Accurate Classification of Benign and Malignant Dermoscopy Skin Lesions using Three Deep Learning Models

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NEXTGEN PRECISION HEALTH
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INTRODUCTION

- Skin cancer is highly prevalent, and its incidence continues to increase
- Early diagnosis is associated with improved outcomes and reduced morbidity
- Dermoscopy is a tool that allows for detailed visualization and risk stratification of concerning skin lesions

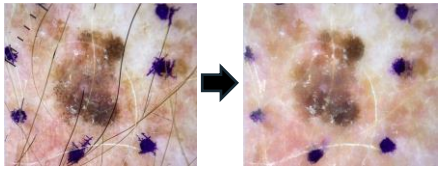
- We propose a novel artificial intelligence deep learning tool used for differentiating between benign and malignant skin lesions under dermoscopy

OBJECTIVES

The aim of the project is to detect the presence of malignant lesions using different deep learning algorithms at MU Healthcare.

METHODS

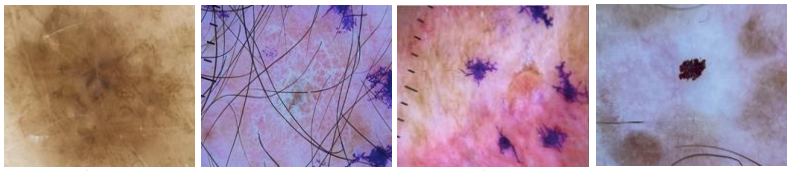
- Retrospective chart review to obtain 770 de-identified dermoscopy images
  - Inclusion criteria: clearly focused and contained entire skin lesion
  - Coded as 'malignant' or 'benign'
  - Zoomed to a width of 600 x 450 pixels
- Three unique image datasets were created:
  - Dataset 1. Original images (n=770)
  - Dataset 2. DullRazor hair remover on images with hair only (n=566)
  - Dataset 3. DullRazor hair remover on all images (n=204)



- Dataset division: training set (70%), validation set (20%), and testing set (10%)
- Three deep learning models, ResNet50, DenseNet121, and Inception-V3, were applied to each data set

EXPERIMENT EXAMPLE

Example: DenseNet121 on Datasets 1-3



	Actual			
	Malignant	Benign	Malignant	Benign
	Predicted			
Dataset 1	Benign	Malignant	Benign	Malignant
Dataset 2	Malignant	Malignant	Malignant	Benign
Dataset 3	Malignant	Malignant	Malignant	Benign

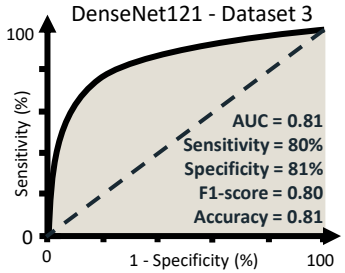
RESULTS

Performance Metric (Dataset1)	Inception-V3	ResNet50	DenseNet121
Accuracy	0.75	0.79	0.81
Sensitivity	0.66	0.86	0.71
Specificity	0.83	0.74	0.88
F1-score	0.75	0.79	0.8
AUC-ROC	0.75	0.8	0.8
Performance Metric (Dataset2)	Inception-V3	ResNet50	DenseNet121
Accuracy	0.74	0.81	0.78
Sensitivity	0.66	0.71	0.71
Specificity	0.81	0.88	0.83
F1-score	0.73	0.8	0.78
AUC-ROC	0.73	0.8	0.77
Performance Metric (Dataset3)	Inception-V3	ResNet50	DenseNet121
Accuracy	0.70	0.79	0.81
Sensitivity	0.86	0.71	0.8
Specificity	0.57	0.86	0.81
F1-score	0.70	0.79	0.8
AUC-ROC	0.71	0.79	0.81

$Accuracy=(T_p+T_n)/(T_p+T_n+F_p+F_n)$; $Sensitivity=T_p/(T_p+F_n)$; $Specificity=T_n/(T_n+F_p)$; $F1\text{-}score=2\times P\times R/(P+R)$
T_P = true positive; T_n = true negative; F_P = false positive; F_n = false negative

DISCUSSION

- DenseNet121: deep learning with tool highest overall performance
- Accuracy of DenseNet121 to differentiate malignant or benign lesions is improved by hair removal techniques



- Also studied the interpretability of the tested deep learning models using SHapley Additive exPlanations (SHAP) values → hair removal increased importance of red and blue pixels

CONCLUSIONS

- Artificial intelligence in combination with dermoscopy has the potential to allow for early diagnosis of cutaneous malignancies
- These models may have implications to improve virtual access to care or aid in primary care skin cancer diagnosis
- Future efforts to further classify images: malignant melanocytic, malignant non-melanocytic, benign melanocytic, and benign non-melanocytic.

ACKNOWLEDGMENTS

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References

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