A Critical Review of Deep Learning Methods for Crack detection Optimization in Non-Destructive Testing

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Abstract

NDT techniques play a pivotal role in ensuring the structural integrity and safety of various components in industries such as aerospace, automotive, and civil engineering. Among the wide range of defects that NDT aims to identify, cracks are one of the most common and critical types. Traditional crack detection methods have been extensively studied and employed over the years due to their reliability and cost-effectiveness. Most other methods of NDT need visual inspection because an operator will typically need to search for flaws. As computer vision continues to advance, its applications across a range of sectors, including object recognition, image segmentation, and image classification have grown significantly. One important area of research within computer vision is image denoising and crack detection, particularly in NDT. NDT is a technique used to evaluate and inspect materials or components without causing damage to the object being tested.

Traditionally, crack detection in NDT has been performed using image processing techniques such as thresholding, mathematical morphology, and edge detection(Lau et al. 2020). The improvement of image quality has become a crucial area of focus in various fields, including medical imaging, industrial applications, construction safety, and medical diagnostics and NDT. Recent advancements in machine learning (ML) and AI have revolutionized research programs in numerous domains, offering new opportunities for optimization and enhancement(Patnaik, Babu, and Bhave 2021). The field of medical imaging has witnessed significant advancements in the application of AI Deep Learning algorithms for automatic defect detection, image enhancement, and denoising(Luo, Zeng, and Chen 2022). These developments have made it easier to extract essential information from documents, websites, and images using Optical Character Recognition techniques.(Patnaik, Babu, and Bhave 2021)

Introduction:Cracks in materials and structures pose significant risks, leading to failures, reduced performance, and even catastrophic events. Thus, it is essential to find cracks early on in order to guarantee the dependability and safety of different components. Traditional crack detection techniques, such as visual inspection or conventional NDT methods, have been widely used for many years. However, these techniques frequently have issues with sensitivity, efficiency, and accuracy. Image denoising, restoration, edge detection, and enhancement are fundamental problems in image processing, computer vision, and AI(Y. Sun et al. 2006). For a variety of applications, image quality is crucial such as NDT, automatic control, robotics, imaging, target tracking, and telecommunications. The application of AI technology has garnered increasing attention in the past few years to improve the imaging quality of NDT Images, medical images, industrial applications, and other fields where image quality is crucial (Luo et al., 2022). Recent studies have shown that intelligent algorithms have a significant effect on denoising MRI images and enhancing the imaging quality of NDT and medical images. In the sector of NDT and medical imaging, the quality of images is of utmost importance for accurate diagnosis and treatment.

Objectives:The goal of this literature review is to investigate how deep learning and artificial intelligence (AI) can be used to optimize algorithm parameters for denoising, image enhancement, and automatic defect detection. The investigation of deep learning techniques' uses for image enhancements and automatic defect detection in Non-destructive testing (NDT) is the main goal of this literature review paper.

Conclusions:Industrial product quality is a crucial component of product development, and research on defect-detection technology is extremely vital in terms of practical use for ensuring product quality. The research state of product crack-detection technology and image denoising in intricate industrial processes is thoroughly reviewed in this study. We have thoroughly reviewed the experimental findings of crack-detection methods and compared and analysed deep learning Image denoising and crack-detection techniques with traditional Image denoising and crack-detection methods.

Main Research gaps, which includes lack of preprocessing of image under inspection before defect detection and speed efficiency along with accuracy of Deep learning models for image denoising and crack detection are considered for call of action of our research and development. Optimal parameters for image denoising and parameter tuning for YOLOv8 Deep learning algorithm is primary key areas identified for research as per overall literature review.

Keywords: deep learning, image processing, image denoising, defect detection, crack detection, NDT

1. Introduction

The use of AI techniques can significantly raise the standard of images by automating processes such as defect detection, image enhancement, and denoising. It will be very advantageous to automate these parameters using AI approaches (Chang & Chang, 2015). By automating these parameters, AI algorithms can effectively reduce radiation exposure and imaging time in medical imaging, resulting in improved patient safety and efficiency. Moreover, automatic defect detection using Deep Learning techniques of AI can greatly improve the efficiency and accuracy of quality control processes in industries.

AI Deep Learning algorithms can be trained to identify and classify defects in images with high precision, allowing for early detection and intervention. These algorithms can also enhance the visual appearance of images by reducing noise, improving contrast, and enhancing edges. Furthermore, the application of AI techniques in image enhancement can improve the diagnostic ability of medical professionals (Luo et al., 2022). For example, the usage of convolutional neural network-based algorithms can effectively reduce noise and artifacts, leading to improved image quality in NDT.

Because of its exceptional performance in a variety of domains, including target detection and image recognition, deep learning technology has attracted a lot of interest recently. It has proven to be a powerful tool for automatically recognizing targets, enhancing the intelligence and flexibility of equipment. As visual inspection technology advances, deep learning-based detection techniques are being used more and more in a variety of industries, such as the production of steel plates and pipes, to identify surface defects (Yu, 2022). The existing deep learning target detection algorithms can be broadly classified into two categories: two-stage detection algorithms, represented by fast R-CNN and Mask R-CNN, and one-stage detection algorithms, represented by YOLO and SSD. There are differences between these algorithms in terms of speed and accuracy of detection. Two-stage detection algorithms, like fast R-CNN and Mask R-CNN, achieve high accuracy but require multiple stages of computation, which results in slower detection speed. In contrast, one-stage detection algorithms, like YOLO and SSD, offer a relatively balanced trade-off between detection accuracy and speed.

2. Traditional techniques in NDT

a. Noise presence in Images under Inspection

Noise Model. In digital images, impulse noise corruption is particularly prevalent. Impulse noise is always dispersed randomly throughout the image and is never related to or independent of the image pixels. Therefore, unlike Gaussian noise, an impulse noise-corrupted image does not have noise in every pixel; instead, there will be noise in certain pixels but not in the others. Impulse noise can be divided into two categories: salt and pepper noise and random valued noise. When noisy pixels in an image have a value of either salt (white) or pepper (black), the result is a mixture of black and white patches.(Gupta, Chaurasia, and Shandilya 2013).

Variety of Noise (Gabhel and Hiradhar 2014). Different noises have their own traits and are ingrained in images in various ways.

Gaussian Noise. Over the signal, Gaussian noise is uniformly distributed. From a noisy image, each pixel's actual value and a randomly distributed noise value are added together. The probability density function [pdf] of this noise is modeled after the normal distribution. It also goes by the name of Gaussian distribution. The continuous level of noise in the image's dark parts makes up a significant portion of an image sensor's read noise.

Salt and Pepper Noise. Other names for the salt-and-pepper noise are spike noise, impulse noise, and shot noise. It is typically brought on by incorrect memory locations and camera sensor pixel elements, which lead to timing issues during the digitization process. This noise can be caused by memory cell loss, for example.

- When the camera's sensor cells malfunction.
- As a result of transmission or digitization faults involving synchronization.

Speckle noise. This is a type of multiplicative noise. Almost all coherent systems, including SAR images, ultrasound images, etc., exhibit this kind of noise. Random interference between the coherent responses is what causes this noise.

Amplification Noise. An additive, Gaussian, pixel-by-pixel, and signal-intensity independent model of amplifier noise is the most common type. An important component of an image sensor's "read noise," or the constant noise level in the image's dark portions, is amplifier noise. The distribution of this kind of noise is Gaussian.

b. Traditional Image Denoising techniques in NDT

Noise in images is typically unwanted and upsetting. It always has a detrimental impact on more advanced processing operations like image registration and segmentation. As a result, image denoising becomes a crucial step that is necessary for better image comprehension and interpretation. Image denoising is a critical step in processing of images, focusing on the removal of noise while preserving important image features. It is pivotal in applications ranging from medical imaging to NDT.

Defect Detection techniques are often sensitive to noise in images, making it difficult to accurately detect and differentiate cracks from their background. To address the issue of noise in images, various image denoising techniques have been developed and studied in the context of NDT.

Any filtering technique aims to maintain edges and other similar visual properties while successfully suppressing noise in uniform regions and also to create a natural-looking appearance (Gabhel and Hiradhar 2014).

Evolution of image denoising methods. The primary challenge in image processing is to reduce noise in damaged images. A spatial domain technique has first been used. Speed is one of the largest benefits of this filter domain approach, however, it has the disadvantage of losing edges., which are recognized as discontinuities in the image. In contrast, the wavelet domain approach has the advantage of being able to preserve edges. Consequently, as wavelet domain became more prominent, numerous wavelet domain denoising algorithms were introduced. Later, it was discovered that thresholding an undecimated wavelet transform using translation invariant techniques could significantly increase perceptual quality. To get comparable results, multiwavelets were also used(Gupta, Chaurasia, and Shandilya 2013).Wavelet has been widely used in the last few years to reduce noise and has shown to be an effective tool that surpasses many common denoising filters due to its desired qualities(Quan n.d.).

Different Denoising Techniques. Techniques for filtering and denoising data include wavelet thresholding, transform domain filtering, and spatial filtering. Linear filters and non-linear filters are additional categories for spatial filtering. Mean and Wiener filters are examples of linear filters. Rank-conditioned, weighted median, relaxed median, and rank selection are a few different non-linear median type filters(Gupta, Chaurasia, and Shandilya 2013).

Spatial frequency filtering and wavelet domain filtering are two approaches of transform domain filtering. Low pass filters (LPF) are employed by performing the Fast Fourier Transform (FFT) in the spatial frequency domain denoising approach. Here, the process of denoising is achieved by establishing a cut-off frequency. Wavelet domain filtering is used because the Discrete Wavelet Transform (DWT) allows the signal energy to concentrate in a small number of coefficients. Therefore, a small number of coefficients with rising Signal to Noise Ratio (SNR) and a comparatively fairly significant number of coefficients with low SNR make up the DWT of the noisy image. Inverse DWT is used to recreate the image after the noisy coefficients with low SNR have been eliminated. As a result, the observations' noise is eliminated or filtered. For the goal of image denoising, a variety of thresholding techniques, including hard and soft thresholding, are used. Because it produces a more aesthetically pleasing image and lessens the sudden sharp changes that happen with hard thresholding, soft thresholding is favoured to hard thresholding (Gabhel and Hiradhar 2014).

Highlighting the benefits of fuzzy denoise filters offer over conventional filters for removing different kinds of sounds from the image. The many fuzzy filters each perform better with a particular kind of noise, such as impulse noise, for example, FIRDM, FIRE, and FSM. Filters like GOA, GDFF, and MRF do well in eliminating Gaussian noise. In comparison to more conventional techniques, fuzzy filters work well with different kinds of noise. The goal is to find a universal filter with a fuzzy foundation that can eliminate any kind of noise from an image.(Agrawal and Sinha 2015).

Limitations Of Traditional Denoising Techniques. Traditionally, image enhancement techniques in NDT have relied on conventional algorithms that often struggle to handle complex or noisy data. In order to improve the pertinent image content, It is necessary to strike a balance between noise reduction and the preservation of the original image features (Quan n.d.).

Traditional methods often struggle to effectively eliminate noise without compromising image details, leading researchers to explore the possibilities of deep learning techniques for image denoising in NDT. Limitations of traditional denoising methods, such as median filtering and wavelet denoising, in handling various noise types and preserving image details.

c. Traditional Crack detection in NDT

Conventional crack detection techniques have been widely utilized in the field of NDT to assess the structural integrity in various objects. Over the years, many various kinds of NDT have emerged, ranging from straightforward visual and leak testing to cutting-edge ultrasonic or radiography. Every substance that needs testing has unique characteristics, some of which are better suited to one kind of NDT than another. NDT techniques vary according to how they test, the equipment needed, the speed and coverage they offer, and, in some circumstances, the safety measures required.

Overall, there isn't a single "best" NDT method. The approach that most closely satisfies the requirements of the company utilizing it is the optimal approach in any given situation. In the modern industrial setting, NDT systems are frequently valued for their speed, usability, and breadth of applications.

Traditional Techniques. Different classic non-imaging crack detecting methods are employed in NDT. These methods include acoustic emission, dye penetrant testing, ultrasonic testing, radiography and dye penetrant testing. Regarding crack detection sensitivity, size estimation, portability, use, and adaptability to diverse materials, each approach has its own benefits and drawbacks. Since most traditional detection techniques still require manual assistance to complete detection, they are not very adaptable and are constrained by the equipment life and manufacturing accuracy. This is especially true when instrument debugging is necessary prior to testing and the equipment development cost is high. Due to their adaptability and lack of reliance on human help, cutting-edge defect-detection approaches Among the key technologies for automating fault diagnosis, In recent years, deep learning approaches have become more and more popular (J. Wang et al. 2018).

The new technologies are more accurate and less expensive than old defect detection techniques, but they still rely on a lot of learnt data to update their models and raise inspection accuracy. Thresholding, mathematical morphology, and edge detection are frequently employed image processing techniques for crack segmentation in NDT.

Limitations Of Traditional Crack Detection Techniques. Traditional crack detection techniques have several limitations that can hinder their effectiveness in identifying cracks. Firstly, visual inspection methods heavily rely on human judgment and are prone to subjective errors, leading to inconsistencies in crack detection. Moreover, the level of accuracy of visual inspection is limited by factors such as lighting conditions, operator experience, and fatigue. Dye penetrant testing is another popular old method that entails putting a coloured liquid on a material's surface and watching to see whether it seeps into any cracks.

However, this technique can only be used on surfaces that are easily accessible; it is unable to find hidden or beneath the surface cracks. Ultrasonic testing is another widely used method but has limitations as well. It requires close interaction alongside the material being tested and may not be appropriate for uneven or irregular surfaces. Additionally, ultrasonic waves can be absorbed or scattered by certain materials, leading to inaccurate results.

Advantages Of Imaging Crack Detection Technique. The imaging crack detection technique offers several advantages over traditional crack detection methods. Firstly, it provides a non-destructive approach, allowing for the inspection of structures without causing any damage. This is particularly important when dealing with delicate or valuable materials, where destructive testing would be impractical or costly. Secondly, imaging crack detection provides high-resolution images that can capture even the smallest cracks or defects.

This level of detail allows for more accurate and reliable assessment of structural integrity. Additionally, imaging techniques can be automated and integrated into existing systems, reducing the requirement of manual labor and increasing efficiency. The capacity to analyse large amounts of data quickly and accurately enhances productivity and reduces inspection time. Furthermore, imaging crack detection techniques are versatile and can be used for various materials and structures, including complex geometries.

The classic surface defect inspection approach, which does not harm the workpiece, primarily makes uses an object's physical properties including acoustic, optical, and electromagnetic. The most used inspection technology is machine vision (MV). Because of its advantages in terms of automation, safety, efficiency, and non-intrusiveness, many manufacturers and scientific research institutions support it. Image qualities are the foundation of MV inspection technology. To manually extract the desired characteristics from the image, feature extraction operators must be designed. Defect assessment must then be finished using ML classifiers. Edge FE techniques and threshold segmentation are frequently employed. Its main benefit is its quick inspection speed. It is not necessary to teach more than a few samples to understand the impact of fault inspection.

However, this method's design of FE operators presents a challenge. Because different faults have distinct characteristics, multiple FE operators must be constructed in line with the parameters of each type of defect. This has a high effort requirement and limited universality(License et al. 2023).

The imaging crack detection technique offers several significant advantages over traditional crack detection techniques. First of all, it offers a non-contact, non-destructive way to find cracks, removing the need for direct touch with the item being examined. This not only ensures the safety of delicate or valuable materials but also reduces the risk of further damage. Additionally, imaging crack detection techniques allow for enhanced accuracy and precision in crack identification.

d. Deep Learning Technologies in Imaging

A broad spectrum of applications, from object identification and segmentation to picture classification, have been made possible by deep learning, which has had a significant impact on the area of imaging. The foundations of deep learning in imaging are as follows: Models for deep learning(Kaur et al. 2021):

Supervised and unsupervised learning are two fundamental categories of ML, they differ in how they process and utilize labeled data.

Supervised Learning. Below are the high-level details:

- **Labeled Data:** In supervised learning, the algorithm is provided with a labeled dataset. This means that for each input data point, there is a corresponding target or label that indicates the correct output or class.
- **Goal:** The learning of a mapping from input data to the proper output or label is the main objective of supervised learning. It aims to generalize from the provided examples and make accurate predictions on new, unseen data.
- **Examples:** Image classification, speech recognition, regression (predicting a continuous value), and natural language processing tasks like sentiment analysis are among the frequently used applications.
- **Training:** During training, the algorithm adjusts its parameters to minimize a predefined loss function that measures the difference between its predictions and the true labels.
- **Predictions:** The usefulness of the model is assessed based on how well it matches the true labels after training on fresh, unlabeled data.

Unsupervised Learning. Below are the high-level details:

- **Unlabeled Data**: Unsupervised learning operates on datasets that lack explicit labels or targets. The algorithm that runs the program looks for structures, correlations, or patterns in the data.
- Goal: Unsupervised learning aims to find hidden structures or patterns in the data. It often involves tasks like clustering, dimensionality reduction, and density estimation.
- **Examples:** Applications include clustering similar documents, reducing the dimensionality of high-dimensional data, and finding anomalies or outliers in a dataset.
- **Training:** Unsupervised learning models don't aim to predict specific labels. Instead, they learn representations or groupings that reveal the inherent structure of the data.
- **Predictions:** Models of unsupervised learning differ from supervised models in how they anticipate outcomes. They produce outputs that describe the data's underlying characteristics.

Semi-Supervised Learning. A blend of unlabeled and labeled information is employed in semi-supervised learning. By using this method, models that were trained mostly on the bigger collection of unlabeled information perform better due to the tiny amount of labeled data.

Reinforcement Learning. Reinforcement learning is a separate category that involves an agent interacting with an environment. While it doesn't directly fit into the supervised/unsupervised paradigm, it uses reward signals to learn optimal actions and policies.

In summary, the key distinction between supervised and unsupervised learning lies in the accessibility of labeled data and the learning objectives. Supervised learning focuses on predicting known labels, while unsupervised learning aims to uncover hidden patterns or structure within unlabeled data. Semi-supervised learning combines elements of both, and reinforcement learning deals with agent-environment interactions and rewards. Below are few of the known supervised and Unsupervised models:

CNNs. Likewise referred to as convolutional neural networks, are the foundation of deep learning in imaging. They are specialized neural networks that are very good at processing grid-like input, making them ideal for tasks involving images.

Convolutional Layers. The convolution operation, a key element of neural networks, gives CNNs their name. The learnable filters (kernels) in convolutional layers slide over the input data to extract features. Each filter is in charge of spotting particular patterns or characteristics in the input, including edges, corners, or more intricate structures. A feature map, which draws attention to certain input features, is the result of the convolution procedure.

Pooling Layers. CNNs frequently employ pooling layers to scale down the spatial dimensions of the feature maps. Common pooling methods include max-pooling and average-pooling, which down sample feature maps by utilizing the highest or lowest value found in a given area.

Activation Functions. Convolution and pooling processes are followed by non-linear activation techniques like ReLU (Rectified Linear Unit). They alter the model's linearity, enabling CNNs to recognize intricate patterns and connections in the data.

Fully connected layers. Because every neuron in the entirely interconnected layers is connected to every other neuron in the layer above, the network is able to learn intricate correlations between features. After several convolutional and pooling layers, CNNs typically include one or more fully linked layers. These tiers make the ultimate decisions and correspond to specific classes or outputs(Yamashita et al. 2018).

Recurrent neural networks (RNNs). RNNs are a less popular option than CNNs, but they can be utilized for jobs like video analysis that require processing sequences of images.

Transfer Learning. A single assumption that the training and test sets of data originate from the same feature space and distribution is necessary for many ML approaches to function successfully. When the distribution shifts, most of statistical models have to be redone from the beginning using freshly acquired training data. In many real-world applications, gathering the required training data and recreating the models might be costly or challenging. It would be best if gathering the training data took less time and effort. Under such conditions, transfer of expertise or transfer learning across task fields might be beneficial. The aim of transfer learning is to learn from the related learning. The variations in image acquisition, such as the application of different scanning techniques or scanners, serve as one example. Another illustration is comparable to data classification jobs, such as finding distinct types of irregularities. Formally, the same region's data samples are used for both training and testing(Pan and Yang 2010).

U-Net. This architecture that has two paths, a contracting path and an expanding path. The context is captured via a contracting path termed an encoder path, while accurate localization is made possible by the decoder path. The contracting path does a sequence of down sampling processes to acquire the reduced image scale and collected information. To locate the pixels or voxels, a sequence of different up sampling procedures is gathered. The design is specifically separated into four sections, including the encoder decoder path (a) convolution operations (b) down-sampling operations (c) and up-sampling operations (d) concatenation operation (Ronneberger, Fischer, and Brox n.d.).

Deep learning in imaging is the technique of analysing and processing images using deep neural networks. Deep learning algorithms, which can be deployed for a number of tasks like image classification, segmentation, and denoising, can learn to recognize patterns and characteristics in images by analysing enormous volumes of data. Deep learning approaches for image denoising have demonstrated promising results in the removal of noise from images, particularly in situations when traditional denoising techniques are ineffective.

Deep learning technologies make reference to the properties of image denoising to suggest intelligent solution approaches that are incorporated in numerous hidden layers with end-to-end connectivity. Contrarily, traditional ML approaches for picture denoising rely on manually created features and shallow learning models rather than deep neural networks. Deep learning approaches have demonstrated increased proficiency in handling complex, high-dimensional data and are capable of autonomously deriving attributes from its contents without requiring human enhancement of features(Tian n.d.).

3. Role of Deep Learning

a. Deep Learning Role in Image Enhancement in NDT

The field of AI's deep learning has completely changed image denoising. Convolutional Neural Networks (CNNs), in particular, are deep learning programs that have demonstrated impressive capabilities in comprehending and improving images. The benefits of deep learning include enhanced noise reduction capabilities, flexibility in handling a variety of situations, and the capacity to catch minute information.

Deep learning-based approaches offer the power to pick up knowledge automatically complex features from raw data and deliver exceptional performance compared to traditional methods. However, with recent advancements in deep learning, there has been a growing interest in utilizing neural networks to challenges related to image enhancement tasks.

The development related to deep learning approaches for image denoising has considerably benefited from the proposal of large data analysis and Graphic Processing Unit (GPU). Deep neural networks, which are computationally demanding and require enormous quantities of data to develop appropriate representations, may now be trained more quickly thanks to GPU acceleration. Big data analysis has made it feasible to train deep learning models on large datasets, which has significantly improved performance for image denoising applications. Thanks to these advancements, deep neural networks with millions of parameters may now be trained, allowing them to learn sophisticated representations of picture data and execute image denoising jobs at the cutting edge(Tian n.d.).

Several deep learning denoising algorithms include:

- DnCNN
- RED30
- MemNet
- FFDNet
- CBDNet
- RIDNet
- MWCNN

These methods, which use a variety of designs and training strategies, learn mappings from noisy images to clean images employing deep neural networks. DnCNN, for example, uses a deep convolutional neural network with residual connections to develop a residual denoising function. Batch normalization and residual learning are coupled to expedite training and enhance denoising performance. Unlike normal discriminative models that train specific models for specific noise levels, a single DnCNN model may manage blind Gaussian denoising given uncertain noise level. Three common image denoising tasks can be trained on a single DnCNN model: JPEG image deblocking with different quality factors, single image super-resolution with different upscaling factors, and Gaussian denoising with uncertain noise level. Numerous experiment results demonstrated that the suggested approach not only produces good image denoising but also has a promising run time due to GPU implementation, in addition to creating good statistical and qualitative image denoising efficiency. We will look at appropriate CNN models in the future for jobs like basic image restoration and denoising images with genuine complex noise(K. Zhang et al. n.d.).

MemNet processes the input image in a multi-scale way using a recursive structure and a memory block to hold intermediate features. Using a noise level map as input, FFDNet employs a neural network with full convolution to handle images with different noise levels.

To gradually reduce noise from images, CBDNet employs a cascaded architecture and a coarse-to-fine method. RIDNet learns a hierarchical representation of image features using a residual-in-residual dense block. MWCNN uses a multi-level wavelet decomposition convolutional neural network to teach itself a non-linear mapping of noisy images to clean ones. On numerous benchmark datasets, our deep learning denoising algorithms demonstrated state-of-the-art performance and showed encouraging results in practical applications(Tian n.d.).

b. Deep Learning's role in NDT crack detection

Over the past few years, imaging crack detection techniques have emerged as a promising alternative that overcomes the drawbacks associated with traditional methods. This innovative approach utilizes advanced imaging technologies to capture high-resolution images of cracks within a material or structure. By analysing these images using sophisticated algorithms and image processing techniques, it becomes possible to detect cracks with improved accuracy, enhanced sensitivity, and reduced human error(Cha and Choi 2017).

Deep learning methods have become a potential solution for image denoising and crack identification in NDT, as a means of overcoming the drawbacks of conventional image processing approaches. A subclass of ML algorithms known as deep learning algorithms is applied to simulate intricate patterns and correlations seen in data.

Compared to connect detection procedures of NDT deep learning algorithms utilized in visual images for pavement crack identification offer several advantages, including the ability to overcome limitations pertaining to the material being detected, faster processing speed, and lower cost (Lu et al. 2022). A study conducted by Muduli et al. demonstrated Deep learning algorithms' efficacy in crack detection by applying a binary classification semantic segmentation approach. Their model achieved accurate classification and segmentation of cracks, allowing for the identification of not only the existence but also the topology and dimensions of cracks. In addition to deep learning algorithms, other image denoising techniques have also been explored in the research of NDT. These include hyperbolic tangent filtering and canny edge detection algorithms. However, these techniques were discovered to be ineffective for images with a high level of background noise and unclear cracks (Qu et al., 2021). The drawbacks of conventional image processing methods in crack identification and distinction has led researchers to explore deep learning algorithms for image denoising and crack detection in NDT (Xie 2023). In NDT applications, deep learning methods like the semantic segmentation technique and anchor-based object detection program have been extensively utilized for crack detection(Chen and Shen n.d.).

One commonly used deep learning program for crack detection in NDT is the U-Net model. The U-Net model, proposed by (Ronneberger, Fischer, and Brox n.d.), is a convolutional neural network architecture especially created for image segmentation tasks. Jenkins et al. (2018) have demonstrated the successful application of the U-Net model for semantic segmentation of road and pavement surface cracks. In the subject of structural monitoring, specifically pipe inspection and crack analysis, there is a dearth of recent work, despite the growing usage of Deep Learning in computer vision applications.

4. Various deep learning methods strengths and weaknesses of each architecture

Convolutional Neural Network (CNN) benefits include high accuracy, strong generalizability, and suitability for massive amounts of data. Long training times and high data requirements are disadvantage(Convolutional, Network, and Optimizer 2018).
Benefits of an autoencoder neural network include good feature extraction and suitability for tiny data sets. Inability to manage complex data are limitations(K. Sun, Zhang, and Zhang 2016).
Benefits of a Deep Residual Neural Network are High generalization capacity, appropriate for large-scale data, and accuracy. Complex structure, high computational cost are disadvantages (Prathiba, Jose, and Saranya 2019).
Full Convolution Neural Network benefits include good in feature extraction, appropriate for small-scale data Inability to manage complex data are limitations (Xue and Li 2018)(X. Zhang, Saniie, and Heifetz 2021).
Recurrent Neural Network's benefits include its ability to handle sequential data and its suitability for time-series data. Long training times and limited ability to handle complicated data are drawbacks(Jaeger and Box 2009).
Because of their accuracy and efficiency, You Only Look Once (YOLO) family real-time item detection models have gained popularity.

YOLOv1. The YOLO model's first iteration was known as YOLOv1. In a single assessment, bounding boxes and class probabilities are directly predicted from entire images using a single neural network. The bounding boxes and class probabilities are estimated for each grid cell when the image is segmented into a grid. Although YOLOv1 is well known for its rapid detection speed, it may not be as adept at handling small objects as other models(Redmon et al. n.d.).

YOLOv2. This updated version of YOLOv1 is recognized as YOLOv2. It uses a more advanced neural network design and integrates several novel concepts to improve detection accuracy. Anchor boxes, which facilitate the identification of small objects, are another addition to YOLOv2. YOLOv2 outperforms YOLOv1 in regards to speed and accuracy(Redmon and Farhadi n.d.).

YOLOv3. The third iteration of the YOLO model is recognized as YOLOv3. In comparison to YOLOv2, it employs a more intricate neural network architecture and includes a several fresh methods to boost detection precision. A feature pyramid network (FPN) additionally contained in YOLOv3 to enhance the identification of objects at various scales. YOLOv3 outperforms YOLOv2 in regards to speed and accuracy(Redmon n.d.).

YOLOv4. The YOLO model's next to YOLOv3 iteration is recognized as YOLOv4. To raise detection accuracy and speed, it employs a more sophisticated neural network architecture than YOLOv3. To increase detection accuracy, YOLOv4 uses a CSPDarknet53 backbone and incorporates a path aggregation network (PAN) and a spatial pyramid pooling (SPP) component to improve detection accuracy. The most rapid and precise YOLO model to date is YOLOv4(C. Wang and Liao n.d.).

YOLOv5. The YOLOv5 deep learning neural network is widely utilized in computer vision and other ML jobs. Because of YOLO algorithm's superior performance in complicated and noisy data contexts, availability, and usability when combined with popular programming languages like Python, it has steadily gained favor in the data science field.
The 10 distinct structures that make up the YOLOv5 model are called YOLOv5n, YOLOv5s, YOLOv5m, YOLOv5l, YOLOv5x, YOLOv5n6, YOLOv5m6, YOLOv5l6, and YOLOv5x6 + TTA. However, only the first five—nano, small, medium, big, and xlarge—are frequently taken into account for study. They differ primarily in regards to the quantity of feature extraction modules and convolution kernels, and consequently, in view of the quantity of neural network parameters, which is significant from a practical standpoint when working with YOLO models(Horvat 2022).
Time spent training YOLOv5 models on the pilot Face Mask identification dataset, in hours.
YOLOv5n = 1.17
YOLOv5s = 0.83
YOLOv5m = 1.83
YOLOv5l = 2.83
YOLOv5x = 8.67
After the manuscript was accepted for review, MT-YOLOv6 and MT-YOLOv7 were released online in June and July 2022. Both versions perform better than YOLOv5 in view of object detection accuracy, training, and classification speed, as reported. It should be noted that versions 6 and 7 do not belong to the YOLO sequence, YOLOv5 continuous to be official YOLO release.

5. Research Gaps and Obstacles

a. Image denoising Research gaps

Image denoising aims to produce a clean image x from a noisy one y, where y = x + n, n denotes the additive white Gaussian noise (AWGN).

We know that the previous image is essential for image denoising based on our understanding of ML. Many other techniques have been proposed in the last 10 years for models using image priors, including the Markov random filed (MRF) method, BM3D, NCSR, and NSS. These techniques have two shortcomings despite their good image denoising performance. These algorithms must first be optimized, which raises the cost of computing. These approaches are non-convex, which means that manual adjustments are necessary to optimize performance(Tian n.d.).

Some discriminative learning strategies were put out to overcome the issues. To learn the image prior, a trainable nonlinear reaction diffusion approach was suggested. A cascade of shrinkage fields is incorporate to integrate the half-quadratic algorithm and the random field-based model into a single design.

Although approaches enhance image denoising performances, they are only compatible with the designated earlier forms. Another flaw is that these methods are unable to handle blind image denoising by applying a model.

There are numerous research gaps and prospects for more investigation in the area of image denoising research, which is an active area of study. Some significant areas for future research in picture denoising are listed below:

Generalization to Real-World Noises. Numerous deep learning denoising techniques in service today are built to handle Gaussian noise or synthetic noise models. More reliable techniques are required to efficiently denoise images that have been impacted by a different kind of real-world noise sources, including sensor noise, compression artifacts, and environmental influences.

While supervised learning has been extensively used in image denoising, semi-supervised and unsupervised approaches have received less attention. Research on techniques that can learn from data with unclear labels or utilize both labeled and unlabeled data is needed.

This is a continuous endeavour to create precise noise models that can better represent the features of various noise sources. To construct noise models that are dynamic and adaptive to various settings, more study is required. A major obstacle is creating more resilient and flexible models that are able to effective handle and generalized well to various real-world noise scenarios.

Multimodal and Multi-sensor denoising. Images taken by various sensors or modalities are applied in many real-world circumstances. Growing interest has been shown in the field of research with numerous potential uses, including NDT and medical imaging, with emphasis on creating deep learning models that can successfully denoise multimodal or multisensor data.

Denoising in low-light and harsh situations, such as night vision or underwater imaging, continues to be difficult. Given the scarce light and difficult climatic circumstances, specialized procedures are necessary for these situations.

EdgePreservation and Detail Enhancement It is still difficult to strike a compromise between noise reduction and the preservation of tiny visual characteristics, such as edges and textures. An ongoing research gap is the creation of deep denoising algorithms that can more effectively distinguish between noise and crucial image features.

Hardware acceleration. Numerous applications, such as video processing and autonomous systems, real-time picture denoising is crucial. The critical area of development is the investigation of hardware acceleration and effective algorithms that can function on devices with limited resources.

Deep Learning Interpretability. Deep learning models are frequently considered as "black boxes." As CNNs and other deep learning techniques have proliferated in image denoising, there is an increasing need for research on model interpretability, which entails figuring out why a network chooses to denoise a particular way and offering confidence estimates for its predictions.

Adaptive Denoising. Research is needed to design deep learning denoising algorithms that can alter their strength and tactics in accordance with the unique properties of the provided image or scene are still a work in progress. This might entail automatic noise level and type detection training.

Benchmark Datasets. It is essential for assessing and contrasting the success of various denoising algorithms to develop and maintain standardized benchmark datasets with a wide range of noise kinds and intensities. Curating such datasets should be the main focus of research.

Data efficiency and Transfer Learning. Research may be interested in investigating the application of transfer learning and pretrained models for image denoising, where models trained on one type of noisy data can be adjusted for another. For Data efficiency, it takes an immense amount of labeled data to train deep denoising models, but this may not always be possible, especially in cases where the domain is specialized or there are new types of noise. Research is necessary to look at techniques, such as transfer learning and data augmentation, for training denoising models with little data.

To further increase the precision, adaptability, flexibility, robustness and usability of denoising models for a different kind of applications of NDT, and more, researchers in deep learning for image denoising can concentrate on filling up these research gaps.

b. Crack detection Research gaps

The accuracy and effectiveness of crack detection could be greatly increased by using deep learning techniques, which are frequently used in fields like manufacturing, materials science, and infrastructure inspection. However, there are a number of knowledge gaps and difficulties in this area:

Limited and diversified Datasets. There aren't many large-scale, diversified datasets containing annotated crack photos. A difficult task in research is compiling high-quality information that include an acceptable limit of materials, types of cracks, and environmental factors.

Generalization to New Materials. Deep learning models could have trouble generalizing to new surfaces or materials. Models that can accurately identify cracks in a broad spectrum of materials, such as concrete, metal, or composites, must be established via research. Finding minuscule, undetectable flaws that are difficult for the human eye to see is a difficult task. For early detection and maintenance, it is crucial to create models that can accurately identify and categorize small cracks.

Transfer Learning for Limited Data. There is a dearth of labeled data for deep learning models in many real-world applications. It is vital to look at transfer learning and few-shot learning methods that can use accumulated knowledge from linked datasets.

Real-TimeProcessing. Real-Time crack detection is crucial in applications like autonomous systems and infrastructure inspection. Deep learning models and algorithms must be improved for real-time execution on devices with limited resources.

Multi-Modal Data Integration. In certain circumstances, integrating image data with data from additional sensor modalities, like as LiDAR or thermal imaging, might improve crack detection accuracy. An expanding field of study is the efficient integration of multimodal data and the utilization of complementary data information is an emerging area of research.

Robustness to Environmental Conditions. Crack detection models' performance can be impacted by environmental factors as noise, weather, and lighting. A research need exists in the creation of models that are resilient to changes in environmental conditions.

Semantic Understanding. Deep learning crack detection algorithms frequently concentrate on identifying and categorizing cracks. For more detailed inspection reports, research on models that can convey a semantic understanding of the environment where the cracks develop is crucial.

Transparency. Deep learning crack detection models are frequently referred to as "black boxes." It is beneficial to conduct research on techniques for improving model transparency, explaining the judgments made by these models, and making them easier to understand.

Human-in-the-loop. Deep learning models and human knowledge combined in a "human-in-the-loop" system can increase the accuracy of crack detection. It is of interest to conduct research on the best ways to incorporate human operators into the process.

Evaluation Metrics. For fair comparisons between various methodologies, it is crucial to create standardized evaluation metrics and benchmarks for evaluating the effectiveness of crack detection models.

Filling in these research gaps might result in the creation of deeper learning crack detection methods that are more precise, dependable, and useful, with applications in materials science, construction, and many industries. These fields require more study, which is essential for accurate inspection systems.

c. Crack detection Research gaps with YOLO Deep Learning method

Limited Datasets. There aren't many high-quality datasets available that are particularly developed for crack detection. For YOLOv5 model training and evaluation, large-scale, diversified, and annotated datasets must be created and curated. A research challenge is also how to deal with class imbalance issues in these datasets.

Anomaly Detection. Finding uncommon or unexpected abnormalities is sometimes required while looking for cracks in a broad spectrum of contexts, such as manufacturing, infrastructure, or construction. Research interests include the development of YOLOv5 models that can successfully handle anomaly detection in addition to conventional crack detection.

Real-World Variability. The lighting, occlusions, and crack appearance in real-world photographs can be complex. Research is needed to create YOLOv5 models that can generalize well to different environmental conditions and are robust to such variability.

Multi-Modal Data. In some applications, cracking detection may incorporate multi-modal data. For example, pictures may be combined with data from other sensors, such as thermal imaging or LiDAR. There is a need for more research on the efficient integration and application of multi-modal data with YOLOv5 for enhanced fracture detection.

Localization and Severity Assessment. Although YOLOv5 is capable of localizing cracks, another research problem is determining the severity and potential consequences of identified cracks. For maintenance and safety applications, it is beneficial to create models that can identify cracks as well as categorize and rate their importance.

Large-Scale Deployment. Scalability, real-time performance, and hardware requirements are problematic when implementing YOLOv5-based crack detection systems in practical applications, such as infrastructure inspection or industrial quality control. large-scale deployment and system integration research is needed.

Noise and False Positives. Managing the impacts of noise and reducing false positives on crack detection results is a significant problem. This problem can be solved by creating methods for pre-processing, post-processing and enhancing model confidence estimation.

Original YOLOv5 deep learning algorithm has limitation for small crack detection and extreme aspect ratios of image which is improved by (Shi and Yang 2022).

Few issues with the attention mechanism-based YOLOv5 steel surface flaw identification method. These issues include the need for more algorithm testing and optimization in real-world scenarios with tangible results, the significance of paying attention to recalls of all types of defects during algorithm training, and the increased number of parameters as a result of the algorithm's addition of one attention mechanism(Shi and Yang 2022).

6. Evaluation

a. Evaluation of Image Denoising

To evaluate the efficiency and performance of your denoising models, deep learning image denoising evaluation is essential. The quality of denoised images can be assessed using a broad spectrum of metrics and techniques. Here are a few often employed methods for measuring the effectiveness of deep learning systems for image denoising:

Peak Signal-to-Noise Ratio. PSNR is frequently applied metric to assess how well denoised images compare to the original, noise-free images. It gauges the proportion of a signal's maximum allowable power to corrupting noise power. Better denoising performance is indicated by higher PSNR values.

Structural Similarity Index. SSIM determines the degree to which the original and denoised images are architecturally similar. Structure, contrast, and brightness are all considered. Better denoising performance is indicated by higher SSIM values.

Mean Squared Error (MSE). Although MSE is frequently used to calculate PSNR, it may also be applied as a stand-alone metric to assess the typical squared variations between pixel values in the noise removed and original images. Goodier denoising performance is shown by lower MSE values.

Root Mean Squared Error (RMSE). It calculates the arithmetic mean of the pixel value differences between the original and denoised images. Better denoising performance is shown by lower RMSE values.

The mean absolute error (MAE), which compares the pixel values in the original and denoised images, is a measurement of the average absolute error. Lower MAE values signify better denoising performance, similar to RMSE.

Normalized Mean Square Error (NMSE). NSME statistic measures the energy of the noise that has been retained in the image compared to the energy of the noise in the original image. Better denoising is indicated by lower NMSE values.

b. Evaluation of Crack detection

Depending on the particular objectives and specifications of the project, the best evaluation metric for crack detection must be chosen. The choosing of metrics should be in line with the intended use because different measures highlight various elements of model performance. Here are some evaluation metrics that are frequently used in crack detection and the factors to take into account for each:

IoU. Also known as the Jaccard Index, measures the overlap between ground truth and forecast bounding boxes. When evaluating the spatial alignment between anticipated and actual fractures, this metric is appropriate for object detection tasks. Good spatial localization is indicated by a high IoU.

- Advantages: Offers a precise evaluation of localization accuracy.
- Cons: Missed cracks and false negatives are not taken into account.

Average Precision (AP). The precision-recall curve for various IoU thresholds is summarized by average precision (AP). It is a well-liked object detection metric and is suitable when you need to take into consideration different degrees of confidence in your detections.

- Advantages: Considers recall and precision over different IoU thresholds.
- Cons: Calculation may be more difficult.

Precision and Recall. Recall is the ratio of true positives to all true positive cases, while precision measures the ratio of true positive detections to all true positive predictions. These metrics are beneficial for assessing the trade-off between precision, which measures accuracy, and recall, which measures the capacity to identify all cracks.

- Advantages: Offer information on both correctness and comprehensiveness.
- Cons: They don't offer a solitary, impartial metric.

F1 Score. It is the harmonic mean of recall and precision. It provides a fair evaluation that considers each false negatives and false positives. This statistic is helpful when you require just one statistic that strikes a balance between recall and precision.

Accuracy. It quantifies how accurately forecasts were made overall. It refers to the proportion of cases that were successfully predicted to all instances. Although accuracy is a popular metric, it might not be appropriate if the dataset is unbalanced and contains a large number of non-crack cases.

- Advantages: Simple to comprehend and calculate.
- Cons: In datasets with imbalances, it may be misleading.

MCC. A statistic that considers both true and erroneous positives and negatives is the Matthews Correlation Coefficient (MCC). It offers a balanced measure of classification performance and is appropriate for datasets with imbalances.

- Advantages: Suitable for datasets with imbalances.
- Cons: Not as simple to understand as some other measures.

Area AUC-ROC. Also known as the Receiver Operating Characteristic Curve. They are used to evaluate the trade-off between true positive rate (sensitivity) and false positive rate. Using AUC-ROC, the ROC curve's performance is reduced to a single number. This measure is useful for problems that need to be binarily classified. For issues requiring binary categorization, this metric is helpful.

- Advantages: Offers information about how well the model can distinguish between crack and non-crack instances.
- Cons: Localization may not take the IoU factor into account.

The specific goals of crack detection project should be taken into account while selecting an evaluation metric. For instance, IoU, AP, or F1 score may be more important if prefer precise geographical localization. F1 score can be an excellent option if final target is to strike a balance between precision and recall. A combination of measures is frequently taken into account to get a complete picture of model's performance.

7. Application and Case Studies

There are various uses for deep learning-based image denoising and crack detection in fields like remote sensing, medical imaging, and non-destructive testing. Deep learning-based image denoising and crack detection are undoubtedly important applications in NDT. Without causing damage, NDT techniques are employed to evaluate the integrity of components, materials, and structures. These inspections are more accurate and productive because deep learning. Following are some NDT application areas and related case studies:

The Oil and Gas Sector. Deep learning methods are employed to denoise images from radiography, ultrasound, and visual inspections, among other sources. The objective is to enhance the clarity and quality of images used for pipeline and offshore platform structural integrity evaluations and problem detection.
Deep learning models can automatically find and categorize cracks, corrosion, and other equipment and pipeline issues. Case studies include stopping leaks and improving upkeep.

Inspection of Power Lines. To enhance the quality of an image, denoising is applied. However, factors such as illumination and distance might affect the image quality during aerial inspections of power lines. The objective is to increase the precision with which flaws and safety issues are identified. Deep learning models for Crack detection are applied to find wear or damage on insulators and towers, two common parts of power lines. Case studies are designed to streamline examinations and lower the possibility of errors.

Monitoring and Safety. Deep learning algorithms are employed in surveillance and security applications for the purpose of image denoising. Improved image quality makes it easier to identify and follow objects, people, or events. Crack Detection is done to identify structural problems or infrastructure damage, security systems may utilize deep learning, ensuring the safety and security of crucial assets.

Aerospace Sector. Aircraft parts are inspected as part of aerospace NDT. Images taken during crucial component inspections—such as turbine blades or aircraft engines—can be denoised with the aid of deep learning. Crack Detection is done to improve aircraft safety and dependability, deep learning models are utilized to find fatigue cracks and other flaws in aerospace materials.

Transportation by Rail. Deep learning image denoising improves image quality for track, switch, and component inspection in railway maintenance. Detecting wear, damage, and cracks early on is made easier by doing this.
Crack Detection is done to lower the risk of accidents and guarantee operational safety, deep learning models are applied to automatically detect and categorize cracks or other faults in railway infrastructure.

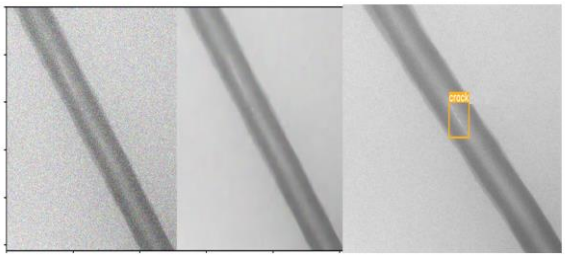
The automation and precision provided by deep learning-based image denoising and crack identification techniques are advantageous for many NDT-related applications. Safety, dependability, and cost-effectiveness in critical infrastructure inspections and maintenance are frequently highlighted in these fields' case studies.

8. Call to action for further research and development in these areas

Deep learning techniques have been increasingly applied to automatic crack detection, offering the potential for improved accuracy and efficiency. Leveraging Deep Learning for Image Denoising and Crack Detection for quicker and more precise crack detection model with image denoising preprocessing process as enabler to achieve required speed and high accuracy.

After critical review and identifying research gaps in automatic crack detection using deep learning techniques, our research call to action is image preprocessing which includes image enhancement in terms of image denoising and optimal YOLOv8 algorithm is further research as our primary scope of work. Optimization of Denoising deep learning algorithm parameters and optimization of hyperparameters of YOLOv8 is our key research areas for high speed and accuracy in crack detection in NDT domain.

a. Research gap and Call to Action.



Input Image Denoised Image Crack Detected Image

Identified scope of Denoising algorithm Research and development.
Setup up of training environment, Collection and preprocess of input images, Design of Architecture which includes adjusting the count of layers, filters, kernel size, learning rate, batch size, activation function, normalization, transfer learning, data augmentation and regularization can all affect the performance and quality of denoising in denoising algorithms, and it's important to experiment and optimize these parameters to achieve the best outcomes for the Image denoising.

Evaluation of model with evaluation criteria like PSNR, SSM …etc. and finally fine tuning of parameters based on evaluation of results. Crack detection includes evaluation of fine tune model and performance measurement on the identified test results using PSNR metrics.

b. Identified scope of YOLOv8 based Crack detection Research and development.

Tuning Hyperparameters includes:
Determine the Measures. Choosing the measures to assess the model's effectiveness. This may be an F1-score, AP50, or another score.

Decide on a tuning budget. Tuning hyperparameters need a lot of processing power. Identifying and deciding computer resources is critical.

Set up the hyperparameters. Choosing a sensible initial set of hyperparameters to begin with. This might be the default hyperparameters that YOLO has defined, or it might be something based on our prior experiments and domain knowledge.

Change the Hyperparameters. Use of mutate method to generate a new set of hyperparameters depending on the present set.

Utilizing the altered set of hyperparameters, train model training will be carried out. After that, the training performance will be evaluated. Logging performance metrics and corresponding and hyperparameters for overall evaluation. During the tuning process, the best-performing hyperparameters will be identified.

References

[1] Agrawal, Neha, and G R Sinha. 2015. "A Survey on Fuzzy Based Image Denoising Methods." 4(05): 528–31.
[2] Cha, Young-jin, and Wooram Choi. 2017. "Deep Learning-Based Crack Damage Detection Using Convolutional Neural Networks." (September).
[3] Chen, Chaoxin, and Peng Shen. "Research on Crack Width Measurement Based on Binocular Vision and Improved DeeplabV3 +."
[4] Convolutional, Modified, Neural Network, and Descent Optimizer. 2018. "Modified Convolutional Neural Network Based on Dropout and the Stochastic Gradient Descent Optimizer."
[5] Gabhel, Manoj, and Aashish Hiradhar. 2014. "Comparative Analysis of Various Image Denoising Techniques : A Review Paper." 3(7): 1877–81.
[6] Gupta, Vikas, Vijayshree Chaurasia, and Madhu Shandilya. 2013. "International Journal of Emerging Technologies in Computational and Applied Sciences (IJETCAS) A Review on Image Denoising Techniques." : 204–8.
[7] Horvat, Marko. 2022. "A Comparative Study of YOLOv5 Models Performance for Image Localization and Classification A Comparative Study of YOLOv5 Models Performance for Image Localization and Classification." (September).
[8] Jaeger, Herbert, and P O Box. 2009. "Reservoir Computing Approaches to Recurrent Neural Network Training." 3: 127–49.
[9] Jenkins, Mark David et al. 2018. "A Deep Convolutional Neural Network for Semantic Pixel-Wise Segmentation of Road and Pavement Surface Cracks." : 2120–24.
[10] Kaur, Amrita et al. 2021. Archives of Computational Methods in Engineering A Survey on Deep Learning Approaches to Medical Images and a Systematic Look up into Real-Time Object Detection A Survey on Deep Learning Approaches to Medical Images and a Systematic Look up into Real - Time Object Detection. Springer Netherlands. https://doi.org/10.1007/s11831-021-09649-9.
[11] Lau, Stephen L H, Edwin K P Chong, X U Yang, and X I N Wang. 2020. "Automated Pavement Crack Segmentation Using U-Net-Based Convolutional Neural Network."
[12] License, Commons Attribution et al. 2023. "Retracted: Inspecting Decorative Ceramic Defects by Fusing Convolutional Neural Network and Image Recognition Computational Intelligence and Neuroscience." 2022.
[13] Lu, Kai-liang et al. 2022. "Comparison of Deep Learning Methods and a Transfer-Learning Semi-Supervised GAN Combined Framework for Pavement Crack Image Identification." 0.
[14] Luo, Rui, Qingxiang Zeng, and Huashan Chen. 2022. "Artificial Intelligence Algorithm-Based MRI for Differentiation Diagnosis of Prostate Cancer." 2022.
[15] Pan, Sinno Jialin, and Qiang Yang. 2010. "A Survey on Transfer Learning." 22(10).
[16] Patnaik, Sudhir Kumar, C Narendra Babu, and Mukul Bhave. 2021. "Intelligent and Adaptive Web Data Extraction System Using Convolutional and Long Short-Term Memory Deep Learning Networks." 4(4): 279–97.
[17] Prathiba, M, Deepa Jose, and R Saranya. 2019. "Automated Melanoma Recognition in Dermoscopy Images via Very Deep Residual Networks Automated Melanoma Recognition in Dermoscopy Images via Very Deep Residual Networks."
[18] Quan, Jin. "Image Denoising of Gaussian and Poisson Noise Based on Wavelet Thresholding."
[19] Redmon, Joseph. "YOLOv3: An Incremental Improvement."
[20] Redmon, Joseph, Santosh Divvala, Ross Girshick, and Ali Farhadi. "You Only Look Once : Unified , Real-Time Object Detection."
[21] Redmon, Joseph, and Ali Farhadi. "YOLO9000: Better, Faster, Stronger."
[22] Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "U-Net: Convolutional Networks for Biomedical Image Segmentation." : 1–8.
[23] Shi, Jianting, and Jian Yang. 2022. "Research on Steel Surface Defect Detection Based on YOLOv5 with Attention Mechanism."
[24] Sun, Kai, Jiangshe Zhang, and Chunxia Zhang. 2016. "Author ' s Accepted Manuscript Generalized Extreme Learning Machine Autoencoder and a New Deep Neural Network Reference : To Appear in : Neurocomputing." Neurocomputing. http://dx.doi.org/10.1016/j.neucom.2016.12.027.
[25] Sun, Yuhui, Peiru Wu, G W Wei, and Ge Wang. 2006. "Evolution-Operator-Based Single-Step Method for Image Processing." 2006(1): 1–27.
[26] Tian, Chunwei. "Deep Learning for Image Denoising: A Survey." : 1–10.

[27] Wang, Chien-yao, and Hong-yuan Mark Liao. "YOLOv4: Optimal Speed and Accuracy of Object Detection."
[28] Wang, Jinjiang et al. 2018. "Deep Learning for Smart Manufacturing: Methods and Applications." Journal of Manufacturing Systems 48: 144–56.
[29] Xie, Yonghua. 2023. "NFFNet : An Encoder-Decoder Net for Crack Detection Based on Noise Filtering Fusion NFFNet : An Encoder-Decoder Net for Crack Detection Based on Noise Filtering Fusion."
[30] Xue, Yadong, and Yicheng Li. 2018. "A Fast Detection Method via Region-Based Fully Convolutional Neural Networks for Shield Tunnel Lining Defects." 0: 1–17.
[31] Yamashita, Rikiya et al. 2018. "Convolutional Neural Networks : An Overview and Application in Radiology." : 611–29.
[32] Zhang, Kai et al. Beyond a Gaussian Denoiser: Residual Learning of Deep CNN for Image Denoising.
[33] Zhang, Xin, Jafar Saniie, and Alexander Heifetz. 2021. "Spatial Temporal Denoised Thermal Source Separation in Images of Compact Pulsed Thermography System for Qualification of Additively Manufactured Metals." In IEEE International Conference on Electro Information Technology, IEEE Computer Society, 209–14.