 *Assessment and inspection tool/ method in QLASSIC*

Defect groups	Tools/ Methods
Finishing	Visual, Visual & Physical
Alignment and Evenness	Visual, Spirit level 1.2 m & Steel wedge, Spirit level 1.2 m, L-square (200 mm × 300 mm) & Steel wedge, Visual & Physical, Visual & Spirit level 1.2m, L-square (200 mm × 300 mm), Physical & Auditory, Visual & Spirit level
Cracks and Damages	Visual, Visual & Physical, Visual & Angle Mirror
Hollowness/ Delamination	Tapping rod & Auditory, Visual & Physical
Joints and Gaps	Visual, Visual & Physical, Steel wedge, Steel gauge, Steel measuring tape, Visual & Steel measuring tape
Materials and Damages	Visual, Visual & Physical
Functionality and Safety	Visual & Physical, Physical, Physical & Auditory

Since 2014, deep learning algorithms have gradually emerged in the construction industry, rapidly becoming a research hotspot in this field [9]. Deep learning has demonstrated significant application potential in defect detection and classification tasks [9], [89], [90], with related studies achieving an accuracy rate of 97.8% [91].

By employing advanced deep learning algorithms such as CNN, Deep Belief Network (DBN), and Stacked Auto-Encoder Network on existing datasets, including the House Dataset [92] and TianChi [93], it is possible to learn from vast amounts of architectural defect image data [94]. These methods enable the automatic identification of defects such as cracks, water infiltration, and spalling, thereby providing essential theoretical and technical support for deep learning defect detection methods based on QLASSIC. Despite significant advancements in the application of deep learning for building defect detection [95]-[97], particularly in image processing and automated inspection, research integrating deep learning with building quality management systems remains largely unexplored. More critically, the lack of standardised defect categories and benchmarks has led to challenges in achieving consistency in defect identification and analysis within quality assessment frameworks. Consequently, the integration of deep learning with QLASSIC holds substantial potential for achieving comprehensive, accurate, and systematic evaluations of building quality. Notably, this research could lead to further developments in the standardisation of defect categories, the generalisation of recognition algorithms, and their adaptation to existing quality management systems.

7. Conclusions

This paper explores the application of deep learning methods within the QLASSIC system, highlighting its significance in several key areas:

- Enhancing the adoption of QLASSIC and upholding high-quality standards. In the context of housing construction, stakeholders include individuals or organisations directly involved in or associated with construction projects. From the developer's perspective, there is a desire for all real estate projects to meet high-quality standards. QLASSIC can assess the construction standards upheld by various contractors and identify any quality issues within buildings. From the contractor's viewpoint, a higher QLASSIC score indicates superior project quality, thereby fostering trust in their capabilities. For end users, homeowners have the option to engage independent QLASSIC assessors to evaluate their properties, ensuring timely insights into safety and construction defects, thus safeguarding their rights. Furthermore, local and governmental authorities recognise QLASSIC as a widely accepted building quality assessment framework, playing a vital role in enhancing industry management and regulation.
- Streamlining workflows to save time and reduce rework costs. The defect detection method discussed in this paper requires developers to acquire a thorough understanding of QLASSIC principles, eliminating the need for extensive user training. This reduces reliance on specialised equipment and manual labour, allowing for automated report generation. Contractors and homeowners can promptly address maintenance recommendations, which enhances overall efficiency, reduces costs, and ensures data consistency and reliability.
- Automated reporting and efficient communication. Traditional defect detection processes often involve manual measurement and data entry, which are time-consuming and prone to errors, frequently resulting in redundant work and resource waste. The defect detection method presented herein can automatically identify and document various defects within buildings, presenting critical information regarding defect types and severity in photographic form within reports, along with appropriate maintenance recommendations. Automated reporting of assessment results is conveyed through intuitive charts and images, facilitating quick and efficient communication among project stakeholders regarding quality standards, discrepancies, and corrective actions.

In summary, this paper reviews the development of QLASSIC and its application to date, focusing on the challenges and potential improvements of this assessment method. In addition, the potential integration of deep learning technologies, which holds significant promise for the application of QLASSIC, yet there remains room for improvement and further research is also being discussed and highlighted. It is suggested that QLASSIC be integrated with quality management systems from other countries or regions, particularly in structural works and sustainability performance assessment. This integration could deepen theoretical discussions and open new avenues for the practical application of QLASSIC. However, it is important to note that the effective training of deep learning models typically requires substantial amounts of data. The challenges posed by data privacy issues, which often result in a scarcity of training data, significantly limit the accuracy and efficacy of these models. Therefore, future research should focus on exploring innovative approaches to effectively address the challenges presented by data privacy.

Acknowledgement

The authors gratefully acknowledge the financial and technical support provided by the Universiti Malaysia Pahang Al-Sultan Abdullah (UMPSA) through grant RDU250322. The support for the laboratory used from Ningxia College of Finance and Economics, China was equally acknowledged and appreciated.

Conflict of Interest

The authors declare that they have no conflict of interest regarding the publication of this paper.

Author Contribution

*The authors confirm contribution to the paper as follows: **Study conception and design:** Lian Huahua, Lim Kar Sing, Liew Siau Chuin; **Data collection:** Lian Huahua, Lim Kar Sing, Lu Yang, Bao Chao; **Analysis and interpretation of results:** Lian Huahua, Lim Kar Sing; **Draft manuscript preparation:** Lian Huahua. All authors reviewed the results and approved the final version of the manuscript.*

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