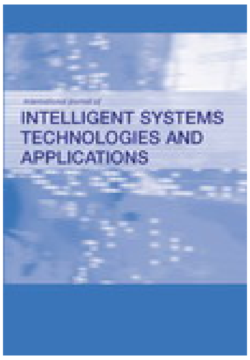

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Improving assaulted medical image quality using improved adaptive filtering network

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Abstract: Regular static convolutions work well for low-frequency information processing but fall short for high-frequency information processing. Dynamic convolution is the recent method that has spatial anisotropy and content-adaptiveness, enabling it to restore complicated and sensitive high-frequency information. The proposed method makes use of dynamic convolution to enhance the learning of multi-scale and high-frequency features. To accomplish this, two blocks – the dynamic convolution block (DCB) and the multi-scale dynamic convolution block (MDCB) are introduced. Dynamic convolution is used by the DCB to improve high-frequency information, whereas skip connections are used to protect low-frequency information. To efficiently extract multi-scale features, the MDCB uses shared adaptive dynamic kernels of increasing size along with dynamic convolution. The proposed multi-dimension feature integration mechanism is used to produce accurate and contextually enriched feature representations. For successful denoising, an improved adaptive dynamic filtering network is useful.

Keywords: image processing; medical image; digital watermarking; encryption; data security; denoising; deep convolutional neural network.

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1 Introduction

The quick development of computer technology has made it possible for image processing techniques to be used, which has improved the quality of images produced by various medical imaging instruments. Noise is the unwanted signal that interferes with important and valuable data. Different categories can be identified depending on the type and origin of the sounds, such as the impulsive and speckle noise or the Gaussian noise (Bindal et al., 2022; Hassan et al., 2022). Noise is either introduced to the image during capture or is added after it is acquired or transmitted via a wired or wireless channel. Due to the increased susceptibility of wireless media to noise, images may degrade and have lower image quality.

In the last two decades, the use of medical imaging and diagnostic methods has increased along with the growth of data science, data analysis, data storage, and the internet. These developments are currently having an impact on the fields of telemedicine and medical sciences, which allow for more precise disease diagnosis and treatment. Similar to images produced with any other imaging technology, medical images are prone to noise and artefacts. Noise continuously deteriorates this imagery throughout picture collection and transmission, producing low-quality, blurry images that makes it difficult to distinguish between diseases. Therefore, image denoising is crucial in the field of biomedical image processing. As a result, noise reduction must be done without sacrificing image quality. Numerous noise reduction methods based on the transform approach, machine learning, filtering method, and statistical method have already been proposed in the literature (Bindal et al., 2022; Hassan et al., 2022; Patil and Bhosale, 2022; Wu et al., 2023; Puli et al., 2022). Each method has its own set of benefits and drawbacks.

The main objective of image denoising technology is to minimise noise while maintaining the original information, including edges. When denoising an image, it is important to keep the texture information, and edge information intact while avoiding the creation of any new artefacts. The similarity between an edge and noise with a constant high intensity value makes it difficult to perform denoising.

The use of spatial domain linear and nonlinear filtering techniques to denoise medical images results in a loss of information at the margins. To get around this issue, transformation domain-based denoising strategies are being taken into consideration. These techniques cover denoising in the wavelet, curvelet, contourlet, and fast Fourier transform domains, among others (Hassan et al., 2022; Patil and Bhosale, 2022; Wu et al., 2023). As image size increases, this domain's performance falls off dramatically. This issue can be handled by utilising machine learning-based denoising techniques that draw inspiration from biological systems, such as Boltzmann machines, autoencoders, convolutional neural networks (CNNs), evolutionary algorithms, etc. Due to the wide range of applications for image processing, the main limitation of these techniques is their computational complexity (Wu et al., 2023).

The significant achievements of the study are as follows:

a to improve the results and quality of the watermark extracted

b to produce accurate and contextually enriched feature representations using a multi-dimension feature integration mechanism

c to achieve imperceptibility through a robust system, to check the similarity between the watermarks extracted before and after the attack, which is not noticeable to anyone.

The further section describes the structure of the paper. In Section 2, a summary of the literature is presented. Section 3 provides details on the proposed method. The computation results for the proposed method are shown in Section 4. In Section 5, conclusions are provided.

2 Related work

The problem of salt and pepper noise in images is addressed by Puli et al. (2022). The proposed technique offers a more precise and effective method for denoising by applying directional filters to separate edges from noise. The article's findings illustrate how effective is the algorithm defined. Treece (2022) introduced a unique bitonic filter that employs a locally adaptable signal domain and modifies it such that it may be used to filter noise from genuine image sensors. These developments have greatly increased noise reduction performance without reducing processing times. The designed method also produces residual images that perform well even when there is a lot of noise.

Adaptive noise variance estimation, nonlinear filtering, and domain transformation filtering are three new techniques that Jia et al. (2022) combined to improve the well-known block-matching and 3D filtering (BM3D) algorithm. The proposed technique maintains the fine details and crisp edges of an image while removing noise. In Annavarapu et al. (2022), the authors describe a novel method for edge identification, picture augmentation, and denoising that integrates the Rudin-Osher-Fatemi, Richardson-Lucy, and BM3D collaborative filtering techniques. The designed method combines algorithms in a hybrid adaptive way, where each algorithm's parameters are changed following the properties of the input image.

Compared to other approaches, this adaptive strategy helps to obtain better denoising performance.

A novel image denoising technique using a bi-dimensional empirical mode decomposition method is described by Satapathy and Das (2022). The proposed method separates the noisy image into several intrinsic mode functions (IMFs) that contain residue. The equalisation is then applied to the filtrate after independently filtering each of the distinctive properties of the IMFs to maintain edge information. Guo (2023) presents a real-time medical image denoising and information hiding model based on deep wavelet multiscale autonomous unmanned analysis, enabling effective denoising of the image while maintaining important features like edges and texture. This major objective of the study is to enhance image perception by reducing image noise and streamlining image processing.

Reyes-Ruiz et al. (2023) identified and explained the combination of visible and invisible watermarking techniques with particle swarm optimisation as a trustworthy and efficient method for preventing the unlawful use of digitised cinematographic images from the cultural heritage of Mexico. Zhang et al. (2022) present a practical unsupervised image denoising method with cutting-edge denoising performance. This method first uses random noise generated by the noise model to construct a dataset of both noisier and noisier images. Second, it trains a model using the noisier-noisier dataset, which is then applied to the improved noisy images to create the targets for the subsequent round. This method is repeated until the required degree of denoising performance is attained.

Gou et al. (2022) offers a novel neural network architecture called multi-scale adaptive network (MSANet) for single image denoising. MSANet is composed of three neural blocks: an adaptable feature block, an adaptable multi-scale block, and an adaptable fusion block. The adaptive feature block learns features that are adjustable to the input noise level while the adaptive multi-scale block extracts features at several scales and adaptively blends them. The adaptive fusion block improves the characteristics even more to produce the final denoised image. The dynamic convolution block (DCB) and the multi-scale dynamic convolution block (MDCB) are two new convolutional blocks for image denoising that Shen et al. (2022) introduce. The DCB uses skip connections to safeguard low-frequency data while dynamic convolution enhances high-frequency data. Using the multi-scale feature integration (MFI) technique, feature representations can be made more precise and contextually rich.

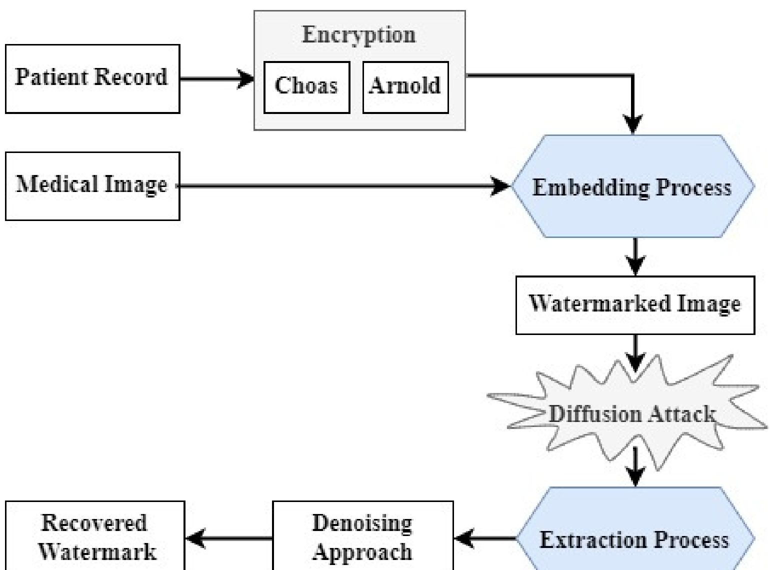
3 Proposed methodology

Digital watermarking is a process used to embed additional information into an image without being perceptible to the human eye. Its purpose is to provide various benefits such as identifying the image's creator, owner, or authorised user. In combination with encryption, watermarking can serve purposes such as data authentication, broadcast monitoring, and copyright protection. In the context of medical image security and the challenges associated with image sharing in telemedicine, a system has been developed that utilises digital watermarking and encryption techniques. The primary objective of this system is to protect the copyright of medical images when they are shared among different medical facilities.

To provide security to the patient's record, which typically contains sensitive personal information, is encrypted using Chaos and Arnold encryption techniques. This encryption ensures that unauthorised individuals cannot access the patient's personal information unless they have proper authorisation. Furthermore, to obtain the watermarked image, the encrypted image is embedded into a cover image with watermarking using pixel colour correlation (WPCC) approach described in Pulgam and Shinde (2022). This approach defines the correlation between pixels colours and the location of the pixel to embed the encrypted data in a manner that it is imperceptible to the naked eye.

The WPCC technique, creates a list of the locations of pixel colour values of the watermarked image. In case of an attack, where some pixel colours may not match any other pixels, the technique finds the closest colour location and sets it for that pixel. This information is then added to the list. By directly working with pixel values, it becomes easier to extract the pixel information from the watermarked image, even after an attack is performed. This facilitates the accurate recreation of the secret image later on.

Figure 1 Overall flow of the proposed system (see online version for colours)



The combination of watermarking and encryption approach used helps to add privacy to the information embedded in cover image. To assess the robustness of the system, multiple attacks are employed to test its resilience. WPCC helps to extract watermark image from distorted watermarked image. When an attack is launched or when operations are carried out on it, the watermarked image usually degrades some of its visual quality. To ensure the delivery of high-quality images with secure data, a system has been developed that combines the principle of image denoising and digital watermarking. Denoising helps to remove unwanted noise or distortions that may be introduced during the watermarking process or as a result of attacks. By applying denoising techniques, the system aims to protect the content and clarity of the images, thereby maintaining their visual quality. After denoising, decryption is applied to extract the watermark image from the watermarked image. The watermark extracted represents the patient's medical record that was inserted during the embedding process. This allows for the retrieval of the embedded information, such as the ownership or identification details associated with the medical image. In the context of healthcare image processing, denoising plays a vital role in enhancing the quality of medical images and enabling a clearer visualisation of the finer details.

Figure 1 illustrates the overall flow of the system, depicting the different stages involved encryption, watermarking, denoising, and decryption. The subsequent sections provide more detailed information on the denoising technique, particularly focusing on the use of deep learning to address the challenges associated with maintaining image quality and reducing the impact of attacks.

3.1 Adaptive dynamic filtering network

The adaptive dynamic filtering network is a denoising method that aims to reduce noise in an input image. It employs a network architecture consisting of four scales, with each scale incorporating a residual connection between the encoder and decoder, except for the lowest scale. The denoising process begins with a 3×3 convolutional layer, which is used to extract shallow features from the noisy input. These features are then passed through the encoder, which consists of a convolutional block and a multi-scale convolutional block. The encoder's purpose is to extract features at multiple scales, allowing the network to capture both local and global information about the image.

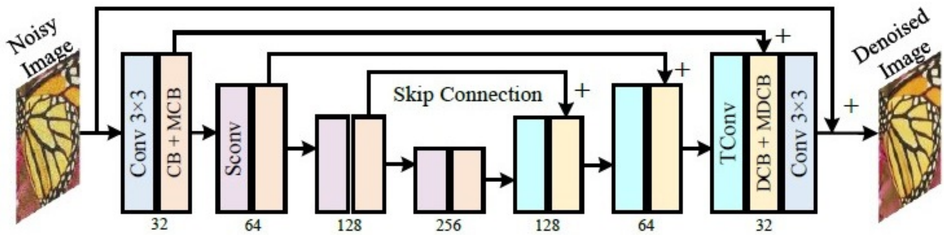
After the encoding stage, the features are reconstructed in each scale using DCB and MDCB in the decoder. The reconstruction process occurs from coarse to fine, meaning that the features are progressively refined and upscaled to obtain the final denoised output. To achieve downsampling and upsampling of the features, the network utilises a 3×3 stridden convolutional layer for downsampling and a 6×6 transposed convolutional layer for upsampling. These operations help to adjust the spatial resolution of the features at different scales.

The number of channels in the encoder and decoder varies across the four scales, ranging from 32 to 256. This variation allows the network to capture features of different complexities and scales, enabling effective denoising across the entire image. The design of the adaptive dynamic filtering network aims to achieve high denoising performance while minimising computational complexity. By incorporating residual connections, multi-scale processing, and dynamic convolutions, the network can effectively denoise images while efficiently utilising computational resources. Figure 2 provides a visual representation of the network architecture and its flow.

3.1.1 Dynamic convolution block

The inclusion of dynamic convolution within the DCB enhances the ability of the network to handle noise. This also improves the restoration performance by leveraging adaptive kernels that are customised to specific image characteristics. This integration of dynamic convolution within the DCB contributes to the overall effectiveness of the adaptive dynamic filtering network in achieving high denoising performance.

Figure 2 Network architecture for denoising (see online version for colours)

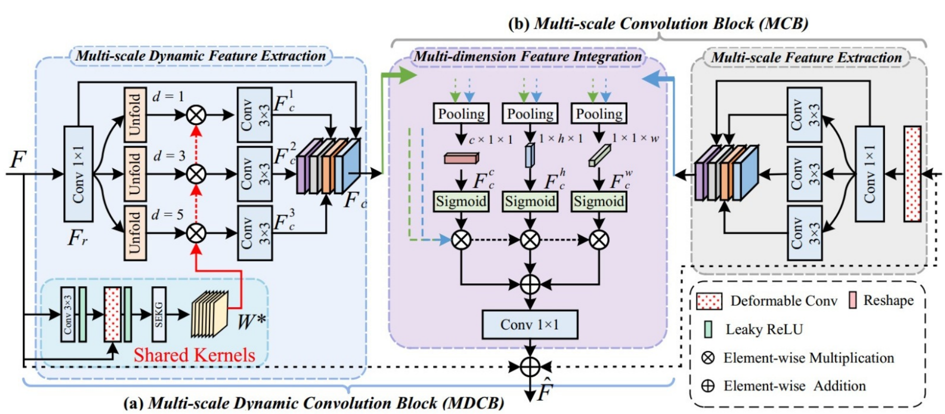


Source: Shen et al. (2022)

3.1.2 Multi-scale dynamic convolution block

The MDCB in the adaptive dynamic filtering network enhances the performance of dynamic convolution on a multi-scale level. It enlarges the receptive field size, utilises adaptive dynamic kernels, shares kernels among multi-scale features to reduce computational complexity, and extracts complementary information from different scales. These design choices contribute to the MDCB's ability to provide more precise, contextually enriched, and effective feature representations for denoising and restoration tasks.

Figure 3 Adaptive filtering network architecture (see online version for colours)



Source: Shen et al. (2022)

After generating the dynamic features at different scales, the next step is to fuse them to create a more informative representation that incorporates both local and global contexts. This fusion is achieved through a MFI mechanism. The MFI mechanism utilises a weighted sum to integrate the features from different scales. The weights used in the weighted sum are learned by a set of convolutional layers. This allows the network to adaptively combine the features from different scales based on the content of the input image. By learning the weights through the convolutional layers, the network can dynamically adjust the contribution of each scale's features during the fusion process. This adaptive combination of features helps to capture both local details and global contextual information, leading to a more comprehensive representation that improves denoising and restoration performance.

The ADFNet incorporates a multi-dimensional attention-guided mechanism, as depicted in Figure 3. This mechanism aims to effectively combine the features from different scales while emphasising relevant regions and suppressing irrelevant regions.

The feature integration process involves the following steps:

- *Average pooling along different dimensions:* The feature maps from each scale are averaged pooled along different dimensions. This pooling operation helps to capture contextual information in three groups.
- *Channel-wise attention:* Channel-wise attention is applied to the averaged feature maps obtained in the previous step. By applying attention at the channel level, the network can focus on the most informative channels and suppress noisy or irrelevant ones.
- *Multiplication with attention maps:* The attentive features are obtained by multiplying the calibrated features resulting from the channel-wise attention, with the attention maps derived from different dimensions. This multiplication operation helps weight the features based on the attention maps, emphasising important regions and suppressing less relevant ones.

The attentive features are denoted as F_c^c, F_w^c and F_h^c, which represent the attentive features from channel-wise, width-wise, and height-wise attention, respectively as shown in equations (1), (2) and (3). It involves applying a sigmoid function to the averaged feature maps obtained through average pooling to generate a spatial attention map ranging from 0 to 1. This attention map is then element-wise multiplied with the original features to obtain the attentive features for each attention.

$$F_c^c = Sigmoid(AvgPool(F_c)) \otimes F_c \tag{1}$$

$$F_w^c = Sigmoid(AvgPool(F_c)) \otimes F_c^c \tag{2}$$

$$F_h^c = Sigmoid(AvgPool(F_c)) \otimes F_w^c \tag{3}$$

where F_c denotes the final output received after multi scale dynamic feature extraction.

To fuse the attentive features and enhance the information flow, equation (4) shows the addition of the three attentive features (F_c^c, F_w^c and F_h^c). A 1×1 convolutional layer ($C_{1\times1}$) is then applied to this sum to fuse the features and obtain the final output of the multi-scale dynamic convolution block, F'. The addition of the local residual learning, denoted by F, further enhances the information flow.

$$F' = F + C_{1\times1}(F_c^c + F_w^c + F_h^c) \tag{4}$$

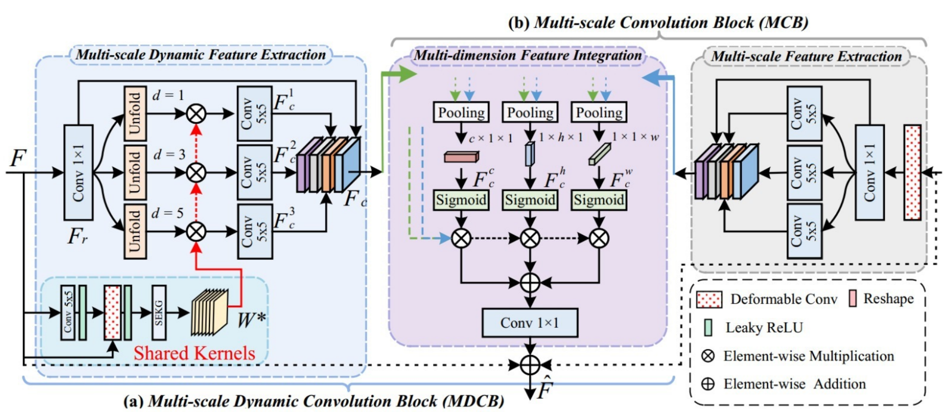
3.2 Improved adaptive dynamic filtering network

Convolutional filters or kernels play a crucial role in image processing and computer vision tasks. The convolution operation, which involves sliding the kernel over the input image and computing dot products, allows for feature extraction and transformation of the image representation. By changing the values of the convolutional kernel, different types of filters can be applied to the image. For example, a 3 × 3 kernel can be used for edge detection, a blurring filter, or a sharpening filter. The choice of the kernel size and values determines the specific type of operation being applied to the image. In deep learning architectures, stacking multiple convolutional layers allows for the learning of increasingly complex and abstract features. Deeper networks can capture higher-level information and can be more effective for tasks that require sophisticated understanding and reasoning, such as object recognition.

The choice of kernel size, number of layers, and overall network architecture is crucial. It depends on the specific problem being solved, available computational resources, and the desired level of feature abstraction. It is a trade-off between the receptive field size, which captures global context, and computational efficiency. Depending on the characteristics of the dataset and the complexity of the task, a smaller kernel size such as 3 × 3 might still be sufficient to capture meaningful patterns and achieve good performance. In some cases, a combination of different kernel sizes like 3 × 3, 5 × 5, or even larger at different layers of the network can be used to strike a balance between local and global feature extraction.

Hence to achieve the optimal performance proposed system IADFNet introduces the use of multi-scale dynamic convolution blocks, where the size of the convolution filter is improved from 3 × 3 to 5 × 5. This larger kernel size allows for the extraction of more extensive spatial information and can capture more complex patterns within the image. Figure 4 represents the architecture of IADFNet.

Figure 4 Improved adaptive dynamic filtering network (IADFNet) (see online version for colours)



The complexity of the learned features in a neural network is influenced by various factors, including the network architecture, activation functions, and the size of the input and output layers. Using larger kernel sizes in convolutional layers does introduce more weights and parameters to learn, which can increase the expressive power of the model. Larger kernel sizes allow for the integration of information from a wider receptive field, enabling the extraction of more global and contextual features from the input data. This can be beneficial for capturing larger structures or patterns that span across multiple local regions in the image.

4 Experimental results

The approach described has been tested and analysed using various cover medical images, such as ultrasound (US), computed tomography (CT), X-ray, and magnetic resonance imaging (MRI). These images were obtained from public medical databases (Medical Image Database, 2020) with a resolution of 512×512 pixels. The patient's medical report is used as a watermark image in the experiments, with a size of 256×256 pixels. The experiments were conducted on a laptop with an Intel Core i3-4005u CPU operating at 1.70 GHz and 4 GB of RAM. The laptop was running the Windows 8.1 operating system, and the experiments were implemented using MATLAB 2018. The sample input image and patient record used as a watermark are shown in Figure 5.

Figure 5 Sample input images and watermark image

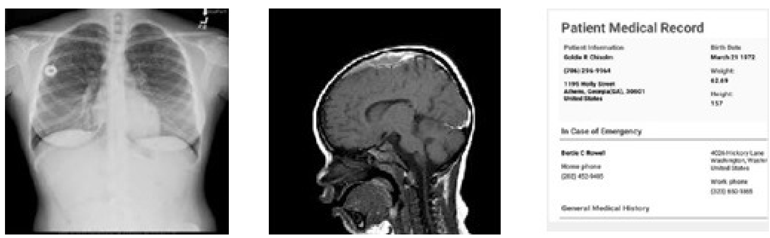
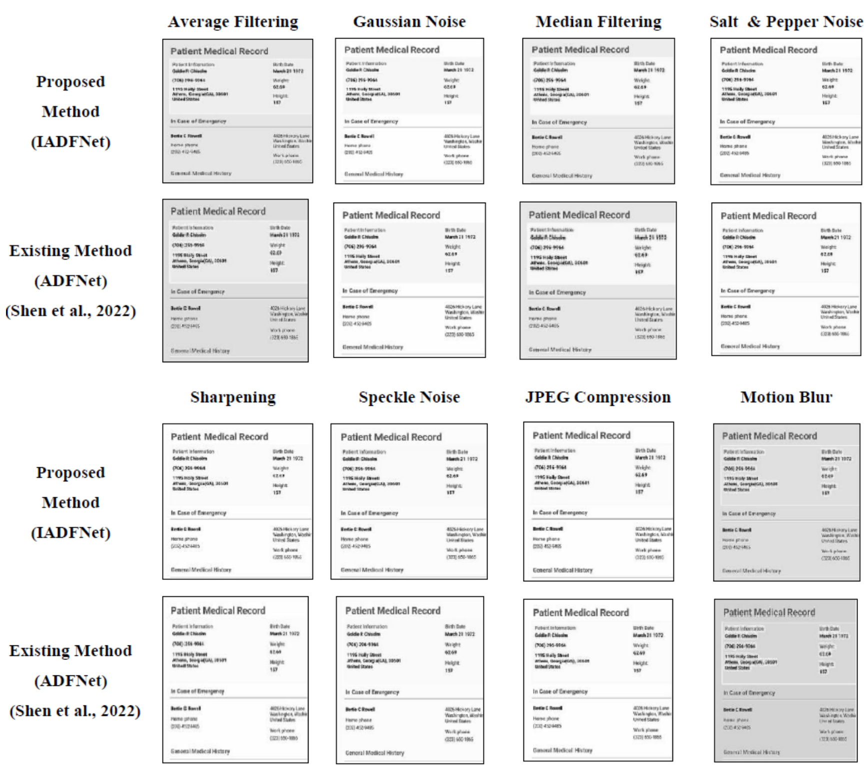


Figure 6 Extracted watermark after performing different attacks on chest X-ray image



To evaluate the reliability of the proposed methodology, several attacks were applied to the watermarked images. These attacks included the addition of noise, filtering, rotation, compression, resizing, and other similar operations. One specific aspect of the methodology is the denoising approach, which aims to improve the quality of the watermark images and enhance their readability and usability. The proposed denoising method is designed to reduce noise and artefacts in the watermarked images, thereby enhancing the visibility and legibility of the embedded watermark. To evaluate the performance of the proposed denoising approach, a comparison is made with an existing method, ADFNet (Shen et al., 2022). Figure 6 illustrates the results obtained from the proposed denoising approach, showcasing the improvement in image quality and the clarity of the watermark in comparison with the existing one.

The fidelity of the embedding algorithm of the IADFNet system is assessed using two quantitative measures: the structural similarity index measure (SSIM) and the peak signal to noise ratio (PSNR). These measures provide objective metrics to evaluate the quality and similarity of the watermark image before and after attacks. Higher SSIM values and higher PSNR values indicate better similarity and higher quality, respectively. The SSIM quantifies the structural similarity between two images. It takes into account the luminance, contrast, and structural similarity components of the images. The formula for calculating SSIM is defined as follows:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)} \tag{5}$$

where μ_x, μ_y are the average values of the compared images, σ_x, σ_y are the standard deviations of the compared images, σ_{xy} is the covariance of the compared images and C_1 and C_2 are small constants to avoid division by zero.

PSNR measures the difference between the original and distorted images in terms of signal-to-noise ratio. The formula for calculating PSNR is typically defined as:

$$PSNR = 10\log\left[\frac{(2^v-1)^2}{MSE}\right] \tag{6}$$

Here, v is the minimum number of bits that can represent possible maximum intensity in a given image and mean square error (MSE) is calculated for the quality of the system's performance.

The proposed system aims to address attacks that intentionally degrade images by adding noise signals, which can lower the visual quality and potentially remove the watermark information from the watermarked item. In these attacks, the watermark is often considered an additive noise signal mixed with the host signal. The IADFNet method is designed to effectively extract and recover the precise watermark information even after various attacks have been applied. The proposed method can create excellent-quality images with a high PSNR of 47.95 dB across a variety of medical imaging modalities.

Resisting attacks is an important characteristic of any watermarking system, as it ensures the robustness and reliability of the embedded watermark. By evaluating the performance of the proposed strategy under different attack scenarios, it is possible to assess its ability to maintain the quality and readability of the watermark image. The results presented in Table 1 demonstrate high values of metrics such as SSIM and PSNR, indicating the effectiveness of the IADFNet method in preserving the quality of the watermark image even after attacks. It protects the watermark against intentional or unintentional manipulations, such as noise addition, filtering, rotation, compression, resizing, and others. Overall, the proposed system demonstrates its capability to effectively extract and preserve the watermark information even under various attacks, as evidenced by the high-quality images and the comparison results with the existing system.

Table 1 Comparison of quality of watermark image retrieved from the distorted chest X-ray image

Attack	*IADFNet*		*ADFNet (Shen et al., 2022)*	
	PSNR	*SSIM*	*PSNR*	*SSIM*
Median	25.4569	0.9593	22.9483	0.9393
Gaussian noise	42.5304	0.998	38.8746	0.9952
Salt and pepper noise	44.8985	0.9993	44.8985	0.9993
Speckle noise	41.0035	0.9979	40.7523	0.9978
Sharpening attack	47.958	0.9994	45.1388	0.9989
Rotating attack	16.1978	0.869	13.7172	0.7976
Motion blur	19.2002	0.9115	16.7365	0.8687
Average filter	22.2903	0.947	19.8657	0.917
JPEG compression	45.8158	0.998	43.2325	0.9958
Gaussian low-pass filter	22.2958	0.9471	20.1011	0.92
Histogram equalisation	40.0376	0.9982	37.402	0.9969
Rescaling	43.8817	0.9983	42.5557	0.9973

5 Conclusions

Noise can be a big problem in medical imaging, where precise and accurate analysis is essential for identifying and analysing diseases. It can hide details, introduce artefacts, and make it difficult to accurately diagnose and analyse medical conditions. This can have serious consequences, including misdiagnosis and potential harm to patients. To overcome these challenges and ensure the reliability of medical imaging, noise reduction techniques are essential. Denoising is used as a pre-processing technique where, the quality of medical images can be improved, enhancing the visibility of relevant information and facilitating more accurate analysis and diagnosis. CNNs leverage the power of convolutional filters by learning the optimal weights of the filters during the training process. This enables the network to automatically extract and discover useful features specific to the task at hand. In the IADFNet system, a dynamic convolution block and a multi-scale dynamic convolution block are introduced to enhance the representation of high-frequency and multi-scale features using larger kernel sizes. By incorporating dynamic convolutions, which can adaptively generate kernels, the network can effectively capture and process information in a more flexible and context-aware manner. The multi-scale dynamic convolution blocks further improve the feature extraction process by enabling the network to capture features at multiple scales. This is particularly valuable in tasks that require analysing images at different levels of detail or detecting objects of various sizes. Through experiments, the system's efficiency and effectiveness in denoising tasks have been validated, highlighting its potential for improving image analysis and processing tasks.

There are many things that could be improved in order to get better outcomes. For example, salt and pepper noise keeps the mark on the images even after attack, that degrades the fine details of the images and it has to be removed. The proposed system should be further extended to identify whether the attack was performed or not. Also, the system should be able to identify the type of attack performed to extract the data.

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