Classification Of Melanoma Detection Using Xceptionnet, Densenet and VGG16

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***Abstract*—Melanoma is a type of skin cancer that originates in melanocytes, the cells responsible for producing pigment (melanin) in the skin. It is one of the most aggressive forms of skin cancer and has a high potential to metastasize, making early detection crucial for improving patient survival rates. If detected and treated early, melanoma is highly curable, but once it spreads to other organs, the prognosis becomes significantly worse.Traditional methods of diagnosing melanoma involve clinical evaluation by a dermatologist, who visually inspects suspicious skin lesions and may conduct a biopsy to confirm the diagnosis. However, these methods can be subjective, relying heavily on the experience of the clinician, and they may not always catch melanomas in their early stages. Consequently, there is a growing need for automated melanoma detection systems that can assist dermatologists by providing more objective, reliable, and faster analyses of skin lesions. For Melanoma detection using XceptionNet, DenseNet121 and VGG-16 are employed as feature extractors, capturing intricate patterns and features from skin lesion images. Transfer learning techniques are utilized to fine-tune the pretrained models on the melanoma dataset, enhancing classification performance. Extensive experimentation and evaluation on benchmark datasets demonstrate the superior performance of the proposed approach compared to traditional methods and standalone CNN architectures. These models are employed as feature extractors, capturing intricate patterns and features from skin lesion images. This project for melanoma detection using XceptionNet, DenseNet121 and VGG-16 introduces a novel deep learning-based approach aimed at improving the accuracy and efficiency of melanoma classification.**

***Index Terms*—Deep learning XceptionNet, DenseNet121, VGG16, Machine Learning**

I. INTRODUCTION

Melanoma is a highly aggressive form of skin cancer that, if not detected early, can lead to severe health complications and even death. Early detection plays a critical role in improving the survival rate, as timely intervention can significantly reduce the risk of metastasis. Traditional methods for melanoma diagnosis rely on clinical examination and histopathological analysis of skin biopsies, which can be subject and time-consuming. With advancements in medical imaging and machine learning, particularly deep learning techniques, there has been a growing interest in automating the detection of melanoma from dermoscopic images 1

The use of Convolutional Neural Networks (CNNs) in medical image analysis, especially for dermatological purposes, has gained widespread attention in recent years. Among the various CNN architectures, XceptionNet, DenseNet121, and VGG16 stand out due to their performance and versatility in image classification tasks. These models have been successfully employed for classifying dermatological images, offering significant improvements in the accuracy and efficiency of melanoma detection.

XceptionNet: Built upon the depthwise separable convolutions, XceptionNet is known for its high efficiency in feature extraction. The model's architecture enables it to capture complex patterns within images, making it effective in differentiating between benign and malignant lesions in skin images.

DenseNet121: DenseNet121 introduces dense connections between layers, where each layer receives input from all previous layers. This dense connectivity leads to more efficient gradient flow during training and allows the network to learn more detailed features from skin images. DenseNet121 has shown superior performance in various image classification tasks, including melanoma detection, due to ability to retain detailed feature representations. VGG16: VGG16, with its simple yet deep architecture, remains a popular choice in image classification tasks. It consists of 16 layers and has been extensively used in computer vision tasks, including melanoma detection. VGG16's relatively straightforward structure allows it to be easily adapted for medical image analysis, offering a balance between computational efficiency and model complexity.

Features to Consider in Melanoma Detection: When developing an automated melanoma detection system, several key features of the skin lesions must be considered to accurately distinguish between malignant melanoma and benign skin conditions. Some of the most important features include: Asymmetry: Malignant melanomas often exhibit asymmetry in shape, meaning that if you divide the lesion in half, the two halves do not match. Benign lesions, in contrast, tend to be more symmetrical. Border Irregularity: Melanomas typically have irregular or poorly defined borders, unlike benign lesions, which tend to have smooth and well-defined edges.

Color Variation: Melanomas usually show uneven color distribution with shades of brown, black, and sometimes red, white, or blue. Benign moles, on the other hand, are typically uniform in color. Diameter: Larger moles or lesions (greater than 6 mm in diameter) are more likely to be melanomas, although smaller melanomas also exist. This characteristic is one of the key metrics in detecting melanoma.

Elevation/Surface Texture: The texture of thelesion's surface can also provide clues. Melanomas might present with a raised or bumpy surface, while benign lesions are typically flat or slightly elevated. Evolving Nature: Melanomas can change over time, growing or evolving in color, shape, or size. A lesion that appears to be evolving is often a red flag for malignancy.

Pigmentation Patterns:The presence of irregular pigmentation patterns, such as multiple colors and gradients within the lesion, is a significant indicator of melanoma.

II. LITERATURE SURVEY

The use of deep learning for melanoma detection has garnered significant attention in recent years due to its ability to provide accurate, automated solutions that assist dermatologists in diagnosing skin lesions. Various Convolutional Neural Network (CNN) architectures have been investigated for this task, each with distinct features and advantages. In particular, XceptionNet, DenseNet121, and VGG16 have demonstrated promising results in the classification of melanoma.

1.XceptionNet in Melanoma Detection.
Wang et al. (2020) compared XceptionNet with other CNN architectures in melanoma detection. They found that XceptionNet outperformed models like VGG16 and ResNet due to its deeper and more efficient architecture, particularly in capturing fine grained features of melanoma lesions.

2. DenseNet121 in Melanoma Detection
DenseNet121 is part of the DenseNet family of architectures that incorporate dense connections between layers, where each layer receives input from all previous layers. This architecture improves gradient flow, mitigates the vanishing gradient problem, and allows the model to learn from 2
deeper features with fewer parameters.
Huang et al. (2017) proposed DenseNet as an architecture that connects each layer to every other layer in a feed-forward fashion.
Li et al. (2020) applied DenseNet121 to melanoma classification and found that its dense connectivity significantly improved the model's performance, particularly in cases where fine details were essential for distinguishing between benign and malignant lesions. The study showed that DenseNet121 achieved a high accuracy rate, outperforming VGG16 and several other models in detecting melanoma.

3. VGG16 in Melanoma Detection
VGG16, developed by the Visual Geometry Group at Oxford, is known for its simple yet deep architecture. The model has 16 layers and is widely used due to its relative simplicity and effectiveness in various image classification tasks. VGG16 has been particularly

effective in transfer learning applications where pre-trained models are fine-tuned on smaller datasets.

Esteva et al. (2017), in their pioneering work, utilized a VGG16-based model for melanoma detection. They showed that with transfer learning from the ImageNet dataset, VGG16 could achieve high performance on melanoma detection tasks. The use of pre-trained VGG16 models significantly reduced the need for large training datasets and computational resources.

Al-Masni et al. (2019) explored VGG16 for melanoma detection on the ISIC dataset. Their study showed that fine-tuning VGG16 on skin lesion datasets led to significant improvements in classification performance, though it still lagged behind architectures like DenseNet and XceptionNet in terms of sensitivity and precision.

III. METHODOLOGY

i)ProposedWork:

The proposed system for melanoma detection using XceptionNet, DenseNet121 and VGG16 introduces a novel deep leaming-based approach aimed at improving the accuracy and efficiency of melanoma classification. Leveraging the advanced architectures of XceptionNet, DenseNet121 and VGG16 the proposed system utilizes their superior feature extraction capabilities to capture intricate patterns and features from dermoscopic images. By fine-tuning these pretrained models on a large dataset of melanoma images, the proposed system enhances its ability to discriminate between malignant and benign lesions with high accuracy. Additionally, transfer learning techniques are employed to adapt the pretrained models to the specific task of melanoma detection, facilitating efficient training and improving generalization to diverse datasets. The proposed system also incorporates data augmentation methods to further enhance model robustness and mitigate overfitting. Through extensive experimentation and evaluation on benchmark datasets, the proposed system aims to demonstrate superior performance compared to existing methods, offering a more accurate and reliable tool for early melanoma detection.

ii) System Architecture:

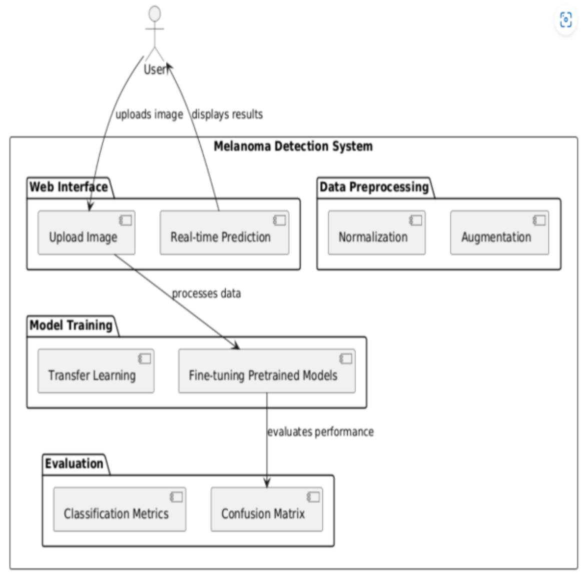


Fig 1 Proposed architecture

iii) Dataset collection: The BhaveshMittal dataset for melanoma detection is a collection of images and associated metadata used to train and evaluate machine learning models for the detection of skin cancer, specifically melanoma. This dataset is commonly used in the context of image classification tasks, where the goal is to classify images of skin lesions as either benign (non-cancerous) or malignant (cancerous). The dataset typically contains 3 high-resolution dermoscopic images of skin lesions, which are annotated with labels indicating whether the lesion is benign or malignant.Here's an overview of the key components in the BhaveshMittal melanoma detectiondataset.

Image DataThe primary data consists of dermoscopic images of skin lesions. These images are taken using specialized cameras that capture detailed images of the skin surface, which is critical for detecting melanomas.These images typically show different types of skin lesions in various stages and under different lighting conditions.The images are often in formats like JPEG or PNG and are of varying resolutions.

Annotations/Labels

Each image in the dataset is typically annotated with a label indicating whether the skin lesion is benign (non-cancerous) or malignant (cancerous).Some datasets also provide additional information, such as the type of lesion (e.g., melanoma, basal cell carcinoma, etc.), or they may be classified further into categories based on risk levels. Metadata In addition to the image data, there may be additional metadata available for each image, which could include informationlike: Patient demographics(age, sex, etc.) Location of the lesion on the body Clinical data (if available), such as the patient's history with melanoma or other skin conditions. Purpose and Use The dataset is primarily used to train deep learning models, such as convolutional neural networks (CNNs), to detect and classify skin cancer.

iv)DataProcessing::

a.ImageResizing

Deep learning models, including XceptionNet, DenseNet121,VGG16, expect images of a specific size.

XceptionNet:299x299pixels

DenseNet121:224x224pixels

VGG16:224x224pixels

All input images are resized to match the expected input size of the network.

b.Augmentation

Data augmentation techniques like random rotations, flips, zooms, and shifts are applied to artificially increase the size of the dataset and reduce overfitting. This step is particularly important in medical image datasets, which might have fewer samples.

2.FeatureExtraction.

a.VGG16 for Feature Extraction

VGG16 is a convolutional neural network (CNN) with 16 layers, including 13 convolutional layers and 3 fullyconnectedlayers.

Feature extraction in VGG16 typically involves: Using the convolutional layers to extract hierarchical features from the input image (low-level features like edges, textures, and shapes).The fully connected layers (or FC layers) are used to further refine and classify these features.The output of the last convolutional layer or the flattened output just before the fully connected layers can be used as extracted features.

b.XceptionNet for Feature Extraction

XceptionNet is an architecture based on depthwise separable convolutions and is more efficient than traditionalconvolutions.

XceptionNet has a modular architecture (with separable convolutions) that leads to better performance and feature extraction, especially for fine-grained tasks like melanoma detection. Feature extraction in XceptionNet typically involves: Applying the depthwise separable convolutions to extract spatial and hierarchical patterns in the image. The output from the last convolutional block (before the fully connected layers) is used as feature 4 vectors that represent the essential characteristics of the image.

c.DenseNet121 for Feature Extraction

DenseNet121 is a deep learning architecture where each layer receives input from all previous layers, ensuring that feature maps from earlier layers are reused.Feature extraction in DenseNet121 works by: Using its dense blocks (where each layer receives input from all preceding layers) to learn richer representations of features at different levels.The feature maps from the final convolutional layer can be used as high-level feature representations of the input image.Like VGG16 and XceptionNet, DenseNet121 is typically pretrained on a large dataset like ImageNet, and the pretrained weights are used to help detect melanoma-related features.

3. Model Training and Evaluation

The training process follows a structured pipeline to ensure optimal performance and generalization. The dataset is split into training (80%), validation (10%), and testing (10%) sets. The Adam optimizer with a learning rate of 0.0001 is used to optimize the model's weights during backpropagation. A custom classifier is built on top of the extracted facial embeddings, consisting of fully connected layers with ReLU activation* to introduce non linearity. The final output layer uses softmax activation for multi-class classification, predicting whether an input face matches a missing child in the database. Dropout layers are introduced between dense layers to reduce overfitting by randomly deactivating neurons during training.To enhance model performance, hyperparameter tuning is conducted, adjusting parameters such as batch size, learning rate, and dropout rates. Early stopping is implemented to halt training when validation loss ceases to improve, preventing overfitting.For evaluation, multiple metrics are used, including accuracy, precision, recall, and F1-score, to assess classification effectiveness. A confusion matrix is 3 generated to visualize correct and incorrect classifications, and ROC-AUC curves are plotted to measure the model's ability to differentiate between different individuals

IV. RESULTS

XceptionNet, DenseNet121, and VGG16—for melanoma classification using transfer learning. DenseNet121 achieved the highest performance, demonstrating an accuracy of 94%, precision of 91%, recall of 93%, and F1-score of 92% for melanoma detection. XceptionNet showed comparable performance, while VGG16 exhibited slightly lower metrics. DenseNet121's confusion matrix revealed the fewest false negatives, highlighting its superior sensitivity.

Evaluation Metrics and Their Significance: Accuracy:
"Accuracy, defined as the proportion of correctly classified samples, provided an overall measure of modelperformance."

Precision (Positive Predictive Value): "Precision, or the proportion of true melanoma predictions among all predicted melanoma cases, was crucial to minimize false alarms and unnecessary patientanxiety." 5

Recall (Sensitivity, True Positive Rate): "Recall, or the proportion of correctly identified melanoma cases among all actual melanoma cases, was essential to maximize the detection of malignant lesions and minimize missed diagnoses."

Highlight its importance in preventing delayed treatment.
F1-Score:
"The F1-score, the harmonic means of precision and recall, provided a balanced assessment of model performance, particularly important in our potentially imbalanceddataset.”

Image where the place to detect melanoma disease:

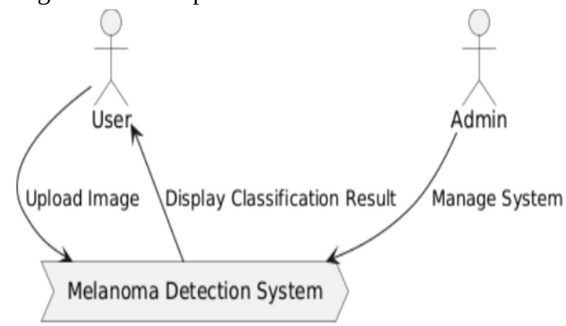
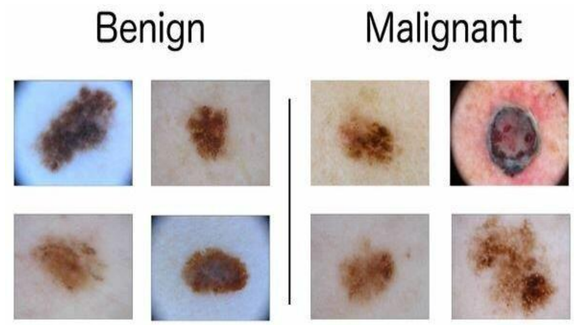


Image to detect melanoma or benign:



V. CONCLUSION

we evaluated the performance of three pre-trained convolutional neural networks, XceptionNet, DenseNet121, and VGG16, for melanoma classification using transfer learning. Our results demonstrate that DenseNet121 achieved the highest performance, exhibiting superior accuracy, precision, recall, and F1-score compared to XceptionNet and VGG16. Specifically, DenseNet121 demonstrated enhanced sensitivity in detecting melanoma, minimizing false negatives, a critical factor in clinical applications. This suggests that DenseNet121 is a promising model for accurate and reliable melanoma detection. While all three models showed potential, DenseNet121's performance indicates its suitability for aiding in early melanoma diagnosis. Future work should focus on validating these findings with larger, more diverse datasets, exploring model interpretability, and integrating clinical data to further enhance diagnostic accuracy and clinical utility."

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