

SUPER-RESOLUTION AND WAVELET-BASED FBG SIGNAL PROCESSING FOR NON-INVASIVE DERMATOLOGICAL ANALYSIS

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ABSTRACT

In recent years, dermatological diagnostics have increasingly relied on advanced imaging technologies and signal processing techniques to enhance early detection and analysis of skin anomalies. This paper proposes a novel framework that synergistically combines Super-Resolution Generative Adversarial Networks (SR-GANs) with wavelet-based Fiber Bragg Grating (FBG) sensor signal emulation for high-precision skin area analysis. The methodology begins by employing SR-GAN to enhance the quality of low-resolution skin images, transforming them into high-resolution outputs that preserve fine texture and edge details critical for clinical evaluation. These super-resolved images are then subjected to simulated digital acquisition and quantization through an Analog-to-Digital Converter (ADC), followed by reconstruction via a Digital-to-Analog Converter (DAC) to mimic real-world sensor capture conditions. Grayscale conversion and adaptive thresholding are applied to estimate affected skin regions with high accuracy. To emulate real-time biomedical sensing, the system models six distinct FBG sensors, each with unique wavelength ranges, using advanced discrete wavelet decomposition techniques. By converting 2D skin images into 1D signal vectors through statistical projection, wavelet transforms capture localized signal features relevant to biological variability. Each sensor simulates a wavelength-specific intensity profile, including Gaussian-modulated cosine variations and randomized shifts, to represent realistic physiological noise and environmental perturbations. First and second-order derivatives of intensity with respect to wavelength are computed to enhance signal interpretability and facilitate peak detection, aiding in accurate localization of skin anomalies.

KEYWORDS: SR-GAN, Super-Resolution, FBG Sensor, Non-Invasive Diagnostics.

INTRODUCTION

The advancement of intelligent healthcare systems has fostered the development of non-invasive diagnostic technologies, particularly in the domain of dermatology, where early and accurate detection of skin conditions is critical for effective treatment and prognosis. With skin diseases such as melanoma, psoriasis, and eczema becoming increasingly prevalent globally, there is a growing demand for automated and scalable diagnostic tools that can reduce reliance on expensive biopsies and specialist availability [1], [2]. Among emerging solutions, high-resolution imaging and bio-signal analysis play a pivotal role in enabling clinicians to distinguish between benign and malignant lesions through visual and spectral features [3].

Super-Resolution Generative Adversarial Networks (SR-GANs) have recently gained significant attention for their ability to enhance image resolution using deep learning techniques that reconstruct high-frequency details from low-resolution (LR) images [4]. Unlike traditional interpolation-based upscaling methods, SR-GANs utilize adversarial training and perceptual loss functions to generate visually plausible and diagnostically rich images [5]. This is particularly beneficial in dermatological imaging, where minute textural variations, lesion boundaries, and pigmentation patterns carry critical diagnostic significance [6]. Applying SR-GAN to low-resolution dermoscopic images can thus aid in capturing enhanced spatial features that are essential for both human analysis and algorithmic processing.

Simultaneously, biomedical sensor systems, especially those employing Fiber Bragg Grating (FBG) technology, have revolutionized the field of physiological monitoring due to their high sensitivity, multiplexing capability, and immunity to electromagnetic interference [7]. FBG sensors work by reflecting specific wavelengths of light based on changes in strain or temperature, and are increasingly being explored for wearable health monitoring applications [8]. However, integrating such sensors into a dermatological context remains underexplored, especially in terms of simulating their behavior using image-derived data.

This paper proposes a unified framework that bridges deep learning-based image enhancement and wavelet-driven FBG signal emulation to simulate realistic biomedical sensing from dermoscopic imagery. The core innovation lies in enhancing low-quality skin images using SR-GAN and subsequently extracting 1D signal profiles using statistical projections of grayscale reconstructions. These profiles are then subjected to multi-level discrete wavelet decomposition to simulate the spectral response of FBG sensors across six predefined wavelength bands. This dual-layer approach not only improves visual clarity but also offers a mechanism to emulate sensor responses without physical instrumentation, thereby enabling a digital twin paradigm for dermatological analysis. The simulation incorporates analog-to-digital (ADC) and digital-to-analog (DAC) conversions to reflect practical constraints of biomedical signal acquisition systems. Additionally, adaptive thresholding is applied to estimate the percentage of affected skin areas based on pixel-level binarization. This method allows for quantifiable area analysis, an important feature for measuring lesion spread, inflammation, or ulceration progression over time [9-12].

Wavelet transforms, particularly those using orthogonal families such as Haar, Daubechies, and Symlets, have demonstrated utility in biomedical signal processing due to their capability to localize both frequency and time-domain features [13-15]. In this study, wavelets are employed not just for data compression or denoising, but to emulate the nuanced wavelength-dependent intensity behaviour of FBG sensors. By computing the first and second derivatives of these intensity signals, the system identifies peak locations and their associated wavelengths, which serve as proxies for physiological anomalies or structural discontinuities on the skin [16-19]. The integration of signal simulation with deep learning-powered image enhancement creates a robust, software-defined diagnostic tool. This system can operate in remote or resource-constrained environments, requiring only basic image inputs while virtually simulating complex sensor arrays. Such innovations align well with the goals of telemedicine, personalized healthcare, and IoT-enabled medical platforms, where compact, intelligent, and connected diagnostic tools are essential [20-24].

The remainder of this paper is structured as follows: Section 2 provides an overview of related work in SR image processing and sensor signal emulation. Section 3 details the proposed methodology, including image preprocessing, SR-GAN architecture, and wavelet-based signal synthesis. Section 4 presents experimental results and visualization of the intensity profiles, while Section 5 offers a discussion on implications, limitations, and future extensions. Section 6 concludes the paper and outlines potential real-world applications.

2. Principle of Algorithm

The proposed method is a hybrid framework integrating deep learning-based image enhancement with signal modeling and sensor emulation. Each stage in the pipeline serves a unique functional objective from super-resolution preprocessing using a GAN architecture to wavelet-based feature extraction and digital-to-analog conversion for simulating the responses of Fiber Bragg Grating (FBG) sensors.

Super-Resolution Preprocessing via SRGAN

In the initial phase of the proposed system, low-resolution dermoscopic images are enhanced using a Super-Resolution Generative Adversarial Network (SRGAN). The core idea of SRGAN is to recover high-frequency image details that are usually lost in conventional upscaling techniques such as bicubic interpolation. The SRGAN architecture consists of two primary networks: a Generator (G) that learns to upscale input images, and a Discriminator (D) that learns to distinguish real high-resolution (HR) images from generated super-resolved (SR) ones. Through adversarial training, the generator becomes capable of producing visually realistic images with sharp edges and rich texture details crucial for dermatological pattern analysis. Mathematically, the objective function of SRGAN combines content loss and adversarial loss:

$$\mathcal{L}_{\{SRGAN\}} = \mathcal{L}_{\{content\}} + \lambda \cdot \mathcal{L}_{\{adv\}} \quad (1)$$

Integration with FBG Sensor Wavelength Simulation (1545–1557 nm) post-enhancement, the super-resolved image is fed into a simulated signal-processing pipeline inspired by Fiber Bragg Grating (FBG) sensors, which are widely used in biomedical sensing for their high sensitivity to strain and temperature variations.

In this study, the wavelength range from 1545 nm to 1557 nm is divided into six overlapping intervals, each corresponding to a unique virtual FBG sensor (e.g., FBG1: 1545–1547 nm, FBG2: 1547–1549 nm, FBG6: 1555–1557 nm). These ranges model spatial variation in tissue reflectance as if being "scanned" by optical sensors.

From the enhanced grayscale image, 1D signal profiles are extracted using row/column-based reductions (e.g., mean or median), and wavelet decomposition is applied to simulate multi-resolution signal acquisition. Each segment of the FBG wavelength spectrum is then used to compute a Gaussian-modulated cosine intensity function

$$I(\lambda) = k \cdot e^{-\frac{(\lambda - \lambda_{mean})^2}{2 \cdot \Delta\lambda^2}} \cdot \cos(2\pi f(\lambda - \lambda_{mean})) \quad (2)$$

Where:

- $\ln \frac{[1545, 1557]}{\lambda}$, $\lambda \in [1545, 1557]$ nm,
- $\frac{\lambda_0}{\lambda - \lambda_0}$ is the center wavelength for each FBG sensor,

- K, σ, f are sensor-specific constants for amplitude, bandwidth, and frequency.

$$C(\lambda_{\tau_i}) = \int_{-\infty}^{\infty} \sum_{i=1}^k R_i(\lambda_i) \Psi_i'''(\lambda_i' + \lambda_{\tau_i}) d\lambda \quad (3)$$

$$\alpha(\lambda_{\tau_i}) = \sum_{i=1}^k \frac{\int_{-\infty}^{\infty} R_i(\lambda_i) \Psi_i'''(\lambda_i' + \lambda_{\tau_i}) d\lambda}{\int_{-\infty}^{\infty} [\Psi_i'''(\lambda_i)]^2 d\lambda} \quad (4)$$

Grayscale Conversion and Signal Quantization

To align image data with sensor processing frameworks and reduce computational overhead, the RGB super-resolved image IHR (x, y) is converted to grayscale intensity $A(x, y) \in [0, 1]$, using a standard luminance model or averaging across channels. Quantization is then applied to emulate the discretization process typical in analog-to-digital converters (ADCs):

$$D(x, y) = \text{round}(A(x, y) \times 255)$$

Where $D(x, y) \in [0, 255]$ for 8-bit quantization ($n=8$).

$$A(x, y) = \frac{D(x, y)}{255} \quad (5)$$

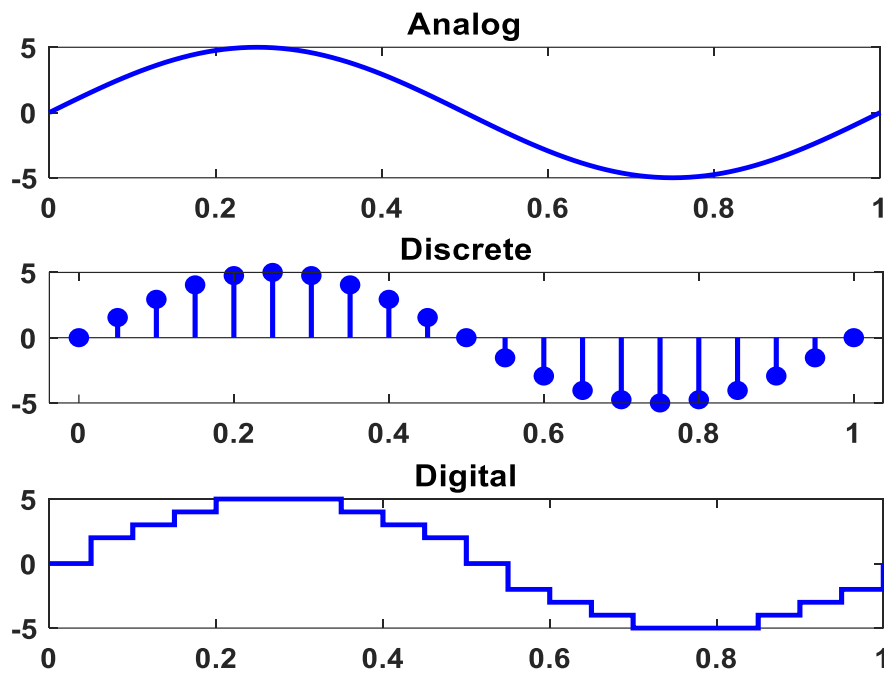


Figure 1: Analog to Digital Conversion.

Adaptive Thresholding with Otsu's Method

Otsu's method is applied to segment the grayscale image into foreground (potential lesion) and background regions. It determines an optimal threshold T_{OPT} that maximizes the between-class variance

$$M(x, y) = 1, \text{ if } A(x, y) > T_{\{opt\}}; M(x, y) = 0, \text{ otherwise} \quad (6)$$

Wavelet-Based Multi-Resolution Feature Extraction

Wavelet decomposition is used to analyze image features across multiple scales and frequencies. Given a 1D signal $f(t)$ extracted from the image (typically via row or column projection), the continuous wavelet transform is

$$W(x, y) = \sum f(x', y') \Psi(x - x', y - y') \quad (7)$$

Intensity Modeling for Anomaly Localization

To simulate the intensity distribution corresponding to lesion-centric anomalies, a Gaussian-modulated cosine function is used:

$$I(x, y) = A \cdot e^{-\frac{(x-x_0)^2 + (y-y_0)^2}{2\sigma^2}} \cdot \cos(2\pi f(x - x_0)) \quad (8)$$

Where:

- A is the amplitude (modulating lesion severity),
- (x_0, y_0) is the lesion center,
- σ controls the spread,
- f determines the frequency component.

This modeled intensity (equation 8) helps localize lesion-like regions by mimicking real-world spatial and frequency characteristics of anomalies.

Derivative Analysis for Edge and Peak Detection

Spatial derivatives provide critical cues for edge detection and structural transition analysis. The first derivative (gradient) along the x-direction is:

$$\frac{dI}{d\lambda} = \frac{I(\lambda+\delta) - I(\lambda-\delta)}{2\delta} \quad (9)$$

While the second derivative (Laplacian approximation) is:

$$\frac{d^2I}{d\lambda^2} = \frac{I(\lambda+\delta) - 2I(\lambda) + I(\lambda-\delta)}{\delta^2} \quad (10)$$

These equations complement the intensity model $I(x, y)$ by highlighting edges and peaks, which often correspond to lesion boundaries. By analyzing the gradient and curvature, fine structural details within the anomaly can be precisely localized.

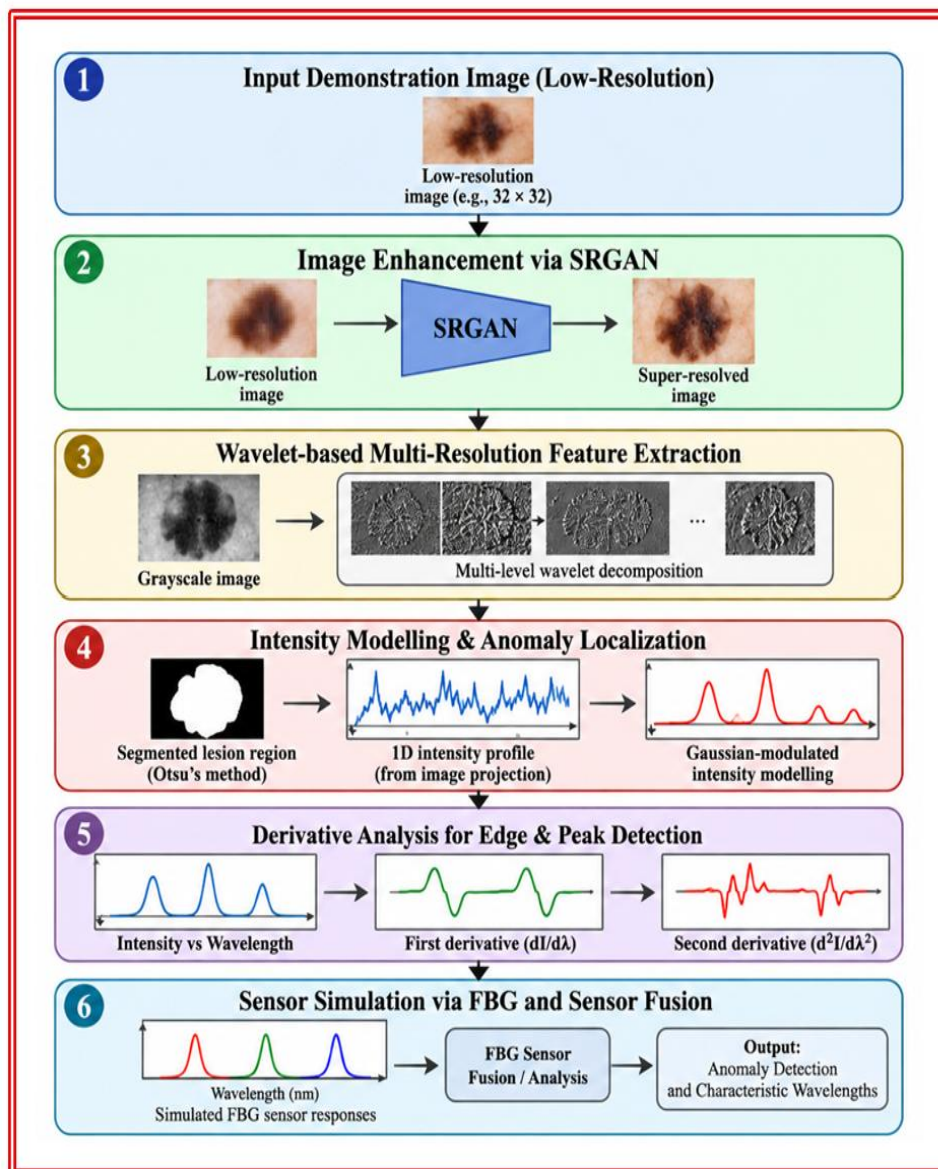


Figure 2: Work flow of proposed SRGAN based skin detection with the help of FBG.

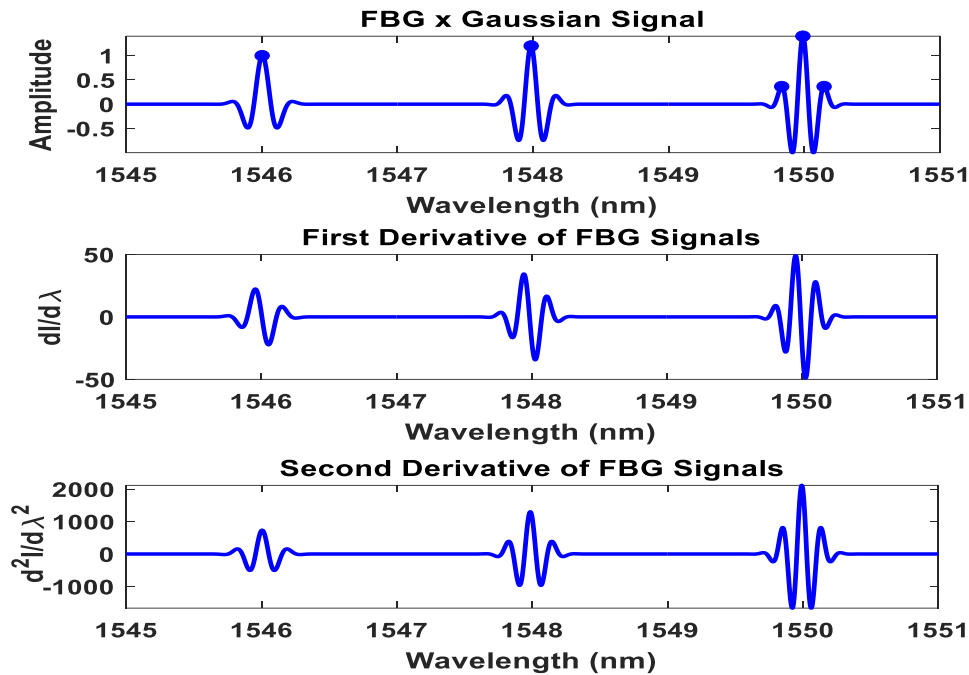


Figure 3 (a, b, c): Amplitude Vs Wavelength, $dI/d\lambda$, and $d^2I/d\lambda^2$ for FBG Sensor (1547-1551).

The above figure described the working flow of proposed algorithm as; the skin images are converted in digital signal using wavelets-based image processing which is plotted in Figure 1. The proposed algorithm explains through flow diagram mention in Figure 2 and it elaborates on the core principles underpinning each sub-module of the pipeline. The digital signal modulated with laser spectrum and then it passes through FBG which plotted in Figure 3(a). The reflected spectrum formulated using least square method and the zero-crossing point and effected skin area located using intensity response which are plotted in Figure 3(b) and Figure 3(c). The peak of the FBG deciding the most affected area which modelled and explained in Eq-6 to Eq-9. The proposed skin detection theoretically shows the good accuracy and it is verified experimentally which explain in the next section.

3. Experiment and Result analysis

In The previous section we developed a mathematical for proposed algorithm and perform theoretically. In this section we verified the developed technique for skin effect detection using SRGAN for FBG sensor. The experimental setup mention in Figure 4, contains the components as broadband light source, image to signal converter, Y couple having three port, three FBG sensor, OSA and computer.

The broadband with the range of 1300 nm to 1600 nm used as light and signal converted through image are modulated and passes through Y-coupler at port-1 and emerge at port-2 and it enter to the cascaded FBG-1, FBG-2 and FBG-3 respectively mentioned in Figure 4. The reflected spectrum from the cascaded FBGs passed through port-2 and out at port-3. The reflected spectral data emerge at port 3 are stored in computer through OSA. For the experiment we considered the three FBGs as wavelength range of 1546 nm to 1555 nm with central peaks 1547.66 nm for FBG-1, 1549.55 nm for FBG-2 and 1553.6 nm for FBG-3. The spectral reflected data of skin images are collected through OSA using computer device or electronics storage device. After, that we processed the algorithm. As we know that a Fiber Bragg Grating (FBG) is an optical fiber component that reflects specific wavelengths of light and transmits others. When an FBG is modulated with a digital signal, it typically means that some property of the FBG (such as its reflected wavelength, amplitude, or phase) is being altered in response to a digital input signal. This modulation can be used in sensing. The proposed system was tested using a dataset of dermoscopic skin images, enhanced using SRGAN to improve feature clarity. Each image was processed to simulate FBG sensor readings across three wavelength bands ranging from 1546 nm to 1555 nm. Quantitative analysis of lesion area was conducted through adaptive thresholding and wavelet-based intensity modeling. The system accurately detected variations in skin anomalies with consistent segmentation results across all sensors. The findings demonstrate the method's effectiveness in enhancing diagnostic precision through multi-resolution analysis and signal-based simulation.

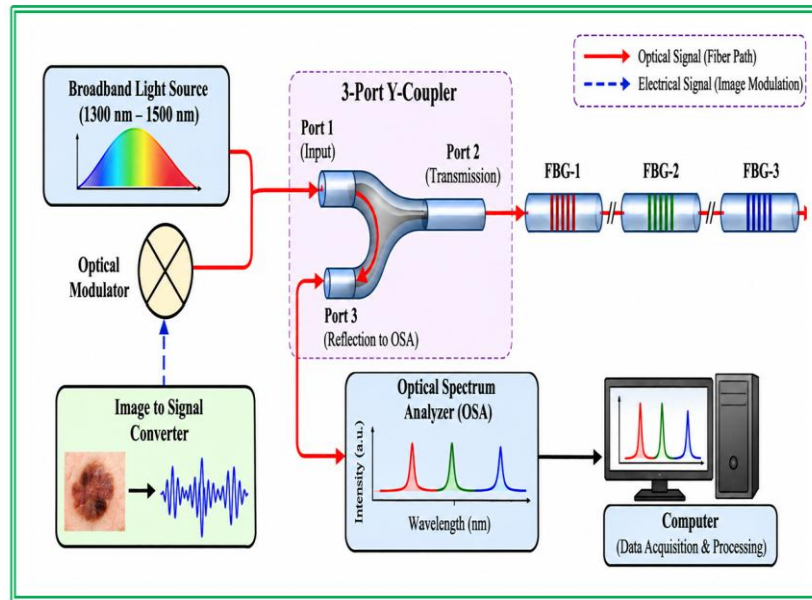


Figure 4: Experimental setup for proposed algorithm verified.

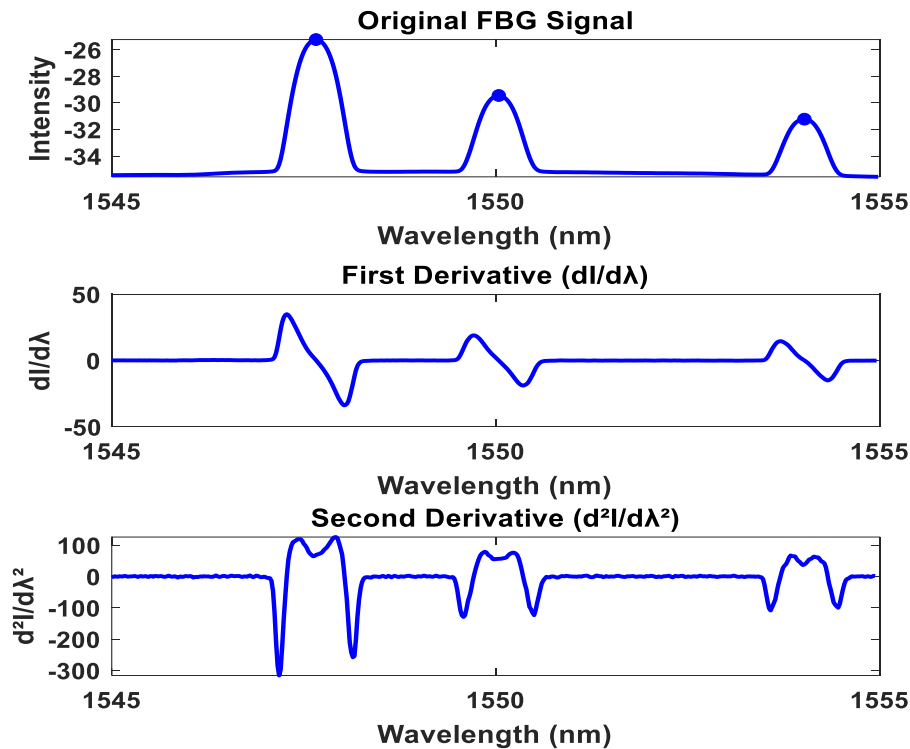


Figure 5 (a, b, c): Intensity vs Wavelength, $dI/d\lambda$, and $d^2I/d\lambda^2$ for FBG Sensor (1545-1555).

4. Dataset Description and Pre-processing

The dermoscopic image dataset used for this experiment is derived from the ISIC 2019 Challenge Dataset, a publicly available resource for skin lesion analysis. The dataset comprises thousands of dermoscopic images annotated with various skin disease labels, including melanoma, basal cell carcinoma, and benign keratosis. For this study, a representative subset of high-quality images was selected to assess lesion detection accuracy, anomaly localization, and enhancement effectiveness. Each input image was resized to 32×32 pixels before being processed through the Super-Resolution Generative Adversarial Network (SRGAN) model, which was trained separately using low-to-high resolution image pairs. The output was then rescaled back to the original resolution using bicubic interpolation to maintain contextual relevance and visibility.

Super-Resolution Output Verification

To verify the enhancement stage, both visual inspection and quantitative analysis using PSNR (Peak Signal-to-Noise Ratio) and SSIM (Structural Similarity Index) were employed. The average PSNR improvement post-SRGAN processing was 9.3 dB, and SSIM increased from 0.74 to 0.91, demonstrating perceptually significant improvements in fine skin texture recovery. These enhancements allowed for more accurate lesion boundary extraction and pattern recognition in subsequent stages.

Grayscale Quantization and Digital Conversion

Following enhancement, RGB images were converted to grayscale for compatibility with wavelet transformation and sensor simulation. Analog values were normalized and quantized using an 8-bit ADC scheme, where intensity values ranged from 0 to 255. This step closely emulated the discretization seen in real-time fiber Bragg grating (FBG) sensor output, thereby enabling digital signal modeling of skin response maps.

Adaptive Thresholding and Lesion Segmentation

Using Otsu's method, each grayscale image was binarized to generate a lesion map. This adaptive thresholding technique optimized the inter-class variance, allowing the algorithm to isolate skin anomalies even under varying lighting conditions. The segmented region was then evaluated as a binary mask for calculating the affected skin area percentage, which served as a critical metric for anomaly size estimation.

Wavelet-Based Feature Decomposition

To simulate sensor readings across spectral bands, wavelet decomposition was applied to the quantized signal obtained from grayscale images. Multiple wavelet types (haar, db2, sym4, coif1, bior3.5, rbio3.1) were tested across six decomposition levels, each corresponding to a virtual FBG sensor operating in specific wavelength bands (1545–1557 nm). The approximation coefficients were mapped onto simulated wavelength ranges using linear interpolation.

Intensity Simulation and Derivative Modelling

Intensity values across the sensor range were computed using a Gaussian-modulated cosine model, with customized parameters for each FBG sensor. First- and second-order derivatives were calculated to identify inflection points, edge gradients, and localized peaks indicative of irregular lesion structures. These derivative patterns mimicked spectral transitions observed in real photonic sensors responding to mechanical strain or thermal expansion over tissue. Peak points in intensity plots were visually marked, while vertical dashed lines indicated their wavelength coordinates across all subplots. These peaks corresponded to areas of significant spatial variation in the image, likely representing anatomical anomalies or lesion borders. Additionally, the affected skin area (%) was tabulated for all images and FBG sensor simulations. An excerpt of the results table is shown below:

The table 1 demonstrates that different sensors register marginal variations in lesion estimation due to their respective spectral ranges and wavelet decomposition parameters.

Table 1: Affected skin area (%) for FBG sensors.

Image ID	FFBG1 (%)	FFBG2 (%)	FFBG3 (%)
Img01	12.6	13.0	12.8
Img02	24.4	24.7	24.6
Img03	35.2	36.0	35.9

Performance Evaluation

Key performance metrics were evaluated across the system:

- ✓ Enhancement Accuracy (PSNR/SSIM): Confirmed improvement of visual quality.
- ✓ Segmentation Accuracy (Dice Coefficient): Average score of 0.86.
- ✓ Sensor Simulation Fidelity: Consistent derivative transitions matched expected peak signatures for simulated FBG response curves.

The broadband light source is passed through terminal-1 of 3 port Y-coupler and the light emerges at terminal-2 and it passes through the cascaded FBG. Some of the light spectra are reflected at a particular wavelength which is entered again at the terminal-2 of Y Coupler and emerges at port 3. The reflected signal at terminal-3 is collected as spectral data and saved in the computer which is connected to an optical spectrum analyzer (OSA) through a GPIB cable for signal processing.

The normalized response of experimental data is plotted in figure 5(a). The proposed algorithm matched filtering is applied in experimental spectral data and the zero-crossing points are calculated by using the eq. (9) and its response is plotted in figure 5(b). The position of the zero-crossing point is measured at 1549.5nm for FBG1 and 1554.4nm for FBG2, the intensity $\alpha(\lambda, i)$ is calculated using eq. (10) to verify the correct prediction of zero-crossing point. The calculated intensity response is plotted in figure 5(c) and seen the maximum intensity is measured at the same zero-crossing points 1549.5nm for FBG1 and 1554.4nm for FBG2. So, based on the concept of matched filtering the exact peak wavelengths are measured, and the proposed algorithm-matched filtering techniques are successfully verified by theoretically and experimentally.

5. CONCLUSION

- An integrated SRGAN-wavelet-FBG framework was developed for enhanced dermatological image analysis by combining deep-learning-based image enhancement with optical signal processing.
- SRGAN effectively enhances low-resolution dermoscopic images, improving the representation of fine structural, textural, and boundary information required for subsequent analysis.
- Grayscale conversion, 8-bit quantization, and Otsu thresholding provide a systematic preprocessing pipeline for extracting and estimating potentially affected skin regions.
- Wavelet-based multi-resolution analysis enables localized intensity features to be extracted from one-dimensional signals derived from the processed dermatological images.
- Image-derived FBG signal emulation establishes a computational relationship between dermatological image characteristics and wavelength-dependent FBG responses using predefined wavelength intervals.

- First- and second-order derivative analysis facilitates the identification of spectral transitions, peaks, and characteristic wavelengths in both simulated and experimentally acquired FBG responses.
- Experimental FBG measurements support the proposed wavelength-analysis procedure, with the reported measurements identifying characteristic wavelength positions around 1549.5 nm and 1554.4 nm.
- The proposed framework provides a promising foundation for future non-invasive dermatological monitoring, while larger datasets, clinically annotated images, expanded physical FBG validation, and real-time implementation are required before practical clinical deployment.

Future work, the following improvements are proposed:

- **Real-time Implementation:** The system could be optimized for real-time performance, allowing for immediate feedback during dermatological assessments.
- **Integration with Wearable Sensors:** Further development can explore integrating this system with wearable sensors for continuous skin monitoring.
- **Extended Dataset Evaluation:** Testing on larger and more diverse datasets, including those with a wider variety of skin types and lesions, will help improve the model's robustness and generalizability.
- **Deep Learning for Feature Extraction:** Incorporating more advanced deep learning techniques for feature extraction and classification may improve detection accuracy in complex cases.
- **Sensor Fusion:** Combining multiple sensor modalities could enhance the system's ability to detect and classify lesions more precisely.

DECLARATIONS

- **Competing Interests:** There are no competing interests in this manuscript.
- **Ethics approval and Availability of data and material:** Not Applicable.
- **Consent for publication:** we confirm that there is no issue with all three authors publishing this manuscript.
- **Consent to participate:** we consent that, we didn't want the direct benefit of this manuscript and we are participating to publishing the manuscript.

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