GC-123 Deep Learning-Based Skin Cancer Detection

Abstract

Skin cancer is increasingly becoming a severe health problem globally today, but early detection is essential to enhance survival rates. Nonetheless, conventional diagnosis relies largely on visual examinations by dermatologists, which can be subjective and time-consuming. This research examines the application of deep learning for the automation of skin cancer detection based on dermoscopic images from the HAM10000 dataset. The models VGG19, densenet121 and resnet152 will be trained and evaluated, with class imbalance addressed using data augmentation strategies. The outputs will demonstrate the applicability of deep learning to improve skin cancer diagnosis. Classification optimization using ensemble modeling and its improved architecture with an attention u-net to offer segmentation integration for improved lesion localization and explainability will be future research.

Introduction

Skin cancer is one of the most common cancers worldwide, with melanoma being among the deadliest forms if not detected early. Visual inspection and dermoscopy are standard diagnostic methods but require high expertise and are prone to inter-observer variability. Deep learning, particularly CNNs, has shown immense promise in automating image-based medical diagnoses. This research project aims to evaluate multiple CNN architectures to detect and classify different types of skin lesions from dermoscopic images.

Dataset Description

The HAM10000 (Human Against Machine with 10,000 training images) dataset is a benchmark collection of 10,015 dermoscopic images used for skin lesion classification. Each image is labeled into one of seven skin disease categories, such as melanoma and basal cell carcinoma, and has been annotated by dermatology experts. The dataset presents a significant class imbalance, which is addressed using data augmentation during model training. It serves as the foundation for training deep learning models including VGG19, Inception V3, MobileNet V2, and ResNet50.

Class Name	Abbreviation	Description	Image Count
Melanocytic Nevi	NV	Benign mole	6,705
Melanoma	MEL	Malignant skin cancer	1,113
Benign Keratosis-like Lesions	BKL	Non-cancerous skin growths	1,099
Basal Cell Carcinoma	BCC	Common skin cancer	514
Actinic Keratoses	AKIEC	Precancerous lesions	327
Vascular Lesions	VASC	Blood vessel-related lesions	142
Dermatofibroma	DF	Benign fibrous lesion	115
Total			**10,015**

Table 1: Class Distribution in HAM10000

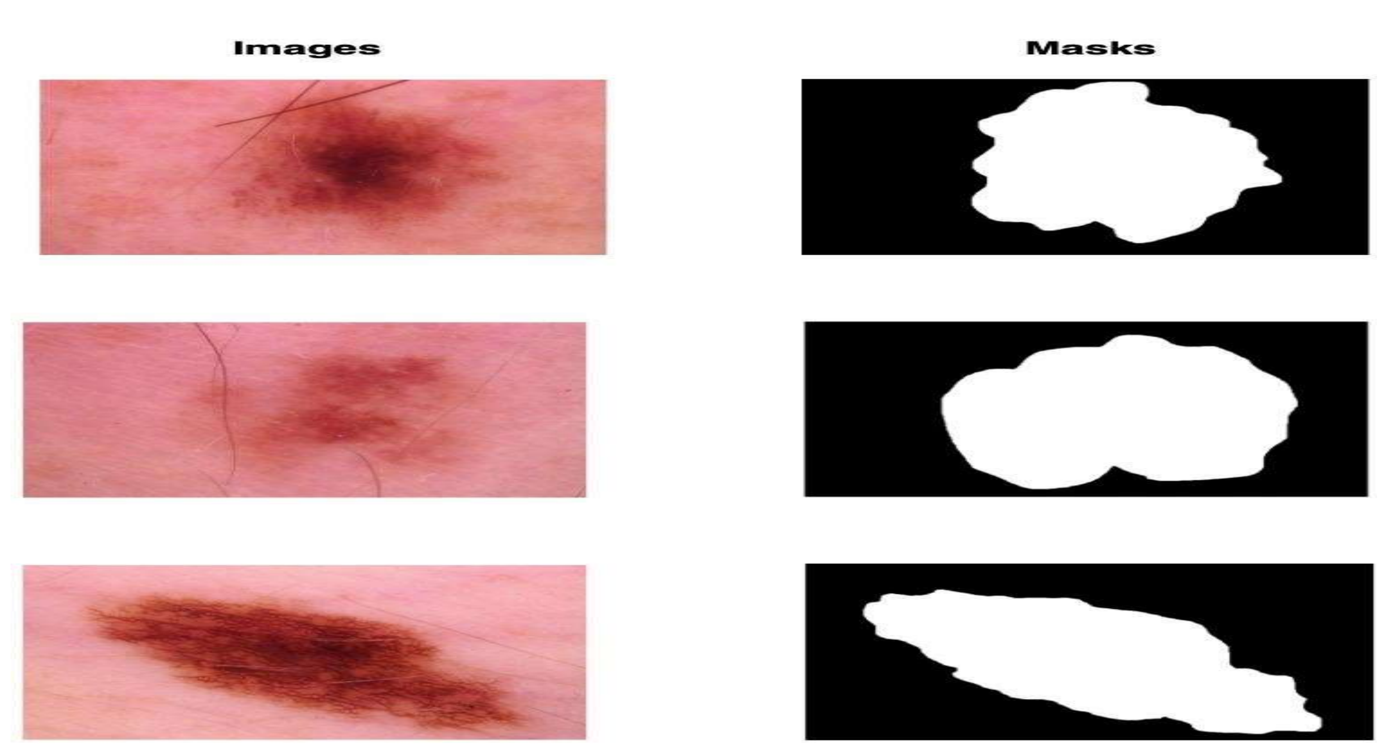


Fig 1: images and corresponding masks

Methodology

1. Dataset Preparation
•**Dataset Used:** HAM10000 (10,015 dermoscopic images, 7 skin lesion classes)
•**CSV Metadata:** Labels and image names stored in GroundTruth.csv
•**Preprocessing:**
• Resized all images to 224×224 pixels.
• Normalized pixel values using ImageNet mean and std.
• Converted segmentation masks to binary for lesion detection.

2. Data Augmentation
•Applied to classification dataset to reduce class imbalance:
• Rotation, flipping, zooming, shifting, color jitter.

3. Model Architectures
Multiclass Classification Models (7-class):
Efficient Net B0
DenseNet121
MobileNet V2

4. Ensemble Learning
•Combined predictions from MobileNetV2, EfficientNet B0, and DenseNet121 using majority voting.
•Ensemble achieved improved accuracy and F1-score over individual models.

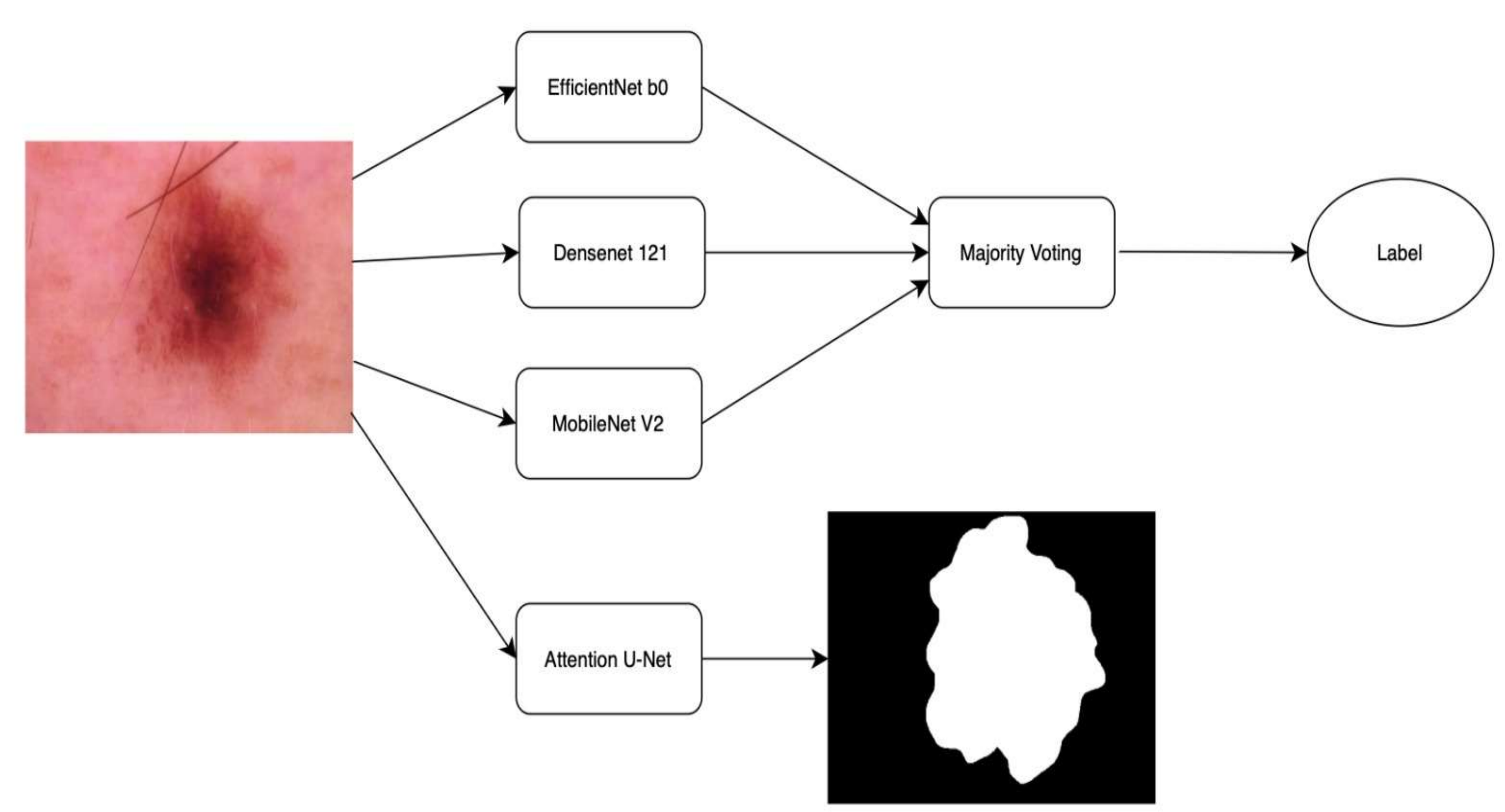
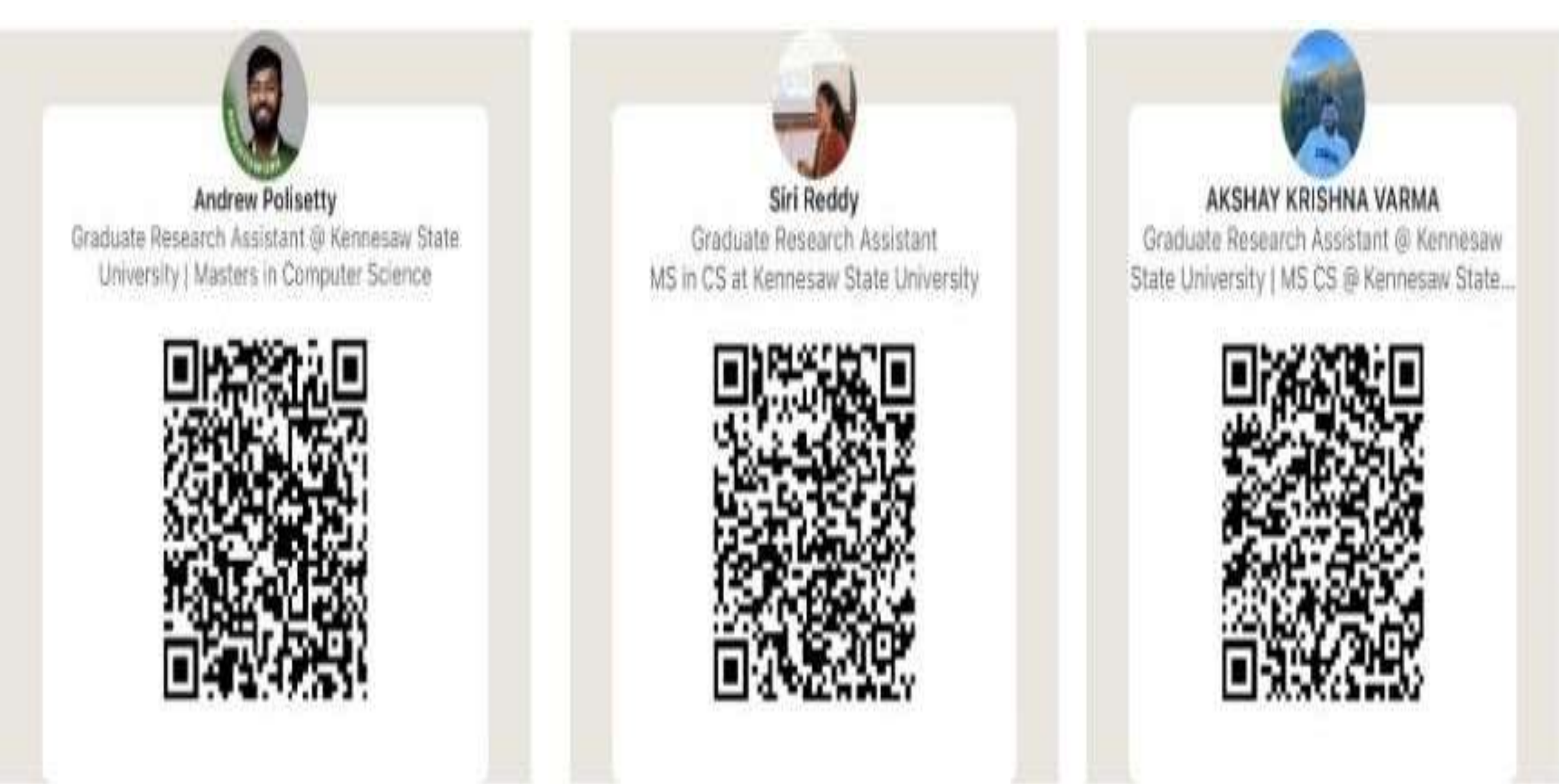


Fig 2:Model architecture combining classification and segmentation (Attention U-Net) for skin cancer detection.

Contact Information



Results

Classification Performance:
We evaluated three deep learning models—ResNet-152, VGG19, and DenseNet121—for multi-class skin lesion classification. ResNet-152 achieved the highest individual accuracy at **85%**, followed closely by VGG19 at **84%** and DenseNet121 at **82%**. While each model performed well independently, their close performance suggests they capture complementary features of the input data.
To leverage their combined strengths, we implemented a **majority voting ensemble** approach. This ensemble method improved the overall classification accuracy to **89%**, highlighting its effectiveness in reducing model-specific biases and enhancing robustness. The performance boost also suggests diverse decision boundaries among models, making ensembling a powerful strategy for medical image classification.

Segmentation Performance:
For the lesion segmentation task, we compared **U-Net** and **Attention U-Net** architectures. U-Net achieved **83% accuracy**, while Attention U-Net outperformed it with an accuracy of **87%**. This improvement demonstrates the value of attention mechanisms in focusing on critical regions of dermoscopic images, which is essential for precise lesion boundary detection.
Qualitative results further showed that Attention U-Net produced cleaner and more accurate segmentation masks, particularly in challenging regions with complex textures or irregular shapes. These findings indicate that attention-enhanced architectures are better suited for high-precision tasks in medical image analysis.

Model	Accuracy	F1 score	Precision	Recall
EfficientNet b0	0.9767	0.9759	0.9773	0.9767
MobileNet V2	0.9479	0.9466	0.9486	0.9479
DenseNet121	0.8750	0.8840	0.9177	0.8750
ResNet 150	0.8301	0.8174	0.8217	0.8301
InceptionV3	0.8088	0.8029	0.8444	0.8088
Ensemble model	0.9887	0.9885	0.9889	0.9887

Table 2: Classification Results

Model	Dice Coefficient	IoU	Loss
U-Net	0.9252	0.8619	0.0997
MobileNet V2	0.9462	0.8982	0.0699

Table 3 :Segmentation Results

References

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