Utilizing Machine Vision for Accurate Identification and Classification of Skin Diseases

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Introduction

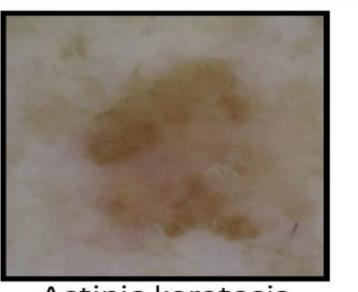
- 1. Skin diseases are widespread and can be difficult to diagnose accurately due to the subjective nature of traditional visual assessments by dermatologists.
- 2. This project explores how machine vision can be optimized to provide accurate and fair skin disease diagnoses. It specifically investigates the impact of data augmentation techniques on model performance across different demographics.
- 3. The aim is to develop a robust diagnostic model that performs reliably across diverse populations, contributing to more equitable healthcare outcomes and enabling faster, more consistent skin disease diagnosis in clinical settings.

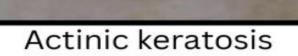
Research Method

- 1. Used a skin disease image dataset with 9 classes, split into train (60%), validation (20%), and test (20%).
- 2. Applied different data augmentation to improve model generalization.
- 3. Fine-tuned a pretrained AlexNet, replacing the final layer for 9-class output.
- 4. Trained for 50 epochs using Adam optimizer and weighted cross-entropy to address class imbalance.
- 5. Evaluated performance using accuracy, confusion matrix, and classification report.
- 6. Focused on fairness by balancing class weights and comparing results across all classes.

Findings and progress thus far

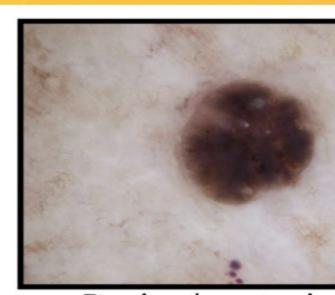
- 1. Trained on 29,320 images; tested on 4,888 images across 9 classes.
- 2. Achieved 84.23% test accuracy after 50 epochs using pretrained AlexNet.
- 3. Data augmentation and class weighting helped reduce bias but didn't fully close the gap for rare classes.











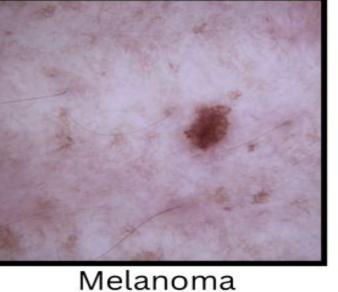
Benign keratosis



Dermatofibroma



Melanocytic nevi



Melanoma



Squamous cell carcinoma



Vascular lesions

These are the few images of the dataset.

Obstacles faced/overcome

- 1. Some classes had very few samples, making it hard for the model to learn them effectively.
- 2. Limited data in rare classes increased the risk of the model memorizing training data.
- 3. Training deep models with large datasets and augmentation was resource-intensive.
- 4. Ensuring consistent performance across all skin types and conditions was challenging.



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