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DETECTING BUILDING DEFECTS WITH DEEP LEARNING

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Abstract Building defects on external walls can include cracks, mould, dampness from waterproofing failures, fungus growth due to high humidity, and paint peeling. These building defects are commonly caused by wear and tear, improper maintenance, and weather conditions. The identification of these defects is very important to maintain the structural health and safety of buildings, which are often a large financial asset. Manual visual inspection is a traditional technique for defect detection and the most laborious way to identify wear defects, in addition to other nondestructive testing procedures that determine defect properties. Advances in DL and computer vision are expected to improve the efficiency of defect detection. For instance, the DL-based YOLOv10 (You Only Look Once) method provides real-time defect detection that is fast and accurate. This study provided the YOLOv10 technique for the automated detection and localization of building defects. In addition, this study not only makes defect detection more efficient but also helps researchers to advance the overall inspection process with more efficiency.

Key words: deep learning, machine learning, artificial intelligence, big data, data science, applied AI, applied mathematics, building health monitoring, structural analysis, architecture,

AMS Mathematics Subject Classification: 68-XX.

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1 Introduction

Degradation of buildings is unavoidable due to weather conditions, wear and tear, and improper maintenance. It is very important to understand the significant types of building defects that can affect various aspects of a building's condition (Faqih and Zayed, 2021 [9]). Building defects such as cracks in walls, water leaks, dampness, mould, paint peeling, and poor construction can lead to the degradation of buildings. Detecting these building defects is important to maintain the structural health and safety of buildings. Building plays a crucial role in the development of cities. Its development with organized maintenance is one of the key characteristics of developed cities. Efficient condition monitoring is essential to sustain its functional requirements (Mohseni et al., 2023 [30]). As per the International Council for Research and Innovation in Building and Construction - Working Commission W086: Building Pathology (CIB-W086) report (Freitas and Peixoto, 2013 [11]), such building defects can accelerate the degeneration of buildings, which can lead to a yearly maintenance cost of up to 5% of the total construction cost.

It is really important to understand different types of defects and the factors affecting them to correctly assess the building condition. Sometimes, minor defects can become major if they are not identified. It can lead to serious issues that will become more challenging to solve. Moreover, one type of defect may cause other types of building defects. Buildings deteriorate at different rates based on their design details, quality of materials, construction methods and standards, environmental conditions, the skill of the workers, and how the building is used. Design is an important factor contributing to hidden defects in buildings. About 66% of the defects discovered early in usage could have been avoided with better design (Chong

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and Low, 2006 [5]). Weather related factors include sunlight, rain, wind, and humidity. When humidity moves from wet areas to dry areas, it can lead to the growth of algae and fungus. Low quality building materials are often damaged by destruction and accidents, and sometimes materials deteriorate faster than expected. Poor design frequently causes issues from loads and residential. Geological problems, such as cracks from soil settlement, can be particularly dangerous. In a study by (Chong and Low, 2006 [5]), these factors were investigated. The authors examined 74 buildings over nine months and found that moisture from damp areas, weather, low material quality, and usage were the primary factors. The study concluded that these defects could be potentially avoided by using better materials, implementing damage prevention measures, treating water leakage, improving design details and conducting thorough site assessments. In addition, many studies have identified the common defects in buildings, such as reinforced corrosion from chemical reactions within the concrete, which reduces the durability of beams and pillars. Roof leakage, caused by water pressure and poor concrete filling. Cement oozing, or salt staining, results from poor construction and an improper mixture of concrete. Cracks and popping in tiles are due to adhesive failure. Wall cracks can occur due to vibrations from the metal support system for the air conditioning system. Exposed metal installations are sensitive to rapid corrosion due to environmental factors. Lastly, a lack of construction knowledge and maintenance expertise plays a major role in building defects (Kian, 2001 [21]) (Marshall et al., 2009 [28]). It is also considered a building defect when weed plants, vines, moss, or roots start growing from cracks in the wall due to dampness which damages the building faΓ§ade. The plant's roots penetrate the wall, causing further cracks and deterioration, which can lead to serious structural damage. Such defects are presented in Figure 1.

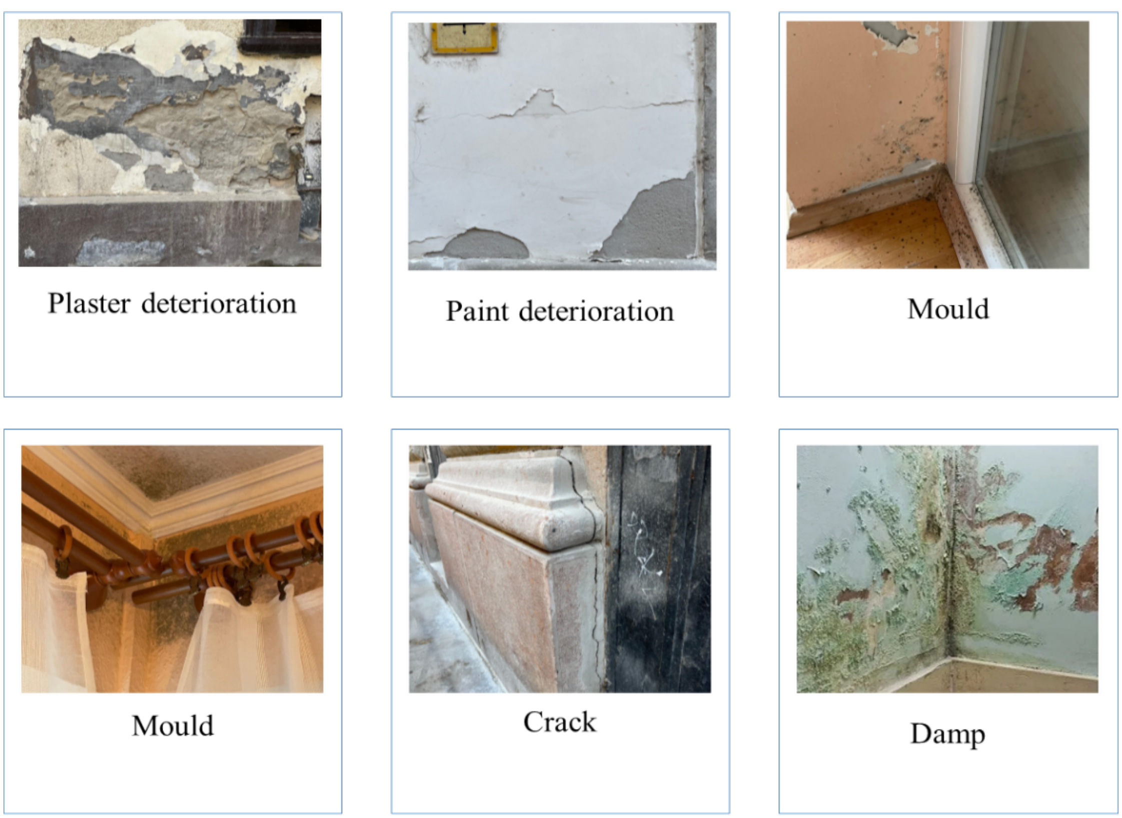

Figure 1: Examples of building defects.

Numerous studies investigate various building defects and provide detailed information. In this study, we will focus on the dampness defect. The term “dampness” refers to the condition where a sufficient amount of moisture causes deterioration in building walls. Dampness in the buildings is caused by many factors, primarily involving the presence and movement of moisture. Moisture in the atmosphere consists of invisible water vapor. This vapor moves in response to temperature changes and can form water droplets. The formation of these droplets on surfaces is caused by condensation, which depends on the temperature and humidity of the air. Leakages from roofs, walls, and issues in plumbing systems can also promote excessive moisture into the building. Another common cause is poor ventilation, which leads to high humidity. Damaged and weak insulation can also contribute to raising the humid air. Additionally, environmental factors like heavy rain and flooding can escalate the dampness issues (Thomas, 1986 [42]). When moisture from the ground rises through a building's walls, rising dampness happens. This occurs as a result of capillary action forcing moisture in an upward direction via porous materials like plaster or bricks. Elevated groundwater levels, inadequate drainage, and deficient damp proofing are some of the factors that cause rising damp. Rain can enter buildings through fences, chimneys, and roof drain systems, especially during windy conditions. This frequently affects wind exposed facades and roofs. Where faulty construction, bad workmanship, bad design, and negligence can make the issue worse. (Bakri & Mydin, 2014 [2]). Dampness can also come from wet areas in buildings, including bathrooms and kitchens, that have poor plumbing fixtures. Dampness changes with different environmental conditions. Additionally, Dampness can leave stains and traces of mould, and moss. When the dampness is visible, it can be seen in the form of mould, fungus, and stains on the surfaces. Such signs confirm that the building is damp.

Dampness and mould have a significant number of serious effects. It can have serious health impacts on adults, children, and infants, affecting the respiratory and allergy systems. There is a higher chance of respiratory illnesses like asthma, bronchitis, and other chronic lung diseases. (Mendell et al., 2011 [29]). According to a review conducted by (Fisk et al., 2007 [10]) dampness-related risk factors in residential buildings are related to significant increases in different important respiratory health issues, including a 50% rise in asthma cases. The electrical system is a critical part of a building's structure. When water leaks due to dampness it can lead to serious short circuits and fire hazards. This can create significant life threatening risks for the occupants. Furthermore, dampness can lead to the corrosion of metal parts in the building structure. This can cause structural damage, weakened stability, and major safety problems. This degradation could potentially affect the building's structural integrity and safety and require expensive maintenance. Lastly, due to dampness, paint and plaster can peel off from walls and roofs, damaging the building's appearance. It can damage floor coverings like tiles and carpets. Paint can also degrade because it expands and contracts due to fluctuations in temperature, seasonal changes, exposure to sunlight, and pollution, leading to flaking, peeling, blistering, and fading. This study focuses on mould, stains, and paint deterioration, which are the most common and interconnected defects resulting from dampness (Thomas, 1986 [42]) (Bakri, & Mydin, 2014 [2]). Buildings that are damp promote the growth of mould, corrosion of metals, wood parasites, and decomposing fungus; all of these are harmful to the health and comfort of residents. In order to prevent dampness, buildings should be well ventilated. Excessive moisture can be eliminated by keeping the surface warm above the dew point temperature. Which can be achieved by proper heating and better thermal insulation (Thomas,1986 [42]) (Bakri & Mydin, 2014 [2]). The service life of existing building structures can be increased by correctly inspecting building defects using an organized condition assessment before they collapse, which can reduce the need for maintenance and repairs (Paulo et al., 2014 [31]).

The basic method for inspecting buildings for defects is human visual inspection. This method is time-consuming, expensive, and labor-intensive. As a result, new methods to support or replace manual inspections are essential (Tan et al., 2024 [39]). In the early stage of defect detection, researchers used visual inspection, vibration testing, and non-destructive testing (NDT) methods to detect the defects. Numerous techniques have been developed to detect defects by analyzing vibrations. These techniques apply to a variety of structures, such as buildings, bridges, dams, and road surfaces (Lifshitz & Rotem, 1969 [25]) . However, these methods have shifted to traditional defect detection approaches, which involve measurement, feature extraction, and classification to identify defects using machine learning (ML) methods. For instance, artificial neural networks (ANN) were used by (Mansour et al., 2024 [27]) to predict the shear strength of concrete beams. Support vector machines (SVM) were utilized by (Hoang, 2018 [16]) to analyze features extracted by image processing and classify them into specific categories, and by (Hadjidemetriou et al., 2018 [15]) for automatically detecting and quantifying pavement patches. Genetic algorithms (GA) and multilayer perceptron (MLP) were compared by (Rababaah, 2005 [36]) to improve the automated classification of asphalt pavement cracks using computer vision. Random forest (RF) was employed by (Shi et al., 2016 [37]) to automatically detect cracks. Fuzzy logic was used by (Pragalath et al., 2018 [35]) to determine damages caused by different types of defects, such as corrosion, mould, fatigue, shrinkage, honeycombing, and loading. Additionally, Bayesian approaches were used to improve the accuracy of assessing building damage after an earthquake, as demonstrated by (Erazo & Hernandez, 2016). On the other hand, computer vision techniques are becoming more popular because they provide clear graphical representation of defect detection in red, green, and blue (RGB) images (Stephen et al., 1993 [38]) (Abdel-Qader et al., 2003 [1]). The defect features still need to be identified manually when using computer vision techniques. It requires a sufficient amount of light to identify the defects. Problems like blurriness and shadows affect their effectiveness, and conventional ML techniques are less efficient at classifying various kinds of defects. It has been a challenge to identify defects with varying light, temperature, and noise conditions. For this, more advanced learning techniques are required to effectively classify these defects. To address the challenges associated with traditional ML methods, (Cha et al., 2017 [4]) proposed a deep learning (DL) method to detect the defects more effectively. DL techniques use multiple layers to analyze and understand the complex data. It is able to automatically identify detailed damage features from images by learning a large labeled dataset. DL has shown significant results in fields like object detection, image recognition, and virtual assistant. In order to improve defect detection, (Cha et al., 2017 [4]) combined DL with a convolutional neural network (CNN) to solve the problem of manually identifying and categorizing damage using traditional approaches. This method automatically extracts required features from images and was able to detect concrete cracks with 97% accuracy even in difficult situations like blurriness and shadows. Furthermore, a faster region-based convolutional neural network (Fast R-CNN) was developed to improve this model. This method shows a high accuracy of 87.8%, allowing for real-time defect detection (Cha et al., 2018 [4]). This study also highlights the development of augmented reality (AR) and unnamed aerial vehicles (UAVs), which make it possible to combine virtual data with real world conditions. This feature shows that AR with UAVs can visualize defect data from computer vision, making inspections more efficient. However, it is also important to discuss the challenges associated with implementing this technology, as highlighted by (Ellenberg et al., 2014 [7]). The literature includes many studies on defect detection, and recent research has increasingly focused on the automated detection of defects using DL in structures damaged by earthquakes (German et al., 2012 [14]) (Ji et al., 2018 [18]) (Vetrivel et al., 2018 [43]) (Tarutal et al., 2020 [40]). In this study, it is important to provide the most recent and commonly used DL methods along with their applications and accuracy, as detailed in Table 1. Along with, a brief summary of each method, and its relevance to building defect detection is also presented to offer a comprehensive understanding of their effectiveness in the field of building defect detection.

Table 1. Identification of building defects using DL methods with their accuracy.

Reference	**Application**	**Modeling technique**	**Accuracy**
Cha et al., 2017	Crack detection in buildings	CNN	98%
Ji et al., 2018	Identification of collapsed building in post- earthquake	CNN	78.6%
Perez et al., 2019	Detecting building defects	CNN	87.50%
Cumbajin et al, 2024	Defect detection in ceramic pipes	CNN	98%
Kalantar et al., 2020	Detection of damaged building in post- earthquake	CNN	76.86%
Kung et al., 2021	Defect detection in building	CNN	87.75%
Vetrivel et al., 2018	Disaster damage detection	CNN, TL	85%
Jayaraju et al., 2022	Crack detection in buildings	CNN, RNN	99%
Garrrido et al., 2021	Identify and classify building faΓ§ade defects	R-CNN	92.8%
Kuchipudi and Ghosh, 2024	Automated detection of building defects	R-CNN	98%
Yang, 2024	Defect detection in building	Fast R-CNN	94%
Lee et al., 2020	Detection of building faΓ§ade defects	Fast R-CNN	62.7%
Wang et al., 2021	Automated detection of building defects	Mask R-CNN	78.97%
Ma, 2020	Detection of collapsed building in post- earthquake	YOLOv3	90.89%
Fu & Angkawisittpan, 2023	Defect detection in heritage buildings	YOLOv5	99.2%
Tan et al., 2024	Detecting building defects	YOLOv5, DeepSORT, AR	78.63%
Jiang et al., 2021	Crack detection in buildings	U-Net	97.82%
Peng et al., 2021	Detection of building defects	Center Net, Fuzzy Clustering	90%
Perez and Tah, 2021	Structural health monitoring of buildings defects	Tensor flow, TL, SSD Mobile Net	80%

A CNN based approach is used by (Cha et al., 2017 [4]) for detecting the cracks on the buildings. The images of these defects are used as a dataset. The proposed network recorded the accuracy of 98% using 40 K images having 256 × 256-pixel resolution. The sliding window technique is utilized for the scanning of high resolution images to obtained the clear vision of defects. This proposed method is very effective at good lighting condition. Infrastructural damage by Haiti 2010 earthquake is assessed by (Ji et al., 2018 [18]) using the CNN method. The dataset is obtained from very high resolution satellite images. Firstly, to reduce the imbalance, three balancing methods are integrated with CNN which are random over-sampling, random under-sampling, and cost-sensitive. After balancing steps, the proposed network achieved the overall accuracy of 78.6% with width larger than 46-pixel resolution. This performance can be improved using more training data using advance ensemble DL methods. Building condition assessment are time and cost consuming, laborious with safety risks. For this (Perez et al., 2019 [34]) proposed a CNN trained network to automatically detect the building defects like mould, fungi, stain and paint deterioration. A total of 2,622,224 $\times$ 224 image dataset are used with Visual Geometry Group 16 (VGG-16) classifier on ImageNet. Different augmentation techniques are used to generate large dataset to make the model more robust. The proposed model is also compared with ResNet-50, and Inception models with class activation mapping (CAM) technique. The model shows an overall accuracy of 87.50%.

An automatic defect detection system is developed by (Cumbajin et al., 2024 [6]), using CNN techniques. The dataset is generated using high resolution camera with good lighting conditions. ResNet is utilized as a CNN network with training from scratch (TFS), transfer learning (TL), and fine-tuning (FT) to achieve the high accuracy of 98% and F1-score of 97.29%. Automatic and visual inspection techniques using remote sensor images are traditional methods to detect building defects. However, shadows and light condition making it more challenging. For this (Kalantar et al., 2020 [20]) developed three CNN models, such as twin model, fusion model, and composite model, using remote sensor images from the 2016 Kumamoto earthquake, Japan. The twin model achieved the highest accuracy of 76.86%. Deterioration of building faΓ§ade are public safety hazard, which required active maintenance and timey repair of building defects. Apart from traditional method, (Kung et al., 2021 [23]) developed a CNN model to automatically detect and localize the building defects. The total 5680 images obtained from UAV with a resolution of 224 $\times$ 224 and 3024 $\times$ 4032 pixels are used as a dataset. The data is augmented to solve the overfitting problem. The proposed model is fine-tuned with transfer learning and VGG classifier and achieved the overall accuracy of 87.75%.

In a study by (Vetrivel et al., 2018 [43]), severe building damages are automatically detected by using 3D images from UAVs. A multiple-kernel-learning algorithm was utilized to integrate the 3D features for classification. The integration of CNN and 3D features significantly achieved the overall accuracy of 85%. The condition of buildings is mostly affected by the environmental condition. It can be in a form of cracks, mould, stain and paint deterioration. (Jayaraju et al., 2022 [17]) focuses on the cracks defect and utilized and compared CNN and Recurrent Neural Network (RNN) methods. The dataset contains 40,000 RGB images of cracks with 4032 $\times$ 3024 pixel. As a result, the CNN method achieved highest accuracy of 99%, whereas RNN achieved only 45% accuracy. (Garrido et al., 2021 [13]) explored the process of defect identification of building faΓ§ades. The data is achieved from InfraRed Thermography (IRT). A total of 826 thermal images were used. The classification of these dataset is done by using spatial and temporal DL models. The spatial model which is Mask R-CNN is used to detect and classify different defects and the temporal model which is Gated Recurrent Unit (GRU) is used to estimate the depth of defects automatically. The proposed Mask R-CNN method achieved an accuracy of 92.8%. A region-based convolutional neural network (R-CNN) method is used by (Kuchipudi & Ghosh, 2024 [22]) to automatically detect and localize the defects in concreter structures. The ultrasonic image dataset is generated with synthetic aperture focusing technique. The performance of the model is compared with the "you only look once" YOLOv4 model. The developed R-CNN model achieved the accuracy of 98%., which was not possible with the YOLOv4 model. In an experimental study conducted by (Yang, 2024 [45]), Fast R-CNN method is used to detect the building defects. For this, building wall cracks are simulated to evaluate the detection accuracy. A 4032 × 3024-pixel image taken by cell phone is used to develop image recognition technology. Later, it is compared with traditional method and DL based methods like Fast R-CNN. Where, the proposed Fast R-CNN model achieved the accuracy of 94%. (Lee et al., 2020 [24]) proposed a monitoring system that detect the building faΓ§ade defects using an object detection method based on DL method to efficiently detect the defect. A Fast R-CNN method is employed to accurately detect the delamination, cracks, peeled paint, and water leaks defects. The image of these defects were obtained using a digital camera with a resolution of 800 × 600. pixels. The proposed Fast R-CNN model achieved an average accuracy of 62.7% for all type of defects. Automatic detection of unreinforced concrete buildings using image segmentation method integrated with Mask R-CNN method is presented by (Wang et al., 2021 [44]) in his study. Street view images of Salina Cruz city, Oaxaca State, Mexico are used as a dataset. The total 10,541 building images are classified using segmentation method. Later using Mask R-CNN the unreinforced concrete buildings are successfully identified with a 78.97% average accuracy.

Figure 2: Taxonomy of DL methods for detecting building defects.

Collapsed buildings in Yushu and Wenchuan earthquake in china are detected and localized using CNN based YOLOv3 model by (Ma, 2020 [26]) in his research study. A sample of 2180 remote sensing images with 416 × 416 pixels are used as a dataset. Three different models which are YOLOv3, YOLOv3-ShuffleNet, and YOLOv3-S-GIoU are utilized and compared to detect the collapsed buildings in post-earthquake. The YOLOv3 model achieved an ideal accuracy of 90.89%. A YOLOv5 based model with Swin Transformer is developed by (Fu &

Angkawisittpan, 2023 [12]) to automatically detect the surface defects of heritage buildings. A total 2400 images with 512 × 512 pixels of moss, cracking, alkalization, staining, and deterioration defects are used. The YOLOv5 model is used for classifying and detecting only plant penetration defects. Whereas, the Swin Transformer is used for image segmentation and detecting other defects like cracking, alkalization, staining, deterioration, and moss. The Swin Transformer achieved 95.78% accuracy while YOLOv5 model achieved highest accuracy of 99.2%. In addition, (Tan et al., 2024 [39]) developed an AR-based defect inspection application using YOLOv5 and DeepSORT algorithms for real-time defect detection and tracking. The proposed system combines computer vision, AR, and building information modeling (BIM) to improve the defect inspection process. To develop the model, a dataset of 7,430 images with a resolution of 2532 × 1170 pixels is utilized. AR-based method achieved an accuracy of 78.63%. (Jiang et al., 2021 [19]) presented an efficient method for defect detection and visualization of buildings using DL based method. The 3D phots are collected using drones and cameras. The U-Net method is used for image segmentation to detect and localize the defect. The developed model achieved an overall accuracy of 97.82%. Building faΓ§ade and its falling is very common building deterioration defect. For this (Peng et al., 2021 [32]) proposed a DL based method to identify debonding defect. An UAVs based thermography detection method is integrated with Center point network and fuzzy clustering to quantify and recognize such defects. A dataset of 1000 images with 640 × 480 pixels is utilized. The proposed model performed accurately and achieved an accuracy of above 90%. (Perez and Tah, 2021 [33]) developed a DL based model to detect the building defects which can be used to assess the condition and health of buildings. The 875 images of building defects such as cracks, mould, stain and paint deterioration are collected for the dataset. Data augmentation technique is used to improve the dataset. VGG image annotator is used to annotate the images. Tensor Flow model is integrated with single-shot multibox detection (SSD) Mobile Nets to detect the defect using mobile phone. This developed real time defect detector performed well and achieved 80% accuracy. After discussing and presenting a brief review of the most used DL methods, a taxonomy categorizing these methods based on their respective authors can be seen in Figure 2. This can provide a clear overview of the different DL methods and their contributions of building defect detection. Considering the above-mentioned DL methods for the application of detecting building defects, it is apparent that CNNs, R-CNN, Mask R-CNN, Faster R-CNN, RNN, TL, YOLO and other ensemble methods are the most popular. Here, it is worth mentioning that the value of accuracy can be different across studies. In addition, the values of accuracy in some studies were calculated for different methods. To ensure a fair comparison of the DL methods, we standardized the accuracy percentage and calculated the average when there were multiple accuracy values are reported. Any possible error is cross checked. The comparative performance analysis of DL methods for detecting building defects using percentage of model accuracy are presented in Figure 3.

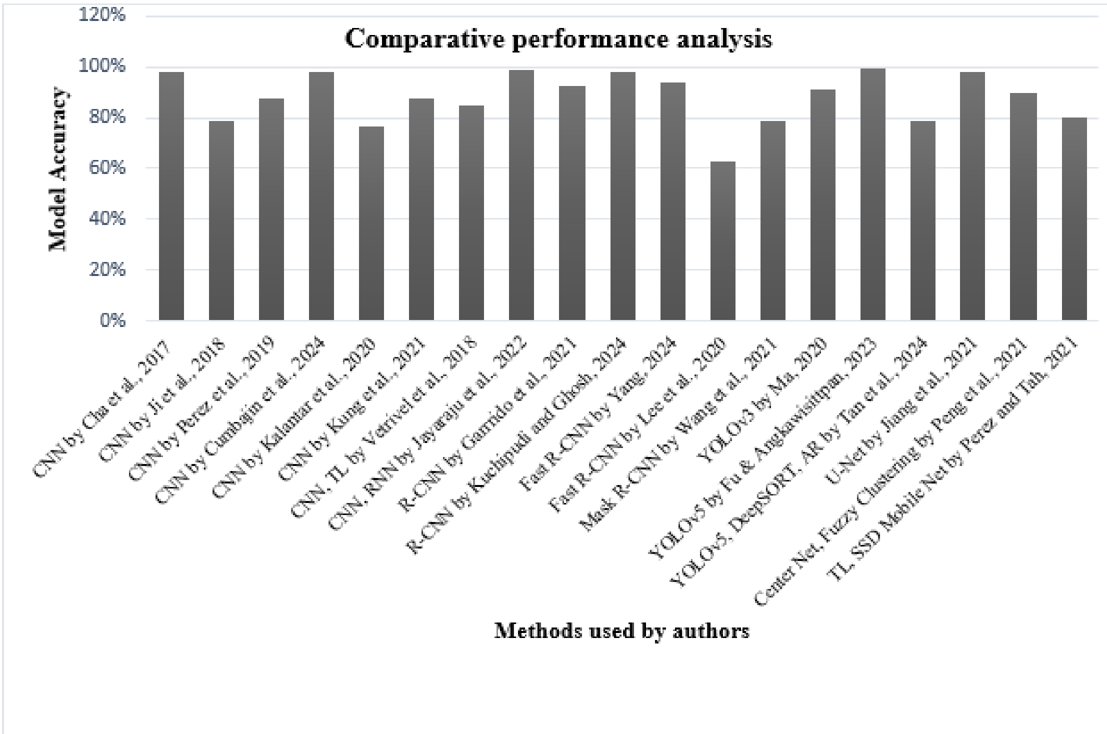

Figure 3: Comparative performance analysis of DL methods for detecting building defects.

It has been notice that, the CNNs are most widely used DL method due to their efficiency and strong performance in handling complex datasets, particularly in the cases where image datasets are not clear. This comparative performance analysis suggests that the limitations of major DL methods such as accuracy, instability, performance, and robustness can be improved by hybridizing different DL methods or using ensemble variations. This trend is likely to develop the future of building defect identification.

Based on the above research, there has been a lack of focus on applying advanced DL techniques to improve the smart sensors for identifying building defects with more efficiency. There is a notable research gap in automated building condition assessments, even though buildings are a major financial asset. The primary aim of this research is to explore the use of the DL-based YOLOv10 method for real-time defect detection. This approach will allow YOLOv10 to perform defect detection processes with high speed and efficiency. This study will focus on detection and localization of key defects in buildings such as cracks, mould, paint peeling, and stains. The analysis process will include only clear images to avoid problems like blurriness and shadows. The future study will explore the limitations and challenges associated with the YOLOv10 method. It is also important to highlight the recent developments that align with the objectives of our research. (Perez et al., 2019) make a significant contribution by employing a DL based CNN method with transfer learning for automatic detection and localization of building defects. This study by (Perez et al., 2019) is related to our research on automated defect identification and its localization. Their research provides insightful information, and we will utilize their dataset to further develop and advance our own research.

2 Materials and Methods:

There are some significant DL networks, such as R-CNN, Faster R-CNN, DNN, and the YOLO series (v1 to v8), have been widely applied to damage detection and localization tasks, identifying issues like mould, dampness, paint deterioration, and other building defects. YOLO is a regression-based method. In order to utilize the YOLO model, an input image is passed through a CNN to extract the features. The image is divided into a grid, and each grid cell's class and location are predicted in a single pass. The objects in each cell are predicted, along with a confidence level. After this, YOLO removed duplicate boxes and kept the most accurate predictions using a method known as Non-Maximum Suppression. The final output is a set of predicted bounding boxes and class labels for each object in the image. Because of this, YOLO is a fast and effective method in identifying multiple factors in one single pass (Ma et al., 2020 [26]). It is worth mentioning that YOLO models simplify the process by using a single regression output to predict both the object class and bounding box coordinates, unlike Fast R-CNN, which uses separate outputs for classification and box coordinates (Terven et al., 2023 [41]). A schematic representation of the YOLOv3 model is shown in Figure 4.

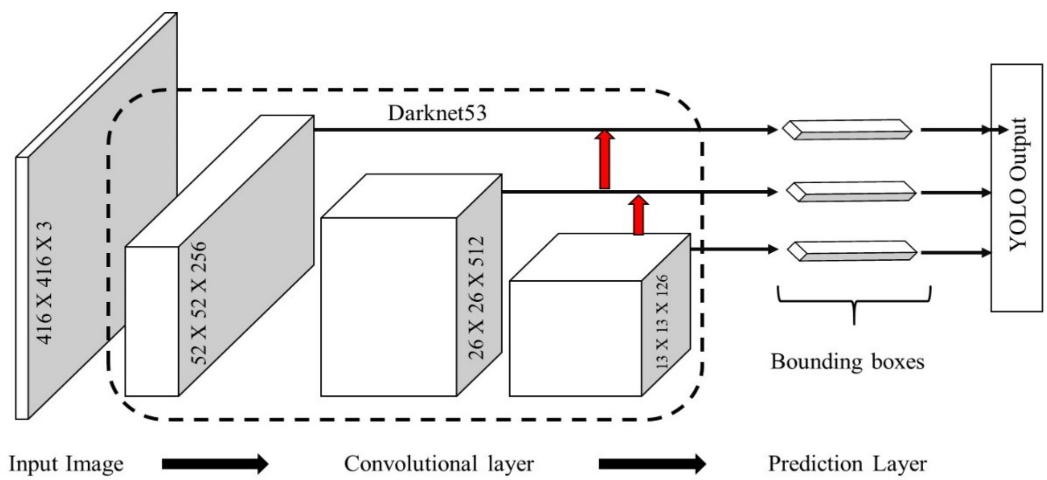

Figure 4: Schematic representation of the YOLOv3 model, with red arrows indicating the process of up-sampling performed twice.

The YOLOv3 network structure, as presented in the study by (Ma et al., 2020 [26]). The process starts with resizing the input image to 416×416×3 pixels. After feature extraction using Darknet53, the image is transformed into a 13×13×126 feature map. Additionally, two more feature maps of size 26×26×512 and 52×52×256 are created. The detection occurs at three different scales. The feature map being up-sampled two times to merge the information across scales. This up sampling helps to provide more accurate detections. Each cell predicts three bounding boxes using anchor boxes, and the best-fitting box is selected. The network predicts the center (XY), width and height (WH), score of confidence, and category of object for each bounding box. The final output is based on the set of predicted bounding boxes and class labels for each object in the image. The YOLO series performs well in balancing speed and accuracy, making it ideal choice for such applications. For example, (Zhang et al., 2022) employed the ResNet18-YOLOv2 model with GPR for automatic void detection on airport runways. (Zhang et al., 2020) utilized YOLOv3 to detect various types of concrete damage in highway bridges. (Yu et al., 2021) developed a YOLOv4 model for UAV-based crack detection on bridges, using focal loss to improve the detection accuracy. (Zhao et al., H]

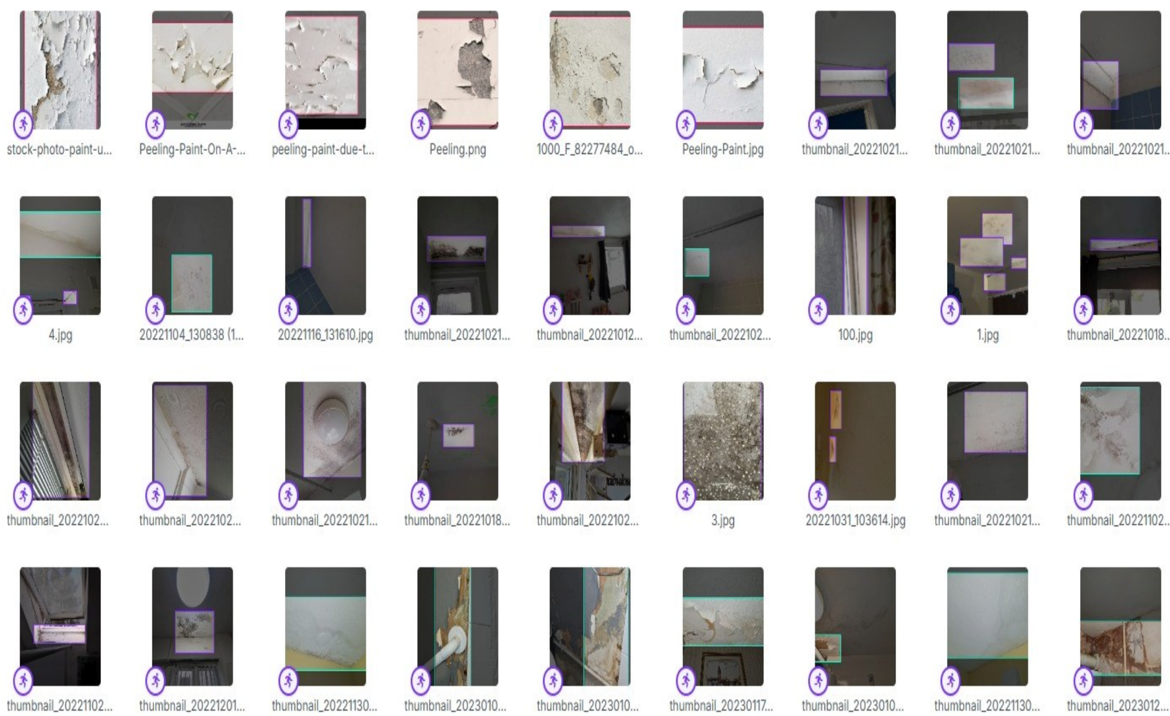

Figure 5: A sample of dataset used to train the model.

2022) proposed a YOLOv5-based method for UAV-based dam damage detection, integrating a 3D reconstruction model to improve performance. It can be concluded that YOLO models have evolved into YOLOv10 by integrating advanced techniques such as ResNet18 and 3D reconstruction to enhance accuracy, speed, and efficiency in object detection. The latest version, YOLOv10, is particularly effective in detecting and localizing building defects. They balance speed and accuracy, making them ideal for real-time damage detection applications like UAV inspections. These models demonstrate improved detection accuracy for issues like mould, dampness, cracks, and other structural damage. Overall, YOLO-based models have proven to be an efficient tool for maintaining the safety and integrity of critical infrastructures, which is why YOLOv10 has been chosen for its superior performance in our study.

This research aims to develop a DL based YOLOv10 model to classify the dampness defects as mould, damp, and paint deterioration as peel. To develop a robust dataset, images of such defects are collected from different sources, cropped, and resized. The sample of image dataset used in this work is shown in Figure.5. The data is labelled into 4 classes such as mould, damp, and peel. The YOLOv10 model is pre-trained on a large dataset and then fine-tuned for this task to achieve the efficient results. In addition, this study also explores the challenges of identifying these defects due to their irregular shapes, colors, and other environmental factors such as location, background, and lighting condition. Further sections detail the dataset preparation, training process, and evaluation results, demonstrating YOLOv10's effectiveness in classifying dampness defects accurately and efficiently.

3 Results

Figure 6. displays the examples of correctly classified defects. The images in this figure illustrate cases where the model successfully predicted the correct class for damp, mould, and

peeling, respectively. Whereas, Figure 7. shows the examples of defects classification errors. The images in this figure demonstrate different cases where the model failed to predict the correct class. As demonstrated YOLOv10 works well in spotting building defects, but its performance depends on the type of defect. Since mould was more common in the dataset, the model learned to detect it more accurately than damp or peeling paint. The plots also suggest that while some defects share similar features, mould stands out more clearly, which explains the stronger results. The confidence curves reveal that the model is precise, but it sometimes misses damp and peeling defects, especially when they are less obvious. The precision-recall curve backs this up, which shows mould as the most reliably detected class. Overall, the model handles clear and well-defined defects well, but to improve detection of subtle ones, we'll need more balanced training data and smarter ways of teaching the model to pick up on fine details.

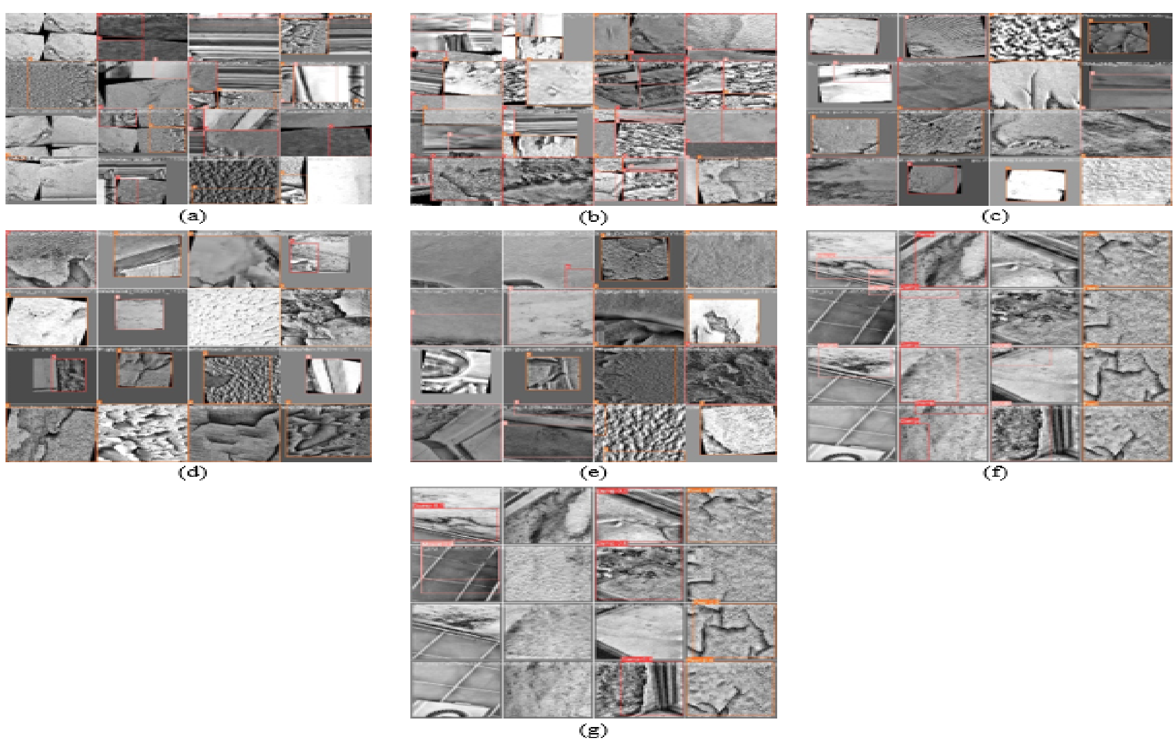

Figure 6: (a) (b) (c) (d) (e) (f) & (g) are the examples of the correct classification.

Figure 7: (a) (b) (c) & (d) are the examples of the classification errors.

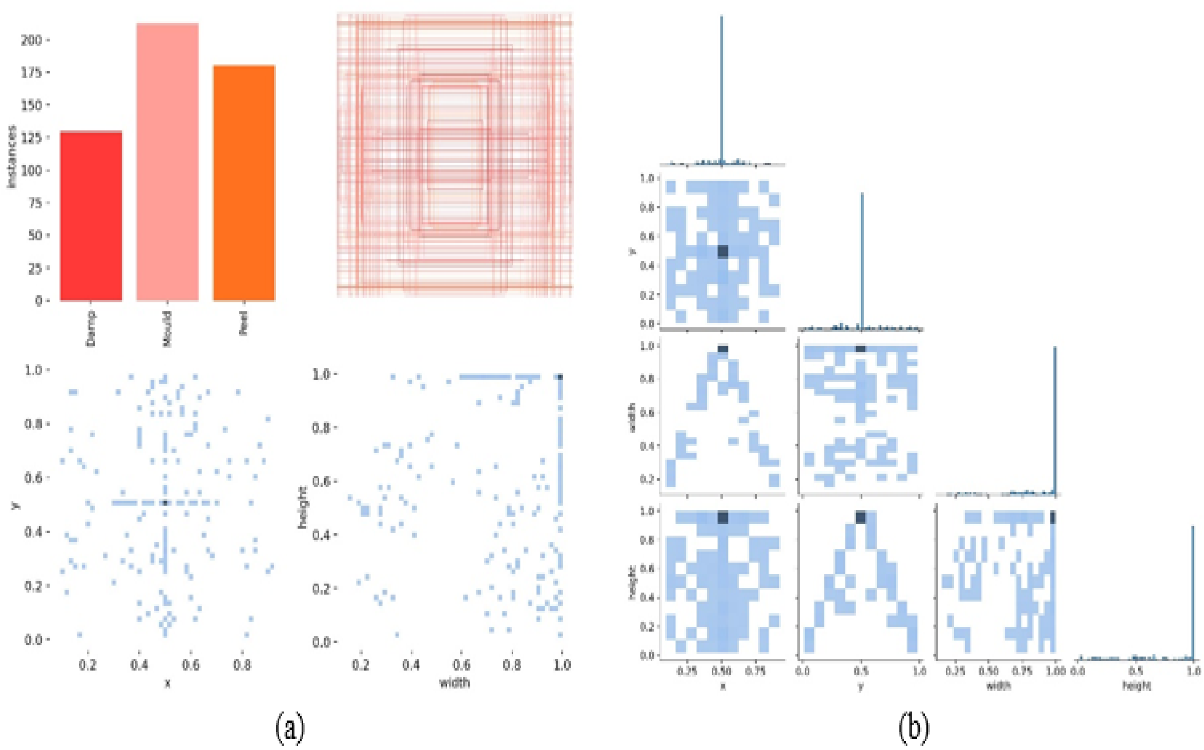

Figure 8: (a) Visualization of Class Lables (b) Correlation Between Class Labels

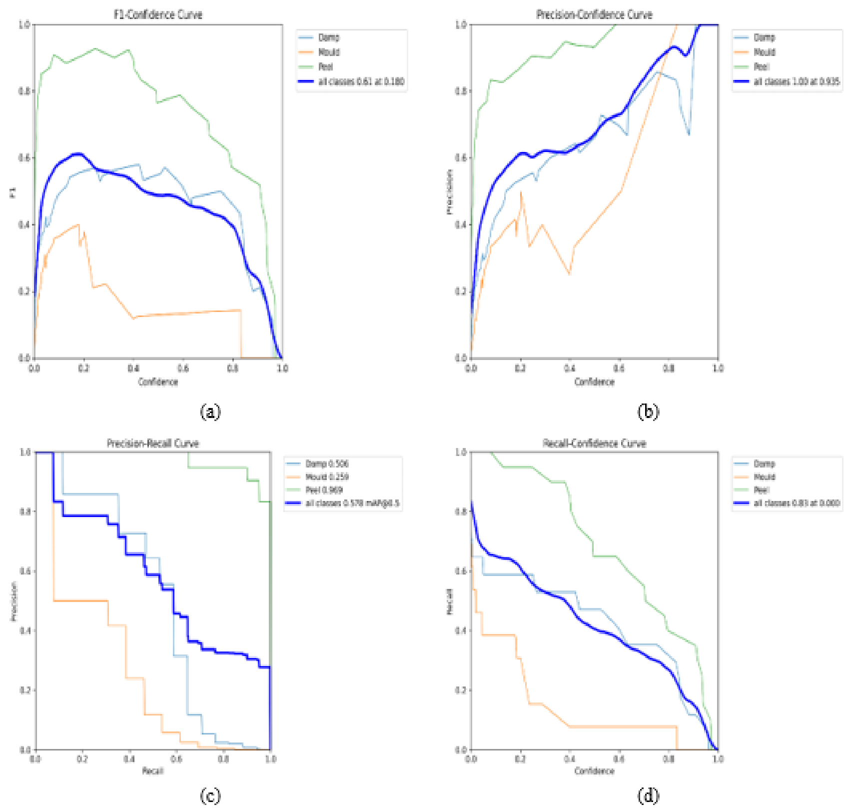

Figure 9: (a) F1-Confidence Curve, (b) Precision-Confidence Curve, (c) Precision-Recall Curve, (d) Recall-Confidence Curve.

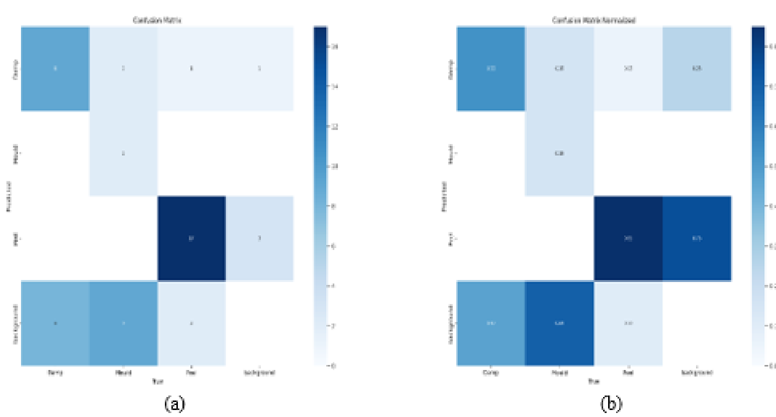

Figure 10: (a) Confusion Matrix, (b) Normalized Confusion Matrix

4 Conclusion

Our results show that the YOLOv10 model can detect building defects with promising accuracy, but performance varies across defect types. The confusion matrices highlight that mould was detected with high precision and recall, while damp and peeling paint showed more misclassifications, which suggests visual overlap or dataset imbalance. The precision-confidence and F1-confidence curves indicate that the model maintains strong precision even at higher confidence thresholds, but recall drops for harder classes like peeling. The precision-recall analysis confirms this trade-off, with mould reaching the best balance while damp lags behind. Overall, the model demonstrates that real-time automated detection of defects is feasible, though improving recall for subtle defects will require more diverse training data or additional feature cues.

5 Abbreviation

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Abbreviation	**Definition**	**Abbreviation**	**Definition**
CIB-W086	International Council for Research and Innovation in Building and Construction - Working Commission W086: Building Pathology	UAVs	Unnamed Aerial Vehicles
NDT	Non-Destructive Testing	VGG-16	Visual Geometry Group 16
ML	Machine Learning	CAM	Class Activation Mapping
ANN	Artificial Neural Network	FT	Fine Tuning
SVM	Support Vector Machine	3D	3 Dimensional
GA	Genetic Algorithm	RNN	Recurrent Neural Network
MLP	Multilayer Perceptron	IRT	InfraRed Thermography
RF	Random Forest	GRU	Gated Recurrent Unit
RGB	Red, Green, Blue	R-CNN	Region Based Convolutional Neural Network
DL	Deep learning	YOLO	You Only Look at Once
CNN	Convolutional Neural Network	BIM	Building Information Modeling
Fast R-CNN	Faster Region Based Convolutional Neural Network	SSD	Single-Shot multibox Detection
AR	Augmented Reality		

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