Melanoma Cancer Classification Using Convolutional Neural Networks (CNNs)

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Abstract

Melanoma is a serious and potentially deadly form of skin cancer, but early detection significantly improves survival rates. In this study, we explore the application of deep learning techniques, specifically Convolutional Neural Networks (CNNs), for the automated classification of melanoma from dermoscopic images. We utilized a curated dataset of 13,900 images and applied three different deep learning models: a custom CNN, a VGG16-based model, and a ResNet50-based model. Preprocessing techniques, including normalization and data augmentation, were employed to enhance model performance. Our results demonstrate that ResNet50 achieved the highest accuracy, outperforming the other models. These findings highlight the potential of deep learning in aiding early melanoma diagnosis and support its integration into clinical decision-making systems. Future work will focus on improving model generalization and deploying lightweight models suitable for real-world applications.

1 Introduction

Melanoma is the most aggressive and deadly form of skin cancer, originating from melanocytes—the cells responsible for producing melanin, the pigment that gives skin its color. While melanoma accounts for only about 4% of skin cancer cases, it is responsible for the majority of skin cancer-related deaths [1].This paper explores how deep learning can be used to classify melanoma from skin lesion images. CNNs are known for their ability to automatically learn important features from images, making them ideal for image classification tasks.And perform a comparative analysis between multiple models.

1.1 Motivation

Early detection of melanoma can save lives. However, diagnosing melanoma from skin images can be challenging for doctors. Using deep learning models like CNNs can help automate this process and assist doctors in making more accurate diagnoses.

1.2 Problem Statement

The problem we are addressing is the classification of skin lesions as either melanoma or non-melanoma. This is a difficult task because skin lesions can look very similar, so having an automated system to assist doctors is crucial.

2 Literature Review

Skin cancer remains one of the most prevalent and life-threatening cancers worldwide, with melanoma being particularly aggressive if not detected early. Traditional diagnostic methods, such as visual inspection and dermoscopy, have limitations in accuracy and sensitivity, especially for early-stage lesions that lack distinctive features. As a result, computer-aided diagnosis (CAD) systems, particularly those leveraging deep learning (DL), have emerged as promising tools to enhance early and accurate detection. Recent advancements in convolutional neural networks (CNNs), including architectures like AlexNet, VGG, ResNet, and DenseNet, have demonstrated remarkable success in skin lesion classification. These models excel in extracting intricate features from dermoscopic images, improving diagnostic precision beyond conventional methods. For instance, studies utilizing transfer learning and ensemble techniques have reported classification accuracies exceeding 90% on benchmark datasets such as HAM10000 and ISIC. However, challenges persist, including the need for large, diverse datasets to mitigate biases—such as the underrepresentation of darker skin tones—and the computational complexity of deploying deep models in real-world clinical settings [6].

Kumar Lilhore et al. (2024) [3] conducted a study that proposed a hybrid deep learning model combining Standard U-Net for precise lesion segmentation and an Improved MobileNet-V3 architecture optimized with Bayesian hyperparameter tuning for feature extraction and classification. The model achieves exceptional performance on the HAM10000 dataset, with 98.86% accuracy, 97.84% precision, and 96.35% sensitivity, surpassing existing models like VGG-16 and ResNet-152v2. However, the study acknowledges limitations, including the high computational complexity of the hybrid architecture and the need for further validation on diverse real-world datasets to ensure generalizability. Future work aims to enhance interpretability and reduce resource demands for clinical deployment.

In another study ,they propose an ensemble learning approach to improve melanoma skin cancer detection by combining deep feature embeddings from DCNN (VGG-19), Capsule Network (Caps-Net), and Vision Transformer (ViT) with five machine learning models (KNN, SVM, XGBoost, Random Forest, and Logistic Regression) using majority voting. The method achieves 91.6% accuracy with ViT-based features, outperforming individual models and other feature extractors (DCNN: 91.4%, Caps-Net: 89.6%). While the ensemble is lighter than pure deep learning systems, limitations include dependency on feature extractor performance (Caps-Net underperformed) and a balanced dataset that may not reflect real-world scenarios. Future work could optimize Caps-Net training and test on imbalanced data [2].

in aother study ,the authors compare two convolutional neural network (CNN) architectures, MobileNetV2 and a customized CNN, using the HAM10000 dataset, which contains 10,015 dermoscopic images of various skin lesions. Preprocessing steps, such as image scaling and hair removal, were applied to enhance data quality. The results showed that the customized CNN achieved a higher accuracy of 95% compared to MobileNetV2's 85%, and a web application was developed to facilitate user-friendly melanoma detection. However, limitations include the model's reduced performance when classifying new or augmented images not present in the original dataset, highlighting the need for further improvements in generalizability and robustness [5].

the study proposes a hybrid deep learning framework combining U-Net for lesion segmentation, Inception-ResNet-v2 for feature extraction, and Vision Transformer (ViT) for classification, achieving 98.65% accuracy, 99.20% sensitivity, and 98.03% specificity on the ISIC2020 dataset. Despite its high performance, the model faces limitations, including dataset bias, high computational costs, lack of real-world clinical validation, and limited interpretability of ViT's self-attention mechanisms. Future work aims to develop a smartphone application for practical deployment and improve generalizability through lightweight optimization and clinical trials. [4]

3 Methodology

3.1 Dataset

The dataset comprises 13,900 high-quality dermoscopic images, each uniformly resized to 224×224 pixels, capturing various manifestations of melanoma and other skin lesions. Curated from diverse clinical sources, it supports the development of machine learning models for accurate skin cancer classification, especially distinguishing between benign and malignant cases. The dataset is divided into Benign and Malignant categories in both the training and test folders, making it suitable for building and evaluating skin lesion classification models.

3.2 Preprocessing

Before training the model, all images were rescaled by dividing pixel values by 255 to normalize them between 0 and 1, which helps improve model performance. Data augmentation techniques such as rotation, zoom, shifting, and flipping were applied to the training images to make the model more robust. The dataset was also split into training, validation, and testing sets, with labels organized in a binary format to distinguish between benign and malignant cases.

3.3 Deep Learning Models

For this study, we utilized three different deep learning models to classify skin lesions as either Benign or Malignant: a custom Convolutional Neural Network (CNN), a VGG16-based model, and a ResNet50-based model. Each model was chosen to explore different approaches to image classification, with a focus on optimizing accuracy, precision, and recall.

3.3.1 Convolutional Neural Network (CNN)

The Custom CNN model was designed from scratch, consisting of three convolutional layers followed by max-pooling layers to extract features from the images. The model includes Batch Normalization to improve training stability and a Dropout layer to prevent overfitting. The final output layer uses the sigmoid activation function to classify the images as either benign or malignant.

3.3.2 VGG16

The VGG16 model was used with its pretrained weights from ImageNet. This model has been widely used for image classification tasks due to its deep architecture and powerful feature extraction capabilities. In this study, the VGG16 layers were frozen to retain the knowledge learned from ImageNet. Only the final layers were trained for the specific task of skin lesion classification. The model ends with a Global Average Pooling layer, followed by a Dense layer and a Dropout layer to ensure generalization. Like the custom CNN, it uses the sigmoid activation function at the final output layer.

3.3.3 ResNet

The ResNet50 model, another powerful pretrained model, was chosen for its advanced feature learning capabilities using skip connections. This architecture helps the model retain important information while allowing for deeper networks. Similar to the VGG16 model, the ResNet50 base was frozen and a few additional layers were added on top to classify the images as benign or malignant. It ends with a Global Average Pooling layer and a Dropout layer to reduce overfitting.

Each of these models was compiled with the Adam optimizer , binary crossentropy loss for binary classification tasks, and the performance was measured using accuracy, precision, and recall metrics to evaluate the effectiveness in detecting both benign and malignant lesions.

4 Results

After training the models, we evaluated their performance on the test set. The results showed that ResNet-50 outperformed the other models in terms of accuracy, precision, recall, and F1-score. The CNN performed well but was not as accurate as the deeper models like ResNet and vgg16.

5 Conclusion

In this project, we successfully applied multiple deep learning models, including CNN, ResNet,and VGG16 to classify melanoma from skin lesion images. The results suggest that deep networks like ResNet-50 provide the best classification accuracy. This research shows the potential of using CNNs for automated melanoma detection, which can assist doctors in making faster and more accurate diagnoses. Future work could explore further improvements in model architectures and the use of additional data sources.

References

[1] Lauren E. Davis, Sara C. Shalin, and Alan J. Tackett. Current state of melanoma diagnosis and treatment. *Cancer Biology Therapy*, 20(11):1366–1379, 2019. Epub 2019 Aug 1.

[2] Subhayu Ghosh, Sandipan Dhar, Raktim Yoddha, Shivam Kumar, Abhinav Kumar Thakur, and Nanda Dulal Jana. Melanoma skin cancer detection using ensemble of machine learning models considering deep feature embeddings. *Procedia Computer Science*, 235:3007–3015, 2024. International Conference on Machine Learning and Data Engineering (ICMLDE 2023).

[3] Umesh Kumar Lilhore, Sarita Simaiya, Yogesh Kumar Sharma, Kuldeep Singh Kaswan, K. B. V. Brahma Rao, V. V. R. Maheswara Rao, Anupam Baliyan, Anchit Bijalwan, and Roobaea Alroobaea. A precise model for skin cancer diagnosis using hybrid U-Net and improved MobileNet-V3 with hyperparameters optimization. *Scientific Reports*, 14(1):4299, 02 2024.

[4] Muhammad Mateen, Shaukat Hayat, Fizzah Arshad, Yeong-Hyeon Gu, and Mugahed A. Al-antari. Hybrid deep learning framework for melanoma diagnosis using dermoscopic medical images. *Diagnostics*, 14(19), 2024.

[5] Devika Moturi, Ravi Kishan Surapaneni, and Venkata Sai Geethika Avanigadda. Developing an efficient method for melanoma detection using cnn techniques. *Journal of the Egyptian National Cancer Institute*, 36(1):6, 02 2024.

[6] Maryam Naqvi, Syed Qasim Gilani, Tehreem Syed, Oge Marques, and Hee-Cheol Kim. Skin cancer detection using deep learning–a review. *Diagnostics (Basel)*, 13(11):1911, 2023. Published: 2023 May 30.