Convolutional Neural Networks for Melanoma Screening

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ABSTRACT

Melanoma is the most aggressive and deadliest form of skin cancer, accounting for approximately 75% of skin cancer-related deaths, despite being less common than other skin cancer types. Early diagnosis is critical, as timely intervention—often through minor surgical procedures—can significantly increase patient survival rates. This project presents an automated melanoma screening system that leverages deep learning, specifically a fine-tuned VGG16 Convolutional Neural Network (CNN), to analyze dermoscopic images. The model is trained on a large and diverse dataset from the International Skin Imaging Collaboration (ISIC), enabling it to effectively capture fine-grained features and patterns associated with melanoma. By integrating both lesion localization and classification into a single, streamlined framework, the proposed system enhances diagnostic accuracy and reduces computational overhead. Experimental results demonstrate superior performance compared to traditional multi-stage approaches, highlighting the system's potential as a reliable, scalable, and clinically applicable tool for early melanoma detection.

***Keywords**: Melanoma, Skin Cancer, Dermoscopic Images, Deep Learning, VGG16, Convolutional Neural Network, Automated Diagnosis, ISIC Dataset, Skin Lesion Classification.*

I. INTRODUCTION

Skin cancer is among the most prevalent forms of cancer globally. Melanoma, although less common than other types, is considerably more dangerous and accounts for the majority of skin cancer mortalities. The key to reducing fatality is early detection, enabling minimally invasive interventions with high rates of recovery. Current diagnostic approaches rely heavily on expert assessment of dermoscopic images, which is subject to variability and resource constraints. This study investigates the impact of increasing network depth, breadth, and input resolution on CNN-based melanoma detection. We present an enhanced VGG16-based model capable of minute lesion features. Our method is evaluated on a comprehensive dataset sourced from the ISIC archive, achieving notably high precision and recall. The results affirm the model's competitiveness against state-of-the-art methods in automated melanoma diagnostics.

II. RELATED WORK

The ground breaking study demonstrates that deep convolutional neural networks (CNNs) can achieve dermatologist-level performance in diagnosing skin cancer.

The model, based on the Inception v3 architecture, was trained on over 129,000 clinical images. It achieved high sensitivity and specificity, rivaling human experts. The study underscores the power of deep learning in medical diagnostics and laid a foundational benchmark for future AIdriven dermatology tools.[1]

An ensemble of CNN architectures trained on dermoscopic images to detect melanoma. By combining the predictions from various deep learning models, the ensemble approach improved robustness and classification accuracy. It also introduced advanced fusion techniques, which proved effective in dealing with diverse and imbalanced skin lesion datasets, making it a strong reference for ensemble-based detection strategies.[2]

The study highlights the synergistic benefits of human-AI collaboration. Dermatologists were provided with CNNgenerated diagnostic suggestions while assessing dermoscopic images. Results showed a marked improvement in diagnostic accuracy when human experts utilized

AI assistance. This paper is significant in demonstrating that AI tools can complement rather than replace human judgment in clinical environments.[3]

The research compares the performance of a CNN trained on dermatoscopic images to that of 58 board-certified dermatologists.
The CNN performed comparably in melanoma classification tasks, highlighting its diagnostic potential. The paper supports the idea of using deep learning models as a reliable second opinion or primary screening tool in clinical practice.[4]

Liu et al. developed a large-scale deep learning system capable of differentiating among over 26 common skin conditions, including melanoma. Trained on 16,000 patient cases, the model used clinical images and metadata to produce differential diagnoses. Its strong generalization across diverse populations demonstrated the scalability and inclusiveness of AI in dermatological diagnostics.[5]

The large-scale reader study pits a deep CNN against 58 dermatologists in classifying dermoscopic images. The CNN outperformed most participants, particularly in challenging melanoma cases. The findings support the deployment of deep learning systems in teledermatology and early skin cancer detection, especially in underserved or remote areas.[6]

The paper introduces a method of fusing features extracted from multiple fine-tuned CNN models such as VGG and Dense Net. The fusion strategy enhanced performance and robustness, especially on imbalanced datasets. This work shows how model diversity and feature integration can improve lesion classification accuracy and reduce model bias.[7]

Yu et al. applied very deep residual networks (ResNet) to classify melanoma from dermoscopic images. The paper showcases the benefits of residual learning, allowing networks to go deeper without vanishing gradients. The proposed model achieved state-of-the-art results and demonstrated the effectiveness of deep residual architectures in capturing finegrained lesion features.[8]

III. METHODOLGY

3.1 Skin Lesion Image Collection and Preprocessing

Purpose: To gather high-quality skin lesion images and prepare them for CNN model training.
Functionality : The dermoscopic image dataset used in this study is sourced from the ISIC (International Skin Imaging Collaboration) archive and supplemented by additional publicly available medical datasets. Images are resized to a fixed dimension of 224×224 to align with the input requirements of the VGG16 model.

3.2 Dataset Annotation and Splitting

Purpose: To accurately label each image and create suitable training and testing subsets.
Functionality: Each image is labeled as either benign or malignant, based on dermatologist-confirmed annotations. The data is then randomly divided into training (80%) and testing (20%) subsets. Stratified sampling ensures balanced representation across classes. Data augmentation is applied to increase training diversity through rotation, zooming, horizontal/vertical flipping, and brightness adjustments to reduce overfitting.

3.3 CNN Model Implementation (VGG16)

Purpose: To perform automated melanoma classification based on image inputs. Functionality: The VGG16 model is chosen due to its deep layered structure and proven success in medical image classification. The pre-trained VGG16 is fine-tuned by removing the top layers and adding custom dense layers with ReLU and Softmax activations. The final layer classifies lesions into two classes (malignant or benign). The model is compiled using binary cross-entropy as the loss function and optimized using the Adam optimizer. Transfer learning enables leveraging pre- trained weights while adapting to the melanoma dataset.

3.4 Web Interface and Image Upload

Purpose: To provide a simplified webbased interface for uploading skin lesion images and receiving classification results.
Functionality: A flask based web application

allows healthcare providers to upload lesion images, which are sent to the backend for preprocessing and prediction. The interface also displays the predicted class and confidence level. A history of uploaded images and their diagnosis is maintained for analysis and reference.

3.5 Backend Prediction and Inference Pipeline

Purpose: To handle the complete processing and classification of input images.

Functionality: The backend system performs tasks including loading the trained model, preprocessing uploaded images, performing inference, and returning predictions. Numpy and OpenCV are used for image manipulation, while TensorFlow/Keras handles model inference. Results are processed in real time and logged for validation.

IV. TECHNOLOGIES USED

4.1 Deep Learning Framework and Model Architecture

The core machine learning model is implemented using TensorFlow and the Keras API, which provide high-level abstraction for building and deploying deep learning models. The architecture chosen is VGG16, a pre-trained convolutional neural network known for its depth and ability to extract fine-grained spatial features. The model is fine-tuned on dermoscopic image data to differentiate between benign and malignant lesions.

4.2 Image Preprocessing Image preprocessing is critical for enhancing feature quality and reducing noise in medical images. Tools such as OpenCV, Pillow (PIL), and NumPy are used to resize all images to 224×224 pixels, normalize pixel values, and remove artifacts like hair using morphological operations and filters. Histogram equalization is applied to improve contrast, and grayscale conversion simplifies feature detection. To increase the robustness of the model and reduce overfitting, augmentation techniques such as random rotation, zoom, flipping, brightness shifts, and cropping are applied using TensorFlow's
ImageDataGenerator.

4.3 Data Handling and Processing

Data manipulation, annotation, and analysis are facilitated by Pandas and NumPy, which help in organizing metadata, creating train-test splits, and managing batch processing. Evaluation of machine learning baselines is done using scikit-learn, which provides utilities for calculating performance metrics like accuracy, precision, recall, F1-score, and ROC-AUC. Data loaders and generators are custom-built to feed image batches to the neural network during training and validation.

4.4 Storage and Authentication The application uses SQLite, a lightweight embedded database, for storing user credentials, upload logs, and prediction results. It is interfaced through SQLAlchemy, which simplifies query execution and table management. FlaskLogin is used to implement user authentication, providing secure login sessions and role-based access control to the web portal.

4.5 Model Evaluation and Validation Model performance is continuously monitored using training/validation accuracy curves and loss metrics. Confusion matrices, ROC curves, and classification reports are generated to assess model robustness and sensitivity to class imbalance. K-Fold cross-validation is used to ensure that the model generalizes well across diverse image samples and to detect potential overfitting. Visualization tools like Matplotlib and Seaborn are used to plot evaluation graphs and provide insights into model behavior during training.

V. RESULT

The proposed melanoma screening system using the VGG-16 Convolutional Neural Network demonstrates significant improvements in the early detection of skin cancer. By utilizing a dataset of 3,297 dermoscopic images labeled as benign or malignant and preprocessed into 224x224 pixel RGB arrays, the model was able to effectively learn and classify skin lesions with high accuracy. Unlike previous systems that relied on separate networks for segmentation and classification, this approach integrates the entire process, resulting in improved performance and efficiency. The use of deep learning, particularly the VGG-16 architecture, enables the extraction of fine-grained features essential for accurate melanoma detection. Experimental evaluations on publicly available datasets confirm that the model outperforms traditional methods, supporting its potential use in clinical environments as a reliable computer-aided diagnosis tool. Overall, the system offers a promising solution to reduce mortality by enabling early and accurate skin cancer screening.

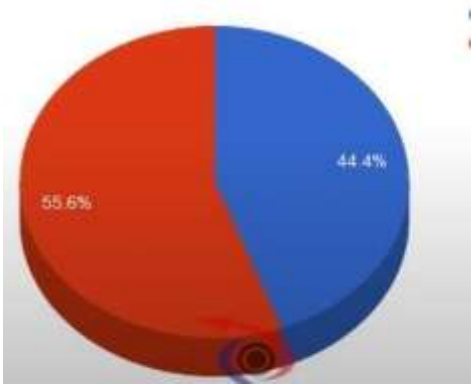

Fig : 5.1

VI. CONCLUSION

This study presents End-to-End melanoma screening framework utilizing a fine-tuned VGG16 CNN. By consolidating pre- processing, training, and inference within a single architecture, our approach simplifies clinical application while achieving high diagnostic accuracy. The encouraging results suggest practical utility in dermatological screening. Future work will focus on expanding the dataset, integrating lesion segmentation, and adapting the model for real-time mobile diagnostics.

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