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Research Paper

Enhancing the Quality of Melanoma Dermatoscopic Images Using Wavelet Coefficients within a Deep Learning Framework

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ABSTRACT

Background: High-quality medical images improve accuracy in diagnosing diseases. Melanoma is a common and deadly skin cancer. Dermatoscopes offer a non-invasive way to capture skin lesions, but dermatoscopic image quality greatly affects diagnosis.

Methods: We propose a deep learning–based method to enhance dermatoscopic image quality using wavelet detail coefficients. ASuper-Resolution Convolutional Neural Network (SRCNN) estimates high-resolution wavelet coefficients from low-resolution images. This approach enables efficient training with fewer samples and lower computational cost. Refinement of these coefficients leads to better image reconstruction, measured using Peak Signal-to-Noise Ratio (PSNR).

Results: Tests on 180 dermatoscopic images show our method achieves a PSNR of 48.99. Previous approaches reached a maximum PSNR of 44.02.

Conclusion: This result shows our framework can provide high-quality images, supporting more accurate melanoma diagnosis.

Keywords: Melanoma; Deep Learning; Wavelet Transform; Dermatoscopic Imaging; Image Resolution Enhancement

Introduction

Melanoma is one of the most common types of skin cancer. It ranks as the fifth and sixth most prevalent cancer in men and women, respectively. Both genetic predisposition and environmental factors contribute to the development of sporadic and familial melanoma. Early diagnosis plays a pivotal role. Detecting melanoma at its initial stages can substantially reduce the high mortality associated with this malignancy. Consequently, the ability to differentiate between benign and malignant skin tumors, as well as to accurately localize lesions, is of critical importance in clinical practice.

Over the past two decades, multiple medical imaging modalities have been introduced for disease prevention and early detection. However, some imaging techniques have side effects, complexity, and costs that limit their routine application to only strictly necessary cases [1]. Medical imaging continues to be the most information-rich source for diagnosis and clinical decision-making. At the same time, it remains one of the most challenging to interpret. In dermatology, dermatoscopes are widely used as non-invasive devices to visualize skin lesions. Despite their clinical utility, the diagnostic accuracy of dermatoscopes alone is often insufficient for reliable decision-making [2].

With the exponential growth of imaging and video data, advanced computational techniques have enabled automated extraction and analysis of clinically relevant information. This reduces reliance on manual interpretation. High-quality imaging is a key determinant in this process. Insufficient clarity in medical images can lead to misinterpretation. This may necessitate additional imaging procedures, increase costs, and, in some cases, result in life-threatening consequences for patients [3]. Achieving higher-resolution images typically requires repeated scanning or the use of advanced imaging equipment, both of which are resource-intensive and time-consuming.

Recent advances in artificial intelligence (AI) have opened new opportunities to address these challenges.

AI-based image processing techniques, particularly deep learning, show strong potential for improving low-resolution medical images. Clearer visualization of fine-grained tissue structures in dermatoscopic images can significantly increase the reliability of distinguishing benign from malignant lesions [4]. Deep learning-based medical image analysis has also helped develop smart diagnostic systems. These systems empower clinicians to make faster, more accurate, and evidence-based decisions [5]. Figure 1 shows dermatoscopic examples of melanoma and a typical benign lesion. This highlights the importance of high-quality imaging for accurate clinical assessment.

Figure 1. Dermatoscopic image overview

Deep learning, including Deep Convolutional Neural Networks (DCNNs), is widely used in computer vision tasks such as image enhancement, denoising, and deblurring. In medical imaging, these techniques improve image quality, which is vital for accurate diagnosis.

The time needed to acquire images affects their quality. Longer acquisition times generally improve quality but are not always practical in clinical settings. For example, some pulmonary patients cannot hold their breath long enough for high-resolution CT scans, limiting image quality [6].

Super-resolution (SR) techniques reconstruct high-resolution (HR) images from low-resolution (LR) inputs. SR methods include single-image super-resolution (SISR), which uses one image, and multi-image super-resolution (MISR),which combines multiple images [7]. Figure 2 shows a typical SISR framework, a foundation for many deep learning–based enhancement methods.

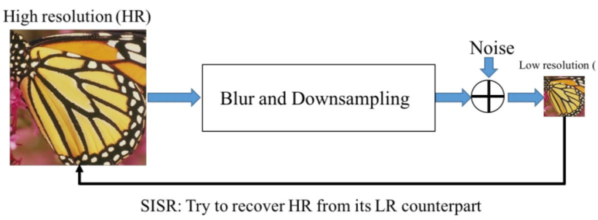

Figure 2. The architecture of the method proposed in [6]

High-resolution single-image reconstruction is a fundamental challenge in computer vision [7]. In recent years, deep learning especially convolutional neural networks (CNNs), has achieved state-of-the-art results. Application include face recognition, medical imaging, surveillance, and natural image processing [8]. In this study, we introduce an external sample–based single-image super-resolution (SISR) framework. The key idea is to estimate the inverse wavelet detail coefficients of thehigh-resolution (HR) image using a CNN trained on low-resolution (LR) inputs. This wavelet-driven strategy offers an efficient, cost-effective alternative to hardware upgrades in digital camera zoom, medical imaging, and satellite imaging. As is common in the field, LR images are generated from HR images using bicubic interpolation.

SISR methods are usually divided into interpolation-based, reconstruction-based, learning-based [9], and external sample–based [10] approaches. Learning-based methods reconstruct HR images from LR inputs using statistical or data-driven models. If the training data matches the best domain well, the approach is called external sample-based super – resolution [11]. This methods key benefit is rapid inference speed. Fast processing allows use on devices with limited computing power, such as smartphones and portable medical systems.

The novelty of our approach is integrating inverse wavelet coefficients in to the SISR pipeline. This helps the network better capture and reconstruct fine-grained image structures. The rest of this article proceeds as follows. Section 2 reviews work in super-resolution and medical image enhancement. Section 3 describes the proposed wavelet-based SISR method. Section 4 presents experimental results and performance evaluation. Section 5 concludes and discusses future research directions.

Previous Researches

With the rapid advancement of deep learning, numerous approaches have been developed to improve single-image super-resolution (SISR). Dong et al. [12] pioneered the use of deep convolutional neural networks for this task by introducing SRCNN, which demonstrated significant improvements over traditional interpolation-based methods. Building upon this work, Kim et al. [13] proposed the VDSR model, a deeper network with 20 convolutional layers that achieved superior performance while maintaining a relatively straightforward training process [14, 15].

Following these advancements, increasingly sophisticated architectures emerged. For instance, fully recursive networks like the DRCN incorporated convolutional and supervision layers to control model parameters and enhance overall performance. Notably, the DRCN was designed based on the residual learning framework, a concept initially introduced by He et al. [16], which effectively mitigates the vanishing gradient problem in deep architectures.

Given this progression, and since the method proposed in this study falls under the category of external sample–based SISR while integrating the wavelet transform, our review primarily focuses on approaches within these two domains. This perspective highlights the relevance of wavelet-based representations and sample-driven learning strategies in advancing the field of super-resolution.

Sample-Based SISR Methods

One of the earliest sample-based SISR approaches was proposed by Freeman et al. [17]. In their work, high-resolution (HR) patches were mapped to their corresponding low-resolution (LR) counterparts using piecewise rules. This line of research advanced with Glasner et al. [18] and Zontak and Irani [19]. They incorporated random Markov models to improve patch mapping consistency and accuracy. Timofte et al. [20] later introduced anchored neighborhood regression (ANR), which efficiently mapped local structural information from LR to HR images [21].

Other researchers addressed the computational challenges of sample-based methods. For example, Yang et al. and Zeyde et al. [22] proposed sparse coding–based approaches. These methods reduced the high memory requirements and computational demands of earlier frameworks. Similarly, Wang et al. [23] and Peleg and Elad [24] introduced nonlinear mapping techniques using sparse basis vectors. These techniques transformed LR patches into their HR counterparts. Nonlinear strategies showed superior reconstruction accuracy compared to linear models [25, 26].

More recently, Dong et al. proposed a CNN-based approach. This method learns the mapping of non-scalable LR image patches, which are interpolated into HR patches. This work marked a significant step toward combining the strengths of external sample-based methods with deep learning. It laid the foundation for modern SISR techniques [26, 27].

SISR Methods based on Wavelet Domain

Wavelet-based methods decompose an image into multiple frequency sub-bands. Including low-pass and high-pass components. This process captures both coarse and fine information. Multi-scale decomposition uses the sparse properties of natural images, providing efficient image representation and reconstruction.

Wavelet transforms have been widely studied for various applications. These include image compression, denoising, enhancement, and edge detection. Notable contributions include the works of Crouse et al. [28], Romberg et al. [29, 30], and Di Sciascio et al. [31]. They demonstrated the effectiveness of wavelet-based representations across multiple imaging tasks.

In super-resolution, wavelet-based methods try to reconstruct HR images by leveraging the relationship between LR approximation bands and HR detail bands. These methods predict or refine the detail coefficients using learning-based models. This enhances delicate structures that are otherwise lost in direct interpolation. This study specifically focuses on integrating wavelet-domain detail coefficients with CNN-based architectures. The goal is to improve dermatoscopic image reconstruction.

Methods

Deep learning is a subset of machine learning algorithms that use data-driven neural networks with multiple hidden layers. Unlike traditional machine learning, which relies on manual feature engineering, deep learning networks can automatically extract features and patterns from training data. This reduces the need for human intervention in feature selection. As a result, the learned representations are data-driven, robust, and task-specific.

In computer vision, one of the first deep learning architectures for super-resolution is the Super-Resolution Convolutional Neural Network (SRCNN).SRCNN creates a direct mapping between low-resolution (LR) and high-resolution (HR) images by learning end-to-end transformations through convolutional layers. The network uses hierarchical feature representations to reconstruct fine-grained image structures. These details are often lost in conventional methods.

Recent studies have shown that SRCNN outperforms classical interpolation methods, such as bicubic or bilinear interpolation, in both image quality and computational efficiency [32]. Its clinical relevance of has been highlighted in several medical imaging applications, These include radiography, chest computed tomography (CT) scans [4], and breast mammography [33]. In each case, SRCNN-based enhancement provided clearer anatomical structures. This enabled improved diagnostic interpretation.

To illustrate its structure, Figure 3 presents an overview of the SRCNN architecture, which serves as the foundation for the proposed wavelet-based enhancement strategy described in this study.

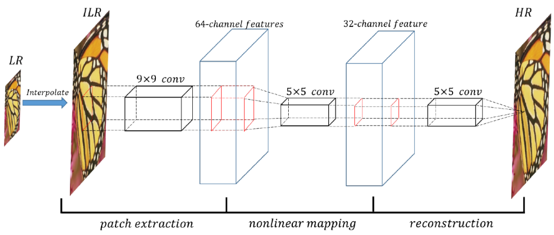

Figure 3. Architecture of the SRCNN model

The wavelet transform provides a spatial–frequency decomposition of an image by applying filters to extract information across multiple scales. Of its variants, the discrete wavelet transform (DWT) is particularly efficient. Its unique multi-resolution properties make it highly suitable for image processing tasks. This capability allows a signal to be decomposed into both coarse structures and fine details. The human visual system exhibits varying sensitivities across frequency bands. Wavelet decomposition effectively models this, supporting perceptually relevant image representations [3, 34].

When a two-dimensional image is subjected to DWT, it is decomposed into four sub-bands. One is an approximation image (low-frequency component). The other three are detail images that capture horizontal, vertical, and diagonal high-frequency information.

These detail sub-bands are critical for reconstructing delicate image structures such as edges and textures. Over time, researchers have developed advanced formulations of classical wavelet transforms. These aim to enhance image analysis and processing capabilities further.

In the context of super-resolution, Kumar et al. [11] proposed estimating the wavelet detail coefficients of a high-resolution (HR) image using its low-resolution (LR) counterpart. This estimation was carried out through the SRCNN framework, demonstrating that incorporating wavelet coefficients allows the network to be trained with fewer samples and reduced computational time, without compromising reconstruction accuracy. Unlike earlier approaches—such as the method by Dong et al. [26], which directly predicts HR pixels from LR inputs—wavelet-based methods emphasize estimating sparse detail coefficients. This distinction leads to higher reconstruction accuracy and improved test-time performance, since the network focuses on reconstructing essential structural details rather than dense pixel intensities.

In this framework, the convolutional neural network is tasked with estimating the detail coefficients from the approximation sub-band of the LR image. This enables the model to recover high-frequency structures more effectively, distinguishing it from pixel-level estimation approaches. A schematic of CNNWSR, the wavelet-based CNN super-resolution method presented in [10], is illustrated in Figure 4.

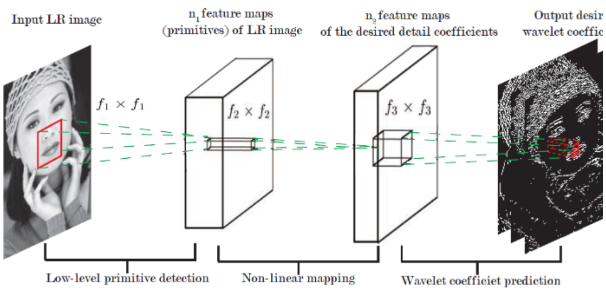

Figure 4. Architecture of the CNNWSR model

As shown in Figure 4, the first layer of the network extracts the LR image from the input. The second layer provides the low-level image to the wavelet map. Finally, by combining in a spatial neighborhood, wavelet coefficients are generated for the three accurate sub-bands. The proposed method in this paper is similar to the one presented in reference [10] for an SISR method. However, in this method, the wavelet inverse coefficients of a high-resolution image are computed based on those of a low-resolution image. For this purpose, the neural network convolution is used as a learning machine.

Criterion for Image Quality Assessment

Image quality changes are evaluated using two main methods: human assessment through visual inspection, and quantitative methods. Quantitative methods are categorized by whether or not they use a reference image.

PSNR is a common quantitative method that measures image quality using a reference image. Higher PSNR values indicate better reconstruction.

MSE is also widely used for quantitative image evaluation and is important in optimization processes.

$$PSNR = 10 * \log_{10} \frac{MAX^2}{MSE} \quad (1)$$

$$MSE = \frac{1}{mn} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i.j) - K(i.j)]^2 \quad (2)$$

MAX refers to the maximum pixel value in the image. Indices i and j represent the image s rows and columns. I is the original high- resolution image, and K is the reconstructed image. To compare methods, first apply the proposed approach to the same reference data [10], then evaluate it on melanoma dermatoscopic images.

Results

In this paper, image resolution is improved first using the Bicubic interpolation method, and then the basic SRCNN method is used to make the image quality even better.

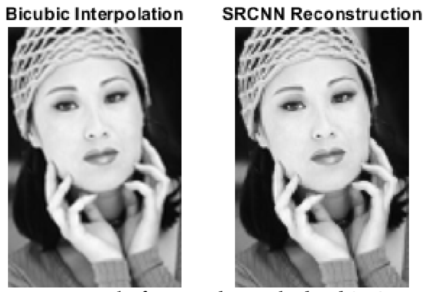

Figure 5. Results from Bicubic method and SRCNN

After calculating the PSNR criterion according to Table 2 for the two methods, the SRCNN method is outperforms Bicubic method by 0.197231 dB in PSNR, with a value of 37.887617 dB compared to the Bicubic method's PSNR of 37.690386 dB.

Furthermore, similar to the CNNWSR method [10], low-resolution images improve image quality compared to SRCNN, which is the most advanced method to date, by using the wavelet detail coefficient estimation of a high-resolution image.

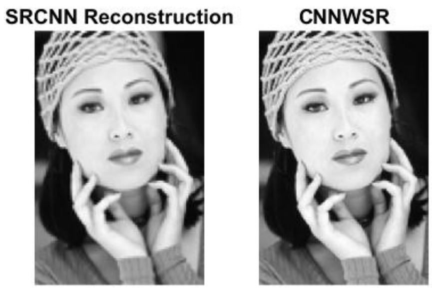

Figure 6. Results from the SRCNN and CNNWSR method

After calculating the PSNR criterion according to Table 2 in the CNNWSR method, with a PSNR of 38.219048 dB, this method is shown to be better than the previous two methods. One of the paper's innovations that, in the CNNWSR method, the wavelet transform is extended to three levels and then evaluated for its effects and results.

Figure 7. Results of the wavelet transform at three levels

Table 1 shows the best network results and the highest PSNR for estimating the first level of wavelet coefficients.

Table 1. PSNR Criterion Comparison for Wavelet Transform at Three Levels

METHOD	PSNR
1-level wavelet CNNWSR	38.219048 dB
2-level wavelet	33.875647 dB
3-level wavelet	30.198194 dB

Another contribution of this paper is estimating detailed coefficients for an inverse wavelet transform of a high-resolution image, thereby improving image quality from a low-resolution image. Figures 8 and 9 Comparison of the proposed method with CNNWSR.

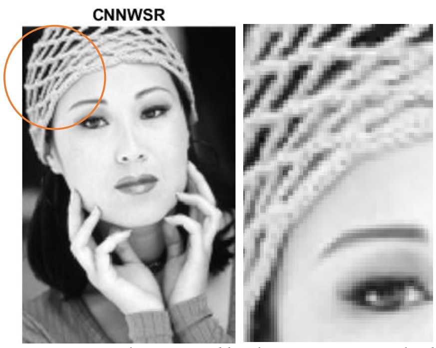

Figure 8. Result generated by the CNNWSR method

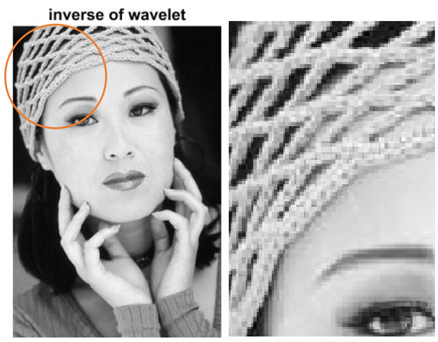

Figure 9. Results obtained using the proposed method

Table 2 shows the top results based on the PSNR criterion for the proposed method. It is also noted that the texture and edges produced by this method display greater reparability and resolution.

Table 2. Comparison of PSNR Criterion across Existing Methods

Methods	PSNR
Bicubic	37.690386 dB
SRCNN	37.887617 dB
CNNWSR	38.219048 dB
Proposed method	48.704783 dB

Table 2 evaluates the PSNR criterion in the proposed methods, indicating that the best results based on this criterion are achieved with the proposed method. Below, the above architectures are applied to melanoma datasets.

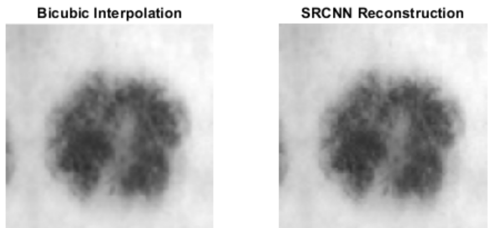

Figure 10. Comparison of results from the Bicubic method and SRCNN on melanoma dermatoscopic images

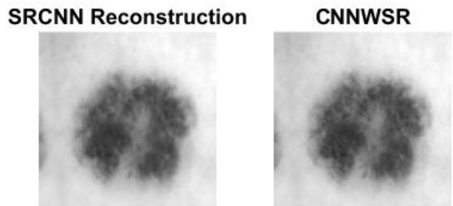

Figure 11. Comparison of results from the SRCNN and CNNWSR methods on melanoma dermatoscopic images

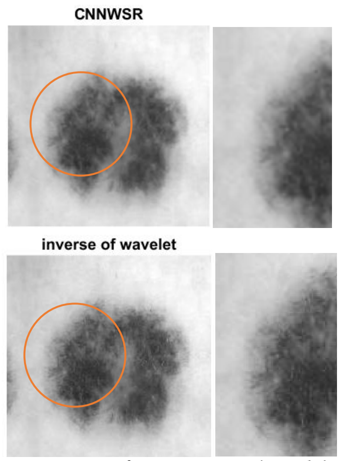

Figure 12. Comparison of CNNWSR results and the proposed method on melanoma dermatoscopic images

After calculating the PSNR criterion according to Table 2 for the two methods mentioned above, the superiority of SRCNN is confirmed by a PSNR of 43.604867 dB, which exceeds that of the Bicubic method with a PSNR of 43.511114 dB. Following a similar approach to CNNWSR [10], image quality improves over SRCNN by estimating wavelet detail coefficients of a high-resolution image from a low-resolution one.

After calculating the PSNR criterion based on Table 3 in the CNNWSR method, with a PSNR of 44.025949 dB, this method outperforms the previous two methods.

According to Table 3, melanoma dermatoscopic images achieve the best results based on the PSNR criterion with the proposed method. Additionally, the texture and edges of the proposed method exhibit higher separability and resolution.

Table 3. PSNR Criterion Comparison for Methods on Melanoma Data

Methods	PSNR
Bicubic	43.511114 dB
SRCNN	43.604867 dB
CNNWSR	44.025949 dB
Proposed method	48.998495 dB

According to Table 3, the proposed method for skin melanoma dermatoscopic images produces a higher PSNR output than previous methods for resolution enhancement.

Discussion

In this paper, we examined several approaches for image resolution enhancement, including Bicubic interpolation, SRCNN, and CNNWSR. Building on these methods, we introduced an external sample–based SISR framework that estimates the inverse wavelet coefficients of a high-resolution (HR) image from its low-resolution (LR) version. Using the Peak Signal-to-Noise Ratio (PSNR) to evaluate performance, we showed that the proposed method reconstructs HR images with notably higher fidelity compared to traditional approaches. These results confirm the effectiveness of combining wavelet-domain representations with CNN-based super-resolution models, especially in dermatoscopic image enhancement [34-37].

To further enhance performance, future research could investigate advanced wavelet families and other multi-resolution transforms. For instance, multidirectional wavelets might improve edge preservation, while the redundant discrete wavelet transform (RDWT) and the Contourlet transform provide better directional sensitivity and texture representation. Additionally, integrating these transformations with modern deep architectures such as generative adversarial networks (GANs) or transformer-based models could lead to even greater improvements in both reconstruction quality and clinical relevance.This study emphasize the potential of wavelet-integrated deep learning frameworks as effective and affordable tools for improving medical imaging. Future research will aim to expand the proposed approach to larger dermatoscopic datasets and other medical imaging types, thereby enabling more precise diagnosis and decision-making in clinical practice.

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Practical Implications

The proposed wavelet-integrated deep learning framework has clear practical value in everyday clinical workflows. By enhancing the resolution and clarity of dermatoscopic images without requiring more advanced hardware or repeated imaging, this method enables dermatologists to visualize lesion borders, pigment networks, and subtle structures with greater accuracy. In routine practice, higher-quality images can support earlier melanoma detection, reduce unnecessary biopsies, and minimize diagnostic uncertainty—especially in busy clinics or remote settings where access to high-end imaging devices is limited. Moreover, the approach's low computational cost and compatibility with portable medical systems make it suitable for teledermatology applications, mobile health platforms, and point-of-care diagnostics, ultimately improving patient outcomes through faster and more reliable image-based assessments.

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Author’s Contributions

This study was conducted through the collaborative efforts of all authors. Dr. Mohammad Tashnehlab served as the principal supervisor, providing the overall conceptual guidance, methodological direction, and critical revision of the manuscript. Dr. Mansoor Fateh, as the co-supervisor, contributed to refining the analytical framework, offering technical consultation on wavelet-based image processing, and reviewing the experimental design and results. Ms. Haleh Fateh, the graduate researcher, was responsible for implementing the proposed model, conducting data preprocessing and analysis, executing the experiments under the supervision of both advisors, and preparing the initial draft of the manuscript.

Ethical Considerations

This study was conducted in accordance with institutional guidelines and internationally recognized ethical standards for research involving human subjects. All dermatoscopic images analyzed in this work were derived from publicly accessible datasets and contained no information that could be used to identify individuals. Because the research involved no direct interaction with human participants, the requirement for informed consent did not apply. The overall study protocol was reviewed and approved by the relevant institutional ethics committees to ensure adherence to ethical and scientific integrity.

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