IFSCC 2025 full paper (1034)

AI-based Hair Damage Quantification and Visualization on Microscopic Hair Images

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1. Introduction

Hair health is a significant aspect of personal well-being, influencing appearance and self-esteem. Consequently, hair care has evolved beyond mere aesthetics, embracing scientific principles to understand, maintain, and improve hair health. Central to this scientific approach is the accurate assessment of hair damage, which can arise from various factors including chemical treatments (coloring, perming) [2], mechanical stress (brushing, heat styling), and environmental exposure (UV radiation, pollution) [3].

Despite its importance, the assessment of hair damage traditionally has relied on subjective evaluations like visual inspection or tactile assessment, which often lack objectivity and reproducibility [6]. This subjectivity poses significant challenges for reliably tracking changes in hair condition, comparing the efficacy of treatments, and establishing standardized benchmarks. Cao et al. [6] highlighted the need for objective methods, proposing multispectral imaging as one alternative, yet a widely adopted, robust quantitative standard remains elusive.

Various imaging modalities offer potential avenues for objective analysis, as illustrated in Figure 1. Scanning Electron Microscopy (SEM) [1, 4] provides high-resolution images for detailed visualization of the hair shaft's surface morphology, particularly the cuticle structure. making it ideal for identifying subtle damage changes like cuticle lifting, cracking, or erosion. Other techniques like analyzing hydroxyl radical [5] presence or employing 3D optical microscopy provide insights into hair structure and chemical changes. Standard 2D optical microscopy, while lower in resolution than SEM, offers accessibility advantages and can reveal damage through changes in overall hair shaft appearance, such as edge roughness.

Artificial Intelligence (AI) [24], particularly deep learning techniques like Convolutional Neural Networks (CNNs) [9, 10, 11], has revolutionized image analysis. These methods excel at automatically learning complex patterns and features from image data, well-suited for analyzing intricate details in microscopic hair images. Applying AI to cosmetic science offers the potential to automate and objectify analyses previously reliant on human interpretation.

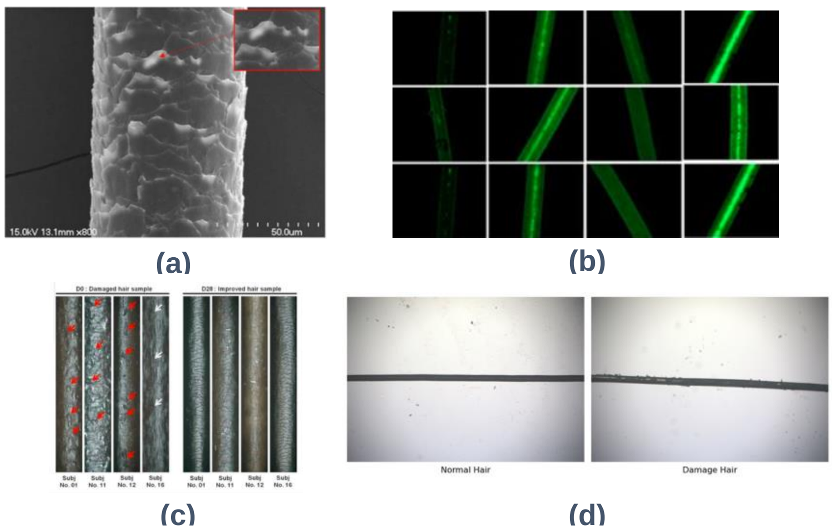

Figure 1. Example of various hair imaging modalities: (a) Scanning Electron Mycroscopy (SEM) image [1, 4]; (b) Hydroxyl radial assay [5]; (c) 3D optical microscopy; (d) 2D optical microscopy.

This study aimes to leverage AI to address the challenges in hair damage assessment using both SEM and 2D optical microscopy images. The core objectives are threefold:

1. Develop high-performance AI image classifiers capable of accurately distinguishing between damaged and normal hair based on both SEM and microscopic images.
2. Propose and validate methods for quantifying the degree of hair damage using the outputs of these trained classifiers, providing objective numerical scores.
3. Devise techniques for visualizing the specific regions identified as damaged, without requiring explicit pixel-level damage annotations (unsupervised visualization).

2. Materials and Methods

2.1. Image Acquisition and Dataset Preparation

SEM Image Dataset. A collection of Scanning Electron Microscope (SEM) [1, 4] images, illustrated in Figure 2, have been acquired from human and dog hair samples exhibiting a spectrum of damage levels due to UV light and bleaching agents. The dataset consists of 369 images in total, categorized based on visual assessment of cuticle integrity into 180 'Normal' and 189 'Damaged' samples. These high-resolution images provide clear visualization of the cuticle layer, crucial for detailed damage analysis.

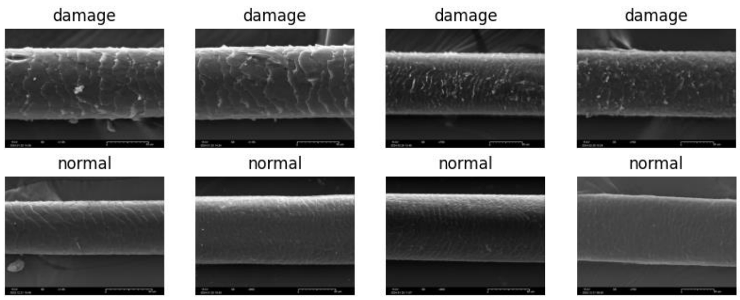

Figure 2. Examples of our SEM Image Dataset, with annotations indicating the presence and extent of hair surface damage (*e.g.*, cuticle disruption or structural irregularities).

2D Optical Microscopy Image Dataset. We have collected a separate dataset with 2D optical microscopy images under standardized conditions. This dataset includes 100 images, balanced between 50 'Normal' and 50 'Damaged'. Labels are assigned based on visual inspection, with damage often manifesting as irregularities and roughness along the hair shaft edges. Examples are illustrated in Figure 3.

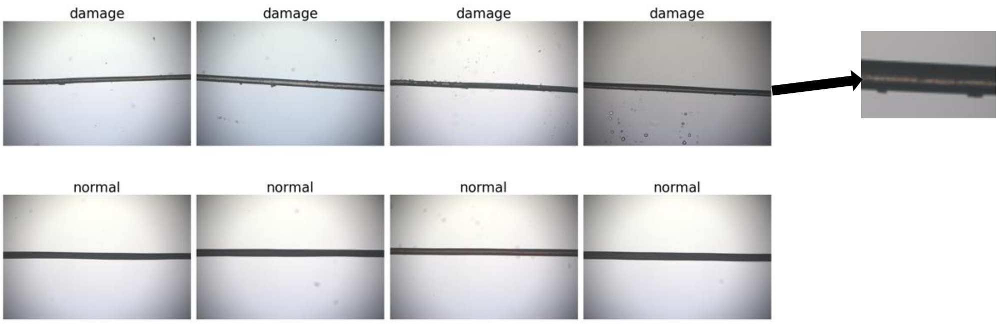

Figure 3. Examples of our 2D optical microscopy image dataset, labeled based on observable features, *e.g.*, surface irregularities and edge roughness along the hair shaft.

Dataset Splitting. We split both SEM and optical datasets into training, validation, and test sets with a 7:1:2 ratio. The training set is used for model optimization, the validation set for model selection, and the test set for final evaluation on unseen data.

2.2. Methodology for SEM Image Analysis

Preprocessing. We first identify the upper and lower boundaries of the hair shaft within the images using Sobel operator [7, 8], an edge detection algorithm sensitive to sharp intensity gradients. This step facilitates subsequent analysis on the hair structure itself. Recognizing the high resolution of SEM images and the localized nature of cuticle damage, we adopt a patch-based strategy. That is, each SEM image is randomly sampled to extract 100 smaller patches, each with dimensions of 224x224. This approach allows the model to learn from diverse regions across the hair surface while managing computational overhead and effectively utilizing the high-resolution detail. We then apply data augmentations with horizontal and vertical flips (with probability of 0.5, respectively) and random rotations (up to 10 degrees), exposing the model to variations in orientation and appearance, which is crucial for handling potential variations in image acquisition [13].

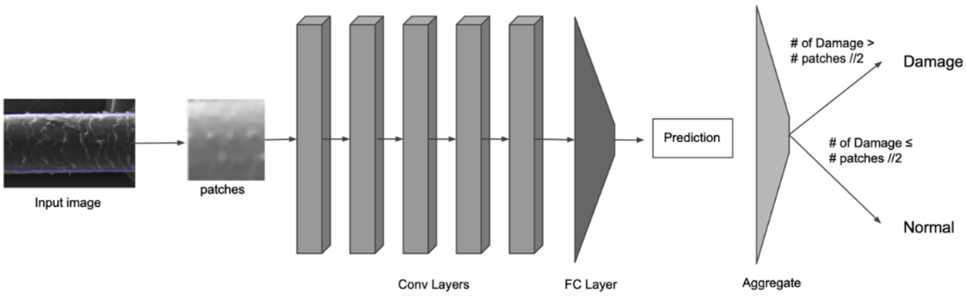

Figure 4. Model architecture of our proposed SEM-CNN for hair damage classification

Model Architecture (SEM-CNN). Figure 4 describes our custom Convolutional Neural Network (CNN) [11, 12, 13] architecture for classifying the image patches. CNNs are particularly well-suited for image analysis tasks as they effectively capture local spatial hierarchies of features, such as textures and patterns of cuticle damage, often with fewer parameters than alternatives like Vision Transformers [18, 19], which typically require larger datasets [16]. The network architecture consisted of 5 sequential blocks, each comprising a Convolutional Layer followed by Batch Normalization [12], which helps stabilize and accelerate training by normalizing the inputs to each layer, reducing internal covariate shift. A final fully connected layer is added for classification. We apply dropout [14] with $p = 0.2$ before the linear layer to mitigate overfitting. This CNN model is trained on image patches of 224x224, randomly sampled from the SEM images.

On an unseen SEM image, we extract 100 224x224 patches using the same random sampling strategy employed at training. Each patch is fed to the trained SEM-CNN model to obtain a prediction (Normal/Damaged). An image-level classification is determined by majority votes; that is, if 50 or more patches out of 100 are classified as 'Damaged', the entire image is classified as 'Damaged'; otherwise, as 'Normal'.

Damage Quantification. We report the total number of patches classified as 'Damaged' for a given image as Damage Score, providing a quantitative measure reflecting the spatial extent of the detected damage. A higher score indicates that a larger area of the hair surface is identified as damaged by the model. We localize the detected damage in two ways. First, we visually overlay semi-transparent red color on the original SEM image for the patches classified as 'Damaged' (*Patch Overlay*). This method provides a direct spatial map of the regions contributing to the 'Damaged'. To provide a smoother and potentially more intuitive visualization of damage distribution, we further propose to apply *Kernel Density Estimation (KDE)* [25] to the centroids of the damaged patches. Using kernels such as Gaussian or Cosine, KDE generates a heatmap where the intensity reflects the density of damaged patches. This approach smooths out the blockiness of the patch overlay, highlighting damage hotspots and allowing for the visual assessment of relative damage severity across different areas within a single image, independent of the overall damage score. Bandwidth selection for KDE can be guided by methods like Silverman's rule of thumb [26].

2.3. Methodology for Optical Microscopy Image Analysis

An initial attempt to apply the same patch-based methodology used for SEM images has yielded suboptimal results, achieving only 65% accuracy. Unlike SEM images, the internal texture within patches of optical microscopy images often lacks sufficient discriminative features to reliably distinguish between normal and damaged hair. Visual inspection indicats that damage in these images is more strongly associated with global characteristics, particularly the roughness and irregularity of the hair shaft edges, rather than localized texture patterns. This observation prompted a shift in strategy as follows.

Preprocessing. Based on the finding that global features are more informative, we use the entire optical microscopy image as input to the model, rather than extracting patches. Prior to model input, each image is normalized to ensure consistent value ranges. We apply the same data augmentation on the training images for robustness.

Model Architecture (Optical-CNN). As illustrated in Figure 5, we use ResNet-18 [15], a variant of CNN, for this data. ResNet [15] architectures incorporate "skip connections" that allow gradients to flow more easily during training, enabling the effective training of deeper networks compared to plain CNNs. We adapt the final layer for our binary (Normal/Damaged) classification task. Given the relatively small size of the optical hair dataset, we employ transfer learning [10, 27] to leverage knowledge from a larger and more diverse dataset, *e.g.*, ImageNet 1K dataset [16]. Starting from the pre-trained weights, capturing general visual features like edges, shapes, and textures, the entire model has been trained for hair damage classification on the optical microscopy dataset. This approach allows the model to adapt the learned general features to the specific characteristics of hair images, often leading to better performance and faster convergence than training from scratch [10]. At inference, a new, normalized whole optical image is fed into the trained Optical-CNN. The model outputs a value between 0 and 1 via a Sigmoid activation in the final layer, classifying the image as 'Damaged' if this output exceeded 0.5, and 'Normal' otherwise.

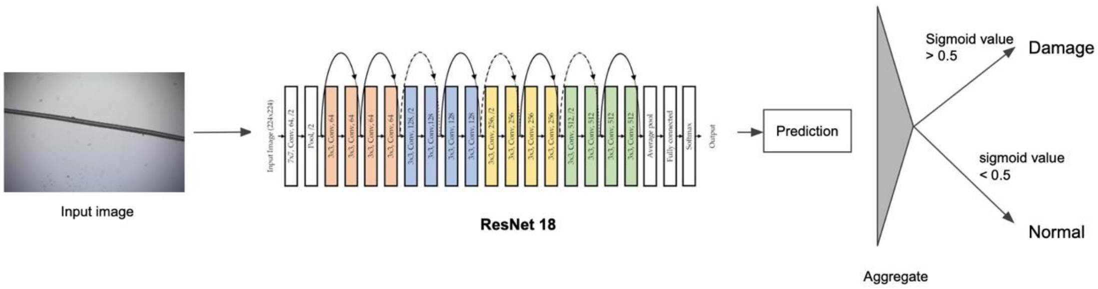

Figure 5. Optical-CNN for hair damage classification on 2D optical micropcopy images.

Damage Quantification. We directly take the sigmoid output (ranging from 0 to 1) as the quantitative Damage Score, representing the model's predicted probability or confidence that the input image belongs to the 'Damaged' class. A higher score indicates greater confidence in the damage prediction. This score provides a continuous measure of predicted damage likelihood, differing from the discrete spatial extent score derived from the SEM method.

Damage Visualization. To visualize the parts of the image mostly influencing the model's decision, we employ Gradient-weighted Class Activation Mapping (Grad-CAM) [17]. It produces a coarse localization heatmap by analyzing the gradient flow into the final convolutional layer (Layer 17 in our case) with respect to the predicted class score. It highlights regions in the input image that positively contributed to the classification decision. There are other CAM variants, such as HiResCAM [21], ScoreCAM [22], and GradCAM++ [23], but we observe that standard Grad-CAM provides satisfactory results in this study.

The resulting heatmap is overlaid onto the original image. Warmer colors (*e.g.*, red) indicate regions with higher confidance for the 'Damaged' classification, while cooler colors (*e.g.*, blue) with less damage or potentially contributing to a 'Normal' classification.

2.4. Implementation Details

Both SEM-CNN and Optical-CNN are trained with batch size of 32, Adam optimizer, Cross Entropy loss (suitable for multi-class or binary classification tasks), an initial learning rate of 0.001, and an exponential learning rate scheduler [28] (decaying the learning rate by a factor of 0.99 after each epoch). The model is trained for 50 epochs with an RTX4090 GPU.

3. Results

We present the performance evaluation of the developed models for SEM and optical microscopy images, including accuracy, damage scores, and visualized examples.

3.1. SEM-CNN Hair Damage Detection

Our SEM-CNN model demonstrates a strong performance in identifying hair damage. The patch-level accuracy, the ratio of correctly classifying individual 224x224 patches, reaches to 87.42%. When aggregating patch predictions to classify entire images using the majority vote, it achieves the image-level accuracy of 93.24%, as summarized in Table 1.

Table 1. Performance of SEM-CNN Hair Damage Detection Model.

SEM-CNN	Test Accuracy
Image	93.24 %
Patch	87.42 %

Quantitative Damage Scores (SEM). The damage score in Figure 6, defined as the number of patches classified as damaged (0-100), shows a strong correlation with the visually assessed severity of hair damage in the test set images. For instance, images depicting severe damage, such as third image in the top row appearing almost melted due to extreme treatment, consistently receives scores at or near 100, indicating that almost all patches are correctly identified as damaged. Conversely, healthy hair images typically receives low scores. All examples used for demonstrating the score's validity are drawn from the test set.

Damage Visualization (SEM). The patch overlay method directly highlights the specific 224x224 regions identified as damaged by coloring them (red) on the original SEM image, as seen in Figure 7. The KDE visualization in Figure 8 provides a smoother heatmap, effectively illustrating the density and distribution of damaged patches. Areas with a higher concentration of damaged patches appear with greater intensity (darker red), allowing for intuitive identification of damage hotspots and assessment of relative damage severity within different parts of the same hair fiber.

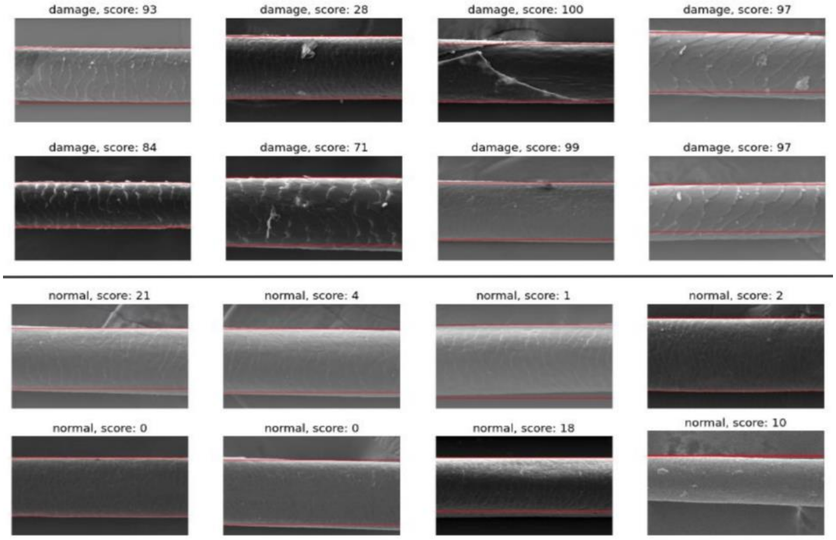

Figure 6. Quantitative damage scores from SEM-CNN. The damage scores show strong correlation with the severity of hair damage.

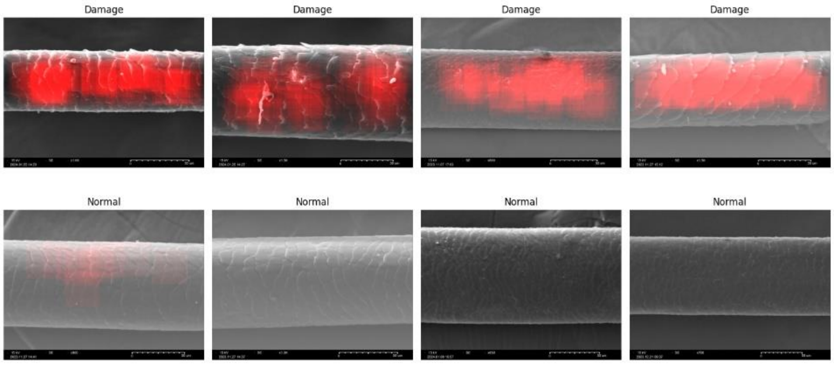

Figure 7. Patch overlay visualization of hair images with SEM-CNN model

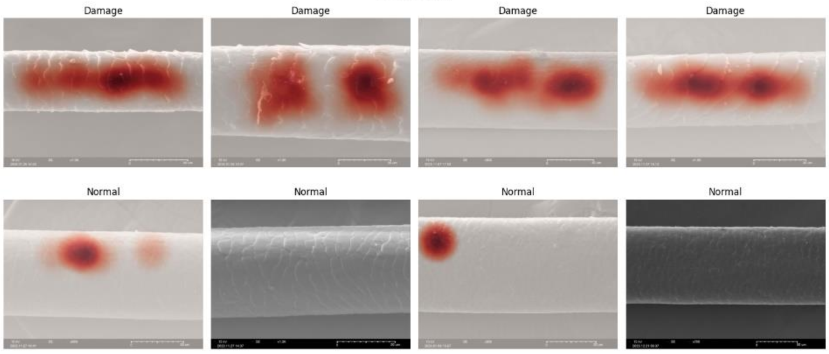

Figure 8. Kernel Density Estimation [25] visualization with SEM-CNN model.

3.2. Optical Microscopy-based Hair Damage Detection

The Optical-CNN model, trained on whole optical microscopy images using transfer learning [10], achieves exceptionally high accuracy, as reported in Table 2. Evaluation on the validation and test sets shows perfect classification performance. Both the validation accuracy and the final test accuracy reaches 100%. This indicates that the model, leveraging pre-trained features and fine-tuned on the optical hair dataset, is able to perfectly distinguish between the normal and damaged samples within the provided test set.

Table 2. Performance of Optical Microscopy-based Hair Damage Detection Model.

Optical-CNN	Test Accuracy
Validation set	100 %
Test set	100 %

Quantitative Damage Scores (Optical). The damage score, defined as the model's sigmoid output (0-1), reflects the model's high confidence in its classifications on the test samples. For damaged images, it consistently yields scores close to 1, while for normal images it produces scores close to 0. See Figure 9 for examples.

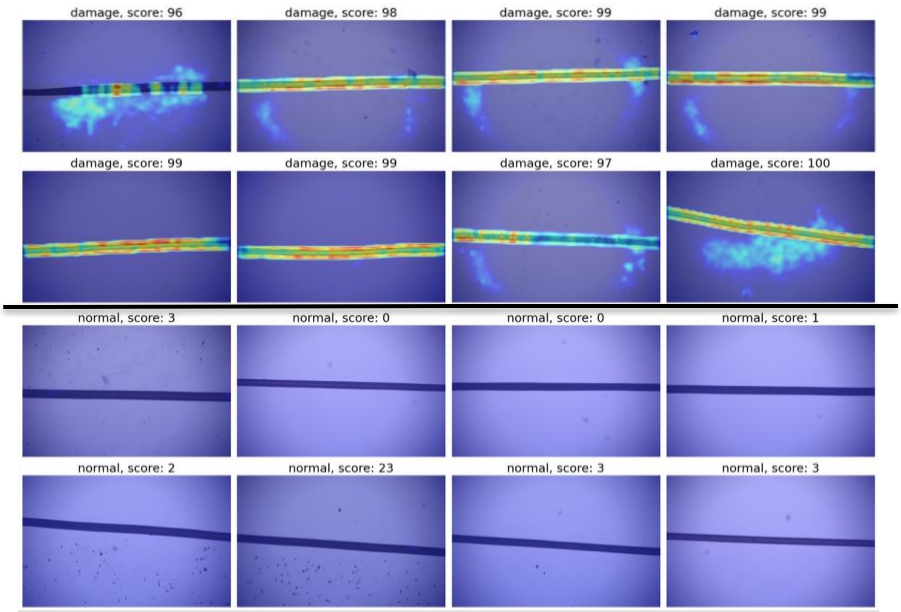

Figure 9. Quantitative damage scores and Grad-CAM [17] visualization of Optical-CNN.

Damage Visualization (Optical). For images classified as 'Damaged', the Grad-CAM heatmaps in Figure 9 typically show strong activation (warm colors) along the hair shaft, often emphasizing the edges or areas with visible irregularities. This aligns with the initial observation that edge roughness is a key indicator of damage in these images. For images classified as 'Normal', the Grad-CAM heatmaps, after applying the Sobel filter [7, 8] based background masking, show minimal or no significant activation on the hair shaft itself. This indicates that the model does not identify strong damage-related features, consistent with the visual appearance of smooth edges in healthy hair samples.

4. Discussion

This study successfully develops and validates two distinct AI-based systems for objectively quantifying and visualizing hair damage using SEM and optical microscopy images. The results demonstrate the capability of deep learning methods to overcome limitations of traditional subjective assessment approaches, achieving high classification accuracy tailored specifically to each imaging modality (93.24% for SEM, 100% for optical microscopy).

On SEM images, characterized surface texture details, a customized CNN architecture identifies fine-grained cuticle features indicative of damage[1,4]. he resulting quantitative damage score provides spatial metrics correlating well with visual assessments. Complementary visualization techniques, including patch overlays and KDE, enable clear localization of damaged regions.

In contrast, the initial patch approach is less effective on optical microscopy images, where discriminative features are more globally distributed, particularly along hair shaft edges. This limitation prompts a strategic shift toward whole-image analysis using a pre-trained ResNet-18 model [15], significantly improving performance via transfer learning from ImageNet-derived features [10,16]. Although perfect test set accuracy has been achieved, caution is advised due to potential dataset-specific limitations. Further validation on larger, diverse datasets would be essential to confirm real-world applicability. Grad-CAM [17] visualizations clarify the model's decision-making by highlighting key regions, especially hair edges.

Also, this work significantly advances automated feature extraction from conventional microscopic images through deep learning (CNN and ResNet), compared to previous approaches, such as multispectral imaging by Cao et al. [6]. The integration of quantitative scoring with interpretable visualizations (KDE, Grad-CAM) represents a meaningful step toward practical, objective hair assessment.

Despite promising results, the study has limitations. The SEM model, tends to miss localized damage if the random patch sampling, resulting in false negatives. Future implementations should consider more advanced sampling strategies or attention-based mechanisms to improve detection[18,20]. Additionally, False positives can occur due to naturally prominent textures or unusual surface characteristics, requiring improved data refinement and robust features. Comprehensive validation across diverse hair types, ethnicities, damage modalities, and varying imaging conditions remains essential for real-world performance [2,3,5].

Future research priorities include addressing these methodological limitations and expanding model capabilities. Particularly, developing robust models compatible with accessible, lower-resolution imaging devices, would significantly enhance clinical and consumer utility. Integration into user-friendly diagnostic platforms could facilitate real-time hair analysis. Additionally, extending the current binary classification framework to distinguish multiple damage types and severity levels would enable more nuanced evaluations, enriching longitudinal studies of hair health and treatment effectiveness.

5. Conclusion

This research demonstrates the effective development and application of AI-based systems for objectively quantifying and visualizing hair damage using SEM and optical microscopy images. Tailored deep learning models—a custom CNN for SEM patch analysis [1,4] and a fine-tuned ResNet-18 for optical image analysis [10,15,16]—achieved high classification accuracy, overcoming limitations of subjective assessments. Our key contributions include 1) Two distinct AI models adapted to SEM and optical imaging, 2) Quantitative damage scores objectively correlated with damage severity, and 3) Visualization methods (Patch overlay, KDE [25] and Grad-CAM [17]) enhancing interpretability. These advancements offer standardized, datadriven tools for precise hair damage evaluation, supporting product development, quality control, and personalized hair health management in cosmetic science.

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