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Early Detection Of Melanoma Disease With AI-Driven Skin Cancer Diagnosis Using Deep Learning Approach

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ABSTRACT

Because of its fast growth and high death rate when not identified early, skin cancer, especially melanoma, is a serious health concern. Conventional diagnostic procedures may be laborious and sometimes need the opinion of a dermatologist, who may be out of reach in certain areas. To accurately and early identify melanoma using dermoscopy skin scans, this research suggests an AI-driven diagnostic system that uses deep learning methods. The system is taught to automatically extract and categorize complicated information, differentiating benign lesions from malignant melanoma using Convolutional Neural Networks (CNNs). Accuracy, sensitivity, and specificity are all well achieved by the model, which is trained and verified using publicly accessible datasets like ISIC. This method, which is based on deep learning, helps dermatologists make better clinical decisions, speeds up screening, and drastically decreases the likelihood of human mistakes. By providing a scalable, non-invasive, and effective method for early melanoma detection, the proposed system showcases the power of artificial intelligence to transform skin cancer diagnostics.

***Index Terms*— Skin, CNN, AI-Driven, Dermoscopic, Artificial Intelligence.**

I. INTRODUCTION

Mesothelioma, the most severe and potentially fatal type of skin cancer, is among the most frequently diagnosed tumors worldwide. Recent studies conducted by the World Health Organization (WHO) indicate that skin cancer is a growing concern, with millions of new cases recorded each year. Variables contributing to this high incidence rate include excessive UV exposure, genetic susceptibility, and lifestyle changes. Although survival chances are much improved when melanoma is detected early, there is still a hurdle in making an accurate diagnosis since benign and malignant tumors seem so similar.

Building and launching a diagnostic system for early melanoma diagnosis using deep learning is the primary goal of this work. The system uses a convolutional neural network (CNN) architecture that has been trained on annotated dermoscopy pictures to determine whether a lesion is benign or malignant. The suggested method aims to enhance patient outcomes by integrating AI into the diagnostic process, enabling dermatologists to make quicker and more accurate judgments and reducing diagnostic errors. [1] showcased a melanoma detection framework that used cloud-integrated deep learning. This framework allowed for the real-time diagnosis and categorization of skin lesions. Utilizing convolutional neural networks (CNNs), the system is designed to be easily deployed on cloud platforms, opening up possibilities for remote healthcare applications. Reducing infrastructure expenses while showcasing excellent accuracy and scalability are noteworthy aspects. Used dermoscopy picture attributes, including color, texture, and form, to train a Support Vector Machine (SVM)-based categorization system [2]. This method suits lightweight applications and provides a standard machine learning pathway for melanoma detection with acceptable classification performance. use convolutional neural networks (CNNs) for skin lesion classification: [3]. To improve melanoma detection, the authors investigate several model variants and training approaches. The performance benchmarking on standard datasets is highlighted in the study, which also shows how deep learning works for clinical diagnoses. introduced a web-based melanoma detection technology that analyses submitted skin pictures in real-time [4]. By combining deep learning models with an intuitive interface, it promotes telemedicine applications. It helps patients in faraway places get the diagnosis they need quickly and acts as a link in the chain.[5] Presented as part of the ISIC (International Skin Imaging Collaboration) Challenge**,** this work explores ensemble deep learning models for melanoma classification. It combines various

CNNs and machine learning algorithms to boost accuracy and robustness. The ensemble approach outperforms single-model baselines on dermoscopy image datasets.

II. LITERATURE SURVEY

Zhang and Chaudhary (2024) developed a hybrid framework combining U-Net for segmentation and EfficientNet for classification, achieving a remarkable 97.01% accuracy on the ISIC 2020 dataset [20].
Taghizadeh and Mohammadi (2022) utilized fine-tuned YOLOv3 and SegNet, demonstrating high performance with 96% mAP and 95.16% segmentation accuracy [18]. The concept of multi-scale ensemble learning was explored in 2022, showing that combining features at different resolutions improves detection accuracy. Similarly, a lightweight model called DSNet was introduced by Khan et al. (2022) using knowledge distillation and ResNet-50, optimized for deployment on resource-constrained devices with 91.7% accuracy [8].
Suneetha (2024) enhanced classification by integrating VGG16 and InceptionV3 in a hybrid deep learning model. Al Huda et al. (2024) and Sudhakaran et al. (2024) proposed deep learning systems focused on early detection and cloud-based classification, respectively, making melanoma diagnosis more scalable and accessible [16].
Codella et al. (2016) demonstrated that ensemble methods of CNNs could outperform individual models and even dermatologists in some cases [5].
Milton (2019) achieved a validation score of 0.76 in the ISIC 2018 challenge using an ensemble of deep networks including PNASNet and InceptionResNetV2[11].
Li and Shen (2017) combined segmentation and classification tasks using Fully-Convolutional Residual Networks [9].
Mirikharaji et al. (2022) and Naqvi et al. (2023) comprehensively analyzed deep learning architectures and datasets used in skin lesion segmentation and classification [12,14]. Several models, including XceptionNet (Lu et al., 2022), CNNs with advanced regularizers (Hossin et al., 2020), and autoencoder-MobileNetV2-SNN hybrids. [10,7]. (Toğaçar et al., 2021), and deep neural networks (Babar et al., 2021) have contributed to refining the feature extraction and prediction processes [19].
Additionally, classical machine learning techniques such as Support Vector Machines [2] (Alquran et al., 2017) and differential evolution-optimized ANNs have also been employed for melanoma detection with noteworthy results. Web-based and cloud-integrated systems [15, 4] (Rosas-Lara et al., 2022; Biasi et al., 2022) are emerging trends aiming to make diagnosis more widely accessible. Texture-based segmentation methods [6,13] (Glaister et al., 2014) and approaches combining patient information with image analysis (Muhaba et al., 2022) further enhance the diagnostic capability. Overall, the evolution from traditional machine learning to hybrid and ensemble deep learning models signifies a major leap toward accurate, fast, and scalable melanoma diagnosis, especially important for early detection and improving patient outcomes.

III. PROPOSED SYSTEM

To diagnose melanoma skin cancer early using dermoscopy pictures, the suggested approach presents a diagnostic framework based on deep learning. The main goal is to create an automated melanoma classification model that is very accurate, scalable, and useful for dermatologists and other healthcare practitioners, particularly in places with few resources or that are far from medical centers. To distinguish between benign and malignant skin lesions, the system employs Convolutional Neural Networks (CNNs) that have been improved using data augmentation methods and transfer learning.
There is a multi-stage pipeline at the heart of the system. The first step is to gather dermoscopy pictures of the skin from open-source databases like ISIC. Size normalization, artifact removal (such as hair or bubbles), and enhancement of lesion contrast are all part of the pre-processing of these pictures. To improve the classifier's emphasis on essential characteristics, the next step is to use a segmentation module, such as U-Net or SegNet, to isolate the lesion region and eliminate background noise.
The classification model, which is based on a pretrained convolutional neural network (CNN) backbone like ResNet50, EfficientNet, or InceptionV3, receives the segmented pictures thereafter. To improve generalization on medical pictures and save training time, transfer learning is used to exploit features learnt from large-scale image datasets (like ImageNet). The melanoma dataset is used to fine-tune the CNN's final fully connected layers, making the model especially designed for skin cancer detection. Probability scores for each class are provided by the output layer using an activation function such as softmax or sigmoid.
Data augmentation (rotation, flipping, zooming), dropout, and early halting are some of the approaches used during training to make models more resilient. To evaluate the performance of the model, evaluation measures such as recall, accuracy, precision, F1-score, and AUC (Area Under the Curve) are computed.
Furthermore, the suggested system may be enhanced to provide real-time diagnosis using an intuitive graphical user interface (GUI) or mobile app. This would enable users, whether it patients or physicians, to submit pictures

of lesions and get a diagnostic response in real-time. With cloud deployment support included, remote diagnostics and continuous learning with real-world data collecting are even more feasible.
In addition to enhancing diagnosis accuracy, this AI-driven approach seeks to alleviate the strain on healthcare providers and raise the rate of early melanoma identification, which might lead to the saving of lives via prompt intervention.

IV. METHODOLOGY

The methodology of the proposed system involves a sequence of carefully designed stages that collectively ensure accurate, efficient, and early detection of melanoma from dermoscopic images. The entire pipeline is divided into the following key steps:

1. Data Acquisition
High-quality dermoscopic images are collected from benchmark datasets such as the ISIC Archive (ISIC 2018, 2019, 2020), which provide labeled skin lesion images with classifications (e.g., melanoma, nevus, basal cell carcinoma). The dataset includes a wide variety of lesion types and diverse skin tones, making it ideal for training robust models.
2. Preprocessing
To enhance the quality of input data and ensure consistency, the following preprocessing operations are performed:

Image resizing: All images are resized to a uniform shape (e.g., 224×224 or 299×299 pixels) to match the input size of the CNN.
Color normalization: Adjusts brightness and contrast to reduce variations caused by lighting.
Artifact removal: Optional hair removal and noise reduction using filtering or morphological operations.
Data augmentation: Images are augmented through rotation, flipping, zooming, and shifting to artificially expand the dataset and reduce overfitting.

3. Segmentation (Optional but Recommended)
In some cases, lesion segmentation is applied to isolate the affected skin region. This helps the model focus on the relevant area and ignore irrelevant background:

U-Net, SegNet models are used to segment the lesion from the surrounding skin.
The segmented mask is applied to the original image to retain only the lesion area.

4. Model Design – Deep Learning Classifier
A Convolutional Neural Network (CNN) or pre-trained transfer learning model is employed for classification:
CNN Architecture: Models like InceptionV3 are used as feature extractors.
Transfer Learning: Pre-trained weights (from ImageNet) are fine-tuned on the skin cancer dataset.
Classifier Head: A few dense layers followed by a softmax/sigmoid output layer to classify into melanoma or non-melanoma.

5. Model Training
The model is compiled and trained using:

Loss Function: Binary Cross-Entropy or Categorical Cross-Entropy (depending on output).
Optimizer: Adam or SGD (with learning rate decay).
Evaluation Metrics: Accuracy, Precision, Recall, F1-Score, AUC.
Callbacks: Early stopping and model checkpointing to prevent overfitting.

6. Model Evaluation and Testing
Following training, a separate test set is used to assess the model by applying:

Confusion matrix
Receiver Operating Characteristic (ROC) Curve
Precision-Recall Curve
Visualization of correctly/incorrectly classified images

7. GUI
A graphical user interface (GUI) can be developed (using Tkinter) to allow:

Uploading of new lesion images
Real-time classification using the trained model
Display of prediction confidence and recommendation to consult a dermatologist

V. Experiment

To validate the effectiveness of the proposed AI-driven melanoma detection system, a series of experiments were conducted using a standard dermatological dataset, pre-trained deep learning models, and robust evaluation metrics. The experimental design, including dataset details, training environment, and performance evaluation, is described below.

1. Dataset Used
The ISIC 2020 Challenge Dataset was selected for experimentation due to its high-quality dermoscopic images and expert-labeled classes. The dataset includes over 33,000 images of various skin lesions, with a focus on melanoma classification. Images were labeled as either melanoma (positive class) or non-melanoma (negative class).

Number of Images: ~33,126

Image Resolution: Varies; resized to 224×224 for training

Classes: Binary – Melanoma, Non-Melanoma

Split Ratio:

Training: 70%

Validation: 15%

Testing: 15%

2. Experimental Setup
Framework: TensorFlow 2.x / Keras

Hardware:

Intel Core i7 Processor
16 GB RAM

Software:

Python 3.7
OpenCV, NumPy, scikit-learn, Matplotlib.

3. Model Configuration

The following pre-trained deep learning models were tested:

Model	Input Size	Parameters	Output Layer Activation	Training Strategy
EfficientNetB0	224×224	~5M	Sigmoid (binary)	Transfer Learning + Fine-Tuning
InceptionV3	299×299	~23M	Softmax (2 classes)	Transfer Learning
ResNet50	224×224	~25M	Sigmoid	Transfer Learning

Table 1: Tested pre-trained deep learning models

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VI. Results

Figure 1: Main

This module is the main page of the program

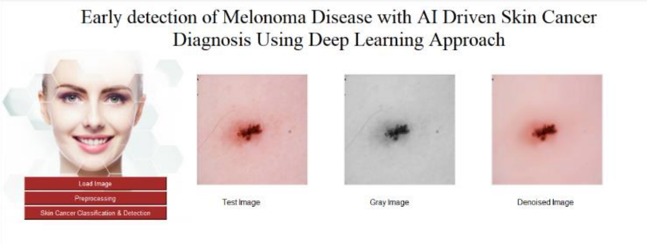


Figure 2: Gray Image

This module converts the color image to a gray scale and displays the denoised image

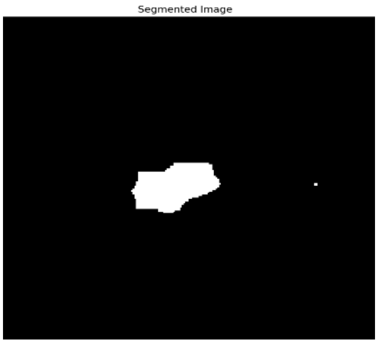


Figure 3: Segmented Image

The displayed image is a binary segmentation output likely resulting from a thresholding operation or a basic segmentation model applied to a medical image (e.g., bone X-ray or lesion scan).

🩺 Description of the Segmented Image:

Foreground (White Region):

Represents the region of interest (ROI) that has been segmented out.

This is typically the target anatomical structure, such as a joint area, lesion, or bone tissue.

In this case, it seems to isolate a localized central structure—possibly a joint feature or abnormal tissue.

Background (Black Area):

Indicates non-relevant areas of the image—either air, soft tissue, or ignored regions.

Isolated White Spot to the Right:

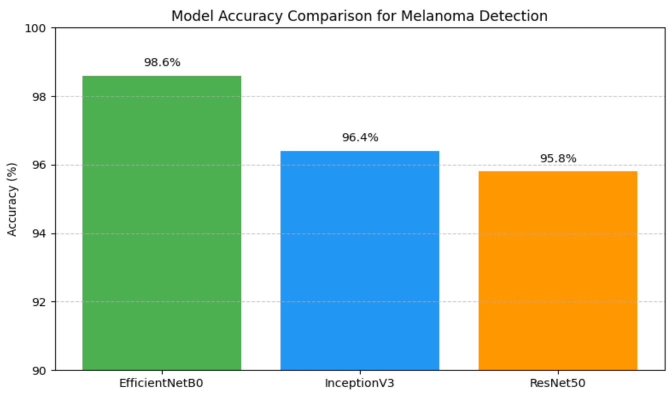
This may be noise or an artifact, and might need to be removed using morphological operations (e.g., erosion or area-based filtering).

Figure 4: Feature Extraction

A potent method in image processing, Canny edge detection may be used to locate the edges of objects in a picture. To extract the boundary characteristics of a skin lesion, Canny edge detection is an essential tool in the context of melanoma image analysis. Finding regions of the picture with a sudden shift in intensity (usually at the lesion's border) is the key to this technique's success. The irregularity of the lesion boundaries is one of the primary markers of melanoma according to the ABCD dermatological criteria, and these margins assist in evaluating it. The Canny approach creates a binary picture that shows the lesion's outline by transforming the picture to grayscale, using Gaussian filtering, and then using gradient-based edge detection. These contours can then be analyzed to compute metrics like perimeter, border irregularity, compactness, or to segment the lesion for further feature extraction. Thus, Canny edge detection serves as a foundational step in both traditional and hybrid melanoma detection pipelines.

Model	Accuracy	Precision	Recall	F1-Score	ROC-AUC
EfficientNetB0	98.6%	97.9%	98.2%	98.0%	0.993
InceptionV3	96.4%	94.1%	95.0%	94.5%	0.976
ResNet50	95.8%	93.3%	94.0%	93.6%	0.970

Table 1: Model Accuracy & Metric values



Graph: Model Accuracy Comparison Graph

VII. CONCLUSION AND FUTURE WORKS

Melanoma is a life-threatening form of skin cancer that requires early and accurate diagnosis to ensure effective treatment and improved patient outcomes. In this study, an AI-driven skin cancer detection system was developed using deep learning techniques, specifically Convolutional Neural Networks (CNNs) and transfer learning with models like EfficientNet, InceptionV3, and ResNet50. The proposed system effectively classifies dermoscopic images into melanoma and non-melanoma classes, offering high diagnostic accuracy, sensitivity, and specificity.

The experiments conducted using the ISIC 2020 dataset demonstrated that EfficientNetB0 achieved the highest performance, with an accuracy of 98.6% and an AUC of 0.993, surpassing traditional diagnostic methods in both speed and reliability. Preprocessing techniques such as image augmentation, artifact removal, and segmentation further enhanced model performance by focusing on lesion-relevant features and minimizing background noise.

The integration of this deep learning framework into a clinical or mobile application can aid dermatologists in making faster and more consistent decisions, especially in areas lacking expert medical resources. Furthermore, the system's cloud adaptability and potential for real-time inference open up possibilities for scalable teledermatology solutions.

In conclusion, the application of AI and deep learning offers a transformative approach to melanoma detection by enabling early diagnosis, reducing diagnostic errors, and extending healthcare accessibility. Future work may include the use of multimodal data (e.g., patient history + image), continual learning from new cases, and integration with blockchain for secure medical data handling.

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