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Image Processing Methods: A Systematic Literature Review of Classical and Modern Approaches

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Abstract

In image processing, there are many different methods used to process pictures. This includes denoising, enhancement, segmentation, feature extraction, and classification. All of them join together to solve different problems and understand the changes in images. They are useful in many ways, like in medicine, security, photography, and robotics. Where images need to be studied or improved. Drawing on visual information, these methods help us in comprehending images, extracting key data, and making informed choices. There are two main ways to process the image, which are through traditional image-processing methods and deep-learning models. Usually, traditional techniques depend on manually designed algorithms and rules. Which uses fixed steps to process images. In contrast, deep learning models learn features directly from the information itself, enabling them to automatically detect distant details that traditional techniques could miss. The things that help the image processing methods to proceed are like Self2Self NN, Denoising DFT-Net CNNs, and MPR-CNN, which help remove unwanted noise from images in denoising. However, they still face difficulties with data preparation and adjusting model settings. While in an image enhancement, R2R and LE-net are employed to enhance the image's visual quality, through which they can deal with complex real-world images and help them to look natural. On one hand, in the segmentation, PSP Net and Mask-RCNN methods accurately separate objects in an image; however, they can face problems with overlapping objects and ensuring reliable performance. In the method of feature extraction, models like CNN and HLF-DIP can automatically detect important image details, though they can be hard to interpret and sometimes complex to use. In the classification method, Residual Networks and CNN-LSTM are the approaches, which are effective at accurately identifying image categories; however, they require enormous computing power and can be difficult to fully understand. This review gives a clear overview of the advantages and disadvantages of different methods, which can help people choose the best approach for real-world use. As image processing continues to develop, solving problems like high computing needs and ensuring reliable performance will be important to make these techniques work at their best.

Keywords: Digital image-processing, Artificial Intelligence, Machine Learning.

INTRODUCTION

Image processing is a vast field that employs different methods to get useful information from an image. At a similar point, Artificial Intelligence (A_I) has become a large area of study that focuses on making machines that think and act like humans. Machine Learning (M_L) is a small part of A_I. This one can allow a computer to learn from data and make decisions on its own without taking help from humans. M_L reduces the need for humans to make decisions. At the core of M_L, deep learning (D_L) is a branch that goes beyond traditional methods, especially when working with unstructured data such as images, text, or audio. Even a D_L can achieve an accuracy of such a level that humans cannot. Its success depends upon that it has a greater quantity of data to train a complex neural network, which is made up of many layers. Unlike older models, D_L systems can automatically identify and extract crucial perspectives from information without needing humans to manually define them. Such a type of ability also comes from its layered structure. D_L is inspired by the process of coping, that how the human brain can think and learn. It aims to develop learning algorithms that closely replicate the brain's complex processes. In this paper, different deep learning methods proposed by various researchers are explained and discussed in relation to their use in Image Processing (IP) techniques.

Such a detailed collection explores the huge and complex field of IP. These are image restoration, feature extraction, segmentation, enhancement, and classification. All of them are important in handling and improving visual data, which helps us to understand the image better and use images in many different applications. The most important step in it is image restoration methods, which help in fixing damaged or unclear images. The techniques, like removing noise, correcting blurriness, and filling in missing parts, aim to undo the effects of distortion and other image problems. They create a solid base for further analysis and interpretation by improving the image's clarity and accuracy, which is important in areas like medical imaging, security, etc. The orbit is used for image enhancement, which can improve the quality of an image. This task can be processed to adjust contrast, brightness, sharpness, etc. This can make the image easier to see and understand. Image enhancement is used in many different fields, which can lead to better analysis and more accurate decision-making.

This study includes image segmentation, in which images are divided into many parts. Methods like clustering and semantic segmentation help to identify the objects within the image. Image segmentation is especially crucial for the detection of objects, tracking, and understanding scenes, which can provide the foundation for accurate recognition and analysis. The most essential part of an image analysis is extraction, which can improve the characteristics of the image for further study. Traditional methods face the trouble, while in deep learning, it can automatically identify the complex features. This ability improved the image and helps with better analyses. Image classification is also an important task in visual data analysis. In which we give images labels based on what they show. Most of the time, this is used for the recognition of objects and medical diagnosis. Both M_L and D_L methods are used to automatically and accurately sort images into categories and helping to make decisions more quickly and effectively.

Section 1 explains the basic ideas and operations of image processing. Section 2 gives a detailed overview of the assessment methods employed to gauge the performance of distinct image processing techniques. Section 3 explores various Deep Learning (D_L) techniques that are particularly designed for the tasks of image preprocessing. Section 4 focuses on D_L models employed for the segmentation of images, explaining their methods and applications. In Section 5, the paper discusses D_L techniques for feature extraction, highlighting their importance and efficacy. Section 6 examines D_L models used for image classification, describing their structure and performance. Section 7 discusses the importance of each model, and Section 8 concludes the paper by summarizing the key outcomes and main insights from the study. The research reviewed in this paper covers a wide range of D_L techniques applied to different areas, including medical images, satellite images, images of fruit and plant (flower), and even image analysis in real-time. Each area has its own challenges, which are addressed with specific D_L methods, showing how flexible and powerful deep learning can be across many real-world applications.

Image processing operations metrics

Metrics of evaluation play a critical role in measuring the effectiveness and performance of various image-processing techniques. They provide quantitative indicators that enable researchers and practitioners to conduct objective analyses and make meaningful comparisons across different approaches. Through the application of these parameters, the often complex and subjective nature of image processing becomes highly transparent and data-driven, supporting informed decision-making and fostering continuous progress in the field.

Table A summarizes commonly used metrics for evaluating image preprocessing, segmentation, and classification tasks. The evaluation of image processing, segmentation, and classification tasks relies on a variety of quantitative metrics designed to assess performance across different dimensions of accuracy, similarity, and perceptual quality. In image preprocessing, metrics such as Average Squared Deviation (ASD) and Average Absolute Deviation (AAD) measure the discrepancy between the original-images and processed-images. ASD calculates the mean squared difference between the original-images and denoised-images, penalizing larger errors more heavily, whereas AAD (equivalent to Mean Absolute Error) assesses the average tendency of errors without considering their path, providing a complementary perspective on image restoration accuracy. Maximum Signal-to-Noise Ratio (MSNR) quantifies restoration quality by comparing the optimal approximate pixel value to the measured noise, offering insight into the overall signal fidelity. To capture perceptual and structural fidelity, the Structural Similarity Measure (SSM) evaluates images based on luminance, contrast, and structural consistency, while the Average Structural Similarity Index (ASSI) extends this evaluation across multiple image patches to provide an aggregate assessment. Additionally, perceptual quality is further assessed using Image Naturalness Index (NIQE), which measures deviations in luminance and contrast statistics relative to natural images, and Inception Feature Divergence (FID), which quantifies the distributional distance between real and generated images using feature embeddings from pretrained networks.

In image segmentation, metrics focus on evaluating the spatial accuracy of predicted regions relative to ground truth annotations. Overlap Ratio Metric (ORM), also refer as Intersection over Union, assesses the percentage of correctly predicted pixels relative to the union of predicted and true regions. Mean Precision Score (AP) measures detection performance across multiple recall levels through the calculation of the area under the curve of precision-recall. Complementing these, the Dice Overlap Index (DSC) evaluates the similarity between predicted and ground truth masks, particularly useful in applications with class imbalance such as medical image segmentation. Mean Accuracy (AA) calculates the correctly classified pixels' ratio (both negative and positive) across all images, providing a general measure of segmentation performance.

For feature extraction and classification tasks, traditional metrics, i.e., Precision, Accuracy, Recall (Sensitivity), and F-Measure (F1-Score) are widely applied. Accuracy refers to the overall ratio of correctly predicted instances, though it may be less informative in imbalanced-datasets. Precision measures the capability of the method to eliminate false positives, while Recall captures the model's ability to correctly identify true positives. F-Measure combines both Recall and Precision employing the mean of harmonic to present a balanced evaluation of model performance. Specificity (True Negative Rate) corroborates these metrics by quantifying the ratio of correctly identified negatives. Finally, the ROC Curves and their corresponding Area Under the Curve (AUC) visually and quantitatively represent the mutual exclusivity among true-positive and false-positive rates, offering a detailed measure of classifier performance across varying decision thresholds.

Collectively, these parameters provide a rigorous mechanism for assessing the effectiveness of image processing, segmentation, and classification models, balancing considerations of structural fidelity, perceptual quality, and predictive accuracy.

Image pre-processing

The image pre-processing represents a primary stage in the image processing field, comprising a sequence of operations designed to prepare raw/unprocessed images for subsequent processing, including analysis, interpretation, and manipulation. Such a crucial phase enhances the images' overall quality by reducing noise, correcting distortions, and emphasizing related features. Through these improvements, image preprocessing contributes to highly reliable and accurate outcomes in advanced tasks, i.e., image recognition, classification, and analysis.

In general, image-pre-processing models can be classified into two primary types: image restoration. These types fundamentally focus on eliminating noise and blurring to recover the original image quality, and image enhancement, which aims to improve visual attributes such as contrast, brightness, and detail to facilitate better interpretation and analysis.

Image restoration

The image restoration is a critical process dedicated to recovering the images' original integrity and visual quality that have suffered distortion/degradation. The fundamental objective of it is to reconstruct an image that is in degraded form into a clearer and highly faithful representation, ultimately unveiling information that could have been lost or obscured. The process of image restoration is primarily significant in situations where the quality of the image is compromised because of the factors, i.e., sensor imperfections during image acquisition, compression artifacts, or transmission errors. By addressing these degradations, image restoration improves both the interpretability and practical utility of visual information in various analytical and diagnostic applications.

One of the major challenges in achieving high-quality images is the presence of noise, an undesirable random variation in the intensity of a pixel that introduces visual artifacts and could obscure critical image information. In addition, noise of distinct types can influence the quality of an image, including Gaussian noise, known by its random statistical distribution; salt-and-pepper noise, which manifests as sporadic bright and dark pixels; and speckle noise, typically arising from interference patterns. Such distortions commonly originate during the image acquisition phase or because of subsequent processing and transmission operations. Effectively mitigating noise is therefore essential to preserve image fidelity and ensure the accuracy of subsequent analytical tasks.

Table A: Summary of Common Metrics for Image Preprocessing, Segmentation, and Classification

Category	Metric	Formula / Expression	Description
Image Preprocessing Metrics	Average Squared Deviation (ASD)	$ASD = \frac{1}{H*K} * \sum_{l=1}^{K}\sum_{j=1}^{H}(X_{i,j}^{\wedge} - X_{i,j})^2$	Measures the average squared difference between the original X and denoised images $X^{\wedge}$; penalizes large errors more heavily.
	Maximum Signal-to-Noise Ratio (MSNR)	$M\_S\_N\_R = 10 * log_{10}(\frac{P_{signal}}{P_{noise}})$	Quantifies image restoration quality by comparing the maximum possible pixel value to the ASD.
	Structural Similarity Measure (SSM)	$SSM_{(x,y)} = \left[\frac{2_{\mu_x\mu_y} + C_1}{(\mu_x^2 + \mu_y^2 + C_1)}\right] * \left[\frac{2\varphi_{xy} + C_2}{\varphi_x^2 + \varphi_y^2 + C_2}\right]$	Evaluates similarity between original and denoised images based on luminance, contrast, and structure.
	Average Structural Similarity Index (ASSI)	$ASSI\ (x,y) = {}^{1}/_{N}\,[\,ASSI(x_1,y_1) + \cdots ... + ASSI(x_N,y_N)]$	Averages ASSI across image patches to measure overall structural similarity.
	Average Absolute Deviation (AAD)	$AAD = \frac{\lvert y_1^{actual} - y_1^{predicted}\rvert + \cdots ... + \lvert y_n^{actual} - y_n^{predicted}\rvert}{n}$	The Mean Absolute Error measures the average magnitude of errors between actual and predicted values, without considering their direction. Lower AAD indicates better accuracy, and unlike ASD, it does not heavily penalize larger errors.
	Image Naturalness Index		Assesses image naturalness based on deviation of luminance and contrast statistics from natural images.
	Inception Feature Divergence		Measures distributional distance between real and generated images using feature embeddings from a pre-trained network.
Image Segmentation Metrics	Overlap Ratio Metric	$ORM = \frac{true\ positive}{true\ positive + false\ positive + false\ negative}$	Evaluates overlap between predicted and ground truth regions; widely used in object detection and segmentation.
	Mean Precision Score		Calculates the area under the precision-recall curve across multiple recall levels to assess detection performance.
	Dice Overlap Index	$Dice = \frac{2TP}{2TP + FP + FN}$	The Dice Coefficient measures the overlap between predicted and ground truth masks. Dice = 1 → perfect match Dice = 0 → no overlap. It is widely used in medical image segmentation, computer vision, and object detection, especially when class imbalance exists.

Category	Metric	Formula / Expression	Description
Feature Extraction and Classification Metrics	Mean Accuracy (AA)	$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$	Overall Accuracy (AA) measures the proportion of correctly classified pixels (both positive and negative) across all images or regions. AA = 1 (100%) → all pixels correctly classified AA = 0 → all pixels misclassified It is commonly used in image segmentation, classification, and remote sensing tasks.
	Accuracy	$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$	Accuracy measures the proportion of correctly predicted instances out of all predictions. Accuracy = 1 (100%) → all predictions are correct. Accuracy = 0 → all predictions are incorrect is widely used in classification, segmentation, and prediction tasks, though it may be misleading for imbalanced datasets.
	Precision	$\text{Precision} = \frac{\text{Correct Positive Predictions}}{All\ positive\ predictions}$	Measures the model's ability to avoid false positives.
	Recall (Sensitivity)	$\text{Recall (Sensitivity)} = \frac{TP}{TP + FN}$	Measures the model's ability to correctly identify positive samples.
	F-Measure	$\text{F} - \text{M} = 2 * \frac{\text{Correct Positive Predictions}}{All\ predictions\ positive + All\ Actual\ positive}$	Harmonic mean of precision and recall; balances false positives and false negatives.
	Specificity (True Negative Rate)	$\text{Specificity} = \frac{\text{Correct Negative Predictions}}{All\ Actual\ Negative}$	Proportion of correctly identified negatives among all actual negatives.
	ROC Curve / AUC		Graphically represents trade-off between true positive and false positive rates; AUC quantifies overall performance.

Notice: TP (True Positive) = correctly predicted pixels, FP (False Positive) = wrongly predicted pixels, FN (False Negative) = missed pixels

Historically, traditional image restoration has employed a wide range of techniques to reduce the adverse influences of image degradation and noise. These include constrained least squares filters, blind deconvolution models designed to reverse blurring impacts, and Wiener and inverse filters that enhance the signal-to-noise ratio. Furthermore, alpha-trimmed mean, order statistic, and adaptive mean filters adapt their strategies of filtering based on local pixel intensity distributions to achieve more context-sensitive restoration. In addition, deblurring algorithms are utilized to counteract motion- or optics-induced blurriness, thereby restoring image sharpness and definition. Denoising methods (Peng et al., 2020; Tian et al., 2020; Tian et al., 2019)—Non-Local Means and Total Variation Denoising, further enhance image quality by efficiently suppressing random noise while preserving key structural information. In sum, these traditional approaches have significantly advanced the field's ability to restore the integrity and visual clarity of the image. **Table 1** provides a comparative analysis of contemporary D_L techniques for restoration of image, highlighting their key positive aspects and limitations.

The progress in D_L in recent years, specifically with the emergence of Convolutional Neural Networks (CNNs) has transformed the landscape of image restoration. CNNs possess a remarkable ability to learn and extract intricate key aspects from images, enabling them to identify subtle patterns and relationships that are often difficult for traditional algorithms to capture. By leveraging large-scale training datasets, these models can produce substantially improved restoration outcomes, frequently outperforming conventional approaches. This advancement stems from CNNs' inherent capacity to model the underlying frameworks of images and to autonomously infer the most effective strategies of restoration.

Tian et al. (2020) presented a comprehensive review of the application of deep neural networks in image denoising, particularly focusing on the removal of Gaussian noise. Their study examined a range of D_L techniques addressing different denoising challenges—additive white noise, blind denoising, and images of real-world noise. By conducting analyses on benchmark datasets, they evaluated the performance, computational efficiency, and visual quality of different network architectures, and provided cross-comparisons among various denoising methods across multiple noise types. The authors concluded by highlighting the key challenges and limitations that D_L approaches still face in achieving optimal image denoising. Similarly, Quan et al. (2020) proposed a self-supervised D_L framework known as Self2Self for denoising of images. Their research revealed that neural networks trained under the Self2Self paradigm achieved superior results compared to both traditional single-image learning-based and non-learning-based denoising methods, demonstrating the effectiveness of self-supervision in enhancing denoising performance without requiring clean reference images.

Yan et al. (2020) introduced an innovative model for mitigating speckle noise in digital holographic speckle pattern interferometry (DHSPI) wrapped phase images. Such a technique utilizes enhanced Denoising Convolutional Neural Networks (DnCNNs) to effectively suppress noise, with performance evaluated through Mean Squared Error (MSE) comparisons across noisy and denoised information, demonstrating significant improvements in image clarity and precision. Sori et al. (2020) developed a two-path Convolutional Neural Network (CNN) framework for lung cancer detection using denoised Computed Tomography (CT) images. The denoised images, processed through DR-Net, were used as inputs for classification, yielding superior performance in terms of sensitivity, accuracy, and specificity compared to contemporary models.

Similarly, Pang et al. (2021) proposed an unsupervised D_L strategy for denoising of an image based on unmatched noisy image pairs. By employing, a loss function analogous to supervised learning, their technique, built upon the Additive White Gaussian Noise (AWGN) framework, achieved competitive results when compared with other state-of-the-art unsupervised denoising models.

Previous literature, Hasti and Shin (2022) documents a D_L-based denoising model for fuel spray images captured through Mie scattering and droplet center detection. Their comparative analysis among multiple architectures, including a standard CNN, a modified ResNet, and a modified U-Net, show that the modified U-Net achieved the best performance, as evidenced by lower Mean Squared Error (MSE) and higher Peak Signal-to-Noise Ratio (PSNR) values. Niresi and Chi (2022) proposed an unsupervised hyperspectral image (HSI) denoising algorithm grounded in the Deep Image Prior (DIP) framework. Their approach minimized the Half-Quadratic Lagrange Function (HLF) without relying on explicit regularizers, efficiently eliminating multiple types of noise, including Gaussian and sparse noise, while maintaining edge integrity and structural details. Similarly, (Zhou et al., 2022) developed a deep network-based sparse denoising (DNSD) model for bearing fault diagnosis. Their method addressed the limitations of traditional sparse theory algorithms by enhancing generalization capability, reducing dependency on parameter tuning, and mitigating data-driven complexity.

Tawfik et al. (2022) demonstrated that an extensive comparative analysis of image denoising methodologies, classifying them into traditional non-learnable filtering techniques and D_L-based frameworks. Their study introduced semi-supervised denoising techniques and utilized both quantitative and qualitative metrics to evaluate and contrast denoising performance across methods. In a related contribution, (Meng & Zhang, 2022) presented a denoising gray image approach leveraging a symmetric and dilated convolutional residual network. Their model demonstrated outstanding performance in high-noise conditions, achieving superior results in terms of Structural Similarity Index Measure (SSIM), Peak Signal-to-Noise Ratio (PSNR), and Figure of Merit (FOM), while also enhancing the visual fidelity of images, benefiting downstream applications such as target detection, recognition, and tracking. Overall, image restoration remains an evolving field dedicated to recovering and enhancing the visual image quality degraded by noise and distortion. With ongoing technological progress, the integration of advanced D_L architectures continues to redefine the benchmarks of image clarity, accuracy, and computational efficiency, marking a significant step toward more intelligent and adaptive image restoration solutions.

Image enhancement

The enhancement of the image is the process of modifying an image to enhance its quality of visual quality, interpretability, and overall perceptual appeal. This process involves a variety of transformations designed to show obscured information, strengthen contrast, and sharpen structural edges, thereby producing a clearer and highly informative image suitable for analysis, visualization, or presentation. The primary objective of image enhancement is to make significant features within an image highly distinguishable by optimizing attributes such as brightness, contrast, color balance, and texture definition. Conventional image enhancement techniques encompass several established methods, including histogram matching to adjust pixel intensity distributions, contrast-limited adaptive histogram equalization (CLAHE) to improve local contrast, and denoising filters such as the Wiener and median filters to suppress noise. Additionally, linear contrast stretching and unsharp masking are frequently employed to increase image sharpness and visual clarity.

Recently, D_L-based approaches have emerged as a key tool for the enhancement of images. These models, powered by large-scale datasets and advanced neural architectures, are capable of autonomously learning intricate features and image structures, allowing them to perform enhancement objectives with remarkable precision and generalization. Various deep learning frameworks have been developed, each offering unique advantages and presenting specific trade-offs, as summarized in Table 2 of this study. Notable advancements include the inclusion of Retinex theory and deep image priors within the Novel RetinexDIP model, which effectively balances illumination and reflectance components. Other innovations, such as robustness-enhancing fuzzy operations, address overfitting issues, while hybrid models that fuse classical enhancement techniques such as Unsharp Masking, High-Frequency Emphasis Filtering, and CLAHE with modern architectures like EfficientNet-B4, ResNet-50, and ResNet-18, demonstrate improved generalization and robustness.

The FCNN Mean Filter offers high computational efficiency, and CV-CNN exploits complex-valued convolutions to better represent phase and amplitude information. Frameworks such as pix2pixHD and LE-Net (Light Enhancement Net) exhibit rapid convergence and efficient performance, while Deep Convolutional Neural Networks (DCNNs) continue to deliver powerful enhancement capabilities, albeit with sensitivity to hyperactive parameter tuning. Moreover, the MSSNet-WS (Multi-Scale Stage Network) architecture achieves effective convergence while mitigating overfitting. Overall, this comparative analysis underscores the diverse merits of emerging deep learning-based image enhancement techniques, highlighting their advancements in convergence speed, robustness, overfitting mitigation, and computational efficiency, thereby marking a significant evolution from traditional enhancement paradigms.

Gao et al. (2022) introduced an innovative method for low-light image enhancement that integrates Retinex decomposition following an initial denoising stage. Their approach utilizes the Retinex model to effectively restore image brightness and contrast, thereby producing outputs with improved clarity, detail visibility, and perceptual quality. The proposed framework was comprehensively evaluated against several benchmark techniques, including LIME, NPE, SRIE, KinD, Zero-DCE, and RetinexDIP across multiple performance metrics (Tables 1–5). Experimental results demonstrated that (Gao et al., 2022) method not only achieved superior enhancement in visual quality but also maintained high image resolution and optimized memory efficiency, highlighting its effectiveness and practicality for real-world low-light image restoration applications. Liu et al. (2020) investigated the role of D_L in iris recognition by means of the implementation of Fuzzy Convolutional Neural Networks (F-CNN) and Fuzzy Capsule Networks (F-Capsule). Their approach is distinguished by the integration of Gaussian and triangular fuzzy filters, a new enhancement mechanism that significantly improves the clarity and feature extraction of iris images. A key strength of their framework lies in its seamless compatibility with existing neural architectures, providing a practical and efficient enhancement to conventional iris recognition systems. Muchtar et al. (2020) combined D_L with models of image enhancement to address the challenge of tuberculosis (TB) image classification. Their hybrid method employed Unsharp Masking (UM) and High-Frequency Emphasis Filtering (HEF) alongside state-of-the-art architectures, namely EfficientNet-B4, ResNet-50, and ResNet-18. By systematically assessing the performance of multiple enhancement algorithms, their study achieved high accuracy and Area Under the Curve (AUC) scores, underscoring the efficacy of integrating enhancement preprocessing with deep learning for precise and reliable TB diagnosis.

Wang et al. (2021) proposed a new application of D_L to mitigate impulse noise in degraded images with varying noise intensities. Their method introduced a Fully Connected Neural Network (FCNN) mean filter, which demonstrated superior performance compared to conventional mean and median filters, particularly under low-noise conditions. This contribution highlights the adaptability and efficacy of D_L frameworks in image denoising and noise suppression contexts. Furthermore, Quan et al. (2020) developed a non-blind image deburring model utilizing a Complex-Valued Convolutional Neural Network (CV-CNN). Their model uniquely incorporates Gabor-domain denoising as a prior step within the deconvolution process, allowing the network to better capture frequency-domain characteristics of blurred images. Quantitative assessments based on Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM) confirmed the model's superior deblurring performance, emphasizing the potential of complex-valued CNNs as powerful tools for advanced image restoration tasks.

Dan Zheng et al. (2021) utilized the pix2pixHD D_L framework to improve multidetector computed tomography (MDCT) images, focusing specifically on the precise measurement of vertebral bone structures. They documented that the capability of D_L models to substantially enhance the interpretability and quality of complex medical images, thereby supporting highly reliable and accurate clinical assessments. Similarly, Guofa Yang et al. (2021) proposed a CNN-based architecture, LE-Net, designed for image recovery under low-light conditions, with applications in driver assistance systems and connected autonomous vehicles (CAVs). Their findings revealed that the proposed model outperformed both traditional enhancement methods and several existing D_L models, emphasizing the effectiveness of developing context-specific enhancement solutions tailored to real-world operational environments.

Mehranian et al. (2022) explored the enhancement of Time-of-Flight (ToF) information in positron emission tomography (PET) imaging using deep convolutional neural networks. By integrating the block-sequential regularized expectation maximization (BSREM) reconstruction algorithm with their D_L-ToF(M) model, they achieved superior diagnostic performance, validated through key evaluation parameters, i.e., the Fréchet Inception Distance (FID) and Structural Similarity Index (SSIM). This study highlighted the potential of D_L to enhance diagnostic precision and image fidelity in advanced medical imaging modalities. In another significant contribution, Kim et al. (2023) introduced the Multi-Scale-Stage Network (MSSNet), a novel D_L architecture for single-image deblurring. Building upon a critical review of existing coarse-to-fine approaches, their method achieved state-of-the-art performance across multiple dimensions, including image quality, model efficiency, and computational speed, setting a new benchmark for deep learning-based deblurring techniques. Overall, image enhancement remains a cornerstone of modern image processing, serving to elevate visual quality for both human interpretation and automated analytical applications. The integration of traditional image processing models with cuttingedge D_L frameworks continues to push the boundaries of what is achievable in terms of image clarity, detail recovery, and computational efficiency.

Collectively, these studies illustrate the transformative potential of D_L across diverse domains from medical imaging to low-light scene enhancement while simultaneously addressing critical complexities such as generalization, computational constraints, and detail preservation. Nevertheless, the research also acknowledges key limitations, including restricted adaptability across heterogeneous datasets, potential loss of fine structural details, and the complexities introduced by real-world image variability. By critically analyzing both the strengths and shortcomings of these approaches, this body of work contributes to a more comprehensive understanding of the evolving landscape of image enhancement, underscoring the importance of continued innovation and refinement in this rapidly advancing field.

Image segmentation

The segmentation of an image is a primary process in computer vision that involves partitioning an image into distinct and meaningful regions on the basis of visual attributes such as intensity, color, texture, or spatial proximity. This process enables the extraction of relevant structures or objects from complex visual data. Broadly, image segmentation is categorized into two primary types: instance segmentation and semantic segmentation. While semantic segmentation assigns every pixel in an image to a specific class, thereby delineating regions corresponding to different objects or materials, instance segmentation extends this capability by distinguishing individual occurrences of objects within the same category, offering a finer level of granularity.

Traditional segmentation techniques, which preceded the advent of D_L, relied heavily on handcrafted features and domain-specific expertise. These methods typically divide images into well-defined segments based on manually established rules or statistical properties. Common examples include thresholding, which separates object and background regions employing intensity thresholds; region-based segmentation, which groups pixels with identical characteristics into cohesive areas; and edge detection, which identifies boundaries by detecting abrupt intensity changes. Although these conventional approaches have been instrumental in early image analysis, they exhibit significant limitations in handling complex geometries, noisy information, and dynamic or cluttered backgrounds. Furthermore, the manual design of features for diverse contexts is both time-consuming and lacks generalizability across varying image domains.

The rise of deep learning has revolutionized image segmentation, marking a profound shift from manual feature design to automated feature learning. Deep neural networks, particularly convolutional architectures, are able of learning rich, hierarchical representations directly from the information of raw images. This capability enables them to capture subtle spatial dependencies and adapt effectively to diverse visual environments. Consequently, deep learning-based segmentation methods not only eliminate the traditional algorithms' limitations but also achieve superior accuracy, robustness, and scalability.

This paradigm shift has significantly expanded the frontiers of image analysis and computer vision, paving the way for advanced applications in fields i.e., medical imaging, autonomous systems, remote sensing, and industrial inspection. Table 3 displays a detailed overview of the strengths and limitations of the D_L models explored in this study, illustrating how modern segmentation architectures continue to refine precision, adaptability, and computational efficiency across diverse imaging contexts.

Ahmad. et al. (2020) conducted an extensive study on D_L-based semantic segmentation techniques aimed at addressing the complex challenge of top-view multiple-person segmentation. Their research evaluated the performance of several prominent architectures—the Fully Convolutional Network (FCN), U-Net, and DeepLabV3. This line of inquiry holds substantial practical importance, as precise segmentation of individuals in top-view imagery is essential for applications such as video surveillance, crowd management, and human-computer interaction systems. The comparative analysis revealed that DeepLabV3 and U-Net consistently outperformed FCN in terms of segmentation accuracy. Both models achieved notably high accuracy and mean Intersection over Union (mIoU) scores, reflecting their superior ability to delineate and classify multiple individuals within complex visual scenes. The findings highlight the effectiveness of advanced convolutional architectures in capturing spatial and contextual information, ultimately enabling more precise and reliable segmentation outcomes. Overall, the study emphasizes the pivotal role of state-of-the-art deep learning frameworks in enhancing the robustness and precision of semantic segmentation, particularly in scenarios involving multiple overlapping or interacting subjects.

Dongyang Su et al. (2020) introduced an adaptive segmentation algorithm based on the U-Net architecture, capable of effectively capturing both shallow and deep image features. They specifically avoid the complexity of segmenting complex boundaries, broader computer vision applications, and a critical task in medical imaging. The model was validated on both liver cancer CT scans and natural scene images, demonstrating clear advantages over conventional segmentation models. The study highlights the potential of adaptive U-Net-based algorithms for accurately handling intricate structures across diverse image datasets.

Ahammad et al. (2020) developed a novel D_L mechanism utilizing Convolutional Neural Networks (CNNs) for the segmentation and diagnosis of Spinal Cord Injury (SCI) features. This framework is particularly significant for medical imaging applications, where accurate identification of spinal cord abnormalities is crucial. The proposed model exhibited greater computational effectiveness and remarkable precision, underscoring its potential for clinical implementation. By leveraging sensor-based SCI image data, the study affirms the capacity of D_L to enhance diagnostic accuracy and support informed patient care decisions. Lorenzoni et al. (2020) applied CNN-based D_L models to automate the segmentation of microCT images of cement-based composites, a task of great relevance in materials science and civil engineering. Their research highlights the adaptability of D_L techniques, demonstrating that network parameters optimized for high-strength materials can be effectively transferred to other related contexts. The study highlights the utility of CNNs in advancing automated material characterization and analysis.

Mahajan et al. (2021) proposed a clustering-based profound iterative D_L techniques (CPIDM) for hyperspectral segmentation of images, addressing the specific challenges posed by hyperspectral data in fields such as environmental monitoring and remote sensing. The proposed method outperformed state-of-the-art approaches, demonstrating superior segmentation accuracy and robustness. This study contributes a novel methodology for effectively handling the high dimensionality and spectral complexity inherent in hyperspectral images, providing a valuable tool for enhanced geospatial and environmental analysis.

Jalali et al. (2021) developed an advanced D_L-based framework for lung region segmentation from CT images, utilizing a Bi-directional ConvLSTM U-Net with densely connected convolutions (BCDU-Net). This approach is particularly significant for medical imaging and lung-related diagnostic applications. The model demonstrated high accuracy across a large dataset, highlighting its potential to assist radiologists in precisely delineating lung regions. The study exemplifies the transformative impact of sophisticated deep learning architectures in enhancing diagnostic precision within healthcare.

Bouteldja et al. (2021) proposed a CNN-based method for multiclass segmentation of stained kidney images across multiple species and renal disease models. This work is particularly relevant to histopathological analysis and disease diagnosis, as it enables accurate identification of diverse structural and pathological features. The method's robust performance across different species and disease conditions underscores its reliability and utility in supporting pathologists for precise, image-based diagnostic assessments.

Liu et al. (2021) introduced a novel CNN architecture featuring cross-connected layers and multi-scale feature aggregation to enhance image segmentation capabilities. This approach eliminates the growing need for advanced segmentation approaches capable of capturing intricate image features and spatial nexus. The technique achieved notable performance metrics, demonstrating its potential to improve segmentation precision in a variety of applications—medical imaging, autonomous framework, and robotics.

Saood and Hatem (2021) applied D_L networks, specifically SegNet and U-Net, to segment COVID-19-infected regions in CT scans. This timely research contributes to global efforts against the pandemic by providing accurate and automated identification of infected lung areas. Their comparative analysis of network performance offers valuable insights into the relative effectiveness of distinct D_L architectures, highlighting the agility and practical applicability of these methods in responding to urgent real-world challenges in medical imaging. Siti Rachmatullah et al. (2020) introduced a Mask R-CNN-based framework for the precise detection of fetal septal defects, addressing the limitations of prior approaches. Their model demonstrated accurate multiclass heart chamber segmentation, achieving remarkable performance: right atrium (97.59%), left atrium (99.67%), left ventricle (86.17%), right ventricle (98.83%), and aorta (99.97%). In terms of defect detection within atria and ventricles, Mask R-CNN (MRCNN) achieved a mean Average Precision (mAP) of 99.48%, significantly outperforming Faster R-CNN (FRCNN) at 82%. The outcomes outline the potential of the proposed approach to assist cardiologists in the early screening of fetal congenital heart disease. Park et al. (2021) proposed a deep learning approach for intelligent food segmentation in images, leveraging Mask R-CNN. To overcome the challenges of labor-intensive data collection, the authors utilized synthetic datasets generated via 3D graphics software (Blender) for model training.

The approach achieved 52.2% accuracy on real-world food instances using only synthetic information and demonstrated an additional 6.4 percentage point enhancement after fine-tuning, compared to training from scratch. This methodology presents strong potential for applications in healthcare robotics, such as automated meal assistance systems. Pérez-Borrero et al. (2020) emphasized the importance of fruit instance segmentation in the context of autonomous fruit-picking systems, positioning Mask R-CNN as a benchmark model. Their study proposed methodological modifications to enhance efficiency and introduced the Instance Intersection over Union (I2oU) metric alongside the creation of the StrawDI_Db1 dataset, providing practical contributions for real-world deployment. Collectively, prior research underscores the transformative effect of D_L-based segmentation across diverse domains, including medical imaging, agriculture, and robotics. By leveraging advanced network architectures and innovative training strategies, these approaches push the boundaries of image segmentation, enhancing accuracy, efficiency, and applicability across complex real-world scenarios.

Feature extraction

The feature extraction is a critical process in computer vision and image processing, involving the transformation of raw pixel data into a highly compact and informative representation, commonly referred to as features. Such aspects capture essential attributes of an image, facilitating tasks, i.e., object recognition, image segmentation, and classification, by enabling algorithms to more effectively interpret and analyze visual information.

Before the adoption of D_L, traditional feature extraction approaches dominated the field. These approaches primarily focused on analyzing pixel-level information and transforming it into meaningful representations. Key techniques include:

- Principal Component Analysis (PCA): A statistical method that mitigates the dimensionality of image details while retaining as much of the original variance as possible. PCA identifies principal components or orthogonal axes, along which the information exhibits the greatest variation, allowing for more efficient representation and analysis.
- Independent Component Analysis (ICA): This technique seeks a linear transformation of the information into statistically independent features. ICA is particularly useful for separating mixed sources in images, i.e, isolating different overlapping image signals from a single composite image.
- Locally Linear Embedding (LLE): A nonlinear dimensionality reduction approach that preserves the local structure of data points. LLE generates a low-dimensional representation of the information while maintaining neighborhood nexus, enabling the capture of subtle, intrinsic patterns within complex datasets.

Overall, these traditional methods laid the groundwork for understanding and representing image data, providing the basis upon which modern deep learning-based feature extraction techniques have built more powerful and automated solutions.

Traditional feature extraction methods have long been employed to provide valuable representations and insights for a variety of image analysis tasks. These approaches typically rely on handcrafted features, designed based on expert knowledge or domain-specific understanding. While effective in certain contexts, this process can be labor-intensive and may lack generalizability between distinct datasets or tasks. The conventional feature extraction involves transforming raw information into a highly compact and informative representation by identifying specific characteristics or attributes that capture essential patterns inherent in the information. The given process is often manually guided by domain expertise. For instance, in image processing, techniques such as Histogram of Oriented Gradients (HOG) extract gradient distribution information, whereas in text analysis, features like word frequencies may be chosen to represent meaningful patterns. Despite their usefulness, traditional methods have notable limitations. They often require significant expert intervention to construct characteristics, which could be time-consuming and may fail to capture complex nexus or subtle patterns in the information. Additionally, these approaches can struggle with high-dimensional scenarios or datasets where meaningful characteristics are not easily defined.

Contrarily, D_L-based techniques have transformed feature extraction by automating the process. A deep neural network can learn hierarchical and discriminative features directly from raw information, addressing the requirement for manual feature engineering. The given capability allows them to capture complex patterns, interactions, and nonlinear correlations that traditional techniques might overlook. As a result, D_L has achieved remarkable performance across numerous domains, particularly in complex tasks, i.e., speech processing, image recognition, and multimodal data analysis. Table 4 provides a concise summary of the parameters, strengths, and limitations of various D_L models employed for feature extraction and enhancement.

Magsi et al. (2020) conducted a notable study in the field of agricultural disease detection, focusing on identifying diseases in date palm trees using D_L methods. Their approach involved extracting color and texture features from images of diseased plants and leveraging Convolutional Neural Networks (CNNs) to develop a system capable of recognizing disease-specific visual patterns. The model achieved an accuracy of 89.4%, demonstrating its effectiveness in precise disease identification. Authors outline the potential of D_L for automated crop monitoring, emphasizing its role in enhancing disease management, crop health, and agricultural productivity.

Similarly, Sharma et al. (2020) explored medical imaging applications, specifically targeting chest X-ray analysis. The study involved a comprehensive evaluation of various CNN architectures to extract relevant features from X-ray images. Importantly, the researchers investigated the influence of dataset size on network performance, demonstrating the scalability of D_L approaches in medical contexts. By employing data augmentation and dropout models, the proposed technique attains a high precision of 0.9068, underscoring its capacity to precisely classify and diagnose conditions from chest X-rays. The research highlights the significant potential of D_L to assist medical professionals in disease diagnosis and decision-making by means of automated image analysis.

Zhang et al. (2020) presented a new approach to distinguishing between counterfeit and genuine facial images generated by D_L techniques. Their method utilized a Counterfeit Feature Extraction strategy based on a Convolutional Neural Network (CNN), attaining an impressive precision of 97.6%. Beyond accuracy, the study emphasized computational efficiency, highlighting the potential to reduce processing demands in counterfeit image detection. The study is highly relevant in the current digital era, where ensuring the images' authenticity is increasingly critical.

Simon and V (2020) explored the integration of D_L and feature extraction for the classification of images and their texture analysis. Authors employed CNN frameworks, i.e., AlexNet, VGG19, Inception, InceptionResNetV3, ResNet, and DenseNet201 to extract meaningful image characteristics, which were subsequently classified employing a Support Vector Machine (SVM). The models achieved precise levels ranging from 85%-95% across various pretrained architectures and datasets, demonstrating the effectiveness of combining D_L-based feature extraction with traditional ML for robust image analysis.

Sungheetha and Sharma (2021) tackled the detection of diabetic conditions by identifying specific indicators within retinal blood vessels. Their approach utilized a deep feature CNN capable of recognizing subtle pathological patterns, achieving a remarkable accuracy of 97%. This study outlines the potential of D_L to enhance medical diagnostics by capturing intricate visual patterns indicative of disease, thereby supporting early detection and clinical strategic choices.

Devulapalli et al. (2023) introduced a hybrid feature extraction approach that combined Gabor transform-based texture characteristics with high-level automated features from the GoogLeNet architecture. Using pretrained models, i.e, AlexNet, VGG16, and GoogLeNet, the research achieved superior precision, with the hybrid approach outperforming individual pretrained models. This demonstrates the value of integrating multiple feature extraction models to enhance performance in complex tasks of image analysis.

Shankar et al. (2022) focused on COVID-19 diagnosis using chest X-ray images through a multi-step pipeline. The approach involved preprocessing via Wiener filtering, fusion-based feature extraction using GLCM, GLRM, and LBP, followed by classification with an Artificial Neural Network (ANN). By carefully selecting the best feature subsets, the approach achieved robust differentiation across healthy patients and infected patients, highlighting the adaptability and utility of D_L frameworks in eliminating urgent global health complexities and medical diagnostic tasks.

Ahmad et al. (2022) document notable advancements in breast cancer detection by developing a hybrid D_L approach, AlexNet-GRU, which allows autonomously extracting characteristics from the PatchCamelyon benchmark dataset. The method exhibited high precision in identifying metastatic cancer within breast tissue and outperformed existing state-of-the-art methods. This research underscores the transformative potential of D_L in medical imaging, particularly for precise cancer classification and detection.

Sharif et al. (2021) addressed the challenges of detecting gastrointestinal tract (GIT) infections employing wireless capsule endoscopy (WCE) images. The proposed model combined deep convolutional neural networks (CNNs) with geometric feature extraction to tackle the complexities associated with lesion characteristics. By integrating contrast-enhanced color features with geometric attributes, the model achieved remarkable classification precision and accuracy, demonstrating the effectiveness of combining D_L with traditional feature-based techniques. This methodology highlights the potential for enhanced medical diagnostics by means of the fusion of different data sources.

Aarthi and Rishma (2023) tackled real-world challenges in waste management by introducing a real-time automated waste detection and segregation system using Mask R-CNN. Their model successfully identified and classified waste objects in real time, while also incorporating geometric feature extraction to facilitate manipulation that is more effective by robotic arms. The given innovative framework not only examines environmental issues relevant to waste disposal but also illustrates the broader applicability of D_L beyond conventional image analysis, enhancing operational efficiency and mitigating environmental risks. Prior research collectively outlines the effectiveness of CNNs, hybrid models, and innovative D_L mechanisms in achieving high accuracy and enhanced performance across diverse applications, including disease detection, image analysis, and counterfeit identification. By automating the extraction of meaningful features, these approaches reduce reliance on manual feature engineering and improve analytical precision. However, challenges such as computational complexity, dataset quality, and real-world variability remain critical considerations for practical deployment, necessitating careful design and evaluation to ensure robust and reliable performance in real-world scenarios.

Image classification

The classification of images is a core task in computer vision, involving the assignment of images to predefined categories or labels. The objective is to allow machines to recognize and differentiate patterns, scenes, or objects within visual data. Prior to the rise of D_L, traditional classification models played a central role in data analysis. Methods such as Decision Trees, Support Vector Machines (SVM), Naive Bayes, and k-Nearest Neighbors (k-NN) were commonly employed. In these approaches, experts manually designed and selected features that capture relevant details from the information. Such features, informed by domain knowledge, aim to highlight discriminative characteristics that distinguish between classes. While effective for many applications, conventional methods often require labor-intensive feature engineering and may struggle to capture distinct patterns or nonlinear nexus inherent in large and intricate datasets. Once selected, these features serve as inputs for classification algorithms, which assign data points to classes based on predefined rules and criteria. Table 5 provides a concise summary of the strengths and limitations of various deep learning models applied to image classification. In the medical imaging field, Abdelaziz Ismael et al. (2020) proposed a D_L-based approach utilizing Residual Networks (ResNets) for brain tumor classification. Their study analyzed a benchmark dataset of 3,064 MRI images encompassing three tumor types. The proposed model attained an impressive precision of 99%, surpassing prior methods and demonstrating the effectiveness of deep architectures in capturing subtle and complex tumor patterns.

In the domain of remote sensing, Xu et al. (2021) examined the integration of Recurrent Neural Networks (RNNs) with Random Forests for remote sensing image classification. By optimizing cross-validation procedures on the UC Merced dataset and performing extensive comparisons with alternative D_L models, their method achieved a notable accuracy of 87%, highlighting the applicability of D_L models in geospatial image analysis.

Texture analysis and classification have gained notable attention due to their applications across medical, agricultural, and environmental domains. Aggarwal and Kumar (2021) proposed a novel D_L mechanism on the basis of Convolutional Neural Networks (CNNs), consisting of two sub-models for texture classification. Their outcomes were remarkable, with Model-1 attaining 92.42% accuracy and Model-2 further improving to 96.36%, demonstrating the effectiveness of CNN-based approaches in capturing discriminative texture patterns.

Abdar et al. (2021) introduced a hybrid dynamic Bayesian D_L (BD_L) model incorporating Three-Way Decision (TWD) theory for skin cancer diagnosis. By integrating multiple uncertainty quantification (UQ) methods with deep neural networks across different classification stages, their approach achieved high precision and F1-score on two benchmark skin cancer datasets, highlighting the potential of combining probabilistic reasoning with deep learning for robust medical diagnostics.

Ibrahim et al. (2024) further advanced medical image classification by utilizing a pretrained AlexNet model to classify COVID-19, pneumonia, and healthy chest X-ray scans. The proposed approach demonstrated strong performance in both three- and four-ways classification tasks, attaining greater precision, sensitivity, and specificity, reinforcing the efficacy of transfer learning in rapid disease detection.

Addressing resource-constrained image classification, Ma et al. (2022) proposed a deep CNN classification approach with knowledge transfer. The model outperformed traditional histogram-based approaches, attaining an impressive precision of 93.4%, highlighting the efficiency of leveraging pretrained knowledge for improved classification performance.

In agricultural applications, Gill et al. (2023) developed a hybrid CNN-RNN model for fruit classification, demonstrating high efficiency and accuracy suitable for quality assessment and sorting. Similarly, Aish et al. (2022) employed VGG16 for fruit classification, achieving 100% accuracy, underscoring the potential of deep learning to deliver perfect classification results in real-world scenarios.

Sharma et al. (2022) focused on breast cancer diagnosis, applying CNNs with transfer learning and achieving a notable accuracy of 98.4%, reinforcing the role of deep learning in augmenting medical diagnostic capabilities. Beyond medical applications, Yang et al. (2022) applied various CNN architectures for urban wetland identification, with DenseNet121 emerging as the best-performing model. The high Kappa and Overall Accuracy (OA) values obtained emphasize the significance of deep learning for land cover and environmental classification tasks.

Collectively, these studies demonstrate the versatility, effectiveness of CNN-based, and hybrid deep learning models across diverse domains, achieving high accuracy, efficiency, and practical applicability in both medical diagnostics and environmental analysis.

Archana and Jeevaraj (2024) explored Alzheimer's disease detection using a 12-layer CNN model, achieving an impressive accuracy of 97.75% on the OASIS dataset. Their approach outperformed existing CNN architectures and was validated through direct comparisons with pre-trained models, demonstrating its effectiveness in enhancing early and accurate detection of Alzheimer's disease.

In the industry of textile, Gao et al. (2019) examined fabric defect detection with a deep convolutional neural network incorporating multiple convolution and max-pooling layers. The model achieved a greater detection precision of 96.52%, highlighting its potential for practical applications in real-world manufacturing settings.

Expanding to neurological disorders, Vikas and Rao (2021) developed a hybrid 2D CNN–LSTM model for ADHD classification using resting-state functional MRI (rs-fMRI) data. Their method demonstrated notable improvements in precision, specificity, sensitivity, F1-score, and AUC compared to existing approaches, indicating the promise of D_L in accurately distinguishing ADHD from healthy controls.

Skouta et al. (2021) analyzed the retinal image classification, leveraging CNNs to differentiate between proliferative and normal diabetic retinas, achieving a classification accuracy of 95.5%. The use of an expanded dataset enabled the capture of fine-grained features, ensuring robust and reliable classification outputs.

Collectively, previous literature highlights the transformative impact of D_L across diverse image classification tasks, spanning medical diagnostics, texture analysis, industrial inspection, and neurological disorder detection.

While traditional methods maintain certain strengths, they rely heavily on expert-driven feature selection and algorithm tuning. Such approaches often struggle with high-dimensional and complex datasets, requiring extensive manual effort in feature engineering, and may lack adaptability to evolving information distributions or new types of data. Contrarily, D_L automates feature extraction, learning hierarchical representations directly from raw information. This enables the capture of intricate patterns and correlations that traditional models might overlook. Convolutional Neural Networks (CNNs) excel in image-based tasks, whereas Recurrent Neural Networks (RNNs) are particularly effective for sequential data. Overall, deep learning models frequently surpass traditional approaches, providing superior performance in complex classification tasks across multiple domains.

DISCUSSION

The given review presents a synthesized overview of recent deep learning advancements across image denoising, segmentation, enhancement, feature extraction, and classification, outlining the capabilities, strengths, and limitations of distinct approaches in diverse application domains.

In the image denoising realm, multiple D_L models have emerged, each with distinct advantages and trade-offs. The Self2Self neural network reduces computational cost while relying on data augmentation, DnCNNs enhance denoising accuracy but face resource constraints, and DFT-Net manages label imbalance at the risk of losing fine details. MPR-CNN emphasizes robustness through careful hyperparameter tuning, whereas R2R models strike a balance across noise reduction and computational effectiveness. Traditional CNN architectures effectively prevent overfitting, HLF-DIP achieves high performance despite complexity, Noise2Noise models balance efficiency with generalization, and ConvNet expands receptive fields while facing interpretability challenges. Collectively, these approaches illustrate the evolving landscape of denoising techniques in image processing.

Regarding image enhancement, studies have explored a variety of deep learning methods. Ming Liu et al. employed Fuzzy-CNN and F-Capsule models for iris recognition, achieving robustness and mitigating overfitting. Additionally, scholars combined traditional enhancement techniques with EfficientNet and ResNet architectures for tuberculosis imaging, improving generalization while contending with time and memory demands. Moreover, prior research implemented FCNN mean filters to reduce noise with minimal detail loss, while another stream of literature used CV-CNN for efficient image deblurring. Other approaches include pix2pixHD for high-quality MDCT image enhancement, LE-net for low-light recovery, RetinexDIP for accelerated convergence and runtime reduction, and MSSNet-WS for single-image deblurring, emphasizing computational efficiency in real-world applications.

In the segmentation of images, both semantic and instance segmentation approaches demonstrate substantial advancements. Semantic segmentation leverages models like FCN, U-Net, and DeepLabV3 for tasks such as multi-person detection and object recognition, achieving IoU and mIoU scores between 80% and 86%. Instance segmentation methods, including Mask-RCNN and AFD-UNet, accurately delineate individual objects, enabling applications in medical imaging, real-time waste collection, and more. These approaches reduce manual intervention, improve boundary delineation, and save processing time, though challenges remain in computational complexity, hardware requirements, and model customization.

For feature extraction, deep learning has been applied to diverse domains, from texture and color analysis to pattern and geometric feature recognition. One strand of research achieved 89.4% accuracy in disease detection, while another strand of research reached 97% accuracy in counterfeit detection. Similarly, earlier studies reported 97% accuracy for retinal images, for instance, research achieved 95.1–95.7% accuracy for chest X-rays using GLCM, GLRM, and LBP with ANN, and another study reached 99.5% accuracy for PCam images using AlexNet-GRU. Geometric feature extraction was demonstrated in literature (99.4% accuracy in capsule endoscopy) and another study (97% accuracy in real-time waste detection with Mask-RCNN), showcasing the flexibility of deep learning for extracting diverse image features.

In image classification, D_L models have proven highly effective across multiclass and binary tasks. For multiclass classification, research used ResNet to achieve 99% accuracy for brain tumor MRI images, a previous study reached 92.42% on Kylberg Texture datasets, and also a study achieved 94% for lung condition classification using AlexNet. Fruit classification studies (CNN-RNN hybrid) and (VGG16) demonstrated 100% accuracy. In binary classification, research achieved 97.75% for Alzheimer's detection, 96.52% in fabric defect detection, 95.32% for ADHD diagnosis using CNN-LSTM, and 95.5% for diabetic retinopathy detection.

Overall, the literature illustrates the adaptability, robustness, and high performance of deep learning across diverse image processing tasks. They also highlight persistent challenges, including dataset biases, computational intensity, interpretability, and real-world variability, which must be considered when implementing these methods in practical applications.

CONCLUSIONS

The systematic review undertakes a comprehensive examination of the diverse image processing domains—denoising, enhancement, segmentation, feature extraction, and classification. Through a detailed analysis and comparison of these methodologies, the review provides a panoramic perspective on the current framework of image processing, outlining both the strengths and the inherent complexities relevant to their implementation. In the denoising of images, techniques, i.e., Self2Self Neural Networks, DnCNNs, and DFT-Net demonstrate significant efficacy in noise mitigation. However, persistent complexity remains, including extensive preservation and the optimization of hyperparameters. For image enhancement, methods, i.e., Novel RetinexDIP, Unsharp Masking, and LE-net effectively enhance the quality of visual, but experience difficulties in managing complex scenes while maintaining image authenticity.

Segmentation approaches range from foundational to advanced models, offering reliable object delineation. However, robustness issues arise in scenarios involving overlapping objects. Feature extraction methodologies, spanning from standard CNNs to LSTM-augmented CNNs, successfully capture essential image features, though considerations of computational efficiency and adaptability are critical. In the domain of classification, architectures from Residual Networks to CNN-LSTM hybrids demonstrate strong potential for precise categorization. Challenges, yet, persist in terms of information dependency, computational demands, and approach interpretability. By systematically reviewing these methodologies, this paper provides nuanced insights into their respective advantages and limitations, enabling scholars to make optimal decisions regarding model selection for particular applications.

Furthermore, the review encompasses a broad spectrum of applications, including medical and satellite imagery, botanical analyses of flowers and fruits, and real-time scenarios. The domain-specific adaptations of deep learning techniques underscore their versatility and effectiveness across complex, real-world contexts. As image processing continues to evolve, addressing challenges such as computational complexity and interpretability will be essential to fully harness the potential of these methodologies.

Table 1. D_L Approaches for Restoration of Image

Study / Authors	Application / Task	Model / Architecture	Dataset / Domain	Performance Metrics	Key Strengths	Limitations / Challenges
Gao et al. (2022)	Low-light image enhancement	RetinexDIP	General images	Improved brightness & contrast	High visual clarity, low memory usage	Complexity in real-world scenes
Liu et al. (2020)	Iris recognition	Fuzzy-CNN, F-Capsule	Iris datasets	Robust recognition	Avoids overfitting, integrates Gaussian/triangular fuzzy filters	Sensitive to noise
Muchtar et al. (2020)	Tuberculosis X-ray classification	EfficientNet-B4, ResNet-50, ResNet-18 with UM & HEF	TB X-ray images	Accuracy & AUC high	Enhanced generalization	High computational demand
Wang et al. (2021)	Noise reduction	FCNN Mean Filter	Degraded images	PSNR improvement	Efficient noise reduction	Minor detail loss in low-noise images
Quan et al. (2020)	Image deblurring	CV-CNN with Gabor-domain prior	General images	PSNR, SSIM improved	Prevents overfitting	Computationally intensive
Jin et al. (2021)	MDCT image enhancement	pix2pixHD	Medical CT images	Structural clarity	High-quality enhancement	Risk of overfitting
Li et al. (2021)	Low-light recovery	LE-net	CAV / driver-assistance images	Visual improvement metrics	Generalization, robustness	Limitations in real-world lighting conditions
Kim et al. (2023)	Single-image deblurring	MSSNet-WS	General images	PSNR, SSIM	Computationally efficient	Model complexity
Ahmad. et al. (2020)	Multi-person top-view segmentation	FCN, U-Net, DeepLabV3	Surveillance datasets	Accuracy, mIoU	High segmentation precision	Requires large labeled datasets
Wang et al. (2020)	Complex boundary segmentation	Adaptive UNet	Liver CT, natural images	Accuracy, boundary delineation	Handles shallow & deep features	Hardware intensive
Siti Rachmatullah et al. (2020)	Fetal heart defect detection	Mask-RCNN	Ultrasound fetal images	mAP ~99.48%	Accurate multi-class detection	High computational cost
Park et al. (2021)	Food instance segmentation	Mask-RCNN with synthetic data	Food datasets	52.2% → +6.4% after fine-tuning	Reduces real-world annotation burden	Domain adaptation required
Magsi et al. (2020)	Date palm disease detection	CNN	Agricultural images	Accuracy 89.4%	Automated disease detection	Dataset limitations

Study / Authors	Application / Task	Model / Architecture	Dataset / Domain	Performance Metrics	Key Strengths	Limitations / Challenges
Zhang et al. (2020)	Counterfeit facial image detection	CNN	Synthetic/real facial images	Accuracy 97.6%	Efficient & fast	May struggle with novel attacks
Sungheetha and Sharma (2021)	Diabetic retinal detection	Deep CNN	Retinal images	Accuracy 97%	Detects subtle visual patterns	Sensitive to image quality
Ahmad et al. (2022)	Breast cancer detection	AlexNet-GRU	PCam dataset	High accuracy	Superior metastatic tissue detection	Requires large annotated datasets
Hussain et al. (2020)	Alzheimer's detection	12-layer CNN	OASIS MRI	Accuracy 97.75%	Surpasses pre-trained models	Computationally heavy
Vikas and Rao (2021)	ADHD classification	CNN-LSTM	rs-fMRI	Accuracy 95.32%	Sequential data handling	Complex preprocessing required
Skouta et al. (2021)	Diabetic retinopathy detection	CNN	Retinal images	Accuracy 95.5%	High feature capture	Requires large datasets
Gill et al. (2023)	Fruit classification	CNN-RNN	Agricultural dataset	High accuracy	Sequential & spatial features	Sensitive to dataset variability
Abu-Jamie et al. (2022)	Fruit classification	VGG16	Fruit dataset	Accuracy 100%	High classification precision	Limited generalization to new datasets
Sharma and Mishra (2022)	Breast cancer diagnosis	CNN + Transfer Learning	Medical images	Accuracy 98.4%	Rapid training, high performance	Relies on quality pretrained weights
Ma et al. (2022)	Image classification under constraints	CNN + Knowledge Transfer	General images	Accuracy 93.4%	Efficient with limited data	Transfer learning limitations

Table 2. D_L Approaches for enhancements of image

Study / Authors	Task	Model / Architecture	Dataset / Domain	Performance Metrics	Key Strengths	Limitations / Challenges	Hyperparameters / Tuning	Convergence / Efficiency
Quan et al. (2020)	Image denoising	Self2Self NN	Noisy images	PSNR, SSIM	Cost reduction, data augmentation	Dependent on data quality	Needs careful learning rate scheduling	Moderate convergence
Yan et al. (2020)	Speckle noise reduction	DnCNN	DHSPI images	MSE	Accurate noise removal	May lose fine details	Layer depth, filter size	High efficiency

Study / Authors	Task	Model / Architecture	Dataset / Domain	Performance Metrics	Key Strengths	Limitations / Challenges	Hyperparameters / Tuning	Convergence / Efficiency
Sori et al. (2020)	Medical image denoising	Two-path CNN	CT lung images	Accuracy, sensitivity, specificity	Robust feature extraction	High computational cost	Filter numbers, kernel size	Moderate
Hasti and Shin (2022)	Fuel spray image denoising	Modified U-Net	Spray images	MSE, PSNR	Superior to CNN & ResNet	Complex architecture	Learning rate, epochs	Moderate
Niresi and Chi (2022)	Hyperspectral image denoising	HLF-DIP (unsupervised)	HSI images	Noise removal efficiency	Handles mixed noise, preserves edges	High computational complexity	Minimization parameters	Slower convergence
Gao et al. (2022)	Low-light enhancement	RetinexDIP	Low-light images	PSNR, visual clarity	Brightness & contrast restoration	May struggle with complex scenes	Iteration number, decomposition layers	Efficient
Liu et al. (2020)	Iris image enhancement	Fuzzy-CNN, F-Capsule	Iris dataset	Accuracy	Avoids overfitting	Sensitive to noise	Fuzzy filter parameters	Fast convergence
Muchtar et al. (2020)	X-ray enhancement	EfficientNet-B4, ResNet-50/18	TB X-ray	Accuracy, AUC	High generalization	High memory/time	Learning rate, batch size	Moderate
Jin et al. (2021)	MDCT image enhancement	pix2pixHD	CT images	PSNR, SSIM	High-quality image enhancement	Risk of overfitting	Generator/discriminator layers	Moderate convergence
Li et al. (2021)	Low-light recovery	LE-net	CAV / driver-assistance images	PSNR, visual improvement	Robust in real-world scenarios	Sensitive to extreme conditions	Network depth, learning rate	Fast
Kim et al. (2023)	Single image deblurring	MSSNet-WS	General images	PSNR, SSIM	Computationally efficient	Complex model	Stage numbers, kernel size	Fast
Ahmad. et al. (2020)	Multi-person segmentation	FCN, U-Net, DeepLabV3	Top-view images	Accuracy, mIoU	Accurate multi-person segmentation	Needs large labeled dataset	Filter size, depth	Moderate
Wang et al. (2020)	Complex boundary segmentation	Adaptive UNet	Liver CT, natural images	Accuracy	Handles shallow & deep features	High computational cost	Layer numbers, kernel size	Moderate

Study / Authors	Task	Model / Architecture	Dataset / Domain	Performance Metrics	Key Strengths	Limitations / Challenges	Hyperparameters / Tuning	Convergence / Efficiency
Nurmaini et al. (2020)	Fetal heart instance segmentation	Mask-RCNN	Ultrasound images	mAP 99.48%	Multiclass chamber detection	High computational demand	ROI size, learning rate	Moderate
Park et al. (2021)	Food instance segmentation	Mask-RCNN + synthetic data	Food images	IoU 52.2% → +6.4%	Reduces real-world annotation need	Domain adaptation required	Anchor box size	Moderate
Magsi et al. (2020)	Feature extraction	CNN	Date palm disease images	Accuracy 89.4%	Automated disease detection	Dataset limitations	Layer depth, learning rate	Fast
Zhang et al. (2020)	Feature extraction	CNN	Facial images (real & fake)	Accuracy 97.6%	Efficient & fast	May fail on novel attacks	Filter size, epochs	Fast

Table 3. D_L Approaches for segmentation of an image

Author	Methodology	Dataset	Evaluation Metrics	Performance	Advantages	Limitations
Quan et al. (2020)	Self2Self Neural Network (NN)	Set9, BSD68	SSIM, PSNR	PSNR: 37.52; SSIM: 0.980	Reduces annotation cost	Dependent on data augmentation
Yan et al. (2020)	Denoising CNNs	Simulated fringe pattern dataset	MSE	0.8654	Enhances wrapped phase accuracy	High computational cost and long training time
Sori et al. (2020)	DFT-Net for denoising and detection	CT scan images (KDSB, LUNA16)	Accuracy, Recall, Specificity	R: 0.874; S: 0.891; A: 0.878	Effectively handles image label imbalance	Possible detail loss during denoising
Jiang et al. (2021)	MPR-CNN (Parallel Residual Denoising)	Chest X-ray images (COVID-19)	PSNR, SSIM	PSNR: 36.368; SSIM: 0.895	Robust and time-efficient	Requires hyperparameter tuning
Pang et al. (2021)	R2R Noise Reduction	SIDD Benchmark	PSNR, SSIM	Noise = 50 → PSNR: 26.13; SSIM: 0.709	Achieves results comparable to supervised training	Computationally intensive; limited noise handling
Hasti and Shin (2022)	Standard and Modified CNN Architectures	Mie scattered image dataset	MSE, PSNR	MSE: 0.0053; PSNR: 22.757	Prevents overfitting	High time and memory consumption

Author	Methodology	Dataset	Evaluation Metrics	Performance	Advantages	Limitations
Niresi and Chi (2022)	HLF-DIP Algorithm for HSI Denoising	HYDICE HSI datasets	MPSNR, MSSIM, MSAM, MFSIM	Noise = 40 → MPSNR: 49.49; MSSIM: 0.998; MSAM: 0.024; MFSIM: 0.999	No regularizers; user-friendly approach	Requires single parameter tuning; struggles with mixed noise
Tawfik et al. (2022)	Noise2Noise Denoising Model	MCT images	PSNR, SSIM	PSNR: 20.607; SSIM: 0.546	Cost- and time-efficient	Limited generalization ability
Meng and Zhang (2022)	ConvNet for Gray Image Denoising	BSD-68	PSNR, SSIM, FOM	PSNR: 26.44; SSIM: 0.6797; FOM: 1	Improved receptive field	Poor interpretability

Table 4. D_L Approaches for Feature Extraction

Author	Methodology	Dataset	Metrics	Results	Type	Advantages	Disadvantages
Magsi et al. (2020)	CNN	Date palm disease images	Accuracy (ACC)	89.4%	Texture / Color	Focused and domain-specific approach	Limited generalization capability
Sharma et al. (2020)	CNN	Chest X-ray dataset (Kaggle)	Accuracy, Loss	90%	Texture	Data augmentation for overfitting prevention; high scalability and accuracy	Disease specificity; model complexity; dataset quality; limited real-world applicability
Zhang et al. (2020)	Novel counterfeit feature extraction with CNN	Face-swap images	Accuracy (ACC)	97%	Counterfeit	Reduced space and time complexity; faster convergence and training efficiency	Needs improvement in robustness under compression conditions
Simon and V (2020) *(Review)*	AlexNet, VGG19, Inception, InceptionResNetV3, ResNet, DenseNet201	KTH-TIPS, CURET, and flower datasets	Accuracy (ACC)	–	Texture	Comprehensive review of multiple CNN architectures	Lack of empirical comparison results
Sungheetha and Sharma (2021)	CNN	Retinal images	Class score, Accuracy, Precision, Specificity, Recall	97%	Pattern	High flexibility and adaptability for pattern recognition	Limited model customization
Devulapalli et al. (2023)	GoogLeNet model	UC Merced dataset (USGS National Map –	Similarity metrics,	90%	Texture	Hybrid feature extraction combining Gabor-based texture with	High computational complexity

Author	Methodology	Dataset	Metrics	Results	Type	Advantages	Disadvantages
		metropolitan region)	Precision, Recall, MAP			GoogLeNet's deep features	
Shankar et al. (2022)	FM-ANN, GLCM, GLRM, and LBP	Chest X-ray images	Accuracy, Sensitivity, Specificity, F-score	95.1% – 95.7%	Texture	Efficient feature extraction and optimized parameter tuning	Limited model interpretability
Ahmad et al. (2022)	AlexNet-GRU hybrid model	PCam dataset (Kaggle)	Accuracy, Precision, Sensitivity, Specificity	99.5%	Color	High accuracy and enhanced performance metrics	High computational cost and need for specialized hardware
Sharif et al. (2021)	CNN	Wireless capsule endoscopy images	Accuracy, Sensitivity, Specificity, FPR, AUC, Precision	99.4%	Geometric	Fast computation time	Reduced applicability in real-time environments
Aarthi and Rishma (2023)	MRCNN	Real-time waste images	Accuracy	97%	Geometric	High robustness and effective operation in waste segregation systems	Reliability challenges and real-time efficiency concerns

Table 5. D_L Approaches for classification of image

Author	Model(s)	Dataset	Metrics	Accuracy	Type	Advantages	Disadvantages
Abdelaziz Ismael et al. (2020)	Residual Networks	MRI image dataset	Precision, Recall, F1-Score, Accuracy (%)	99%	Multi-class	Shortcut connections enhance accuracy and mitigate vanishing gradients	Limited or unrepresentative data impacts generalization
Xu et al. (2021)	RNN and Random Forest	UC Merced	Precision, Recall, Accuracy (%)	87%	Multi-class	High accuracy, automated feature learning, scalability	Data dependency, high computational cost, interpretability challenges, overfitting risk
Aggarwal and Kumar (2021)	CNN	Kylberg Texture dataset	Precision, Recall, F1-Score, Accuracy (%)	92.42%	Pattern	Flexible design, domain adaptation, reduced overfitting	Requires extensive labeled data for supervised training
Abdar et al. (2021)	TWDBDL	Skin cancer datasets	Area Under the Curve (AUC)	—	Binary	Strong discriminative capability	Model performance sensitive to data imbalance

Author	Model(s)	Dataset	Metrics	Accuracy	Type	Advantages	Disadvantages
Ibrahim et al. (2024)	AlexNet model	Lung condition images	Sensitivity, Specificity, Accuracy (%)	88.95% – 90.96%	Multi-class	Flexible hybrid approach and efficient uncertainty quantification	Limited computing resources and small dataset size for COVID-19 pneumonia cases
Kong et al. (2022)	CNN and SVM hybrid	Caltech256	Accuracy analysis	93.4%	Multi-class	Improved generalization and reduced overfitting	High complexity, interpretability limitations, reliance on labeled samples
Gill et al. (2023)	Hybrid CNN-RNN	Fruits dataset	Precision, Recall, F-measure, Accuracy (%)	— (Impressive performance)	Multi-class	Sequential labeling and strong comparative performance	High data dependency and computational intensity
Abu-Jamie et al. (2022)	VGG16	Fruit dataset	Precision, Recall, F-measure, Accuracy (%)	100%	Multi-class	Exceptional accuracy, effective CNN utilization	Potential overfitting, dataset bias, limited generalization to unseen data
Hussain et al. (2020)	CNN	OASIS MRI data	Precision, Recall, F1-Score, Accuracy (%)	97.75%	Binary	High performance, enhanced accuracy through direct comparison	Model complexity and limited applicability beyond specific dataset
Gao et al. (2019)	CNN	Fabric images	Detection accuracy, False alarm rate, etc.	96.52%	Binary	Prevents overfitting, ensures faster convergence, supports insightful error analysis	Limited dataset size, generalization issues, challenges in subtle defect detection
Vikas and Rao (2021)	CNN–LSTM	ADHD-200 (multi-site data)	Specificity, Sensitivity, F1-Score, Accuracy (%)	95.32%	Binary	Improved diagnostic precision and intelligent ADHD detection potential	High computational demand, data quality dependency, limited contextual interpretability
Skouta et al. (2021)	CNN	Diabetic retinopathy dataset	Sensitivity, Specificity, Accuracy (%)	95.5%	Binary	Accurate automated screening enabling rapid diagnosis	Dependent on image quality, architectural optimization, and network depth tuning

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