SKIN

IN-DEPTH REVIEW

Investigating the Performance of VisualDx on Common Dermatologic Conditions in Skin of Color

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ABSTRACT

Background: Artificial intelligence (AI) has been used to create diagnostic models, such as VisualDx, to assist in rapidly diagnosing skin conditions. AI diagnostic models are typically trained on image databases of dermatologic conditions, which are known to underrepresent patients with richly pigmented skin.
Objectives: We investigated whether VisualDx performed differently when classifying conditions across different skin phenotypes and whether images of conditions processed to resemble richly pigmented skin impacts diagnostic accuracy.
Methods: Our image dataset consisted of sixteen common conditions. For each condition, three subgroups were curated: “Fitzpatrick I-III”, “Fitzpatrick IV-VI”, and “Processed”. The “Processed” subgroup contained images from the “Fitzpatrick I-III” subgroup altered to resemble richly pigmented skin. Images were processed by VisualDx to obtain a differential diagnosis list and diagnostic performance was analysed.
Results: Across all subgroups, the highest sensitivity (97%) was seen in hidradenitis suppurativa, prurigo nodularis, and tinea versicolor. Atopic dermatitis, post-inflammatory hyperpigmentation, and basal cell carcinoma demonstrated the lowest sensitivity (23%, 23%, and 27%, respectively). Significantly greater diagnostic sensitivity was noted for all conditions in the “Fitzpatrick I-III” subgroup ($p < 0.001$) except acanthosis nigricans, melasma, and melanoma compared to the “Fitzpatrick IV-VI” and “Processed” subgroups. For all conditions, a reduction in sensitivity and specificity was observed in processed images ($p < 0.001$).
Conclusion: Overall, VisualDx demonstrated diagnostic bias for images in the “Fitzpatrick I-III” subgroup, and colour-editing reduced diagnostic accuracy. These results suggest comprehensive databases should be used for future training of AI diagnostic tools to improve performance in all skin phototypes.

INTRODUCTION

Accurate diagnosis of dermatologic conditions across all skin types is an essential competency for dermatologists. Photographs of skin conditions are used extensively in Dermatology training programs and increasingly in telemedicine for diagnosis. Some conditions can be more challenging to diagnose effectively in darker skin, potentially compromising treatment and

leading to poor patient outcomes.[1] Currently, there is a lack of representation of dermatologic conditions in patients with richly pigmented skin in many dermatology resources and image databases.[2,3] A recent analysis of widely used dermatology textbooks found that images of conditions in those with richly pigmented skin accounted for between 4% and 18% of all images.[2] This limited exposure to skin conditions and their unique presentations in skin of colour makes the diagnosis and treatment of skin pathology in individuals with richly pigmented skin more challenging for healthcare providers, potentially resulting in worse patient outcomes. Several factors contribute to these disparities, including insufficient research on dermatologic conditions affecting skin of colour, inadequate physician education on the treatment and diagnosis of these conditions, and systemic racism.[4]

Artificial intelligence (AI) has recently been used to create diagnostic models to assist clinicians in the rapid diagnosis of skin conditions.[5–7] VisualDx is an award-winning, diagnostic clinical decision support system developed to provide clinical support to enhance the accuracy and efficiency of the dermatologic diagnostic process.[8] This commercial application was designed to aid general practitioners in the accurate diagnosis of a broad spectrum of skin conditions across diverse skin tones.[8] Despite the growth in AI dermatology applications observed over the past decade, evaluation of these diagnostic AI models on real-world data with an equal representation of conditions across all skin phenotypes has been limited.[9] Unfortunately, these AI applications may further disadvantage individuals with skin of colour because photographs of skin conditions in richly pigmented skin are underrepresented in the image databases used to develop and train these applications.[9,10] Consequently, these models exhibit poor performance on images of skin conditions in patients with darker skin tones.[9,11,12]

In an attempt to improve the diversity of image datasets used to train diagnostic models, image processing and deep learning techniques have been used to generate realistic images of dermatologic conditions in patients with richly pigmented skin.[13,14] There is a concern that these processed and colour-edited images may not accurately represent the unique manifestations of conditions in darker skin phenotypes, potentially perpetuating disparities in care.

We sought to investigate whether VisualDx performed differently when classifying sixteen dermatologic conditions across different skin phenotypes and whether the use of image processing to resemble skin conditions in skin of colour further reduces the diagnostic accuracy.

METHODS

Condition and Image Selection

Selection of conditions to develop our dataset involved identification of dermatologic conditions with a high prevalence across multiple skin tones and a potential utility for the use of AI in dermatological practice. Conditions were chosen by consulting an experienced board-certified staff dermatologist. Our dataset consisted of sixteen common or important dermatologic conditions: acanthosis nigricans, atopic dermatitis, basal cell carcinoma, hidradenitis suppurativa, keloids, melasma, melanoma, pityriasis rosea, post-inflammatory hyperpigmentation, prurigo nodularis, psoriasis, seborrheic keratosis, squamous cell carcinoma, tinea versicolor, verruca vulgaris and vitiligo. For each condition,

three subgroups were curated: “Fitzpatrick I-III”, “Fitzpatrick IV-VI”, and “Processed”. The subgroups “Fitzpatrick I-III” and “Fitzpatrick IV-VI” each consisted of 10 macroscopic images representative of each dermatologic condition in Fitzpatrick skin types I-III and Fitzpatrick skin types IV-VI respectively. Initially, between 25 and 30 images were obtained for each subgroup from the publicly available pathology confirmed Diverse Dermatology Images dataset,[9] Dermnet NZ,[15] Global Skin Atlas,[16] and dermatology textbooks.[17,18] Images were excluded from the dataset based on the following factors: images that displayed multiple dermatologic conditions, existed at the extremes of disease severity, were considered to be of poor quality (i.e., blurry, poor lighting, taken from a distance, magnified), or contained artifacts (i.e., rulers, pen markings). Of the remaining images, 10 were randomly selected to form the dataset. The “Processed” subgroup consisted of the images from the “Fitzpatrick I-III” subgroup which were colour-edited using the process described in the following section to resemble richly pigmented skin.

Image Processing for Underrepresented Skin Tones

To artificially alter the images within the “Fitzpatrick I-III” subgroup to resemble richly pigmented skin, half of the images underwent image darkening and the remaining images underwent intensity adjustment. For image darkening, each pixel of the input image p_{input} was scaled to obtain the output pixel - $p_{output} = convert_{8bits}(\alpha\, p_{input} + \beta)$, where α is the contrast value, β is the brightness value, and the function $convert_{8bits}$ saves the pixel as an unsigned 8-bit type. In our experiments we set α=0.45 and β=0.1 to alter each image and obtain a darker version of the image. For the intensity adjustment method, image intensity was adjusted to make faint elements more intense without modifying the intensity of bright objects. Intensity values between 55 and 65 were chosen for all images.

Image and Statistical Analysis

Each image within our dataset was processed by VisualDx to obtain a differential diagnosis list of five conditions. Sensitivity and specificity analysis was performed to analyse the AI diagnostic performance across the image subgroups. The Fitzpatrick skin type, lesion location, distribution, and morphology associated with each image was provided for data processing. Using the differential diagnosis list provided by VisualDx, we computed the true positives and false negatives of each predicted condition. We then calculated the top-k true positives (where k is any cardinal number up to 5) which represent the number of true positives within the top-k predicted conditions based on the condition probabilities provided by VisualDx which are sorted in descending order. Finally, we determined the top-k sensitivity for each condition as follows:

$$top-k_{sensitivity} = \frac{top-k_{true\ positives}}{true\ positives + false\ negatives}$$

This process was repeated for all conditions. The top-k sensitivity measures how often the top-k VisualDx output conditions correctly identify patients with the condition. A top-k sensitivity of 100% means that all positive cases are correctly identified within the top-k differential provided by VisualDx with no false negatives included.

RESULTS

Overall Sensitivity Across all Subgroups

The results of the sensitivity analysis (top-1, top-3, and top-5) are listed within **Table 1** and

illustrated by **Figure 1** and **Figure 2**. Across all subgroups the highest overall top-1 sensitivity was seen in hidradenitis suppurativa, prurigo nodularis, tinea versicolor, and psoriasis (97%, 97%, 97%, and 87% respectively) while atopic dermatitis, post-inflammatory hyperpigmentation, and basal cell carcinoma demonstrated the lowest sensitivity (23%, 23%, and 27%, respectively).

Table 1. Diagnostic sensitivity for each analysed condition.

	Fitzpatrick I-III			Fitzpatrick IV-VI			Processed			Overall		
	Top1	Top3	Top5	Top1	Top3	Top5	Top1	Top3	Top5	Top1	Top3	Top5
Acanthosis Nigricans	0.30	0.80	0.90	0.90	1.00	1.00	0.30	0.80	0.90	0.50	0.83	0.93
Atopic Dermatitis	0.60	0.70	0.80	0.10	0.70	0.70	0.00	0.30	0.50	0.23	0.56	0.66
Basal Cell Carcinoma	0.40	0.70	0.80	0.40	0.50	0.70	0.00	0.50	0.70	0.26	0.56	0.73
Hidradenitis Suppurativa	1.00	1.00	1.00	1.00	1.00	1.00	0.90	1.00	1.00	0.96	1.00	1.00
Keloids	0.80	0.90	0.90	0.50	0.80	0.90	0.50	0.90	0.90	0.60	0.86	0.90
Melanoma	0.60	0.80	1.00	0.80	0.80	1.00	0.60	0.70	0.90	0.66	0.76	0.96
Melasma	0.70	1.00	1.00	0.90	1.00	1.00	0.40	1.00	1.00	0.66	1.00	1.00
Pityriasis Rosea	0.40	0.90	1.00	0.70	0.90	1.00	0.00	0.70	1.00	0.36	0.83	1.00
Postinflammatory Hyperpigmentation	0.30	0.80	1.00	0.40	0.80	1.00	0.00	0.60	0.90	0.23	0.73	0.96
Prurigo Nodularis	1.00	1.00	1.00	1.00	1.00	1.00	0.90	1.00	1.00	0.96	1.00	1.00
Psoriasis	1.00	1.00	1.00	0.90	1.00	1.00	0.70	0.70	0.80	0.86	0.90	0.93
Seborrheic Keratosis	0.70	1.00	1.00	0.70	0.90	1.00	0.50	0.90	1.00	0.63	0.93	1.00
Squamous Cell Carcinoma	0.50	0.90	1.00	0.50	0.90	1.00	0.30	0.80	0.90	0.43	0.86	0.96
Tinea Versicolor	1.00	1.00	1.00	1.00	1.00	1.00	0.90	0.90	0.90	0.96	0.96	0.96
Verruca Vulgaris	1.00	1.00	1.00	0.80	1.00	1.00	0.90	1.00	1.00	0.90	1.00	1.00
Vitiligo	0.90	1.00	1.00	0.70	0.90	0.90	0.70	0.90	0.90	0.76	0.93	0.93

Individual Subgroup Sensitivity

For the "Fitzpatrick I-III" subgroup, the greatest sensitivity was observed for hidradenitis suppurativa, prurigo nodularis, tinea versicolor, psoriasis, and verruca vulgaris, with a top-1 sensitivity of 100% for each condition. The lowest top-1 sensitivity within this subgroup was noted in acanthosis nigricans, post-inflammatory hyperpigmentation, basal cell carcinoma, and pityriasis rosea (30%, 30%, 40%, and 40% respectively). For the "Fitzpatrick IV-VI" subgroup, the greatest top-1 sensitivity was observed for hidradenitis suppurativa, prurigo nodularis, tinea versicolor, psoriasis, and melasma (100%, 100%, 100%, 90%, and 90% respectively). The lowest top-1

sensitivity within this subgroup was reported in atopic dermatitis, post-inflammatory hyperpigmentation, basal cell carcinoma, and keloids (10%, 10%, 40%, and 50% respectively). For the "Processed" subgroup, the greatest sensitivity was observed for hidradenitis suppurativa, prurigo nodularis, tinea versicolor, and verruca vulgaris, with a top-1 sensitivity of 90% for each condition. The lowest top-1 sensitivity of 0% was seen in atopic dermatitis, basal cell carcinoma, pityriasis rosea, and post-inflammatory hyperpigmentation.

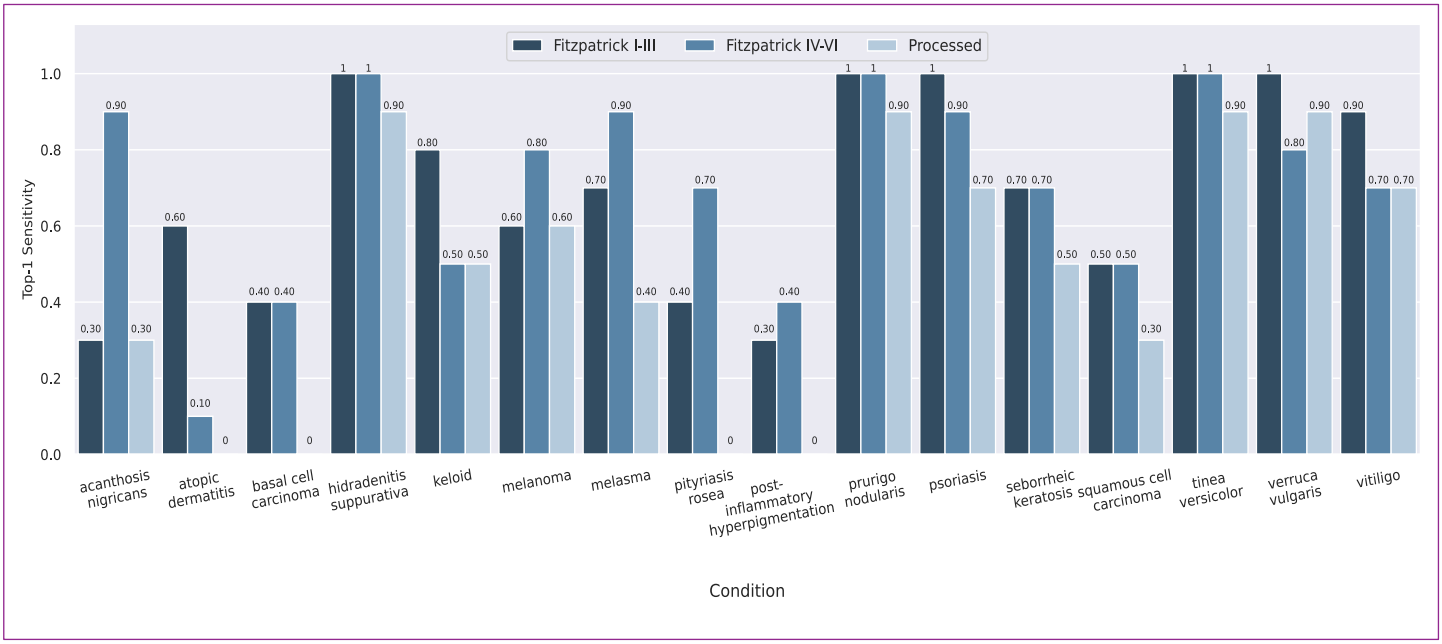

Figure 1. Top-1 sensitivity of VisualDx for each subgroup across all conditions

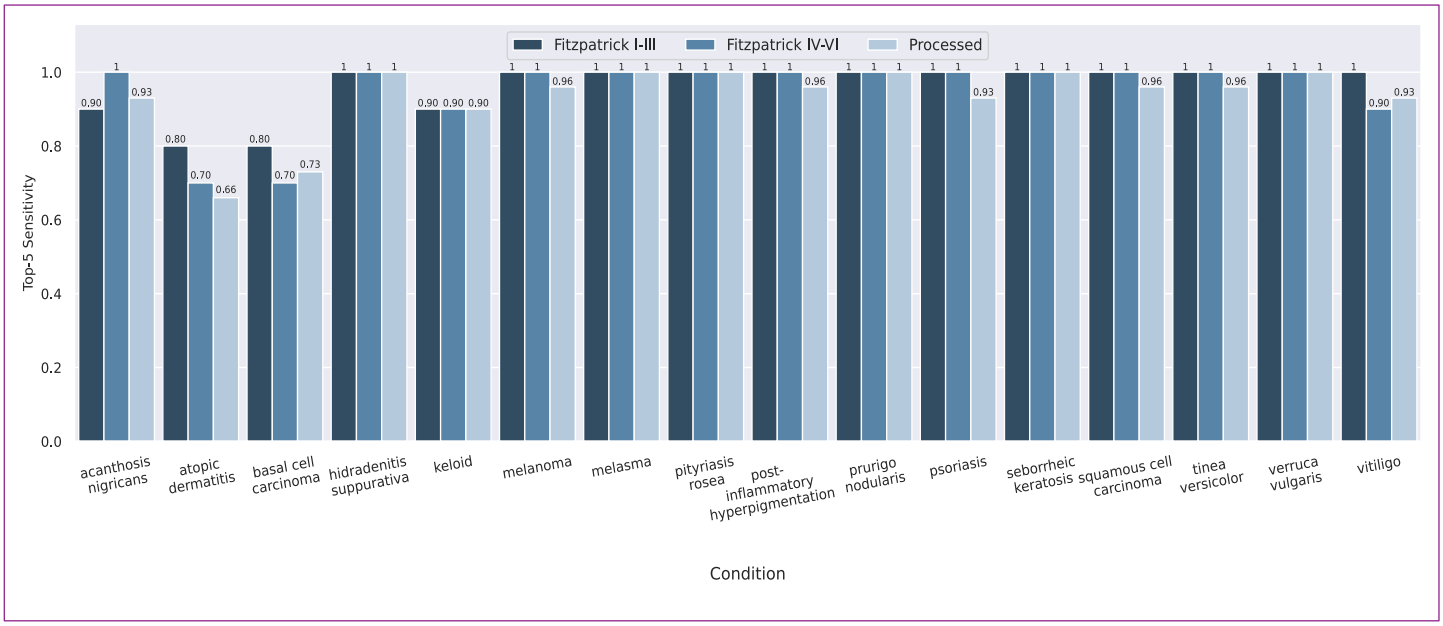

Figure 2. Top-5 sensitivity of VisualDx for each subgroup across all conditions

Sensitivity Comparison Between Image Subgroups

Significantly greater sensitivity was noted for the diagnosis of all conditions in the "Fitzpatrick I-III" subgroup compared to the other two subgroups ($p < 0.001$) except for acanthosis nigricans, melasma, and melanoma, where sensitivity was greater in the "Fitzpatrick IV-VI" subgroup. VisualDx demonstrated significantly greater diagnostic sensitivity for conditions within the "Fitzpatrick IV-VI" subgroup compared to processed images ($p < 0.001$) except for keloids and verruca vulgaris. For all conditions examined, sensitivity and specificity was significantly reduced in processed images compared to the original image from the "Fitzpatrick I-III" subgroup ($p < 0.001$).

DISCUSSION

Across all subgroups, VisualDx demonstrated higher diagnostic accuracy for hidradenitis suppurativa, prurigo nodularis, and tinea versicolor. We hypothesize that this is due to consistency in the clinical presentation of these conditions, regardless of skin colour. VisualDx also consistently demonstrated high sensitivity for psoriasis across all skin types despite observed differences in colour with lesions appearing more purple in the "Fitzpatrick IV-VI" subgroup compared to the characteristic red colour in the "Fitzpatrick I-III" subgroup. This may be attributed to the well-defined and understood morphology (plaque and silvery scale) of this condition which is maintained regardless of patient skin tone.

VisualDx consistently demonstrated poor performance for atopic dermatitis, basal cell carcinoma, and post-inflammatory hyperpigmentation across all skin tones. As these AI models require high quality images for optimum performance, analysis of conditions like atopic dermatitis in which disease manifestations are variable and less obvious in images can produce a diagnostic disadvantage. Atopic dermatitis poses a diagnostic challenge for different AI models as this condition can be difficult to photograph and it is often difficult to convey disease severity through an image. Further, significant variability exists in the manifestations of atopic dermatitis depending on genetics and endotypes.[19–21] For example, in richly pigmented skin, a lichen-planus-like presentation has been described and erythema can appear more pigmented than red.[17,22] These disease features which look different clinically make the diagnosis of atopic dermatitis in images artificially generated even more challenging. Basal cell carcinoma was another condition where VisualDx demonstrated low diagnostic accuracy. This was initially surprising as these lesions are typically well-defined with a classical morphology. The poor performance in images of basal cell carcinoma in richly pigmented skin may be attributed to the greater rate of pigmented basal cell carcinomas seen in patients with skin of colour. Greater than 50% of basal cell carcinomas in patients with skin of colour are pigmented with a pearly brown or black appearance, which differs from the pearly, pink nodules classically described in educational resources.[23] Lastly, low sensitivity was seen for images of post-inflammatory hyperpigmentation which may be due to this condition presenting with a more intense, pigmented, and persistent appearance in those with richly pigmented skin compared to a more erythematous presentation in those with lighter skin.[17] Further, as VisualDx performed poorly for this condition regardless of the image subgroup it is possible this may indicate an intrinsic limitation of VisualDx.

Although VisualDx has a greater representation of dark skin images (28.5%) across common dermatologic conditions compared to other commonly referenced resources such as Bolognia (13.2%), Fitzpatrick's dermatology (15.1%), and Fitzpatrick's Color Atlas and Synopsis of Clinical Dermatology (6.1%), it still demonstrated diagnostic bias for images in patients with lighter skin tones.[24] Greater diagnostic accuracy was seen for images in the "Fitzpatrick I-III" subgroup for the majority of conditions analysed in this dataset except for acanthosis nigricans, melasma, and melanoma. Acanthosis nigricans has a more clinically-distinct appearance in patients with richly pigmented skin and has a greater prevalence affecting 23.3% in African Americans, 5.5% in Latinos, and 34.2% in Native Americans, compared to <1% in Caucasians in the United States.[25,26] Similar to acanthosis nigricans, melasma more frequently affects individuals with Fitzpatrick skin types III-V.[27,28] As a result, it is possible the datasets used to train VisualDx may have had a greater proportion of images of these conditions in patients with richly pigmented skin. Lastly, the improved performance of VisualDx on melanoma images in patients with richly pigmented skin could be attributed to the fact that melanoma appears less frequently in these patients and is often diagnosed at an advanced stage.[29] Images of advanced melanomas are clearly visually distinguished from other conditions and therefore easy for VisualDx to identify and diagnose. Since patients with skin of colour tend to present with more advanced disease, VisualDx demonstrated good performance. Although this may not directly translate to an ability of AI tools to diagnose melanoma earlier in patients with richly pigmented skin, this improved accuracy indicates the potential for AI-guided image analysis to diagnose melanoma across all skin types, including skin of colour.

VisualDx demonstrated superior performance on images in patients with Fitzpatrick skin types IV-VI compared to the processed images across all conditions except keloids and verruca vulgaris. As keloids are more common in patients with skin of colour this finding was expected due to possible training on more images of this condition in those with richly pigmented skin.[30] Verruca vulgaris generally appears similarly across all skin tones and thus it is likely this difference in performance is due to limitations of the AI algorithm.[30]

For the majority of conditions analysed in this dataset, VisualDx demonstrated diagnostic bias for images in the "Fitzpatrick I-III" subgroup. This can likely be attributed to the AI training dataset having an underrepresentation of images in skin of colour. Further, greater colour bias was seen in conditions with varying disease manifestations compared to those with more consistent presentations. We can also conclude that AI transformation of images does not improve accuracy for AI diagnostic models as the sensitivity and specificity was reduced for all transformed images compared to their original images and those in patients with richly pigmented skin.

We acknowledge that our findings are subject to limitations as our dataset consisted of 480 images and covered 16 conditions thus, it is susceptible to bias due to the smaller size. Further, the included conditions were selected in consultation with a single dermatologist and although they are universally considered common, essential, and demonstrate a high prevalence, this still produces bias. Lastly, although care was taken to ensure included images were representative of the condition and uniform across skin tones, this was not always the case, such as with melanoma, where overall, the images in the "Fitzpatrick IV-VI" subgroup

were more severe than those in the "Fitzpatrick I-III" subgroup.

Our results highlight the importance of expanding image databases to include more images of dermatologic conditions in skin of colour. Further, it is essential that care be taken to ensure the use of image processing and colour-editing techniques does not reduce accuracy, possibly perpetuating existing disparities in care. Future training of AI diagnostic tools should be done using more comprehensive databases so that diagnosis can be accurately performed across all skin phenotypes. It is essential to expand education and comprehensive research that highlights the unique manifestations of dermatologic conditions in richly pigmented skin, to ensure the provision of high-quality dermatologic care across all skin phototypes.

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