IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)
An International Open Access, Peer-reviewed, Refereed Journal

# A survey on melanoma detection based on multimodal Explainable Artificial Intelligence

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**ABSTRACT**

Melanoma is a very dangerous kind of skin cancer for which early diagnosis is crucial for successful treatment.In most cases, deep learning models such as convolutional neural networks (CNNs) can be employed to classify skin lesions accurately. But because they are black-box systems, they cannot be implemented in hospitals since they are not transparent.This paper presents a system that integrates an advanced CNN algorithm named EfficientNet with Explainable AI (XAI) methods to improve accuracy, interpretability and transparency in melanoma detection. The model is trained on the ISIC 2016 part 3 dataset, which consist of heterogeneous dermoscopic images of benign and malignant skin lesions. XAI methods offer text explanations of predictions,by indicating the most important features like asymmetry or border irregularities with audio explanations.The SHAP and LIME are utilized to demarcate the regions impacted and the contribution of every attributes towards the malignant character. This enhances the process of explanation and informs decision-making. A web application accessible via a user-friendly interface is created using Gradio that allows patients and clinicians to upload lesion images for real-time analysis. The web application produces reports, such as predictions,confidence scores and rationales, which are downloadable for use in clinical settings.Comparison is made with a traditional CNN and EfficientNetB3 in accuracy, efficiency, and generalization. Experimental results indicate that EfficientNetB3 has an accuracy of 92.7%, surpassing CNN (84.5%) while retaining computational efficiency. This system solves critical challenges in melanoma diagnosis by enhancing accuracy and induces trust through interpretability. The principal aim of this project is to minimize unnecessary biopsies while detecting melanoma and improve early detection leading to improved patient outcomes.

**Keywords**—Convolutional neural networks(CNNs), EfficientNet, Skin lesion classification, XAI, ISIC 2016 Part 3, Gradio.

## I. INTRODUCTION

Skin cancer is the most common form of cancer worldwide, affecting millions of individuals annually. The American Academy of Dermatology approximates that one in five individuals in the United States will develop skin cancer at some point in their lifetime. Skin cancer is divided into three main categories: Basal cell carcinoma (BCC), Squamous cell carcinoma (SCC) and Melanoma. Although BCC and SCC are non-melanoma skin cancers and are less virulent, melanoma is the most lethal because of its rapid growth and high metastatic potential. Melanoma arises in melanocytes, the pigment-producing cells that create melanin, the color pigment of the skin. Although it usually occurs on sun-exposed sites, melanoma may also arise in locations such as the mouth, eyes, or nails. Sustained exposure to ultraviolet (UV) light from the sun or sunlamps is the major cause of melanoma. UV light harms DNA in cells of the skin and causes mutations that can result in the uncontrolled proliferation of melanocytes. Melanin serves to guard the skin against UV light, but fair-skinned individuals, who have lower amounts of melanin, are particularly susceptible. Melanoma incidence has been rising steadily each year. The American Cancer Society predicted 100,640 new melanoma cases in the U.S. in 2024 and an estimated 8,290 deaths. This trend highlights the need for early detection.

Although melanoma can be treated extremely well when caught early, once it has disseminated, treatment becomes more complicated. Physical exams and biopsies are old-fashioned diagnostic procedures that remain mainstream for the detection of melanoma but are limited. Biopsies, being invasive, will cause discomfort, scarring and infection despite their accuracy. In addition, unnecessary biopsies can be done when the lesions are not malignant, provoking patient distress and increasing health care expenses. Early detection not only improves survival rates but also reduces the need for invasive procedures, enhancing patient outcomes and quality of life.

## II. LITERATURE SURVEY

Mario et al.[1] developed a two-step deep learning framework for melanoma classification in dermoscopic images. Mask R-CNN was utilized to detect lesions by cropping a bounding box, and then ResNet152 was utilized for classifying them as benign or malignant. Transfer learning was employed to overcome the size of the dataset, and data augmentation methods (rotation, flipping) were utilized to increase model resilience. Performance was measured by sensitivity, specificity, and ROC curves.

Lina et al.[2] proposed a CNN-based segmentation method that makes simultaneous predictions for segmentation masks and lesion edge contours. The proposed model utilized an adapted ResNet-101 along with a Pyramid Pooling Module (PPM) for accurate detection of the lesion boundary. A Cross-Connection Layer (CCL) further enhanced the segmentation by utilizing edge information and a Multi-Scale Feature Aggregation (MSFA) module enhanced lesion localization. The method attained better Jaccard Index and segmentation accuracy on the ISBI2017 dataset.

Harsh et al.[3] presented a detailed review of machine learning methods in melanoma classification between K- Nearest Neighbors (KNN), Support Vector Machines (SVM), and CNNs. The paper highlighted the strengths of deep learning over conventional methods and noted the challenges that persist, including data imbalance, explainability, and the requirement for large labeled datasets.

Ranpreet et al.[4] introduced an automated melanoma classification model based on a Deep Convolutional Neural Network (DCNN) that was optimized for feature extraction and computational cost. Their model utilized adaptive filter tuning, layer depth optimization, and hyperparameter optimization to achieve maximum performance. The model, when tested on ISIC datasets, had an accuracy of 90.42%, which was better than several previous state-of-the-art methods.

Asmaa et al.[5] investigated melanoma detection with the aid of Artificial Neural Networks (ANNs), utilizing the ISIC 2018 dataset. Hair removal, cropping of the lesions, and contrast normalization were utilized as preprocessing steps. Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT), and gradient transformations were used for feature extraction with a score of 88.98% (DWT), 85.44% (DCT), and 76.07% (gradient-based features).

Mohan et al.[6] proposed a hybrid machine learning model based on Shearlet Transform and a Naïve Bayes classifier for melanoma classification. Multi-resolution lesion features were extracted using Shearlet decomposition, which were then classified by a Naïve Bayes model. The proposed method was found to be 90.5% accurate at the third level of decomposition, proving its efficacy in melanoma classification.

Guang et al.[7] presented a state-of-the-art overview on developments in machine learning-based skin cancer diagnosis. Their work debated deep learning model superiority over dermatologists, with respect to accuracy, sensitivity, and specificity gains. They also touched upon segmentation issues, noise removal, and inconsistency in datasets, suggesting directions for future work in ML-based melanoma classification.

Javed et al.[8] have created transfer learning-based classification model for melanoma using MobileNetV2. Class imbalance was tackled for ISIC 2020 data through rotation and zooming as a data augmentation approach. Higher efficiency and higher accuracy of classification have been provided in the model over traditional CNNs.

Krishna et al.[9] used machine learning and image processing for the detection and classification of skin cancer. They used a hair removal and noise reduction as preprocessing steps followed by k-means clustering-based segmentation. Feature extraction involved asymmetry analysis and Gray Level Co-occurrence Matrix (GLCM), with classification via Multi-Class SVM (MSVM), attaining 96.25% accuracy on the ISIC 2019 dataset.

Sai et al.[10] integrated CNN and SVM models for melanoma classification using color, texture, and shape features to analyze lesions. Their model performed 92% with CNN and 95% with SVM for detecting early-stage melanoma, establishing the success of combining deep learning with conventional ML techniques.

## III. METHODS

### A. Study Design

In this project,the comparison is done betweenthe baseline Convolutional Neural Network architecture and EfficientNet architecture.The main aim is to find out the best architecture that has been trained over the dataset ISIC 2016 Part B dataset.Figure 1 illustrates the components of the project which includes Data collection, Data preprocessing ,Feature extraction,Model training using Convolutional neural network and EfficientNet B3 variant,Integartion of Explainable Artificial intelligence like LIME(Local Interpretable Model-Agnostic Expalanations),SHAP(SHapely Additive exPlanations),textual and audio explanations and a Gradio based User interface where the patient can upload their lesion images and they can get tehir prediction with confidence scores with explanations which enhances the clinician confidence.

## B. Data Collection

The "ISIC 2016 Part 3" dataset is a dermoscopic image collection for skin cancer classification by the International Skin Imaging Collaboration.It contains a training set with 900 images and a distinct testing set with 379 images, and the objective is to determine if a skin lesion is malignant (melanoma) or benign based on the image given.The images are in JPEG format and are labeled with the respective diagnosis (benign or malignant).These images are gathered from the ISIC archive, a data bank of high-quality dermoscopic images collected from many different medical institutions worldwide.

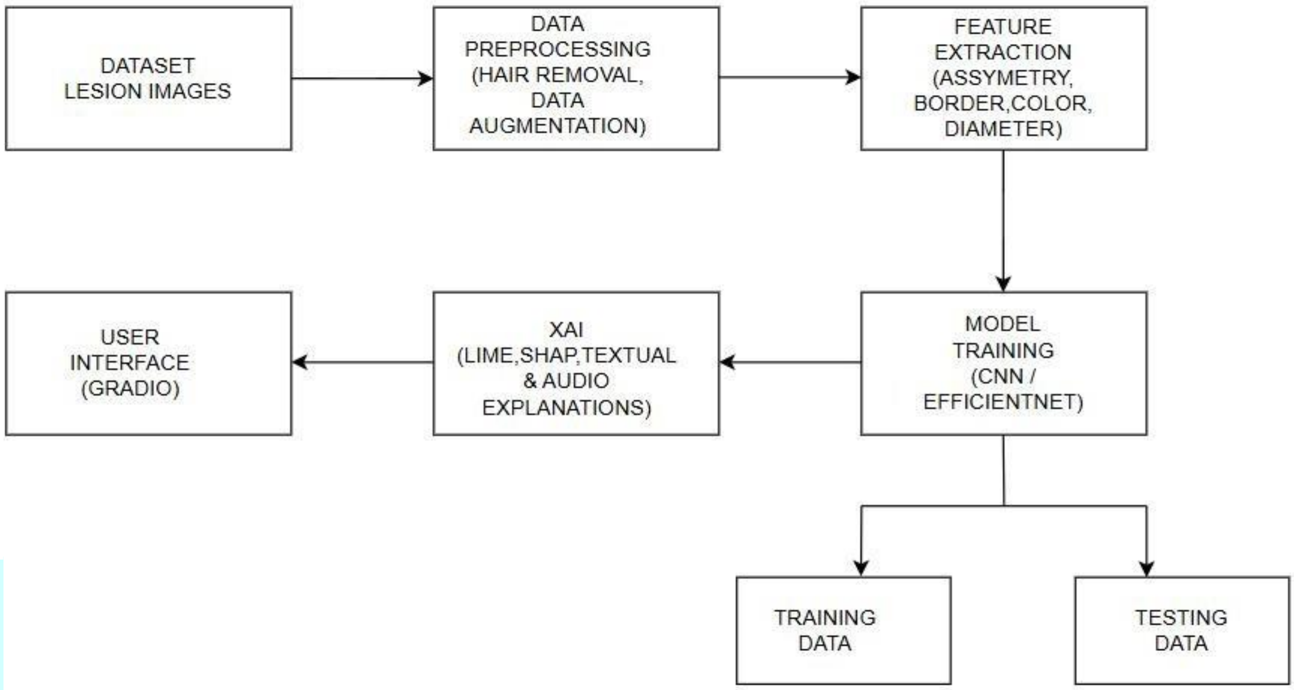


**Figure 1: Architecture Diagram**

## C. Data Preprocessing

The preprocessing flow starts with the removal of hair, which is critical to having a clean lesion analysis. The image is initially converted to grayscale and morphological filtering is performed to identify hair strands. Adaptive thresholding is then employed to segment the identified hair areas, which are then removed with an inpainting operation (cv2.INPAINT_TELEA). This operation makes the lesion structure more visible, minimizing interference from hair artifacts. Then, contrast enhancement methods, incorporated into the data augmentation pipeline, modify brightness and contrast to enhance visibility of lesions. Contrast is also normalized, scaling pixel values from 0 to 1 to prevent instability of the deep learning model during training. To further enhance model generalization, data augmentation is done, such as elastic transformations to add mild warping, rotations of ±40 degrees to mimic different orientations of lesions, and horizontal and vertical flipping to enhance diversity. Coarse dropout is also used, randomly blacking out small areas to render robust model occlusion.

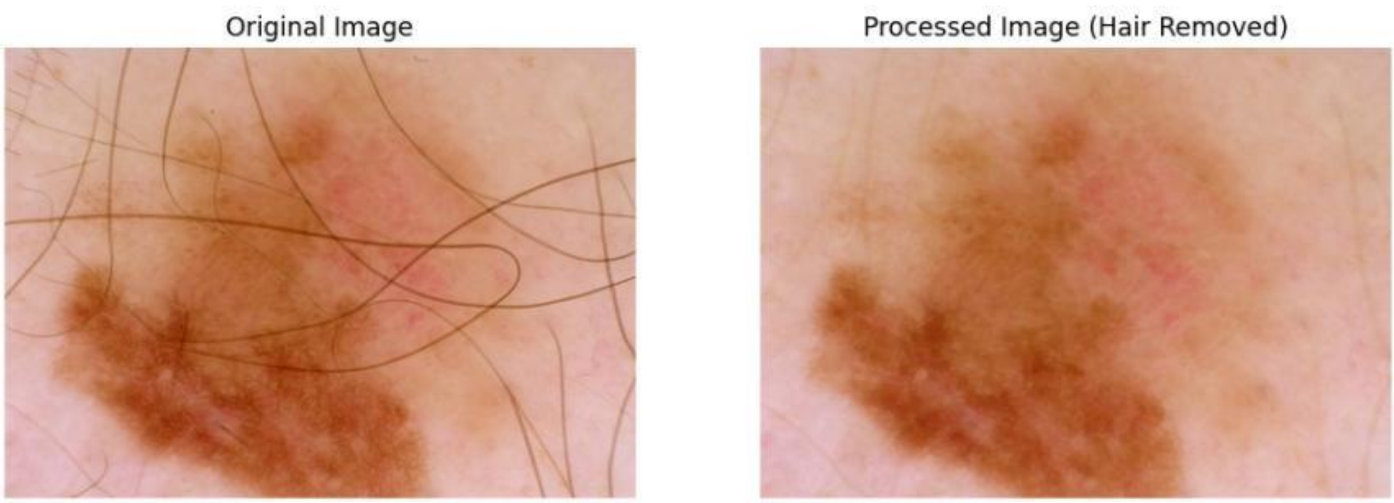


**Figure 2.Hair Removal**

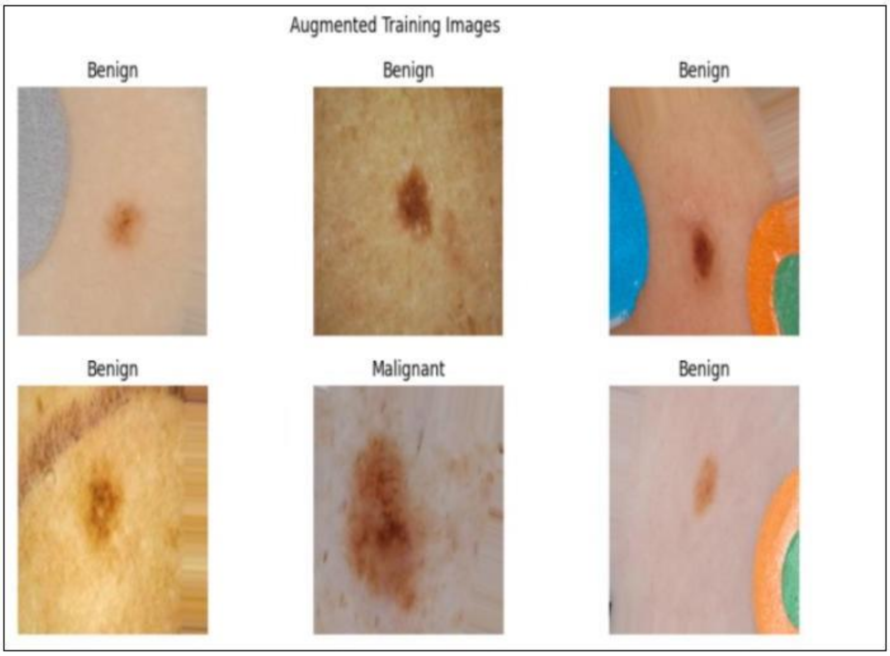


**Figure 3: Augmented training Images**

### D. Feature Extraction

After preprocessing, feature extraction is performed based on the ABCD (Asymmetry, Border, Color, Diameter) criteria. Asymmetry detection is done by dividing the lesion into two halves, mirroring one side, and calculating the pixel difference between them. A greater asymmetry score indicates a more irregular lesion, which is usually related to malignancy. Border irregularity is then determined by converting the image to grayscale, performing Otsu's thresholding, and extracting lesion contours with OpenCV. Contours are sketched on a black background, with jagged and irregular borders suggesting a greater chance of melanoma. Color characteristics are derived through a three-dimensional histogram method, examining differences between RGB channels. Lesions with multiple colors like brown, black, red, white, and blue are more likely to be cancerous. Lastly, diameter calculation is done by detecting lesion areas using Otsu's thresholding and region properties extraction using regionprops. The equivalent diameter of the lesion is computed, for which a diameter above 6mm is a possible marker for melanoma.

### E. Model Training

In this research the performance analysis is done between Baseline Convolutional Neural Network and EfficientNet architectures.

### Baseline Convolutional Neural Network Architecture

A Convolutional Neural Network (CNN) is a deep learning model specifically tailored for the task of image analysis and classification. It is commonly employed in medical imaging, such as melanoma detection, because of its potential to automatically identify significant features from skin lesion images. Unlike conventional machine learning methods where feature extraction is manually preformed, CNNs learn hierarchical patterns from raw image data directly and are extremely effective at recognizing shapes, textures, colors, and borders of skin lesions.

A standard CNN comprises convolutional layers, pooling layers, and fully connected layers. The convolutional layers use filters (kernels) that sweep across the image to pick up patterns like edges, color transitions, and lesion contours. The picked-up patterns are then fed through activation functions such as ReLU, which inject non-linearity, enabling the network to learn sophisticated features. Subsequently, pooling layers, for instance, max pooling downsample the feature maps and decrease the complexity of computations at the cost of preserving most salient information. Following some number of convolution and pooling layers, the feature extracted is flattened and fed to fully connected layers, which is a classifier used to identify if the lesion is malignant or benign. Lastly, softmax or sigmoid activation function is utilized to create the probability of classification.g.

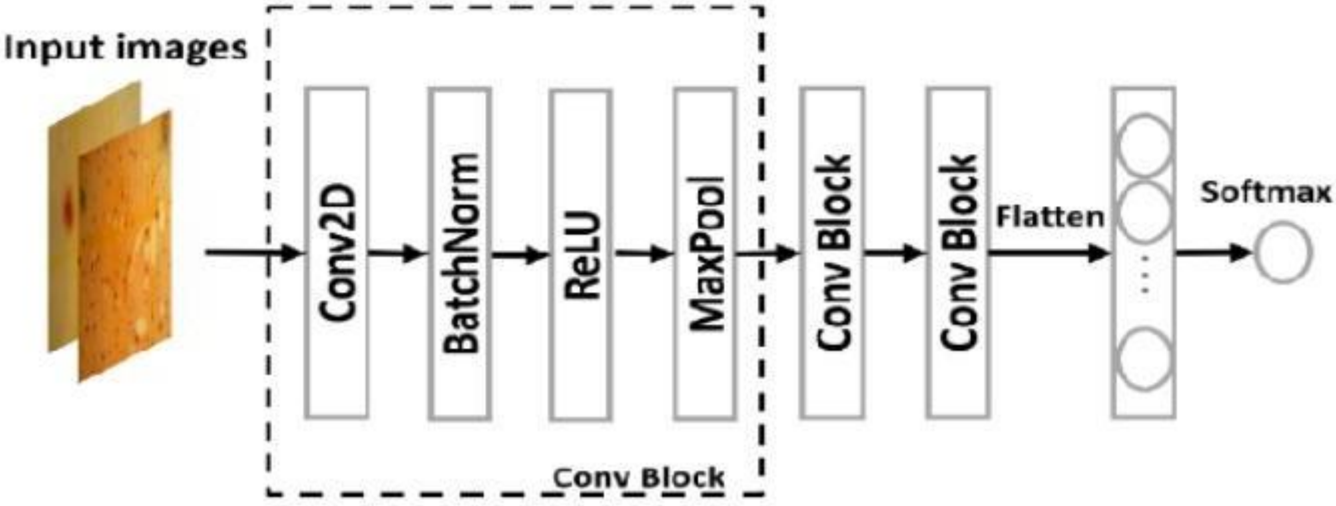


**Figure 4. Baseline CNN architecture**

**EfficientNet Architecture**

EfficientNet was created to better the conventional deep learning models that scale just one dimension at a time. In contrast to the standard architectures, EfficientNet scales depth (number of layers), width (channel number per layer), and resolution (input image size) all at once with a novel compound scaling method. This allows EfficientNet to attain higher accuracy with many fewer parameters, making it suitable for resource-constrained settings while maintaining state- of-the-art performance.

There are various variants of EfficientNet, from EfficientNet-B0 to EfficientNet-B7, each with increasingly improved performance at the expense of higher computational complexity. EfficientNet-B0 is the base model, with a balance between accuracy and efficiency. The B1 to B3 versions have moderate scaling improvements, with improvements in model performance at the expense of slightly higher computational needs. B4 to B7 models, on the contrary, offer the most accurate results but require high computational resources, and thus, are better for high-end purposes where resources are available in excess.

EfficientNet employs compound scaling methodology that ensures all three aspects—depth, width, and resolution—are scaled proportionally to prevent inefficiencies in traditional methods, where only one of the aspects is scaled. This balanced strategy leads to greater accuracy with fewer parameters, improved efficiency by minimizing computational overhead, and a scalable architecture that enables users to select the right model size (from B0 to B7) depending on available resources and desired performance levels. EfficientNet's efficiency and flexibility make it one of the strongest architectures for medical image classification, such as melanoma detection.

In this project, considering the size of the dataset we have chosen the EfficientNet B3 architecture for melanoma classification.

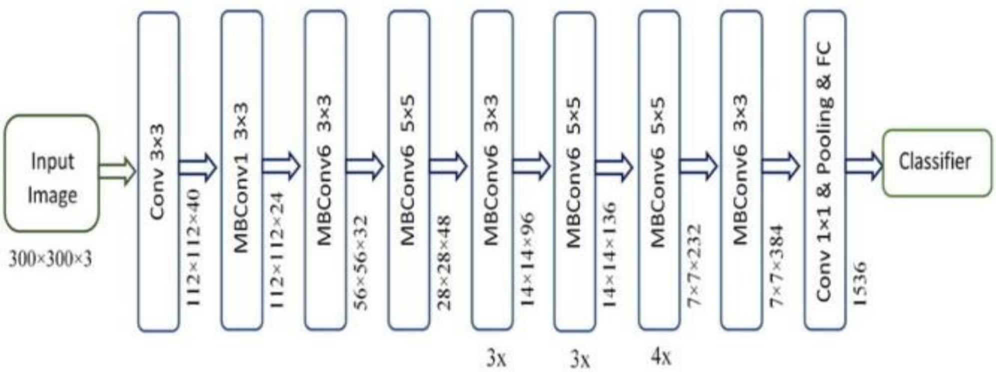


**Figure 5. EfficientNet architecture**

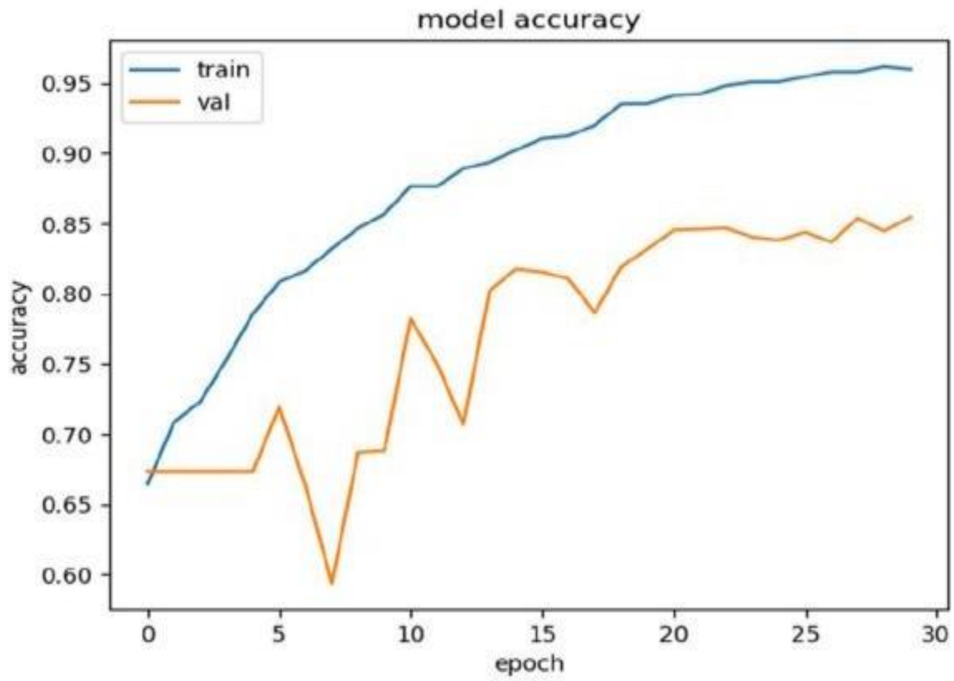


**Figure 6.Model accuracy using Baseline CNN**

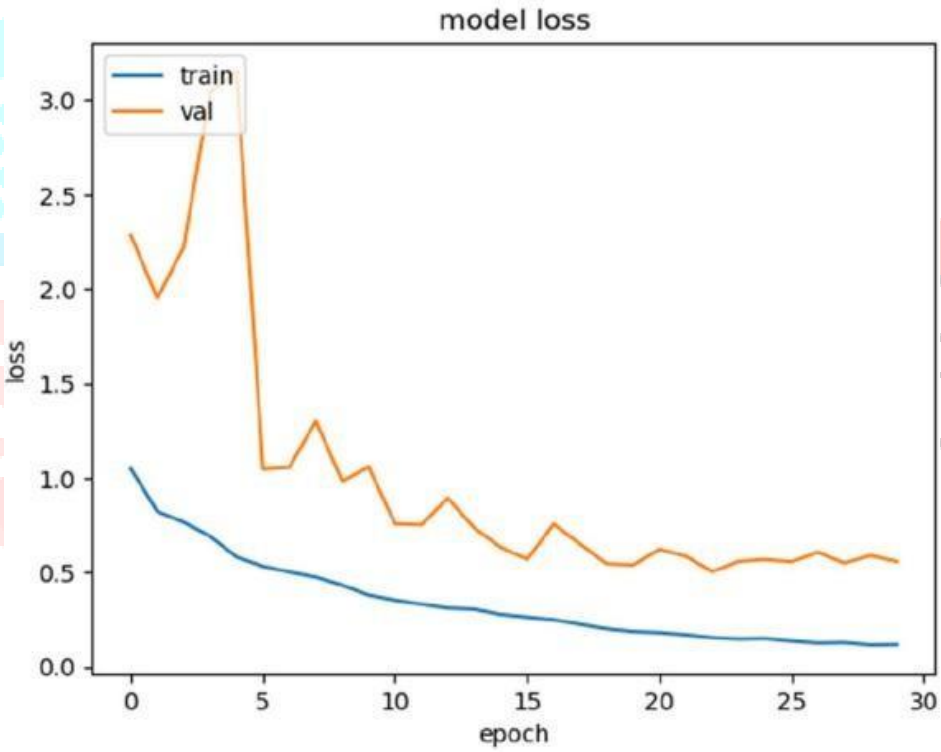


**Figure 7.Model loss using Baseline CNN**

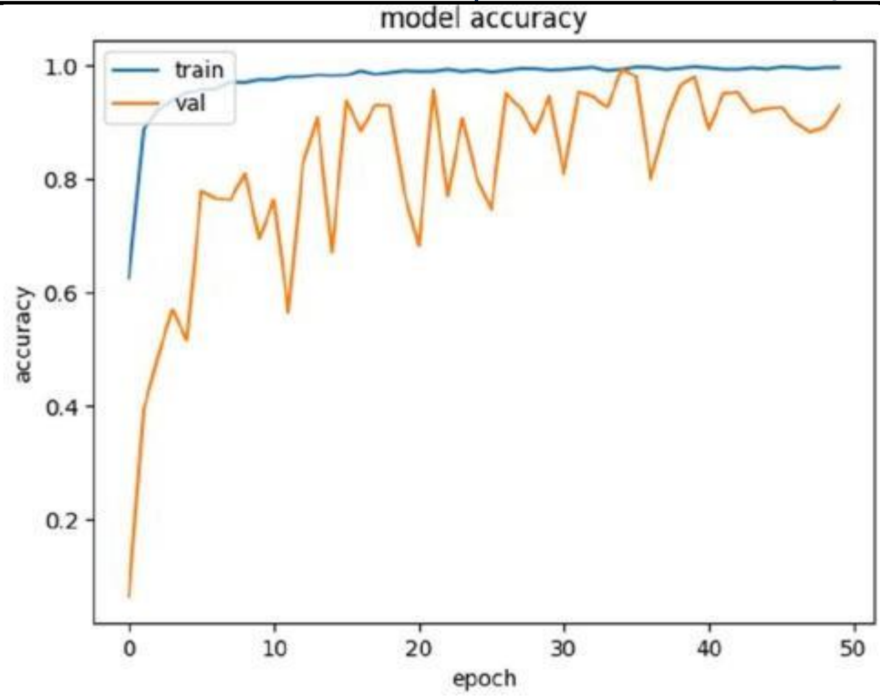


**Figure 8.Model accuracy using EfficientNet B3**

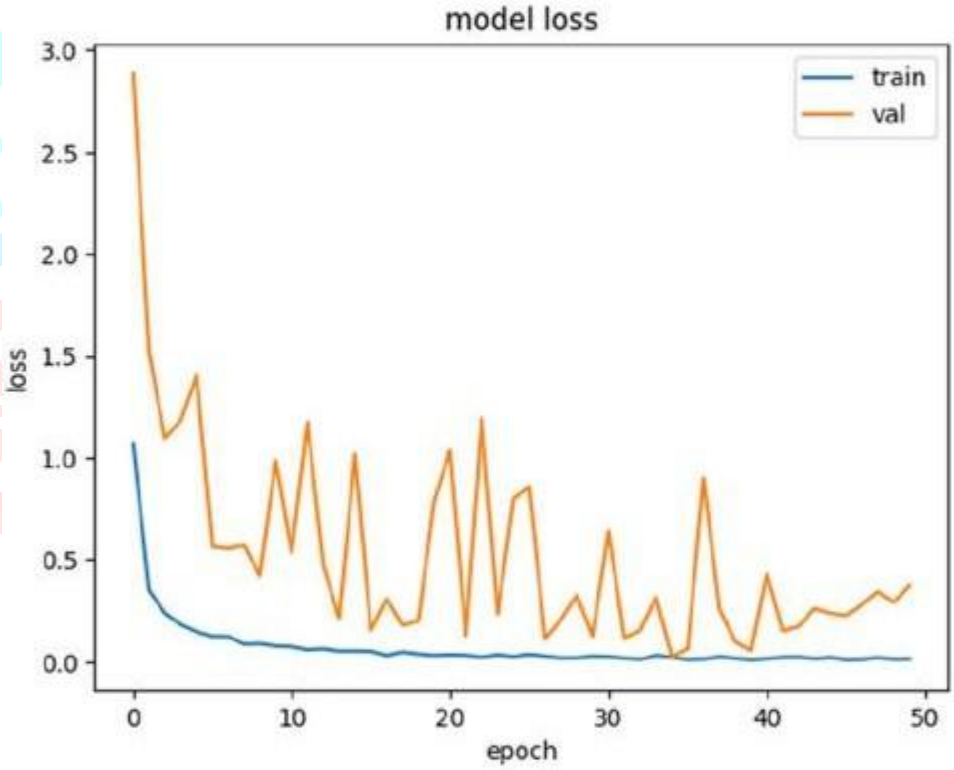


**Figure 9.Model loss using EfficientNet B3**

**F. Explainable AI**

To enhance greater transparency, Explainable AI (XAI) techniques are incorporated in this project .LIME (Local Interpretable Model-Agnostic Explanations) provides explanations for individual model predictions in terms of a local surrogate model. It identifies the most influential features (e.g., lesion asymmetry, border irregularity) on decisions.SHAP (SHapley Additive Explanations) utilizes game theory to provide importance scores for features. It facilitates visualization of global & local model behavior for clinical uptake. For audio explanations gtts(Google Text To Speech) library is used and for report generation fpdf library is used.

**G. User Interface**

Gradio is an open-source library in Python that can be used to build interactive web interfaces for AI models with fewer lines of code. In the detection of melanoma, Gradio offers a friendly interface where patients or doctors can upload images of the skin lesion, get classification outputs, see explanations (LIME & SHAP)and download the reports.

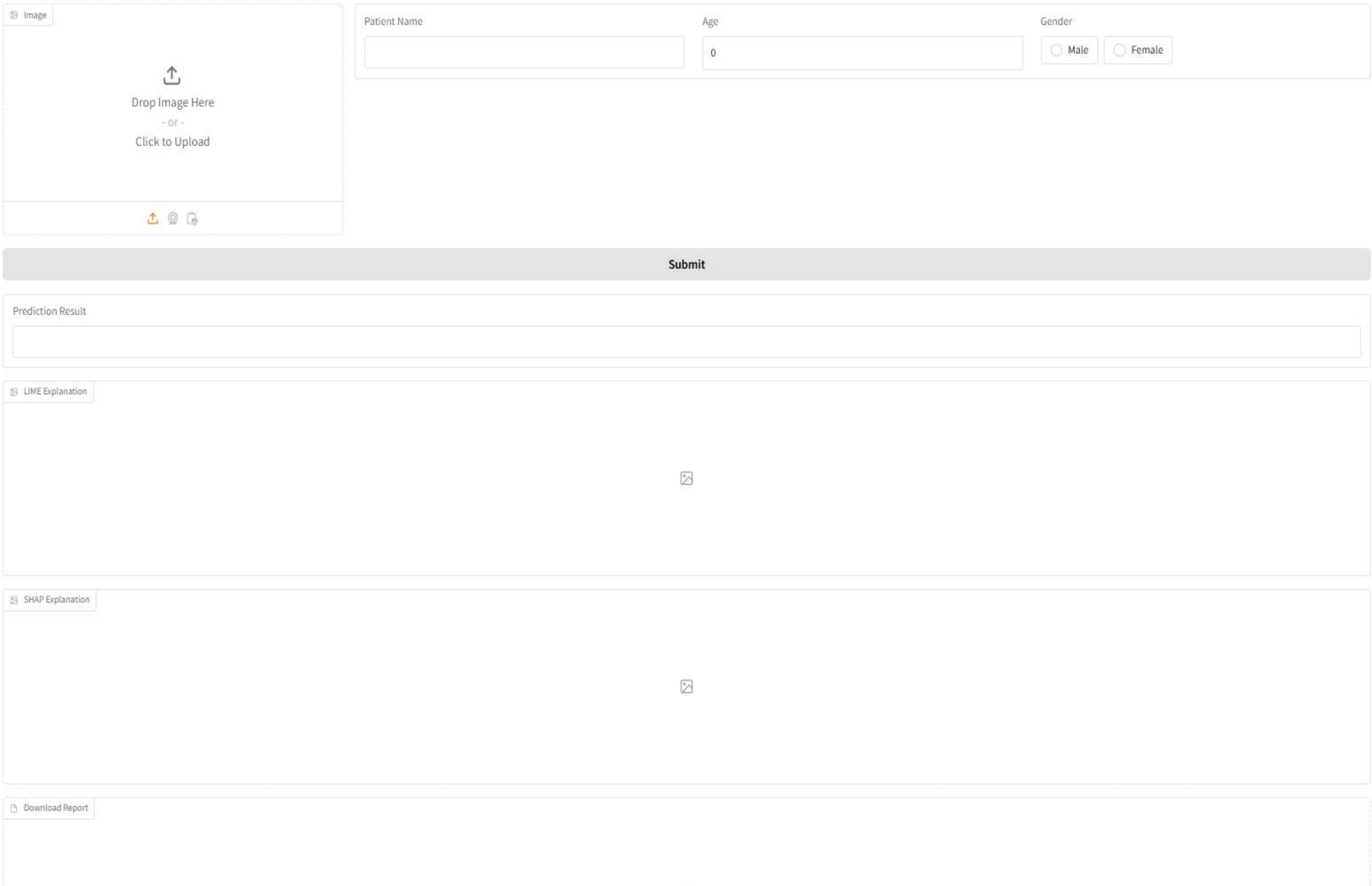


**Figure 10.Gradio Based User Interface**

## IV RESULTS

In this research, we compared the performance of baseline CNN with advanced CNN, EfficientNet.A novel system for early and non invasive detection of melanoma by focusing on both accuracy and interpretability using XAI was developed. By using the EfficientNet architecture, the system achieved high accuracy of around 95% in classifying melanoma using the ISIC 2016 dataset, outperforming Baseline CNN which provided 85% accuracy. The incorporation of LIME and SHAP along with textual explanations and audio explanations through XAI addressed the inherent black-box nature of deep learning models, enhancing confidence for clinicians and interpretability for patients.Also, the user-friendly Gradio-based web interface allowed real-time image analysis, explanatory insights and detailed reporting, making the system practical for clinical applications. Future research in melanoma diagnosis with XAI can concentrate on a few important enhancements like integration of multi-modal data can improve accuracy by including patient demographics, genetic background, and clinical notes in addition to dermoscopic images, resulting in a more individualized diagnosis and deep learning architectures like Vision Transformers (ViTs) and self-supervised learning models can be investigated to enhance feature extraction and generalization, making the system robust.

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