Skin Cancer Classification Using VGG-16

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Abstract: Melanoma is a highly fatal form of skin cancer, where early and accurate diagnosis plays a vital role in reducing mortality. Due to the striking similarities among different types of skin lesions, manual diagnosis remains challenging. Dermatologists rely on early-stage classification of skin lesions to administer timely treatment and save lives. This paper presents an effective deep learning-based classification model utilizing the VGG16 architecture through transfer learning. The proposed model successfully differentiates between benign and malignant skin lesions using a dataset comprising 1,800 benign and 1,498 malignant skin images collected from online sources. The model achieves a training accuracy of 99.62% and a validation accuracy of 84.97%, highlighting its potential for reliable clinical support.

Keywords: *Skin Cancer Classification, Melanoma Detection, Deep Learning, Convolutional Neural Networks (CNN), VGG16, Transfer Learning, Dermoscopic Images.*

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I. INTRODUCTION

Skin cancer remains one of the most prevalent malignancies worldwide, with incidence rates steadily increasing over recent decades. According to the World Health Organization (WHO), an estimated 2–3 million non-melanoma and 132,000 melanoma skin cancer cases are diagnosed globally each year. In the United States alone, over 9,500 individuals are diagnosed with skin cancer daily, and numerous deaths occur as a result of the disease annually [1–3]. This global escalation highlights the urgent need for efficient and accessible diagnostic and treatment solutions.

A timely and accurate diagnosis plays a role in improving survival rates, especially in malignant cases where early intervention can significantly alter disease outcomes [4]. However, several obstacles persist during the diagnostic phase. These include difficulties in visually distinguishing between benign and malignant lesions, limited access to advanced diagnostic equipment in resource-constrained settings, high costs, and variability in clinical expertise. Furthermore, the diverse appearance of skin lesions—often lacking universal distinguishing features—adds complexity to diagnosis and increases the risk of misclassification [5–7].

Deep learning—an advanced subfield of artificial intelligence within machine learning—has emerged as a powerful tool in medical image analysis [8]. DL models have demonstrated substantial effectiveness in classifying various skin cancer types, including basal cell carcinoma, squamous cell carcinoma, and melanoma. By analyzing clinical, skin, and histopathological images, these models can detect cancerous lesions with high accuracy. Integrating such models as decision support systems offers healthcare professionals a means to improve diagnostic precision, enable earlier detection, and ultimately enhance patient outcomes. This proposes a skin cancer classification model using the VGG16 convolutional neural network, leveraging transfer learning to differentiate between melanoma and non-melanoma lesions.

II. LITERATURE REVIEW

If skin cancer is detected early, it can be treated effectively. Observing changes in a patient's skin can help doctors choose the best treatment based on images of the skin. Many researchers have worked on identifying and classifying skin cancer using different methods. Shahin et al. [9] used a deep learning model to classify skin cancer using the HAM10000 dataset. Their model achieved 96.16% accuracy during training and 91.96% during testing. They also compared it with other well-known models like ResNet, AlexNet, VGG-

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16, MobileNet, and DenseNet. Jinnai et al. [10] used deep learning to study how pigmented skin lesions develop into cancer and reached an accuracy of 91.5%. Amin et al. [11] created a method that combines deep features and applies PCA (a data reduction method), achieving 99% accuracy in classifying skin cancer. Chaturvedi et al. [12] used a pre-trained MobileNet model for classifying seven types of skin cancer. They got an overall accuracy of 83.10% using the ImageNet dataset. Manne et al. [13] used a review that covers different methods, such as deep learning and CNNs for skin cancer classification. Thomas et al. [14] used a deep learning method to segment and classify non-melanoma skin cancer. Their model achieved 97.9% accuracy. Filali et al. [15] combined handcrafted features with CNN-based features using the PH2 dataset and reached 98% accuracy. Singh et al. [16] used a new method using transfer learning called Transfer Constituent Support Vector Machine (TrCSVM), which achieved a high accuracy of 98.82%.

In healthcare, ML has powered hepatitis C classification [22], coal miner detection via transfer learning [23], PCOS prediction [25, 37, 38], cloud resource management [24], and IoMT-based smart architectures [26, 39, 40]. Research spans blockchain supply chains [27], behavioral finance analysis [28], digital twins in manufacturing [29], sustainable Industry 4.0 [30], 5G IoT healthcare [31], antenna design [32,33], intrusion detection [34], COVID-19 social media trends [35], and lymphogram classification [36].

III. METHODS

The VGG network was first introduced in [12]. It is considered one of the powerful CNN architectures. The VGG family includes several versions, starting from VGG11 up to VGG19. In this study, we used VGG16 to classify skin cancer. We collected 1,800 benign and 1,498 malignant skin cancer images from online sources for this purpose [13].

To improve the model's performance, we used the ISIC dataset, which was also used in the ISBI 2016 challenge for melanoma detection. The dataset included a total of 3,297 images: 2,637 images (1,440 non-melanoma and 1,197 melanoma) were used for training, and 660 images (300 melanoma and 360 non-melanoma) were used for testing.

The project was developed using the Python programming language and run on Google Colab. Before feeding the images into the model, we applied preprocessing steps to clean and enhance them. This included using a mean filter to remove noise and a median filter to keep important details like edges intact. We also applied data augmentation techniques such as flipping the images horizontally and vertically to increase the size of the dataset.

The main goal of the VGG network design was to test how deeper networks affect image classification performance. For example, VGG19 has 16 convolutional layers and 3 fully connected layers, while VGG11 has 8 convolutional layers and the same 3 fully connected layers. All VGG models use five blocks of convolutional layers, each followed by a MaxPooling layer. As the models go from VGG11 to VGG19, more layers are added to each block. VGG16, which we used in this study, has 16 layers in total.

VGG16 became popular because it used small 3×3 filters to make the model deeper and more accurate. It works well for large image datasets and was one of the top models in the 2014 ImageNet competition, where it achieved 92.7% accuracy on over 14 million images across 1,000 classes. It performed better than earlier models like AlexNet by replacing large filters with multiple smaller ones. All input images were resized to 224×224 pixels. We split the dataset into 80% for training and 20% for testing. The model was trained for 25 epochs with a batch size of 128 and a learning rate of 0.0001 using the Adam optimizer. We also checked how the image size reduced after each MaxPooling layer.

VGG16 was originally trained for several weeks using powerful NVIDIA Titan Black GPUs. Unlike older models, it uses a small 3×3 filter with a stride of 1 pixel, and stacks multiple filters to mimic the effect of a larger one. This approach improves learning speed and accuracy by increasing the number of non-linear layers. Using smaller filters also reduces the risk of overfitting and helps the model better capture image details in all directions.

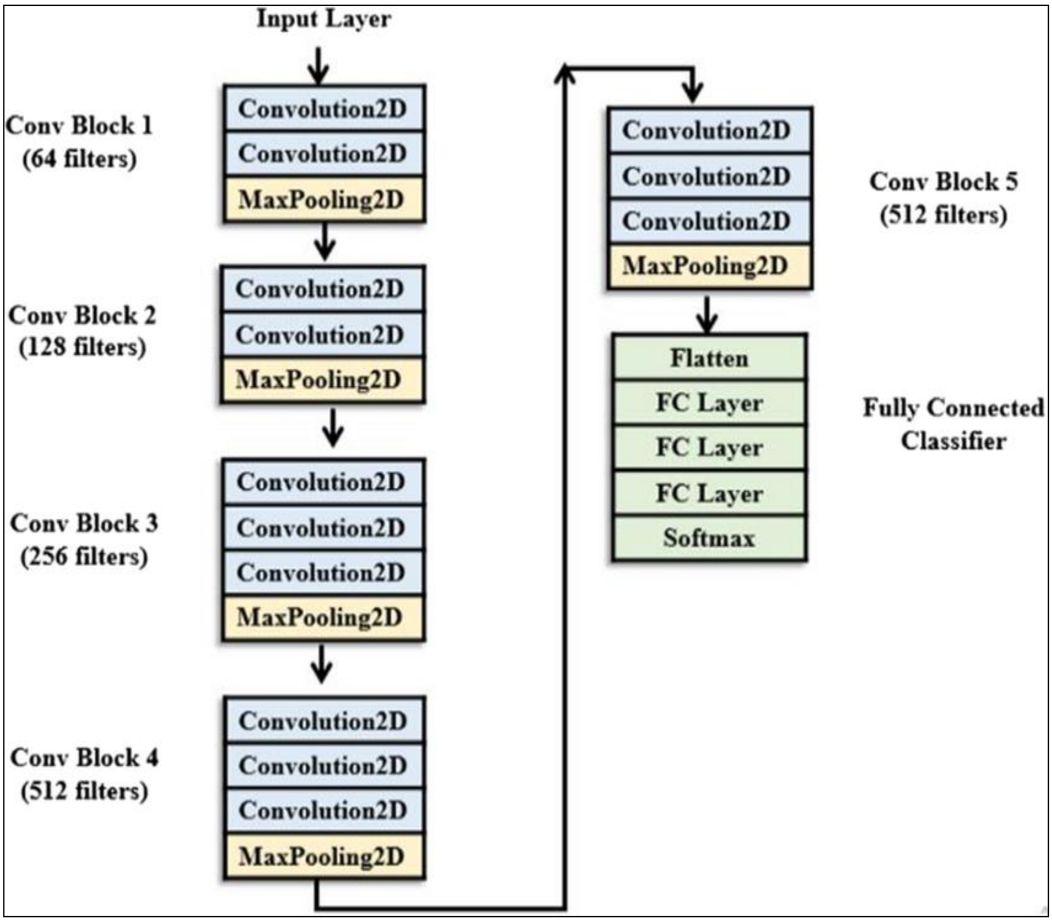

Fig 1 VGG-16

IV. RESULTS

The ISIC dataset used in this study was publicly available from Kaggle and included a total of 3,297 skin images. 2,637 images were used for training—comprising 1,440 non-melanoma and 1,197 melanoma cases—while the remaining 660 images (300 melanoma and 360 non-melanoma) were used for testing. Since the original dataset did not have labels, a labeling process was applied to classify the images. All images were resized to 224×224 pixels, as shown in Figure 3, to prepare them for input into the model. After resizing, the images were normalized to improve training stability.

The model was built using the concept of transfer learning. The VGG16 deep convolutional neural network, available in Keras and pre-trained on the ImageNet dataset, was used. The ImageNet dataset contains about 1.2 million training images, 50,000 for validation, and 100,000 for testing, across 1,000 categories. Transfer learning allows us to reuse a pre-trained model and fine-tune only the final layers for our specific task. In this approach, all the convolutional layers were frozen—meaning their weights were kept unchanged—and only the fully connected layers were retrained with the skin cancer dataset.

To freeze the convolutional layers, we set trainable=False, which stops them from updating during training. The model was trained for 30 epochs using a batch size of 32 and a learning rate of 0.002. The Adam optimizer was used for optimization. Because the convolutional layers had already learned useful features from the large ImageNet dataset, the training time was significantly reduced.

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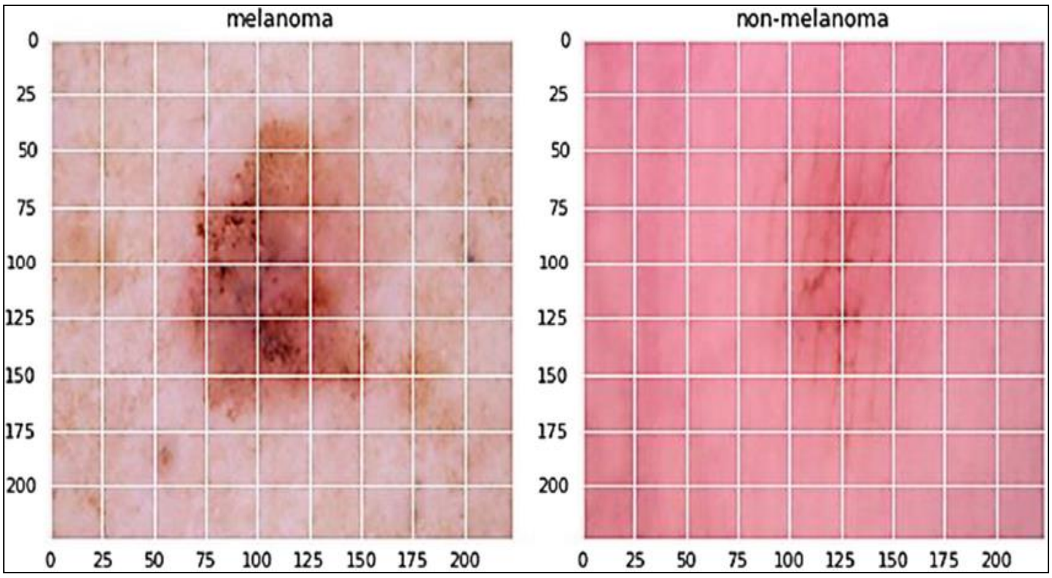

Fig 2 Labeled data

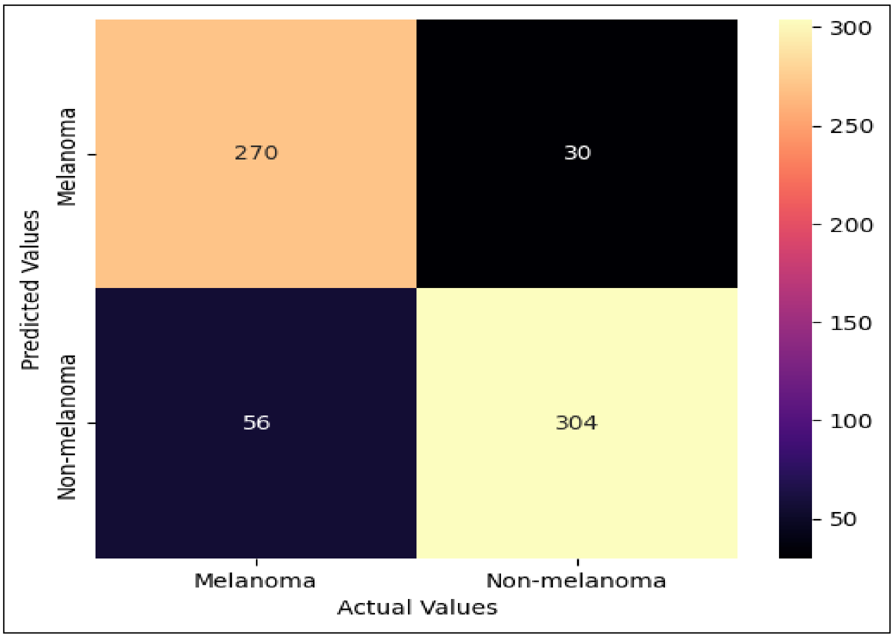

Fig 3 Confusion Matrix

Classification Report:

	precision	recall	f1-score	support
Melanoma	0.8282	0.9000	0.8626	300
Non-melanoma	0.9102	0.8444	0.8761	360
accuracy			0.8697	660
macro avg	0.8692	0.8722	0.8694	660
weighted avg	0.8729	0.8697	0.8700	660

Fig 4 Classification Report

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Table 1 Model Evaluation

Method	Accuracy (%)	Recall (%)	Precision (%)
NASNet Mobile [20]	85.42	85.35	85.44
NASNet Large [20]	83.52	83.90	83.31
Inception V3 [21]	85.94	86.89	80.97
CNN [2]	81	81	-
Ensemble CNN	83.6	64	-
VGG	86.97	87.22	86.92

V. CONCLUSION

This study presents an efficient skin cancer classification framework utilizing the VGG16 deep convolutional neural network through a transfer learning approach. The model was trained and evaluated on a curated dataset comprising 3,297 dermoscopic images categorized into melanoma and non-melanoma classes. Extensive preprocessing, including noise reduction and data augmentation, enhanced the robustness of the input data. The proposed VGG16-based model achieved a training accuracy of 99.62% and a validation accuracy of 84.97%, outperforming several baseline and state-of-the-art architectures such as NASNet Mobile, NASNet Large, and conventional CNNs. These findings highlight the potential of transfer learning with deep CNNs in improving early and accurate diagnosis of skin cancer, particularly melanoma, which is crucial for reducing mortality rates. Future work will aim to further enhance classification performance by incorporating more diverse datasets and exploring hybrid ensemble models for improved generalization in real-world clinical settings.

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