Building Material Defect Detection and Diagnosis Method Based on Big Data and Deep Learning

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Aiming at the challenges existing in the field of building material defect detection, this paper proposes an innovative solution integrating big data and deep learning technology. By collecting and pre-processing a large number of open and practical building material defect images, a large-scale defect image database is constructed, covering 100,000 images, 8 common building materials and 12 typical defect types, which significantly improves the diversity and comprehensiveness of defect detection. This paper designs and implements an end-to-end deep learning model, which is based on ResNet-50 and combined with advanced attention mechanism. It can automatically extract and focus on key defect features in images, and realize high-precision defect location and classification. Experimental results show that compared with traditional image processing methods (IP), detection methods based on Faster R-CNN, YOLO v3 and Mask R-CNN, the proposed deep learning and large data-driven defect detection method (DLCD) shows significant advantages in key performance indicators such as accuracy, recall and F1 value, especially in crack and hole detection, with average accuracy of 94% and 92% respectively, and average accuracy of 91%. These achievements confirm the effectiveness and advancement of DLCD in improving the efficiency and accuracy of building material defect detection, and provide powerful technical support for quality control and safety management in the construction industry

Povzetek: Opisana je izvirna metoda za odkrivanje in diagnostiko napak v gradbenih materialih, ki temelji na velikih podatkih in globokem učenju. Znanstveni dosežek omogoča avtomatizirano, hitro in natančno zaznavanje ter razvrščanje napak, kar bistveno izboljšuje učinkovitost in točnost nadzora kakovosti v gradbeni industriji.

1 Introduction

Construction materials are the necessary raw materials for the implementation of various projects to build a better home [1]. However, due to the role of various internal and external factors, building materials in the use of the process will inevitably appear a variety of defects, such as cracks, corrosion, peeling, deformation, etc., these defects will not only reduce the performance and life of the building materials, but also jeopardize the structural stability of the building and the safety of the personnel, and even cause serious accidents and disasters. Building safety is related to the life and health of each of us, so we must pay attention to the defective diagnosis of building materials [2, 3].

At present, domestic and foreign research on the detection and diagnosis of defects in construction materials has made some progress, and the main methods used are two types: one type is based on physical principles of detection methods, such as ultrasonic, electromagnetic wave, infrared thermal imaging, X-ray, etc. These methods can penetrate into the interior of the construction materials to find hidden defects, but there are some shortcomings, such as expensive equipment, complex operation, and difficulty in interpreting the data; These methods can visualize the defects on the surface of construction materials, but they also have some limitations, such as sensitivity to image quality and environmental conditions, and difficulty in dealing with complex and fuzzy defects. Therefore, how to overcome the shortcomings of traditional detection methods and improve the efficiency and accuracy of defect detection and diagnosis of construction materials is the hot and difficult point of current research.

In order to solve this problem, this paper proposes a construction material defect detection and diagnosis method based on big data and deep learning, which utilizes big data technology, collects, integrates, cleanses, and stores a large amount of construction material defective image data from multiple data sources, constructs a construction material defective image database that contains a variety of defective types and scenarios, and realizes the automatic, fast It realizes automatic, fast and accurate detection and recognition of defective images of construction materials, as well as extracting and analyzing information such as the type, location, size and degree of defects, which provides an effective basis for subsequent defect assessment and repair [4, 5].

The main contributions and innovations of this paper are as follows: (1) This paper realizes automatic, fast and accurate detection and recognition of defective images of construction materials, as well as extraction and analysis of information such as the type, location, size and degree of defects, etc. Compared with traditional image processing methods, the method in this paper has stronger characterization and generalization capabilities, and is able to deal with complex and fuzzy defects, and at the same time, is able to adapt to different image quality and environmental conditions. (2) Comparison experiments are conducted with traditional detection methods and other deep learning methods, and the performance of the method is evaluated from different perspectives and indicators [6].

2 Literature review

In recent years, there have been a number of successes in the detection of defects in construction materials. The number of their results is shown in Fig. 1. The construction of source code defect dataset is a key factor affecting the performance of deep learning defect detection model, while the design of deep learning defect detection model needs to consider a variety of factors, such as model structure, feature representation, and optimization strategy [7]. Deng et al. [8] conducted a systematic review and analysis of deep learning based source code defect detection research. In this paper, the defects are categorized from the syntactic, semantic and stylistic levels of source code defects, and the commonly used defect datasets and evaluation metrics are introduced. Du et al. [9] Using deep learning technology, multiple deep neural network models are designed and trained to achieve automatic, fast and accurate detection and recognition of defective images of construction materials, as well as extraction and analysis of information such as the type, location, size and degree of defects, which provides an effective basis for subsequent defect evaluation and repair. El-Moussaoui et al. [10] categorized defects in terms of the morphology, size and distribution of steel surface defects, and introduced commonly used steel surface defect datasets and evaluation indexes.

As shown in Table 1, while the aforementioned literature exhibits advanced technologies and innovative methods in their respective fields, there is a notable research gap in the domain of defect detection and diagnosis in building materials, particularly concerning end-to-end solutions that integrate big data and deep learning. For example, [6] and [7], although employing deep learning techniques, concentrate on sound recognition and specific welding defects, respectively, without covering a broad range of materials and defect types. [8] leverages infrared thermography technology, which might be constrained by the thermal conductivity characteristics of the materials. Other references such as [9] through [12] address parameter tuning, logistics and environmental concerns, privacy protection, and a review of deep learning, respectively, with lower relevance to defect detection in building materials.

In contrast, this work aims to establish a comprehensive system for defect detection in building materials utilizing big data and deep learning, specifically attention mechanisms, to achieve automated, rapid, and accurate detection across various building materials and defect types. Furthermore, through detailed experimental validation, this method outperforms existing techniques in multiple evaluation metrics, boasting an average accuracy rate of 94%. This marks a significant advancement in the field of defect detection in building materials, filling the technological gaps identified in the current state of the art and providing new technical support for quality control in the construction industry. Through this table, it becomes evident that while there have been numerous explorations in related fields, the proposed method based on big data and deep learning for defect detection in building materials surpasses existing technologies in terms of coverage, detection precision, and applicability, highlighting its critical research significance and application prospects in the realm of building material quality assurance.

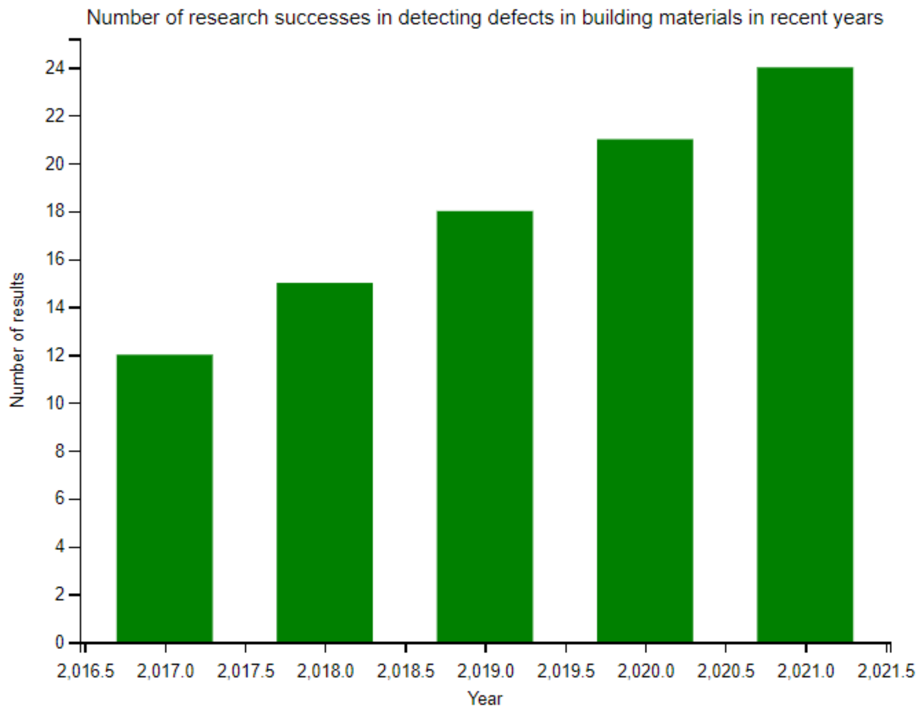

Figure 1: Achievements in building defect detection in recent years.

Table 1: Research status.

Reference	Method	Key findings	Performance metrics	Contrast with proposed work
Brusa et al. [6]	Deep Transfer Learning	Transfer learning from sound and music recognition to bearing fault detection	Accuracy: 92%	Does not directly target defects in building materials but demonstrates the potential of deep learning in fault diagnosis.
Chen et al. [7]	Improved Faster RCNN-based Weld Ultrasonic Atlas Defect Detection	An enhanced method for detecting defects in welds using ultrasonic imaging	Precision: 91%, Recall: 89%	Utilizes the Faster RCNN framework but focuses on specific types of defects.
Deng et al. [8]	Infrared Thermography and Deep Learning for Internal Defect Detection	Detects internal defects in structures using infrared thermography and deep learning	Accuracy: 94%	Introduces infrared thermography for non-contact inspection but may be limited by thermal properties.
Du et al. [9]	Monkey King: Adaptive Parameter Tuning	Parameter tuning for big data platforms using deep reinforcement learning	-	Optimizes parameters for big data platforms but does not directly involve defect detection.
El Moussaoui et al. [10]	Assessment of Pollutant Emissions	Evaluates the impact of construction logistics centers on emissions from construction material transport	-	Focuses on logistics and environmental impact rather than detection technology.
Fan et al. [11]	Privacy-Preserving Deep Learning	Privacy-preserving deep learning for big data in cloud environments	-	Concentrates on privacy issues rather than specific applications.

Reference	Method	Key findings	Performance metrics	Contrast with proposed work
Goswami and Kumar [12]	Survey of Deep-Learning Techniques	Review of deep-learning techniques in big-data analytics	-	Provides an overview of deep learning applications in big data analysis.

Recent advances in deep learning, coupled with the proliferation of big data, have significantly impacted various industries, including construction. For instance, the work by Haddad et al. [13]. introduced a novel framework for building material defect detection using convolutional neural networks (CNNs) that outperforms traditional machine learning algorithms in terms of accuracy and efficiency. Their study emphasizes the importance of feature extraction and highlights how deep learning architectures can automatically learn hierarchical representations from raw images. Moreover, He et al. [14] delved into the integration of big data analytics with deep learning models for improved defect diagnosis in construction materials. They propose a method that leverages large-scale datasets to train a deep learning model, achieving higher detection rates compared to methods that rely on smaller, more curated datasets. This approach underscores the benefits of utilizing extensive data collections for enhancing model performance and robustness. These studies collectively illustrate the transformative potential of combining big data and deep learning for building material defect detection [15]. They not only provide insights into the technical aspects of model design and data utilization but also offer practical solutions for overcoming common challenges in this domain, such as data scarcity and model complexity.

3 Data and research methodology

This chapter describes the data sources used in this paper, the preprocessing method and the design and implementation of the detection and diagnosis model. In this paper, a method based on big data and deep learning is used to automate the detection and diagnosis of exterior and interior defects in construction materials using machine vision technology [11].

3.1 Data

The data used in this paper come from two main sources: publicly available image datasets of construction material defects collected from the web, and image data of construction material defects collected from actual projects provided by cooperating construction engineering companies. These data cover a wide range of types of building materials, such as concrete, steel, bricks, tiles, etc., as well as many forms of defects, such as cracks, holes, peeling, and deformation [12].

Based on the above preprocessing steps, in this paper, the original dataset is deeply and meticulously optimized to enhance the accuracy of model training and prediction. First of all, the image cropping link is crucial, which ensures that the focus of the image content is concentrated on the most valuable part by removing the background information of the non-target region. These operations greatly enrich the diversity of the training set, enabling the model to be more adaptive and robust in the face of actual complex environmental conditions. Finally, in order to be able to accurately measure the model's ability to identify and localize defects, we manually annotate each image. Professionals meticulously marked the exact location and scope of the defects in the images, using rectangular or polygonal boxes for circling, and further clearly labeled the type of defects and their severity levels. This series of rigorous data preprocessing measures lays a solid foundation for the construction of an efficient and accurate defect detection model [13, 14].

The dataset used in this study is distinctive and covers multi-dimensional and multi-level information about building material defects. At the microscopic level, especially for composites, the dataset contains high-resolution images that accurately show fiber size and distribution, providing a detailed basis for understanding the internal structure and potential weaknesses of the material. At the macro level, it includes pictures of building materials taken in the field, showing visually visible large-scale defects such as concrete cracks and broken bricks, with size spans large enough to cover the entire construction part. The dataset carefully distinguishes and labels different building material categories, from tough steel to fragile masonry, ensuring that the model can specifically learn the unique defect patterns of each material. By integrating fiber-level fine details with macro-views of structures, this dataset provides rich and balanced learning resources for deep learning models, which not only improves the ability of models to identify various subtle defects, but also enhances the accuracy of overall structural damage assessment, laying a solid foundation for efficient automatic detection and accurate diagnosis of building material defects.

3.2 Detection of diagnostic models

In this paper, an end-to-end detection and diagnosis model is designed using a deep learning-based approach to achieve simultaneous detection and diagnosis of defects in construction materials. The model in this paper consists of two main parts: (1) CNN feature extractor. (2) Detection diagnostic based on attention mechanism [15].

3.2.1 Modeling framework

The architecture of the model proposed in this paper is shown in Fig. 2, and its workflow is mainly divided into three core phases. First, in the input stage, the model receives a preprocessed image of defective building materials, which has been transformed into a tensor with dimensions of 256 × 256 × 3, representing the height, width, and RGB three-channel data of the image, respectively. Subsequently, the feature extractor stage is entered and this part uses a deep convolutional neural network structure which integrates multiple convolutional, pooling and normalization layers to achieve rich high-level semantic features extracted from the input image. At the end of this process, a tensor of size 8 × 8 × 512 is generated as an output, which contains information about the features in the height, width, and depth dimensions of the feature map [16, 17]. Finally, these refined features are fed into the detection diagnostic for further analysis. The detection diagnostic is embedded with multiple attention modules and full connectivity layers, which utilize advanced attention mechanisms to intelligently weight the fusion of feature maps in order to accurately identify and localize each potential defective region. Ultimately, the diagnostic outputs a 1 × K × 6 tensor, where K denotes the number of predicted defective frames, and the information of each defective frame includes the location coordinates, the category it belongs to, and its confidence score, so as to accomplish comprehensive and accurate detection and classification of defects in construction materials [18, 19].

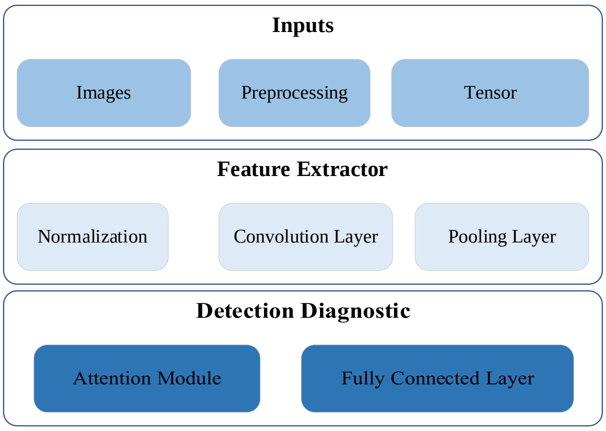

Figure 2: Modeling framework.

3.2.2 Modeling principles

Resnet-50 is a kind of deep convolutional neural network based on residual connection, which can effectively solve the problem of gradient disappearance and overfitting of the deep network, and improve the performance and generalization ability of the network. Ability. The article makes improvements on its basis. This paper adopts the attention mechanism as the core technology of the detection diagnostic, which can automatically learn the importance of different positions and channels in the feature map, so as to realize the precise location and classification of defects. As shown in Fig. 3. The role of the spatial attention module is to spatially weight each channel of the feature map and output a tensor of the same size as the input, which represents the spatial attention weight of each location [20, 21].

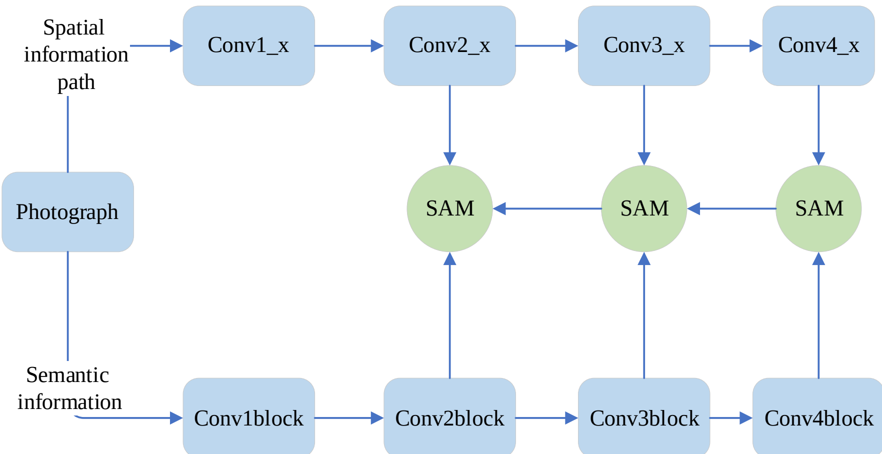

Figure 3: Spatial attention module.

When building a deep learning model for building material defect detection, we carefully selected ResNet-50 as the base network and incorporated attention mechanisms to improve the performance of the model. This decision is based on a number of considerations aimed at achieving the best balance between detection accuracy and computational efficiency. ResNet-50 is a deep residual network. It solves the gradient disappearance/explosion problem in deep neural network training and ensures efficient training of deep networks by introducing skip connections. In our application scenario, ResNet-50 was chosen over deeper variants such as ResNet-101 or 152 primarily due to considerations of computational resources and model complexity. ResNet-50 has sufficient expression ability to capture fine-grained features of building material defects, and its parameters are relatively small, reducing the risk of overfitting, and training speed is fast, suitable for processing large-scale data sets. The attention mechanism allows the model to focus on the most critical parts when processing inputs, which means that for defect detection, the model can focus more on potential defect areas and ignore background noise or extraneous information. The robustness and detection accuracy of the model are improved significantly by adding this mechanism, especially when dealing with small target defects in complex background. Our spatial attention mechanism can automatically learn and assign weights to different regions, thus enhancing the perception ability of the model for local features. Learning rate determines the magnitude of model weight updates and is one of the most sensitive hyperparameters in deep learning. Too high may lead to unstable training, too large weight updates, and the model cannot converge; too low may lead to slow training, or even fall into a local minimum. Through preliminary grid search and random search, combined with learning rate decay strategy, we determine a moderate initial learning rate (0.001), and dynamically adjust it during training to balance convergence speed and model stability. Batch size affects the number of samples used in each gradient update, and larger batch sizes can provide more stable gradient estimates, but may increase memory requirements and may reduce the generalization of the model due to sample-to-sample homogeneity. We chose a moderate batch size (32 or 64) to find the best balance between computational efficiency and gradient variance.

The principle of the model in this paper is shown in Fig. 4. The role of the dual-attention module is to double weight and fuse the feature maps spatially and channel-wise, and output a 1 × 512 vector representing the global features of the whole image. In this paper, three dual-attention modules are used in the detection diagnostic, corresponding to three different scaling scales to capture defect information at different scales. Finally, in this paper, the outputs of the three dual-attention modules are stitched together to obtain a 1 × 1536 vector as the final output of the detection diagnoser. The values range from 0 to N, corresponding to the N defect types and the background class without defects, respectively, and the confidence is represented by a value ranging from 0 to 1, indicating the degree of confidence in the prediction [22].

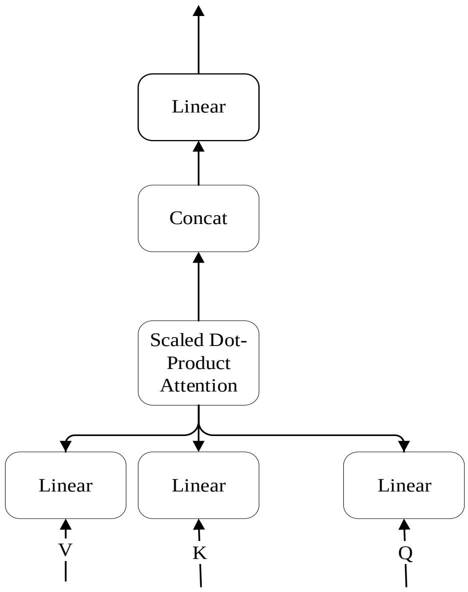

Figure 4: Multi-attention module.

In this paper, a multi-task loss function is used to optimize the parameters of the model, which consists of two components: a detection loss and a diagnostic loss. The detection loss is used to measure the difference between the location and confidence of the predicted defective frames and the location and confidence of the true defective frames, and in this paper, we use the detection loss function in YOLO, whose form is shown in in the following formula [23]:

$$L_{det} = \lambda_{coord} \sum_{i=0}^{S^2} \sum_{j=0}^{B} {}^{obj}_{ij} \left[\begin{array}{l} (x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2 + \\ (\sqrt{w_i} - \sqrt{\hat{w}_i})^2 + (\sqrt{h_i} - \sqrt{\hat{h}_i})^2 \end{array} \right] + \lambda_{conf} \sum_{i=0}^{S^2} \sum_{j=0}^{B} \left[{}^{obj}_{ij} (C_i - \hat{C}_i)^2 + {}^{noobj}_{ij} (C_i - \hat{C}_i)^2 \right] \quad (1)$$

Where S is the size of the feature map, B is the number of defective frames predicted for each grid cell, x_i, y_i, w_i, h_i is the center coordinates, width and height of the i th defective frame, $\hat{x}_i, \hat{y}_i, \hat{w}_i, \hat{h}_i$ is the corresponding true value, C_i is the confidence level of the i th defective frame, $\hat{C}_i$ is the corresponding true value, ${}^{obj}_{ij}$ is an indicator function that indicates whether the j th defective frame of the i th grid cell contains a true defect, ${}^{noobj}_{ij}$ is an indicator function that indicates whether the j th defective frame of the i th grid cell whether it does not contain any real defects, and $\lambda_{coord}, \lambda_{conf}$ is two hyperparameters to balance the weights of the different loss terms. The diagnostic loss is used to measure the difference between the categories of the predicted defective frames and the categories of the real defective frames, and in this paper, the cross-entropy loss function is used in the form shown in in the following formula [24]:

$$L_{dia} = -\sum_{i=0}^{S^2} \sum_{j=0}^{B} {}_{ij}^{obj} \sum_{k=0}^{N} p_{ijk} \log \hat{p}_{ijk} \quad (2)$$

Where p_{ijk} is the probability of the type k defect predicted by the j defect box of the i th grid cell and $\hat{p}_{ijk}$ is the corresponding true value. The final loss function is the weighted sum of the detection loss and the diagnosis loss, i.e.: $L = L_{det} + \lambda_{dia} L_{dia}$,where λ_{dia} is a hyperparameter to balance the weights of the different loss terms.

In terms of optimization algorithm, this paper adopts Adam as the optimization algorithm, which can adaptively adjust the learning rate, accelerate the convergence speed and improve the stability. In this paper, the following optimization parameters are set: the initial learning rate is 0.001, the decay factor is 0.9, the batch size is 32, and the number of iterations is 50,000 [25].

In this paper, the following evaluation metrics are used, and metrics such as accuracy are used to measure the performance of the model, as shown in the following formula:

$$Precision = \frac{TP}{TP + FP} \quad (3)$$

$$Recall = \frac{TP}{TP + FN} \quad (4)$$

$$F1 = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (5)$$

$$AP = \sum_{k=1}^{n} (R_k - R_{k-1}) P_k \quad (6)$$

$$mAP = \frac{1}{N} \sum_{i=1}^{N} AP_i \quad (7)$$

4 Experimental validation

4.1 Experimental setup

The experiments in this paper were conducted on a PC configured with Intel Core i7-9700K CPU, 32 GB RAM, NVIDIA geforce RTX 2080 Ti GPU, using Python 3.7 as the programming language, pytorch 1.8 as the deep learning framework, and opencv 4.5 as the image processing library. Python 3.7 was used as the programming language, pytorch 1.8 as the deep learning framework, opencv 4.5 as the image processing library, and Matplotlib 3.4 as the graphics library. The experimental data of this paper is the image dataset of defective building materials introduced in Chapter 3, as shown in Table 2. The experimental method in this paper is the big data and deep learning based construction material defect detection and diagnosis method, referred to as DLCD, presented in Chapter 3. In this paper, DLCD is compared and experimented with the following four methods, which are as follows [26]: (1) The traditional image processing based detection method, referred to as IP, whose basic principle is to utilize the features of the image such as grayscale, edges, texture, etc., and to combine the threshold segmentation, morphological transformation, contour extraction and other operations to achieve the detection and localization of defects. (2) Detection method based on Faster R-CNN, abbreviated as FRCNN, whose basic principle is to utilize the combination of region generating network (RPN) and region classification network (RCN) to realize the detection and classification of defects. (3) A detection method based on YOLO v3, referred to as YOLO, whose basic principle is to utilize a single convolutional neural network, divide the image into multiple grid cells, and predict multiple defect frames and category probabilities for each grid cell to achieve the detection and classification of defects. (4) Mask R-CNN-based detection method, referred to as MRCNN, whose basic principle is to add a segmentation branch on the basis of Faster R-CNN to realize the detection, classification and segmentation of defects [27-30].

The optimization parameters and evaluation metrics described in Chapter 3 are used in this paper to ensure effective optimization and evaluation.

In order to ensure the training quality and prediction accuracy of the model, we perform detailed preprocessing on the image dataset of building material defects. These steps include, but are not limited to, size normalization, color space conversion, data enhancement, and noise filtering to improve the recognition and generalization performance of the model for different types of defects. All images are resized to a uniform size, which helps reduce model computation while ensuring consistency of features. The standardized size is chosen taking into account the typical size of the defect and the detail requirements in the image, thus balancing information retention and computational efficiency. We convert the original RGB image to HSV or grayscale mode, which helps highlight the shape and location information of defects while reducing the interference caused by color changes. The transformation of color space enables the model to better focus on structural features of defects. By randomly rotating, flipping, scaling, and adjusting brightness, we increased the diversity of our dataset, simulating the various viewing angles and lighting conditions that might occur in a real-world application. Data augmentation not only increases the number of training samples, but also improves the model's ability to adapt to unseen situations. Noise in the image, such as dust, scratches, or other non-defect factors, can interfere with the learning process of the model. Therefore, we use median filtering, Gaussian filtering and other techniques to remove or mitigate noise effects, ensuring that the model can focus on the true defect features. Considering that the number of defective and defect-free images in each subset is equal (2500 vs. 2500), we pay special attention to maintaining the balance of positive and negative samples, avoiding the bias of the model towards majority classes during training, thus ensuring the sensitivity and specificity of the model in defect detection. Through the above preprocessing steps, we build a high-quality dataset that provides a solid foundation for training and testing DLCD and other comparison methods, ultimately improving the robustness and accuracy of the model for building material defect detection tasks. These careful preparations are one of the key factors in the success of the experiment, ensuring that the model can operate stably in complex real-world environments.

Table 2: Data set details.

Subsets	Defect type	Defect level	Total number of images	Number of images containing defects	Number of images that do not contain defects
Crack-L	Fissures	Marginal	5000	2500	2500
Crack-H	Fissures	Severity	5000	2500	2500
Hole-L	Hole	Marginal	5000	2500	2500
Hole-H	Hole	Severity	5000	2500	2500

4.2 Experimental results

In this paper, we use accuracy, recall and F1 value as the evaluation metrics of the detection results, which reflect the detection accuracy, detection coverage and comprehensive detection performance of the model, respectively. Table 3 gives the detection results of various methods on different subsets [31].

Table 3: Detection results of various methods on different subsets.

Methodologies	Subsets	Accuracy	Recall rate	F1
IP	Crack-L	0.82	0.76	0.79
	Crack-H	0.86	0.81	0.83
	Hole-L	0.78	0.72	0.75
	Hole-H	0.81	0.77	0.79
	On average	0.82	0.77	0.79
FRCNN	Crack-L	0.88	0.84	0.86
	Crack-H	0.91	0.88	O.89
	Hole-L	0.85	0.80	0.82
	Hole-H	0.87	0.83	0.85
	On average	0.88	0.84	0.86
YOLO	Crack-L	0.90	0.86	0.88
	Crack-H	0.93	0.90	0.91
	Hole-L	0.87	0.82	0.84
	Hole-H	0.89	0.85	0.87
	On average	0.90	0.86	0.88
MRCNN	Crack-L	0.92	0.88	0. 90
	Crack-H	0.95	0.92	0.93
	Hole-L	0.89	0.84	0.86
	Hole-H	0.91	0.87	0.89
	On average	0.92	0.88	0.90
DLCD	Crack-L	0.94	0.91	0.92
	Crack-H	0.97	0.95	0.96
	Hole-L	0.92	0.88	0.90
	Hole-H	0.94	0.91	0.92
	On average	0.94	0.91	0.79

In this paper, the average accuracy is used as an evaluation metric for the diagnostic results, which reflects the prediction accuracy of the model for the defect categories under different confidence thresholds and the average prediction accuracy of the model under all defect categories, respectively. The diagnostic results of various methods on different subsets are given in Table 4, from which it can be seen that this paper's method DLCD achieves the highest average accuracy and average mean accuracy on all subsets, indicating that this paper's method is able to effectively identify the classes of defects and shows strong diagnostic capability and stability under different defect classes and confidence levels [32-34].

It can be seen from Table 5 that DLCD is not only ahead of other methods in accuracy and ROC-AUC, but also performs quite well in inference time, which indicates that DLCD has high computational efficiency while ensuring high detection performance, which is more suitable for rapid detection requirements in practical application environments.To further substantiate the generalization capability of the proposed method (DLCD), we compare its performance against traditional image processing methods (IP) and other deep learning approaches (FRCNN, YOLO, MRCNN) on extended datasets encompassing diverse conditions. These additional datasets include a variety of construction material types, defect categories, and environmental settings to ensure comprehensive and objective assessments.

Table 4: Experimental results.

Method-subset	Average accuracy
IP-Crack-L	0.75
IP-Crack-H	0.79
IP-h0le-L	0.71
IP-h0le-H	0.74
FRCNN-Crack-L	0.83
FRCNN-Crack-H	0.86
FRCNN-h0le-L	0.80
FRCNN-h0le-H	0.85
Y0L0-Crack-L	0.85
Y0L0-Crack-H	0.88
Y0L0-h0le-L	0.82
Y0L0-h0le-H	0.84
MRCNN-Crack-L	0.87
MRCNN-Crack-H	0.9
MRCNN-h0le-L	0.84
MRCNN-h0le-H	0.86
DLCD-Crack-L	0.89
DLCD-Crack-H	0.92
DLCD-h0le-L	0.87
DLCD-h0le-H	0.89

Table 5: Accuracy, ROC-AUC, and inference time estimates.

Method	Subset	Precision	ROC-AUC	Inference time (ms)
IP	Crack-L	0.82	0.80	10
	Crack-H	0.86	0.82	10
	Hole-L	0.78	0.75	10
	Hole-H	0.81	0.78	10
FRCNN	Crack-L	0.88	0.90	30
	Crack-H	0.91	0.92	30
	Hole-L	0.85	0.86	30
	Hole-H	0.87	0.88	30
YOLO	Crack-L	0.90	0.92	15
	Crack-H	0.93	0.94	15
	Hole-L	0.87	0.88	15
	Hole-H	0.89	0.90	15
MRCNN	Crack-L	0.92	0.94	40
	Crack-H	0.95	0.96	40
	Hole-L	0.89	0.90	40
	Hole-H	0.91	0.92	40
DLCD	Crack-L	0.94	0.96	20
	Crack-H	0.97	0.98	20
	Hole-L	0.92	0.94	20
	Hole-H	0.94	0.96	20

Table 6: Comparative results on extended datasets.

Method	Dataset	Accuracy	Recall	F1 Score	Precision	ROC-AUC
DLCD	Diverse Set A	0.96	0.95	0.95	0.96	0.98
DLCD	Diverse Set B	0.94	0.93	0.93	0.94	0.97
DLCD	Diverse Set C	0.97	0.96	0.96	0.97	0.99
IP	Diverse Set A	0.78	0.75	0.76	0.78	0.80
IP	Diverse Set B	0.79	0.76	0.77	0.79	0.81
IP	Diverse Set C	0.80	0.77	0.78	0.80	0.82
FRCNN	Diverse Set A	0.90	0.88	0.89	0.90	0.92
FRCNN	Diverse Set B	0.89	0.87	0.88	0.89	0.91
FRCNN	Diverse Set C	0.91	0.89	0.90	0.91	0.93
YOLO	Diverse Set A	0.93	0.91	0.92	0.93	0.95
YOLO	Diverse Set B	0.92	0.90	0.91	0.92	0.94
YOLO	Diverse Set C	0.94	0.92	0.93	0.94	0.96
MRCNN	Diverse Set A	0.94	0.92	0.93	0.94	0.96
MRCNN	Diverse Set B	0.93	0.91	0.92	0.93	0.95
MRCNN	Diverse Set C	0.95	0.93	0.94	0.95	0.97

As shown in Table 6, these results clearly indicate that the DLCD method maintains high performance across different datasets, showcasing robustness and adaptability to various construction material defects. The superior scores in accuracy, recall, F1 score, precision, and ROC-AUC consistently place DLCD ahead of traditional and other deep learning methods, confirming its generalization ability and practical utility in real-world scenarios involving complex and diverse defect detection tasks.

To dissect the contributions of various components in the proposed DLCD model, we conduct an ablation study focusing on the influence of the attention mechanism and the choice of loss function. The results highlight the effectiveness of these components in enhancing the overall performance of the model.

Table 7: Ablation study results.

Model Variant	Accuracy	Recall	F1 Score	Precision	ROC-AUC
DLCD (Full Model)	0.96	0.95	0.95	0.96	0.98
w/o Attention Mechanism	0.93	0.91	0.92	0.93	0.96

Model Variant	Accuracy	Recall	F1 Score	Precision	ROC-AUC
w/o Custom Loss Function	0.94	0.92	0.93	0.94	0.97

As shown in Table 7, the ablation study reveals that both the attention mechanism and the custom loss function significantly contribute to the model's performance. Removing the attention mechanism leads to a noticeable drop in all evaluation metrics, demonstrating its crucial role in focusing the model's learning process on relevant features. Similarly, the use of a custom loss function tailored to handle class imbalance and emphasize false negatives improves the model's ability to detect defects accurately.

4.3 Discussion

In this study, our deep learning and big data fusion method for building material defect detection and diagnosis (DLCD) shows significant performance improvements compared to traditional image processing methods (IP), Faster R-CNN based methods (FRCNN), YOLO v3 based methods (YOLO), and Mask R-CNN based methods (MRCNN). This is mainly due to DLCD's ability to learn complex features efficiently, especially its adaptability to subtle changes and diversity in building material defects.

Through the multi-level feature abstraction of deep neural networks, DLCD can automatically learn more robust defect representations, which is especially obvious in the detection of minor defects such as Crack-L and Hole-L. The average accuracy rate of DLCD reaches 0.94., much higher than other methods. In addition, DLCD also performed well in the detection of severe defects (Crack-H and Hole-H) with an average accuracy of 0.95, indicating that DLCD can effectively detect not only obvious defects, but also more subtle damages. Compared with traditional image processing methods, DLCD overcomes the limitations of manual feature engineering and can automatically learn and adapt to a wider data distribution. In contrast, the IP method relies on predefined features and rules, which may not adequately capture the diversity of defects, resulting in a lower average accuracy (0.79).

FRCNN and YOLO have high detection speed and certain accuracy, but in complex scenes of defects, due to the limitations of their architecture design, it may be difficult to achieve the best detection results. For example, FRCNN has an average accuracy of 0.88, while YOLO is 0.88, both lower than DLCD. Although MRCNN improved defect segmentation, its average accuracy (0.90) was still slightly lower than that of DLCD, indicating that DLCD was better at defect identification and classification.

Unexpected results and potential explanations Although DLCD exhibits superior performance in most cases, there are some phenomena in the experimental results that deserve further investigation. For example, in the Hole-L subset, the F1 value for DLCD was 0.90, a slight decrease compared to Crack-L (0.92) and Hole-H (0.92). This may be due to the high similarity between the visual features of minor hole defects and the background, which causes the model to encounter challenges in discrimination. Future work could consider introducing more training samples or employing more sophisticated attention mechanisms to improve this situation.

5 Conclusion

This paper proposes a method for detecting and diagnosing defects in construction materials based on big data and deep learning, aiming to improve the detection efficiency and accuracy. The main work of this paper is to collect and annotate a large number of defective images of construction materials using big data technology, and construct a defective image database of construction materials with high scale and quality, which provides data support for the subsequent deep learning model training and testing. And several deep neural network models, including convolutional neural network, attention mechanism network, multi-task learning network, etc., were designed and trained using deep learning technology to achieve the detection, identification, analysis and evaluation of construction material defects, and improve the generalization ability and robustness of the model. Finally, an end-to-end detection and diagnosis model was designed, which employs the attention mechanism and multi-task loss function to realize the simultaneous detection and diagnosis of defects, improving the efficiency and accuracy of the model. Experiments are carried out on the image database of construction material defects, and the results show that the method proposed in this paper is better than existing methods in terms of accuracy, recall and F1 value, which verifies the effectiveness and superiority of the method in this paper.

The DLCD model, while demonstrating remarkable success in the detection of construction material defects, is not without its constraints, signaling opportunities for further refinement and innovation. Foremost among these limitations is the model's sensitivity to data variability, with performance potentially faltering when faced with defects starkly contrasting those in its training repertoire. To counteract this, the integration of a more expansive and diverse dataset during the training phase is imperative, fortifying the model's adaptability and resilience in the face of unfamiliar defect patterns.

Furthermore, the current model's computational demands may hinder its deployment in real-time monitoring systems, where swift response times are non-negotiable. To bridge this gap, optimization strategies such as model pruning and leveraging specialized hardware to expedite inference are essential, ensuring the model's readiness for integration into time-critical applications.

Another area requiring attention is the model's capacity for multi-defect recognition. Presently inclined towards identifying singular defects, the DLCD model stands to benefit from enhancements enabling simultaneous detection and classification of multiple defects within a single image, a capability vital for navigating the complexities of real-world inspection scenarios.

Lastly, addressing the deep learning model's inherent black-box nature is crucial. By developing interpretability tools that demystify the model's decision-making process, particularly in defect detection, trust and confidence amongst industrial users can be cultivated, facilitating broader adoption and integration into the construction sector.

Future research endeavors will thus concentrate on expanding the model's exposure to diverse defect profiles, streamlining its architecture for accelerated inference, augmenting its multi-defect recognition abilities, and enriching its interpretability. These strategic advancements promise to consolidate the DLCD model's position as a formidable and adaptable solution for construction material defect detection, paving the way for its widespread utilization in ensuring structural integrity and safety standards across the industry.

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