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Design of Digital Filters for Medical Images Using Optimized Learning Based Multi-Level Discrete Wavelet Cascaded Convolutional Neural Network

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Abstract: In digital signal processing, image enhancement or image denoising are challenging task to preserve pixel quality. There are several approaches from conventional to deep learning that are used to resolve such issues. But they still face challenges in terms of computational requirements, overfitting and generalization issues, etc. To resolve such issues, optimization algorithms provide greater control and transparency in designing digital filters for image enhancement and denoising. Therefore, the paper presented a novel denoising approach for medical applications using an Optimized Learning-based Multi-level discrete Wavelet Cascaded Convolutional Neural Network (OLMWCNN). In this approach, the optimal filter parameters are identified to preserve the image quality after denoising. The performance and efficiency of the OLMWCNN filter are evaluated, demonstrating significant progress in denoising medical images while overcoming the limitations of conventional methods.

Keywords: digital filter; image processing; image enhancement; optimization; deep learning

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0 Introduction

Digital filters are tools and techniques that are used to analyze and modify digital images or signals. These filters are used in several applications such as biomedical engineering, audio processing, telecommunications, control systems, and image enhancement. The role of digital filters is to perform noise minimization, amplify signals, etc.[1]. For image enhancement, digital filters boost the image quality and contrast levels. Whereas in the field of audio processing, these tools are used to reduce noise and equalize audio signals[2-3]. Conventional digital filters often involve manual input for parameter adjustments. But efficacy of such algorithms is not enough and is computationally intensive. To improve efficiency, these algorithms are merged with Artificial Intelligence (AI) methodologies[4]. This will make the model auto-adjustable[5-9]. By learning from datasets, AI can fine-tune filter parameters and improves its performance in dynamic environments[10-11]. For example, in adaptive noise cancellation method, AI algorithms can monitor and adjust filter parameters to enhance noise reduction based on specific noise properties in a given environment. The integration of AI and digital filters expands their potential applications and improves their effectiveness in various contexts. IIR (Infinit Impulse Response) digital filters are suggested by Pepe et al.[12] for audio equalization using deep learning methods. The proposed method outperforms more established methods and produces a nearly flat band at a lower computational cost. A cascaded digital filter with a neural network, suggested by Colonel et al.[13], is faster and more accurate compared to various baseline models. However, all these Machine Learning (ML) and Deep Learning (DL) techniques frequently require a significant amount of labeled training data, powerful computing power, and lengthy training procedures.

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Furthermore, the resulting models might not be interpretable, which makes it difficult to comprehend and analyze their internal workings[14-15].

On the other hand, filter design can be done more systematically and openly using optimization algorithms. They are ideal for the design of digital filters because they allow explicit optimization of specific objectives and constraints and can handle complex design spaces and parameter optimization effectively. The ability to fine-tune and customize filters based on specific requirements is made possible by optimization algorithms. This may be advantageous in a variety of applications. Many current studies focused on maintaining edge feature quality during the process of medical image denoising. One of the primary challenges in medical image denoising is to preserve the quality of features that is critical for diagnostic tasks such as identifying tumors.

Therefore, these issues and challenges motivate the researchers to work on enhancing digital filters through AI and optimization algorithms, which helps to address the limitations of traditional digital filters with adaptability in dynamic conditions. Integrating AI into digital filters transforms their capabilities, enabling autonomous optimization, adaptability, and advancing processing functionalities. Moreover, the application of optimization algorithms allows for systematic, precise filter design, optimizing performance across diverse applications. Despite the progress, challenges, such as the need for extensive data, computational resources, and the lack of interpretability in machine learning models, highlight the importance of this research. It aims to develop more efficient, interpretable, and adaptable filtering solutions to meet the complex demands of modern technology applications, particularly in preserving critical features in applications like medical image denoising. Motivated by afovementioned studies, this the paper explores hybrid-optimized deep learning algorithms aiming at achieving denoising while preserving edges in medical images.

Major highlights of this research include:

1) The paper presented a novel optimized learning multi-level DWT-based (Discrete Wavelet Transform) convolution neural network for medical image filters. The use of multi-level DWT with Convolution Neural Network (CNN) makes the multi-scale image feature processing, improving generalization and reducing overfitting.

2) The learning function is optimized using bio-inspired algorithms such as Particle Swarm Optimization (PSO) for better denoising performance and further mitigates overfitting. This optimized learning rate enhances the learning efficiency and reduces computational load.

3) The result ablation study would be presented on different noise levels.

The rest of the paper is organized as: Section 1 presents a literature review highlighting efforts made by other scholars in the realm of image denoising. Section 2 presents the proposed methodology for medical image denoising with algorithm. Section 3 presents model implementation details with result analysis and comparative state of art. Moreover, Section 3 also presents the overall discussion of the methodology used and its benefits. Finally in Section 4, conclusions and future research directions are presented.

1 Literature Review

Elhoseny et al.[16] presented a methodology for medical image denoising using the Bilateral Filter (BF) with selection of optimal parameters such as gaussian and spatial weights. For optimal parameter selection, the author used Dragonfly (DF) and Modified Firefly (MFF) algorithms. Lian et al.[17] used Finite Impulse Response (FIR) filter with swarm intelligence optimization to find local optimum solutions. Improved Artificial Bee Colony (ABC) algorithm was used as parameter optimizer. Karthick et al.[18] proposed a water strider optimization algorithm for designing of FIR filter. Bansal et al.[19] used Lightning Attachment Procedure Optimization (LAPO) for designing bandstop filters by minimizing magnitude and phase errors. Singh et al.[20] used a Grasshopper Optimization Algorithm (GOA) for designing FIR filter by exploring optimal filter parameters. Gautam et al.[21] presented a guided decimation filter for medical image denoising in which the parameters of the filter are optimized using a hybrid optimization algorithm. Yadav et al.[22] implemented a novel swarm-based approach, the grasshopper optimization algorithm (GOA), to build linear phase FIR filters. Srivatsan[23] developed a hybrid optimization approach called Brain Storm-Grey Wolf Optimizer (BSGWO) for cascade FIR filter coefficient finding, combining Grey Wolf Optimizer

(GWO) and Brain Storm Optimization (BSO). Alsahlanee[24] applied dynamic-static topology of Particle Swarm Optimization (DS-PSO) for designing a digital filter with Infinite Impulse Response (IIR), emphasizing the minimization of non-linear mean square error. Wu et al.[25] used Grey Wolf Optimization (GWO) for linear-phase FIR filter design, focusing on the optimal transition-band sample value. They further enhanced this with Lévy Flight (LF) embedding. Dash et al.[26] introduced a unique objective function and combined Differential Evolution (DE) and Particle Swarm Optimization (PSO) to enhance exploitation and exploration capabilities. Yadav et al.[27] developed one-dimensional FIR filters employing a hybrid of the cuckoo and grey wolf search algorithms. They emphasized the analysis of various parameters related to filter performance. Niu et al.[28] presented a modified artificial ecosystem optimizer to reduce the error function, based on a Dynamic Opposite Learning (DOL) technique and a nonlinear adaptive weight coefficient. They demonstrated superior performance in terms of mean and variance values and applied the DAEO (Dynamic Artificial Ecosystem based Optimizer) method to the IIR system identification problem.

2 Methodology Used

Traditional methods for digital filter design, like decimation filters and windowing techniques, often lack precise control over cut-off frequencies. While some issues are addressed using techniques like the least-square method, they still exhibit problems like discontinuities near the band's edges and a sluggish convergence to ideal solutions. As a result, the researchers have started exploring machine learning methods, notably the Convolution Neural Network (CNN)[29-35]. However, even CNNs for denoising filters present challenges like overfitting, intricate training procedures, hyperparameter adjustments, and dealing with varying noise characteristics. The goal is to design CNN-based filters that are optimized to negate these limitations and enhance both denoising performance and efficiency. These machine learning algorithms are quicker to direct exploration towards universally ideal solutions, making them more apt to address diverse filter needs. By minimizing a specific error or objective fitness function, these methods can determine the best filter coefficients. This research primarily aims to craft an advanced digital filter for medical images using an optimized CNN algorithm, pushing beyond traditional methods' boundaries. This paper introduces a digital filter tailored for medical imagery, developed with an emphasis on Optimized Learning Rate and a Multi-level discrete Wavelet integrated Convolution Neural Network, referred to as OLMWCNN.

A detailed model flowchart is illustrated in Figs.1 and 2. Initially, a noisy input image is processed to extract its color sub-components. Then on these components, 2-level discrete wavelet transform (2-DWT) was applied. Subsequently, certain coefficients from each sub-band are chosen and utilized as feature maps within the CNN. Each sub-band undergoes padding before the filter coefficients are extracted during the CNN model's training phase, which has an optimized learning rate. To refine the learning rate, this research utilizes a nature-inspired algorithm like the Particle Swarm Optimization (PSO).

Algorithm: *Proposed Digital Filter Design*

Input: Set of medical images $\{I_1, I_2, \ldots, I_n\}$

Output: Set of denoised images $\{I'_1, I'_2, \ldots, I'_n\}$

```
Begin
  For each image I in {I_1, I_2, ..., I_n} do
    Aug(I) ← augmentImage(I)
    For each Aug(I) do
      SubBands ← multiLevelDWT(Aug(I))
      For each sub-band SB in SubBands do
        Features ← extractFeatures(SB)
        CNNOutput ← CNN(Features)
        FilteredSubBand←extractFilterCoefficients
        (CNNOutput)
        OptimizedSubBand←optimizeLearningRatePSO
        (FilteredSubBand)
        SB ← OptimizedSubBand
      I′ ← IDWT(SubBands)
  Return I′
End
```

The provided medical image digital filter involves several steps, as described below in Sections 2.1-2.4.

2.1 Input Noisy Medical Images

The process starts with obtaining medical images that need to be processed using the digital filter. Firstly, the input image $I_{x,y}$ is taken with the integration of noise factor $N_{x,y}$ for generation of noisy image $I_{c(x,y)}$, mathematically represented as:

$$I_{c(x,y)} = I_{(x,y)} + N_{(x,y)} \tag{1}$$

In this, gaussian noise is introduced.

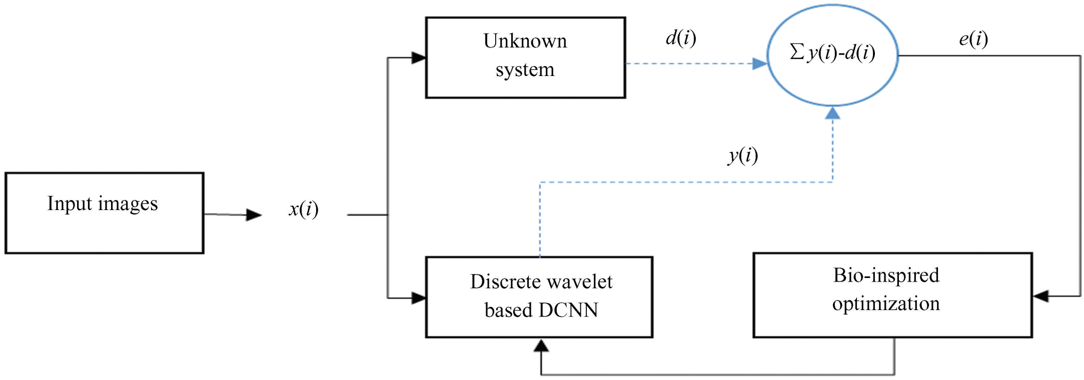


Fig. 1 Proposed digital filter design

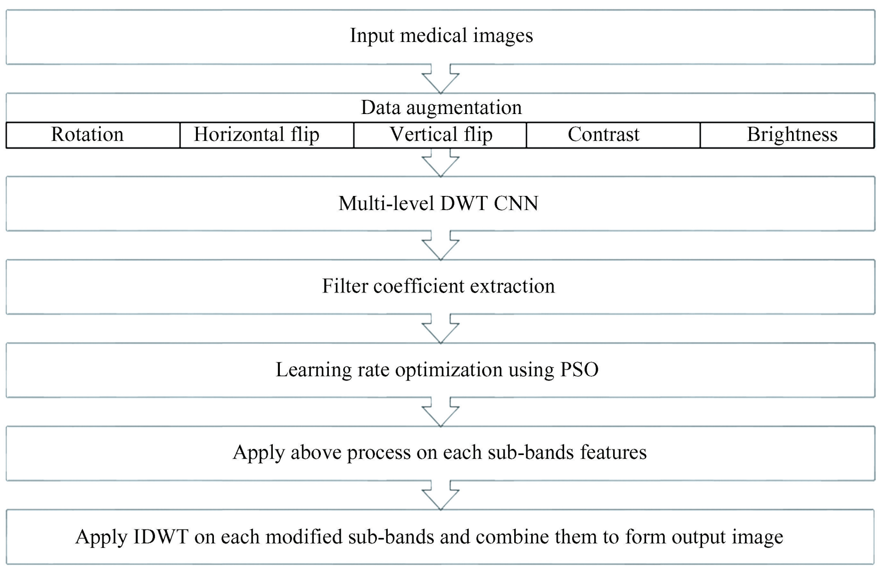


Fig. 2 Flowchart of designed model

2.2 Data Augmentation

Data augmentation is a technique used to increase the diversity of the training dataset by applying various transformations to the original images. The purpose is to improve the model's generalization and robustness by exposing it to different variations of the same data. The following augmentations are applied to the input medical images.

Rotation: The image is rotated by a certain angle to simulate different orientations; Horizontal flip: The image is flipped horizontally; Vertical flip: The image is flipped vertically; Contrast: The contrast of the image is adjusted to make it brighter or darker; Brightness: The overall brightness of the image is adjusted.

2.3 Multi-Level DWT CNN

Discrete Wavelet Transform (DWT) is a mathematical transform commonly used in image processing. In this step, a multi-level DWT is applied to the augmented medical images. The DWT decomposes the image into multiple sub-bands, each represents different frequency components of the image. The number of levels in the DWT determines the number of sub-bands generated. Alongside the DWT, a Convolutional Neural Network (CNN) is used to learn features from each of the sub-bands. The CNN is trained on the generated sub-bands to extract relevant features for further processing.

In traditional DWT, four sub-band filters are extracted i.e. $f^{LL}, f^{LH}, f^{HL}, f^{HH}$. When this is used with CNN, downsampling of input images is performed to extract these sub-band images such as x^1, x^2, x^3, x^4 for respective f^{LL}, f^{LH}, f^{HL}, f^{HH}. Then original image is again regenerated by applying IDWT. In multi-level DWT, these images are further decomposed to obtain more refined sub-bands. During the reconstruction stage, the multi-level inverse discrete wavelet transform is applied to obtain the original image by applying upsampling with the corresponding filter. For image denoising and compression, additional operations like soft-thresholding and quantization are typically applied to process the decomposition result. These operations act as nonlinearities tailored to specific tasks. In this paper, the multi-level wavelet transform is incorporated with convolution layers as presented in Fig. 3. As compared to conventional CNN, the proposed multi-level DWT cascaded CNN network takes advantage of the frequency and location characteristics of DWT, which is expected to better preserve detailed texture in the image.

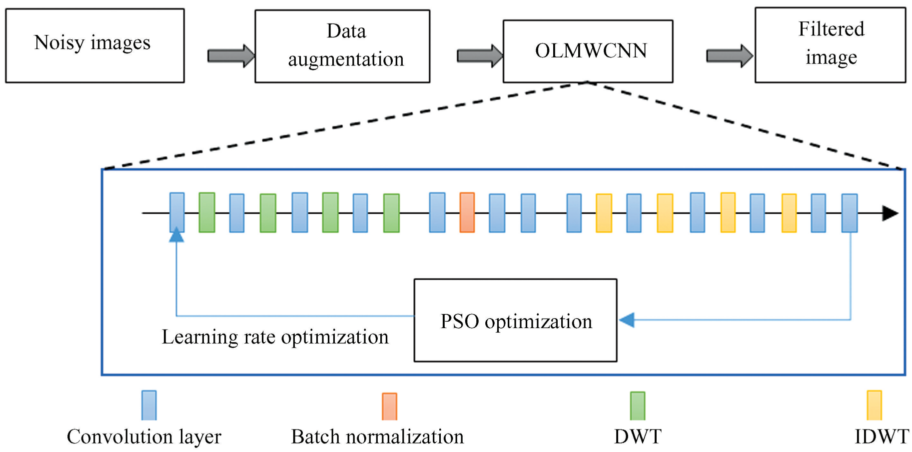


Fig. 3 OLMWCNN architecture

Fig. 3 presents the architecture of the proposed multi-level DWT cascaded CNN model. In this model, it is composed of downsampling and upsampling architecture. The downsampling convolution layer is cascaded with DWT layers, and the upsampling layer is cascaded with IDWT layers. The convolution is composed of conv, batch normalization with RELU (Rectified Linear Unit) activation function.

2.4 Optimized Filter Coefficient Extraction

After training on the sub-bands, CNN efficiently discerns significant attributes, represented as filter coefficients. These coefficients highlight vital patterns or structures within the sub-bands. An emphasis is placed on using an optimized learning rate to pinpoint the best filter coefficients. In our study, we deploy Particle Swarm Optimization (POS) to determine the most efficient learning rate for denoising purposes. Originally conceived for optimizing nonlinear continuous functions, the Particle Swarm Optimization (PSO) algorithm initializes a group of particles. Each particle retains its best-found solution during optimization, while the algorithm records the top solution identified by the entire swarm. The algorithm's effectiveness hinges on specific decisions made throughout its execution. During its operation, particles are initialized with random positions and velocities within an n-dimensional space. Throughout the iterations, each particle's trajectory is swayed by its historically most favorable position, termed as p_best, and the best collective position achieved by the swarm, known as g_best. The updation of velocity vel_n, and position pos_n, for each particle is mathematically represented as:

$$\mathrm{vel}_n = \omega * \mathrm{vel}_n + C_1 * r_{1n} * (\mathrm{p\_best}_n - \mathrm{pos}_n) + C_2 * r_{2n} * (\mathrm{g\_best}_n - \mathrm{pos}_n) \tag{2}$$

$$\mathrm{pos}_n = \mathrm{pos}_n + \mathrm{vel}_n \tag{3}$$

where ω represents the particle's inertia with learning coefficients as C_1 and C_2 respectively. This determines the velocity of the n^{th} particle and respectively converges towards an optimal solution. The optimal solution is obtained with the local best value as $\mathrm{p\_best}_n$ and further global best value ($\mathrm{g\_best}_n$) among them. The workings of the PSO are illustrated in Algorithm 1. Then filter response is updated after obtaining the optimal cost function.

Then the same process of data augmentation, which are DWT, CNN feature extraction, filter coefficient extraction, and learning rate optimization using PSO, are applied to each of the sub-bands generated during the multi-level DWT. This ensures that each sub-band is effectively processed to enhance the overall filtering performance. The above processing are applied on each sub-band using Inverse Discrete Wavelet Transform (IDWT). IDWT is applied to reconstruct the original image from the modified sub-bands. This process aims to improve the quality of medical images, to enhance important features, and to reduce noise or to artifacts, which potentially help to improvce analysis and diagnosis.

3 Results and Discussions

In this section, the paper presents the simulation experiments details and result analysis to validate its efficacy. The training spans over 100 epochs. The simulations would be executed in a Python environment. The computational setup included an Intel(R) Core(TM) i5 processor, clocking between 1.60 and 2.11GHz, complemented by 2GB Graphics. For testing, input images with dimensions of 256 × 256 are used. These medical images are introduced to Gaussian noise, with a varying range from 20 to 50. Afterward, these noise−affected images are processed through our hybrid optimization-based design to filter the noise out. In the following sub-section, we delve into the specific medical image datasets utilized for our analyses.

3.1 Dataset Description

For experimental evaluation, various medical image collections, such as CHASEDB1[36] and MRI[37], are used to conduct our analysis. The CHASEDB1 collection[36] consists of retinal photographs taken from school-aged children of different ethnic backgrounds. Accompanying these images are annotations that detail the actual position of the blood vessels, demonstrating a range of retinal pigmentation levels. Conversely, the MRI collection[37] includes a mixture of brain MRI scans. These encompass both simulated and real images of individuals in good health, as well as those suffering from medical disorders.

3.2 Parameters Used

The following three performance evaluation parameters are used in the paper.

Peak Signal-to-Noise Ratio (PSNR): Enhancing the visual quality of a digital image can be a subjective process. However, to truly assess the efficacy of image enhancement methods, it is vital to have quantitative measurements in place. This is where PSNR comes into play. PSNR gauges the quality of an enhanced image by measuring the ratio of the maximum possible power of a signal to the power of the noise that might compromise its fidelity. This metric is particularly important, given the extensive dynamic range observed in numerous signals, which refers to the disparity between the highest and lowest possible value of a variable attribute.

$$\mathrm{PSNR} = 10 \log_{10} \frac{(L-1)^2}{\mathrm{MSE}} \tag{4}$$

Consequently, L represents the highest possible intensity levels an image can have.

Mean Square Error (MSE): MSE is used to determine the average squared difference between observed and forecasted values. When a model perfectly predicts every observation, the MSE is zero. However, the value of MSE rises with increasing prediction errors. In the context of this study, it is utilized to assess image quality, specifically by measuring the accumulated squared discrepancies between the original and processed images.

$$\mathrm{MSE} = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{i=o}^{n-1} (O(i,j) - D(i,j))^2 \tag{5}$$

where, $O(i,j)$ represents the original image and the filtered image is presented as $D(i,j)$. Here, pixel location is represented as i, j, and m, and n represents the size of the image horizontally and vertically.

Structural Similarity Index (SSIM): It is a perceptual metric that quantifies the degradation in image quality, often resulting from processes like data compression or transmission losses. Essentially, SSIM requires two images for evaluation—a reference image and a processed one. It calculates the perceptual disparities between these two visually similar images. However, without discerning which image is the "original" and which has gone through further processing (e.g., data compression), SSIM alone cannot ascertain which image is superior in quality. Consequently, SSIM is derived from a weighted combination of three related measures.

$$\mathrm{SSIM}(x,y) = l(x,y)^{\alpha} \cdot c(x,y)^{\beta} \cdot s(x,y)^{\gamma} \tag{6}$$

Given the weights, α,β,γ set to 1, the equation can be simplified to the aforementioned form. When comparing samples of x and y, three specific measures are used: l stands for luminance comparison, c signifies contrast comparison, and s represents structural comparison.

3.3 Result Analysis

Table 1 presents the performance evaluation of a proposed model with varying levels of noise. The table showcases the results for different noise levels, measured in standard deviation (σ), and their corresponding values for Peak Signal-to-Noise Ratio

(PSNR), Structural Similarity Index (SSIM), and processing time. The table provides a comprehensive comparison of the proposed model's performance under different noise conditions. As the noise level increases (from $\sigma = 25$ to $\sigma = 50$), the PSNR and SSIM value tends to decrease, indicating that the quality of the processed images becomes worse as the noise level increases. The following observations are inferred from Table 1.

PSNR (Peak Signal-to-Noise Ratio): The highest PSNR value is observed at $\sigma = 25$, where PSNR is 33.71. As the noise level increases, the PSNR value decreases, indicating that the image quality degrades with higher noise levels. The lowest PSNR value is observed at $\sigma = 50$, where PSNR drops to 30.51.

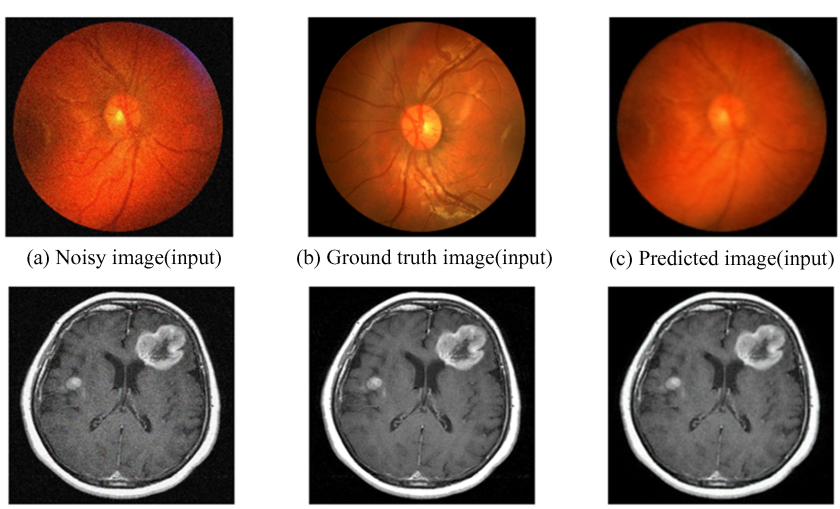
SSIM (Structural Similarity Index): Similar to PSNR, the highest SSIM value is also observed at $\sigma = 25$, where SSIM is 0.846. As the noise level increases, the SSIM values decreases, indicating that the structural similarity between the original and processed images decreases with higher noise levels. The lowest SSIM value is observed at $\sigma = 50$, where SSIM drops to 0.805.

Time: The processing time is generally lower for lower noise levels. As the noise level increases, the processing time also increases. The highest processing time is observed at $\sigma = 30$, where it takes 0.56 units of time, and at $\sigma = 35$, where it takes 0.53 units of time.

Table 1 Performance evaluation of proposed model with varying noise level

Noise level	Image quality assessment techniques		Time (s)
	PSNR	SSIM	
$\sigma = 25$	33.710	0.846	0.13
$\sigma = 30$	32.849	0.838	0.56
$\sigma = 35$	32.344	0.821	0.53
$\sigma = 50$	30.51	0.805	0.42

Fig. 4 presents the visualization of denoising outcomes of the input medical images. Fig. 5 presents the comparison of image-denoising models for the Peak Signal-to-Noise Ratio (PSNR) that represents the quality of denoised images produced by each model. Higher PSNR values indicate better image quality and, consequently, better denoising performance. Fig. 5 lists several existing state-of-art models i.e., DNCNN[29], DeepRED[32], BEMD[33], and BF-GA[34]. Among the presented state-of-art models, the proposed model OLMWCNN outperforms best.



(a) Noisy image(input) (b) Ground truth image(input) (c) Predicted image(input)

(d) Noisy image after denoising (e) Ground truth image after denoising (f) Predicted image after denoising

Fig. 4 Visualization of denoising outcomes on different medical datasets

3.4 Discussions

The proposed method uses an Optimized Learning-based Multi-level discrete Wavelet Cascaded convolutional Neural Network (OLMWCNN) to address challenges such as high computational requirements and overfitting. The key features of the proposed methodology are as follows.

1) Optimized learning rate: The OLMWCNN filter leverages an optimized learning rate to efficiently discern significant attributes and filter coefficients for denoising purposes. This approach helps in achieving better convergence towards optimal solutions while minimizing computational requirements.

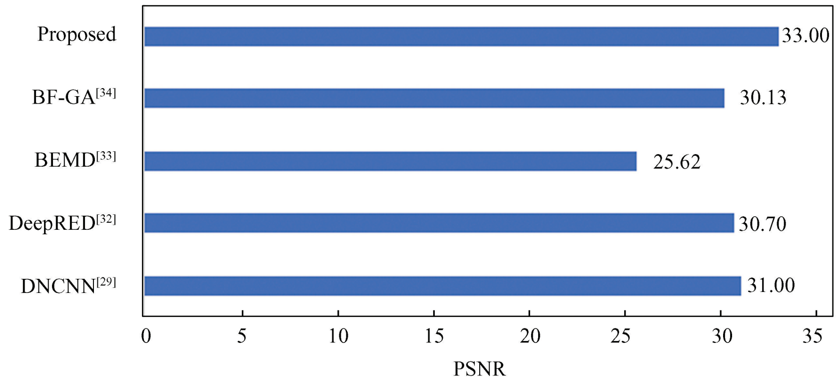


Fig. 5 PSNR comparative state-of-art

2) Multi-level Discrete Wavelet Transform (DWT): By integrating multi-level DWT into the convolutional neural network architecture, the OLMWCNN filter effectively captures and processes image features at different scales, reducing the risk of overfitting and enhancing the network's ability to generalize.

3) Transparency and control: The OLMWCNN filter offers greater control and transparency in filter design, allowing for a more structured approach to image enhancement and denoising compared to traditional deep learning methods.

4) Particle Swarm Optimization (PSO): The OLMWCNN filter utilizes PSO for optimizing the learning rate and determining the most efficient filter coefficients, thereby improving the denoising performance while mitigating overfitting.

By incorporating these strategies, the OLMWCNN filter effectively mitigates the challenges of high computational requirements and overfitting, making it a promising solution for image denoising in medical applications.

The key advantages of using an Optimized Learning-based Multi-level discrete Wavelet Cascaded convolutional Neural Network (OLMWCNN) for digital filter design in medical image processing include:

1) Enhanced denoising performance: The OLMWCNN offers improved denoising performance, as evidenced by this study's results, which demonstrate significant progress in denoising medical images while overcoming the limitations of conventional methods.

2) Greater control and transparency: Compared to traditional deep learning methods, the OLMWCNN provides greater control and transparency in filter design, allowing for a more structured and controlled approach to image enhancement and denoising.

3) Efficient feature extraction: By integrating multi-level Discrete Wavelet Transform (DWT) into the convolutional neural network architecture, the OLMWCNN efficiently captures and processes image features at different scales, leading to enhanced feature extraction and representation.

4) Optimized learning rate: The OLMWCNN leverages an optimized learning rate, along with Particle Swarm Optimization (PSO), to determine the most efficient filter coefficients, thereby improving denoising performance and efficiency.

5) Generalization and adaptability: The multi-level DWT-based approach in the OLMWCNN enhances the network's ability to generalize and adapt to diverse noise characteristics in medical images, making it a versatile solution for various imaging scenarios.

Overall, the OLMWCNN offers a comprehensive and optimized framework for digital filter design in medical image processing, addressing key challenges while delivering enhanced denoising capabilities and efficiency.

4 Conclusions

This study focuses on designing digital filters for image enhancement and denoising using optimization algorithms is presented. The goal is to improve image quality while reducing noise artifacts. This paper introduces the Optimized Learning-based Multi-level Discrete Wavelet Cascaded Convolutional Neural Network (OLMWCNN) for medical image denoising. It addresses challenges faced by deep learning approaches, offering greater control and transparency in filter design. The result analysis is investigated with varying noise ratios. The highest PSNR is observed to be approx. 33, whereas SSIM was approx. 0. 84. Future research can explore additional optimization algorithms or hybrid approaches and integrate machine learning techniques for more advanced image enhancement and denoising capabilities.

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