back.[3,4] Our study showed that HMs follow similar patterns (Fig 1, *C*).

HMs in patients with TSC contain melanocytes with impaired melanogenesis. For melanogenesis, crosstalk between melanocytes and their surrounding cells, such as keratinocytes or mononucleocytes, is necessary.[5] The interaction of the dysfunctional melanocytes with the surrounding cells in the microenvironment where the melanocyte stopped in its migration after a second somatic mutation may lead to the development of HMs in patients with TSC. Furthermore, the upper portion of the back and scapular, which is the site with the highest appearance of HMs, may have a site-specific potential to develop HMs.

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Conflicts of interest

None disclosed.

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Image quality issues in teledermatology: A comparative analysis of artificial intelligence solutions

To the Editor: Deep learning artificial intelligence (AI) models capable of classifying skin lesions have become common in recent years.[1-4] Many models are built using high-quality professional images from publicly available datasets, introducing biases to the data.[5] However, with the rise in teledermatology, patient-recorded images are often taken in poor, unnatural lighting, increasing the likelihood of inadequate contrast, color, or exposure, which presents a challenge to those models.

This work was designed to investigate the behavior of 3 AI models to uncover the impact of classifying imperfect images of skin lesions as benign or malignant. Essentially, we tested 2 hypotheses: (1) "the performance of AI solutions for skin lesion classification decreases as the quality of patient-recorded images also decreases" and (2) "the decrease in performance varies among different models due to their inherent robustness." We trained each model on images from the HAM10000 dataset until each model was capable of classifying lesions as benign or malignant. Finally, we measured the accuracy and sensitivity as the models were tested to classify similar images with varying degrees of blurring and brightness.

Preliminary results (Fig 1) showed that classification accuracy and sensitivity notably decrease as blurring or brightness changes were introduced (confirming hypothesis 1) and that different models behave differently (confirming hypothesis 2). The impact of misclassification after brightness and blurring were applied to the images cannot be

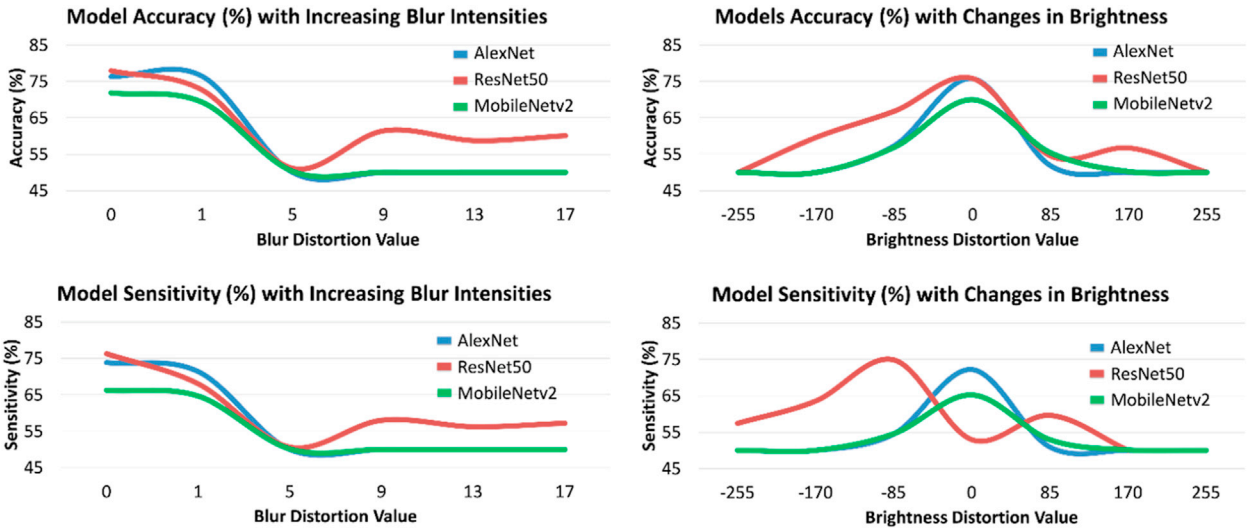

Fig 1. Experimental results: the visualization of 2 performance metrics (accuracy and sensitivity) for 3 deep learning artificial intelligence models—AlexNet, ResNet50, and MobileNetv2—as images with varying degrees of blurring and brightness intensities were classified. Both metrics drop as a result of increased blurriness (in a way that varies in shape and amount depending on the underlying architecture) and variations in brightness.

understated—in some cases, relatively minor variations in either aspect led to the opposite prediction (benign or malignant) for the original image (Fig 2).

The differences in behavior among the 3 selected (and pretrained on ImageNet) models can be attributed to internal details beyond the scope of this article. The findings are dependent on the choice of the dataset, image data augmentation options, and several hyperparameters, which are fine-tuned to achieve the best performance. This is a common aspect of every deep learning study that also applies to this work: had we chosen to train our networks with different design choices, we would have arrived at different results, and the plots in Fig 1 could look slightly different but showing similar overall shape. Moreover, the resulting models would still be brittle and subject to prediction errors for images of slightly different quality.

This study showed a preliminary evidence that just as dermatologists may struggle to deal with poor quality images, so can AI models. Further studies should focus on how to make an AI model aware of these quality issues, eg, by adding lower-quality images to the training set or using a preprocessing stage to label and triage images according to their quality.

In conclusion, although virtual diagnosis using AI models has evolved to serve as "assistive intelligence" and help relieve the teledermatologic workload of busy dermatologists, such models are prone to errors when dealing with lower-quality images. Moreover, due to the inherent brittleness of these models, relatively minor imperfections may lead to major differences in the models' predictions, suggesting that dermatologists should use these models judiciously.

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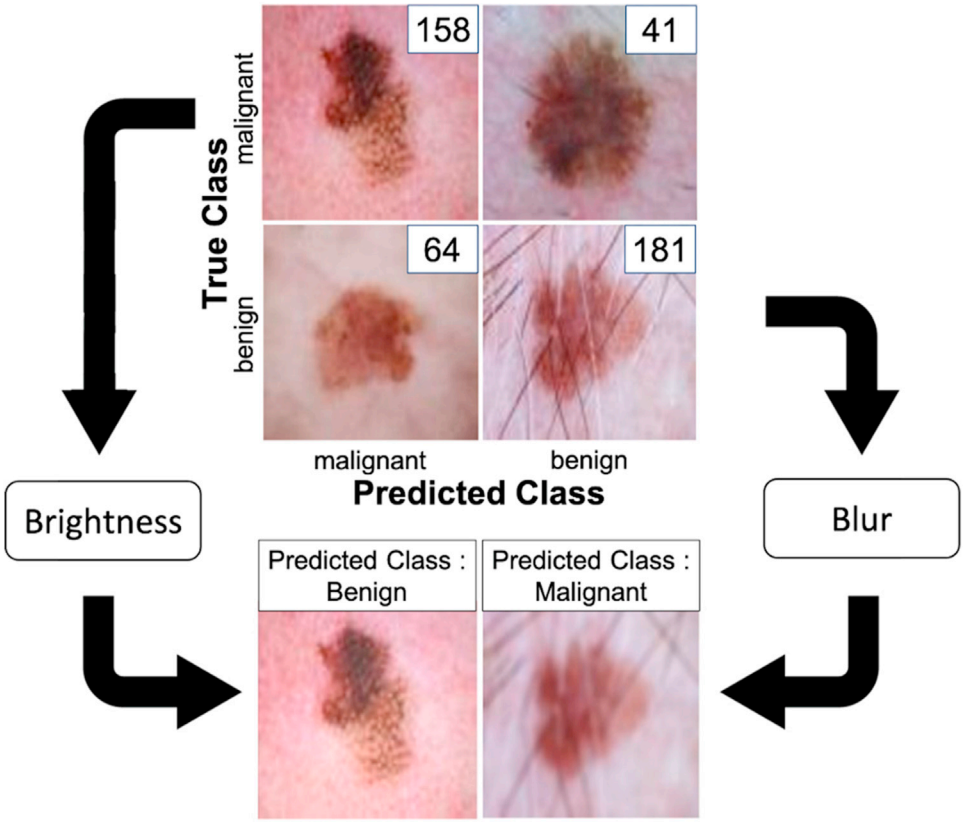

Fig 2. AlexNet misclassification examples after brightness and blurring were applied to the images: minor imperfections led to opposite predictions. The figure displays a confusion matrix of 4 images' "True Class" (along the vertical axis) and "Predicted Class" (along the horizontal axis) with a representative image as well as the number of images that fall within the intersection of the respective "True Class" and "Predicted Class." When slight brightness variation and blurring were applied to the previously correctly classified images, the resulting (brighter or blurry) images were misclassified (ie, the associated predictions flipped from "benign" to "malignant" or vice versa), highlighting the impact of presenting deep learning models with lower-quality images.

Conflicts of interest

None disclosed.

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Attrition of topical calcineurin inhibitor use over time in patients with atopic dermatitis

To the Editor: The American Academy of Dermatology's guidelines recommend topical calcineurin inhibitors (TCIs) for acute and maintenance treatment of atopic dermatitis (AD).[1] TCIs have minimal risk of skin atrophy and discoloration, can reduce the need for topical corticosteroids (TCSs), and have an excellent safety profile, with no evidence of clinically meaningful