Visvesvaraya Technological University

BELAGAVI, KARNATAKA.

ವಿಶ್ವೇಶ್ವರಯ್ಯ ತಾಂತ್ರಿಕ ವಿಶ್ವವಿದ್ಯಾಲಯ

ಬೆಳಗಾವಿ, ಕರ್ನಾಟಕ

A PROJECT PHASE-2 REPORT

ON

"Melanoma Cancer Detection Using Deep Learning and Image Processing"

Submitted to Visvesvaraya Technological University in partial fulfillment of the requirement for the award of Bachelor of Engineering degree in Computer Science and Engineering.

Submitted by

Manjunath V Poojari	**4JN22CS077**
Mannan Faiz	**4JN22CS078**
Nithish T R	**4JN22CS103**
Prajwal P	**4JN22CS111**

Under the guidance of

Mr. Manohar Nelli V, **B.E., M. Tech.,**
Assistant Professor, Dept. of CS&E,
JNNCE, Shivamogga.

Department of Computer Science & Engineering

Jawaharlal Nehru New College of Engineering

Shivamogga - 577 204

Decemeber 2025

National Education Society ®

Jawaharlal Nehru New College of Engineering

Department of Computer Science & Engineering

CERTIFICATE

This is to certify that the project entitled

"Melanoma Cancer Detection Using Deep Learning and Image Processing"

Submitted by

Manjunath V Poojari	**4JN22CS077**
Mannan Faiz	**4JN22CS078**
Nithish T R	**4JN22CS103**
Prajwal P	**4JN22CS111**

Students of 7th semester B.E. CS&E, in partial fulfillment of the requirement for the award of degree of Bachelor of Engineering in Computer Science and Engineering of Visvesvaraya Technological University, Belagavi during the year 2025-26.

Signature of Guide

Mr. Manohar Nelli V, B.E., M. Tech.,
Assistant Professor, Dept. of CS&E

Signature of HOD

Dr. Jalesh Kumar. M. Tech, Ph.D.,
Professor and Head, Dept. of CS&E

Signature of Principal

Dr. Y. Vijaya Kumar B.E., M. Tech., Ph.D.,
Principal, JNNCE

Examiners: 1. ________________ 2. ________________

ABSTRACT

This project presents an automated computer-aided diagnosis (CAD) system for melanoma skin cancer detection using deep learning and image processing techniques. The system analyzes dermoscopic skin images through standard preprocessing steps and lesion segmentation to accurately extract the region of interest. Advanced deep learning models such as Convolutional Neural Networks (CNNs) with transfer learning architectures are trained to classify skin lesions into melanoma and non-melanoma categories. The proposed system addresses challenges such as class imbalance and image quality variations through data augmentation techniques. Developed with a focus on accuracy and efficiency, the system provides reliable prediction results along with performance evaluation metrics such as accuracy, precision, recall, and F1-score. The solution offers a non-invasive, cost-effective, and scalable approach that can assist dermatologists in early melanoma detection, thereby improving diagnostic accuracy and reducing delays in treatment.

ACKNOWLEDGEMENT

On presenting the Project phase-1 report on **“Melanoma Cancer Detection Using Deep Learning and Image Processing”**, we feel great to express our humble feelings of thanks to all those who have helped us directly or indirectly in the successful completion of the Project Work Phase-2.

We would like to thank our respected guide **Mr. MANOHAR NELLI V** Assistant Professor, Dept. of CS & E, who has helped us a lot in completing this task, for their continuous encouragement and guidance throughout the project work.

We would like to thank our respected coordinators **Dr. BENAKAPPA S.M**, Associate Professor, **Mrs. RASHMI V**, Asst. Professor, Dept. of CS&E who has helped us a lot in completing this task, for their continuous encouragement and guidance throughout the project work.

We would like to thank **Dr. JALESH KUMAR**, Professor and Head, Dept. of CSE, JNNCE, Shivamogga and **Dr. Y VIJAYA KUMAR**, Principal, JNNCE, Shivamogga for all their support and encouragement.

We are grateful to Department of Computer Science and Engineering and our institution Jawaharlal Nehru New College of Engineering and for imparting me the knowledge with which we can do our best.

Finally, we also would like to thank our supporting parents and the whole teaching as well as non-teaching staff of Computer Science and Engineering Department.

Thank you,

Manjunath V Poojari 4JN22CS077
Mannan Faiz 4JN22CS078
Nithish T R 4JN22CS103
Prajwal P 4JN22CS111

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

INTRODUCTION

1.1 Overview of Cancer and Skin Cancer

Cells that proliferate and divide uncontrollably are referred to as “cancer”; they can quickly spread and invade nearby tissues if left untreated. Any sort of cancer, not just skin cancer, has the most significant probability of developing into a malignant tumor. Melanoma (mel), Basal-cell carcinoma (BCC), nonmelanoma skin cancer (NMSC), and squamous-cell carcinoma (SCC) are the most common forms of skin cancer. It should be noted that some kinds of skin cancer, such as actinic keratosis (akiec), Kaposi sarcoma (KS), and sun keratosis (SK) are scarce. The exponential growth in digital communication and storage of images has accentuated the need for reliable and secure encryption techniques to protect sensitive visual information from unauthorized access and tampering. As images play a pivotal role in numerous applications, ranging from medical imaging to secure communication, ensuring the confidentiality and integrity of visual data has become paramount, In response to the ever-evolving landscape of cyber threats, this work introduces an approach to image encryption that harnesses the synergies between chaotic map dynamics and a novel scan pattern.

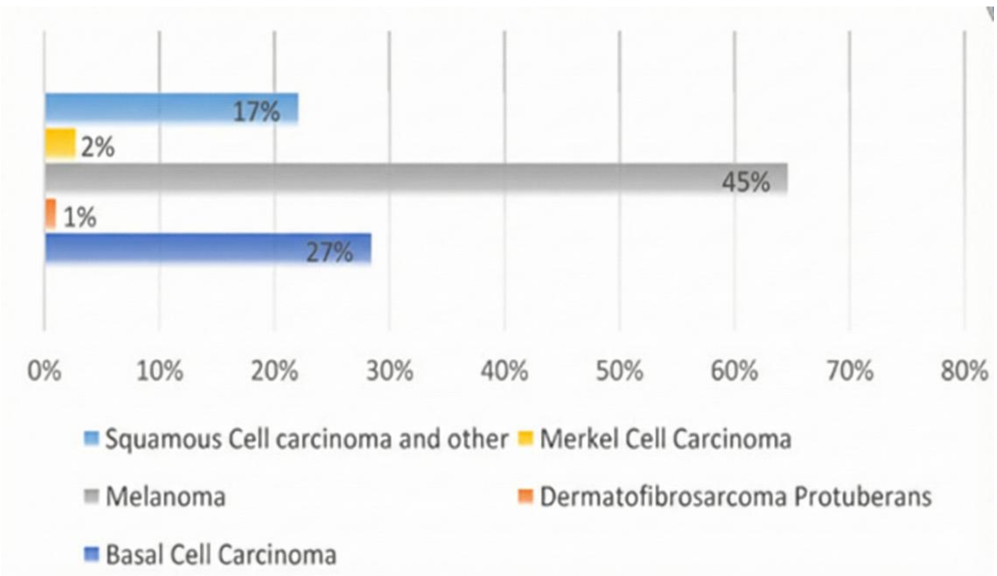


Fig 1.1: Types of Cancer Cells

Malignant and non-malignant skin cancers are among the most common forms of cancer worldwide. The presence of cancerous lesions significantly increases morbidity rates and places a substantial financial burden on healthcare systems. Consequently, researchers have focused on developing algorithms that are highly accurate, robust, and flexible in detecting early signs of skin cancer. Malignant melanocyte cells proliferate rapidly, invade surrounding tissues, and metastasize at early stages; therefore, timely detection is critical for improving patient survival rates. Dermoscopy and epiluminescence microscopy (ELM) are widely used by specialists to differentiate between benign and malignant skin lesions.

In dermatology, magnification and illumination are employed to enhance the visualization of critical medical patterns such as color variations, pigment networks, globules, streaks, and vascular structures. These tools enable the identification of morphological features that are otherwise difficult to observe with the naked eye. Diagnostic frameworks such as the ABCD rule (Asymmetry, Border irregularity, Color variation, Diameter, and Evolution), the 7-point checklist, and pattern analysis techniques assist clinicians in lesion assessment. However, non-professional dermoscopic image interpretation yields a predictive accuracy of only 75% to 80% for melanoma, and the diagnostic process remains time-consuming and highly subjective, largely dependent on the clinician's experience.

Computer-Aided Diagnosis (CAD) approaches have made it easier to overcome these difficulties. CAD of malignancies made a giant leap forward thanks to Deep Learning (DL)-based Artificial Intelligence (AI). In rural areas, dermatologists and labs are in poor supply; therefore, using DL approaches to classify skin lesions could help automate skin cancer screening and early detection. To classify images in the past, dermoscopic images strongly depended on the extraction of handcrafted characteristics. Throughout these promising scientific advances, the actual deployment of DCNN based dermoscopic pictures has yielded amazing results. Still, future development of diagnosis accuracy is hampered by various obstacles, such as inadequate training data and imbalanced datasets, especially for rare and comparable lesion types. Regardless of the restrictions of the dataset, it is vital to maximize the performance of DCNNs for the correct Classification of skin lesions.

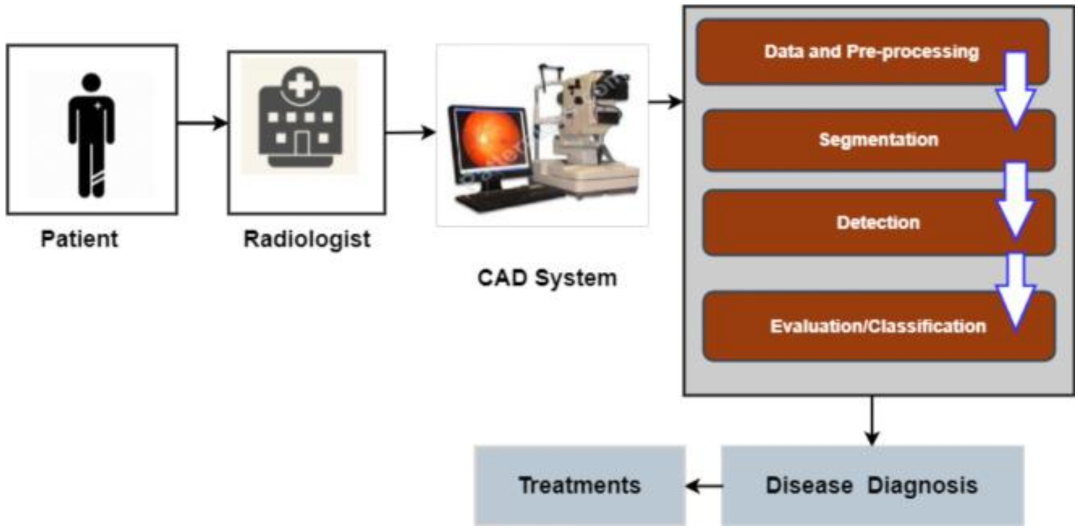


Fig 1.2: Block diagram of the Computer-Aided Diagnosis(CAD) system for skin disease detection

1.2 Literature Survey

1.2.1 Melanlysis: A Mobile Deep Learning Approach for Early Detection of Skin Cancer

Authors: S. A. Arani, Yu Zhang, M. Tanvir Rahman & Hui Yang. (2022).

The study in [8] introduces Melanlysis, a mobile application leveraging deep learning for early detection of melanoma skin cancer. The model is built using EfficientNetLite-0, optimized for on-device deployment via TensorFlow Lite, and designed to work without relying on cloud infrastructure, thus improving privacy, reducing latency, and supporting offline diagnosis.

To combat class imbalance in the **ISIC 2020 dermoscopic dataset (44,108 images)**, the authors employed **Wasserstein GAN (WGAN)** for data augmentation, improving training diversity and avoiding mode collapse. After augmentation and training, the classification model (EfficientNetLite-0) was converted to a .tflite format and deployed into a lightweight Android application for real-time melanoma vs. non-melanoma classification.

Key findings from model evaluation:

- **Melanlysis Accuracy:** 94%
- **Sensitivity:** 92.5%
- **Specificity:** 89.5%

- **F1 Score:** 93%
- Outperformed baseline models like **MobileNetV2 (Accuracy: 93%)** and **ResNet-50 (Accuracy: 90%)**
- **Application latency:** 0.10 ms, with a total size of 23.18 MB

The mobile app uses the phone's camera and OpenCV library to capture real-time images, process them using the embedded model, and return instant results.

Advantage:

- Fully on-device inference enhances speed, privacy, and availability in resource-limited areas (no internet/cloud needed).
- EfficientNetLite-0 with WGAN ensures high accuracy while remaining lightweight for mobile environments.

Disadvantage:

- Updating the offline embedded model requires manual reinstallation of the app.
- Only dermoscopic images are supported, limiting versatility across general clinical photos or mixed data types.

1.2.2 Hybrid Deep Learning Framework for Melanoma Diagnosis Using Dermoscopic Medical Images

Authors: Muhammad Mateen, Shaukat Hayat, Fizzah Arshad, Yeong-Hyeon Gu, and Mugahed A. Al-antari. (2024).

The system proposed in [1] introduces a novel hybrid deep learning framework for the early detection and accurate classification of melanoma skin cancer using dermoscopic images. The approach integrates three powerful components: U-Net for lesion segmentation, Inception-ResNet-v2 for deep feature extraction, and a Vision Transformer for feature refinement and classification. The framework is trained and evaluated on the **ISIC 2020 Challenge dataset**, containing over 33,000 annotated dermoscopic images, and further validated through ablation studies using the **HAM10000 dataset**.

In the preprocessing phase, advanced techniques such as background removal, contrast enhancement, and data augmentation (including rotation, flipping, and scaling) were applied to improve model generalization and dataset balance. The segmentation step, using

U-Net, isolates the lesion area to avoid false detections. Feature extraction is performed using Inception-ResNet-v2, leveraging its residual connections and deep representational capacity. These features are then refined by the Vision Transformer, which applies a self-attention mechanism to capture global dependencies before final classification.
The model achieved **98.65%** accuracy, **99.20%** sensitivity, and **98.03%** specificity.

Advantage:

- The combination of U-Net, Inception-ResNet-v2, and Vision Transformer ensures highly accurate melanoma classification with robust lesion segmentation and advanced global feature learning.
- The model's performance is validated on multiple datasets, demonstrating generalizability.

Disadvantage:

- The framework's complexity and resource-intensive training (especially with Vision Transformers) may limit its deployment on low-resource or real-time systems.
- Requires a large amount of high-quality annotated data and computational power for training and inference.

1.2.3 Skin Cancer Detection Using Deep Machine Learning Techniques

Authors: Olusoji Akinrinade, Chunglin Du. (2024).

The study conducted in [2] presents a robust skin cancer detection framework leveraging a combination of Convolutional Neural Networks (CNNs), Artificial Neural Networks (ANNs), Generative Adversarial Networks (GANs), and few-shot learning to improve melanoma and non-melanoma classification using dermoscopic images. The approach addresses common challenges such as class imbalance, limited training data, and overfitting by employing GAN-based data augmentation, transfer learning, and hybrid ensemble models. The framework utilizes multiple deep learning backbones including ResNet-152, AlexNet, VGG-16, and hybrid CNNs. The dataset used includes ISIC 2017/2018 and HAM10000, with preprocessing steps involving histogram equalization, noise reduction (median filter), and lesion segmentation using Otsu thresholding and ROI extraction.

Classification performance was enhanced by combining CNNs with ANN and fuzzy logic techniques, and GANs were used to synthetically generate realistic skin lesion images to balance datasets.

Key performance metrics achieved include:

- CNN-based classifier: **Accuracy of 97.51%**
- GAN-augmented classification system: **Accuracy of 86.1%**, outperforming baseline ResNet-50 and DenseNet models
- Hybrid model with ResNet-50 and CNN: **AUC of 91.5%**, high sensitivity and specificity

Advantage:

- The system efficiently handles limited and imbalanced data using GANs and transfer learning.
- The hybrid approach integrates multiple neural networks, significantly improving classification accuracy and generalization.

Disadvantage:

- Requires extensive computational resources for training GANs and CNNs.
- High model complexity may hinder real-time deployment in low-resource settings such as rural clinics or mobile apps.

1.2.4 Hybrid Deep Learning Model for Skin Cancer Classification

Author: Dr.Irala Suneetha (2024).

The study in [3] proposes an advanced hybrid deep learning framework for classifying skin cancer from dermatoscopic images. The model integrates two prominent architectures— VGG16 and InceptionV3—to leverage their respective strengths.
VGG16 contributes strong local feature extraction capabilities, while InceptionV3 captures global and fine-grained information, making the combined model highly robust for melanoma and benign lesion classification.
The methodology begins with preprocessing steps, including noise removal using a median filter and resizing images to a uniform resolution. After preprocessing, feature extraction is carried out using the pre-trained VGG16 and InceptionV3 networks. Their outputs are

concatenated and passed to a dense classification layer with a sigmoid activation for binary classification.

The model was trained and evaluated using a dataset of 1,253 dermoscopic images sourced from Kaggle, with 670 images for training and 583 for testing. The training process applied data augmentation techniques (rotation, flipping, shifting, scaling) to improve generalization and avoid overfitting. The model was trained for 40 epochs using the Adam optimizer and binary cross-entropy loss.

Experimental results demonstrate that the hybrid model achieved a classification accuracy of 95.71%, with precision, recall, and F1-score all at 96%. It significantly outperformed single-model baselines:

- **VGG16:** 84.56% accuracy
- **InceptionV3:** 89.34% accuracy

Additionally, the model showed a high AUC score of 0.9566, further validating its diagnostic reliability.

Advantage:

- The hybrid approach significantly improves classification performance by combining local and global feature extractors.
- Achieved high accuracy and balanced metrics, outperforming other ensemble and standalone models on the same dataset.

Disadvantage:

- The system's increased complexity and training time due to dual model integration may pose deployment challenges in real-time or resource-limited environments.
- Requires substantial preprocessing and training infrastructure.

1.2.5 Hybrid Deep Learning Framework for Enhanced Melanoma Detection

Author: Peng Zhang, Divya Chaudhary (2024)

The research in [4] proposes a high-performing hybrid deep learning framework that integrates U-Net for lesion segmentation and EfficientNet-B0 for melanoma classification. The system addresses the challenge of accurate skin cancer diagnosis by combining fine grained segmentation with efficient classification, creating a robust pipeline that improves both localization and decision-making.

The framework was trained on two datasets:

- HAM10000 for segmentation with U-Net (10,015 labeled images).
- ISIC 2020 for classification with EfficientNet-B0 (33,126 images with binary melanoma labels).

To handle data imbalance in ISIC 2020, resampling and augmentation (rotation, shift, flip, zoom) were applied. A novel Data Processing Bridge was introduced to blend U- Net segmentation masks with original images before passing them to EfficientNet, enhancing the classifier's focus on relevant lesion regions.

Key experimental results:

- U-Net segmentation accuracy: 91.2%
- EfficientNet classification accuracy (with blended segmentation input): 99.01%
- AUC score of the classification model: 0.97

Advantage:

- The use of a segmentation-classification bridge enhances lesion-focused learning, leading to superior accuracy.
- EfficientNet's compound scaling ensures high accuracy with low computational overhead, making it suitable even for resource-limited setups.

Disadvantage:

- Requires careful data preprocessing and segmentation and classification stages. architectural integration between.
- Complex training pipeline may hinder real-time deployment without further automation or optimization.

1.2.6 Deep Learning for Melanoma Detection: A Deep Learning Approach to Differentiating Malignant Melanoma from Benign Melanocytic Nevi

Authors: Kreouzi, I., Papageorgiou, E., Skourletopoulos, G., & Vlahavas, I. (2025).

The study in [5] presents a comprehensive comparison of four deep learning CNN architectures—DenseNet121, ResNet50V2, MobileNetV2, and NASNetMobile—for classifying dermoscopic images of skin lesions as either malignant melanoma or benign melanocytic nevi. The framework leverages a dataset of 8825 dermoscopic images sourced from DermNet, divided into training (80%), validation (10%), and test (10%) sets using stratified sampling to maintain class balance.

Advanced image augmentation techniques, including rotation, flipping, shearing, zoom, and brightness adjustments, were applied during training to enhance generalization and prevent overfitting. All models were fine-tuned on ImageNet-pretrained weights, modified for binary classification using a custom top layer consisting of global average pooling, dense layers, dropout, and sigmoid activation.

Key performance outcomes:

- DenseNet121 achieved the highest accuracy (92.30%) and AUC = 0.951
- ResNet50V2 had the highest AUC (0.957) but was largest in size (91.93 MB)
- MobileNetV2 offered the best efficiency with accuracy of 92.19%, smallest size (9.89 MB), and fastest inference time (23.46 ms).

Advantage:

- DenseNet121 and ResNet50V2 showed high diagnostic performance, with DenseNet121 offering the best accuracy and balanced precision-recall tradeoff.
- MobileNetV2 provided an excellent balance between speed, size, and accuracy, ideal for mobile and low-resource settings.

Disadvantage:

- ResNet50V2 and DenseNet121 require significant memory and computational power, limiting use in real-time or portable systems.
- NASNetMobile, although compact, suffered from longer inference times and slightly reduced classification accuracy.

1.2.7 Melanoma Detection Using Deep Learning-Based Classifications

Authors: Ghadah Alwakid, Walaa Gouda (2022).

The system proposed in [6] presents a deep learning-based framework for classifying skin lesions using a combination of a custom-designed Convolutional Neural Network (CNN) and a modified ResNet-50, enhanced by ESRGAN (Enhanced Super-Resolution GAN) preprocessing. The framework is designed for precise melanoma detection and differentiation from six other types of skin lesions using the HAM10000 dataset.

The pipeline begins with ESRGAN-based image enhancement to improve lesion clarity and contrast. Then, segmentation using ground-truth masks isolates the region of interest (ROI). A range of data augmentation techniques (rotation, flipping, zooming, rescaling) are used to resolve class imbalance and improve generalization. The dataset size is increased to 39,430 images after augmentation.

The CNN model is trained with a custom architecture featuring multiple convolutional layers and max-pooling, while the modified ResNet-50 incorporates additional fully connected layers and fine-tunes pretrained ImageNet weights. The models were tested using a 90-10 split on HAM10000.

Key results:

- CNN model: Accuracy = 85.98%, Precision = 84%, Recall = 86%, F1-score = 86%.
- Modified ResNet-50: Accuracy = 85.3%, with comparable precision and recall
- Both models outperform several existing approaches in literature using the same dataset

Advantage:

- ESRGAN preprocessing significantly boosts image quality, leading to better classification performance.
- The CNN model performs better than ResNet-50 in melanoma classification despite having fewer parameters, making it more efficient.

Disadvantage:

- The added ESRGAN and segmentation steps increase overall computational complexity.
- Some lesion types like melanoma and actinic keratosis still exhibit lower precision due to inter-class similarity.

1.2.8 Melanoma Detection Based on Deep Learning Networks

Author: S Devaraneni,(2023).

The project in [7] introduces a melanoma detection framework using transfer learning with ResNet-50 to classify dermoscopic images of skin lesions. The goal is to distinguish between malignant and benign lesions with high accuracy using a pre-trained deep learning model, minimizing the need for building a model from scratch. The model is trained and tested on a dataset of nearly 10,000 images from Kaggle, divided into 80% training, 10% validation, and 10% testing.

The methodology involves data preprocessing, including resizing, Gaussian blurring, color normalization, and hair removal. Data augmentation is extensively used to balance the dataset and improve generalization, involving transformations like rotation, scaling, translation, flipping, and noise addition. Feature extraction is carried out using the ResNet-50 architecture, modified by reducing its depth to 34 layers in later experiments for performance optimization.

Several experiments were conducted with varying learning rates and depths to analyze the model's performance:

- Best result: 91.70% accuracy using a learning rate of 0.0001 and depth of 34
- The use of ResNet-34 (reduced from ResNet-50) showed improved accuracy in some cases due to simplified architecture.

Advantage:

- High classification accuracy with optimized ResNet-50 architecture and transfer learning
- Extensive hyperparameter tuning (learning rate, depth) boosts performance without training from scratch

Disadvantage:

- The model is sensitive to hyperparameter changes and may suffer from overfitting without proper regularization
- Requires significant preprocessing and computational power for training and testing, which may limit deployment in real-time applications.

1.2.9 Developing an Efficient Method for Melanoma Detection Using CNN Techniques

Authors: Devika Moturi, Ravi Kishan Surapaneni, and Venkata Sai Geethika Avanigadda (2024)

The system presented in [5] introduces a bio-inspired deep learning pipeline for the early diagnosis of skin cancer, particularly melanoma, using dermoscopic images. The architecture is based on a combination of hand-crafted image features and features derived from a nonlinear extension of State-Controlled Cellular Neural Networks (SC- CNNs), termed NLSC-CNNs. The process begins with dermoscopy image pre- processing using SC CNNs to enhance and stabilize lesion features. Subsequently, a set of 16 hand-crafted features are extracted to emulate the traditional ABCDE diagnostic criteria (Asymmetry, Border, Color, Diameter, Evolution). These features are complemented by six deep-learned morphological features produced by NLSC-CNNs.

The combined feature set is arranged into 32×32 matrices and passed to a Deep Convolutional Neural Network (ConvNN) for classification, which consists of several convolutional, ReLU, and max-pooling layers. The system was validated on the publicly available PH2 dermoscopy image dataset and demonstrated improved sensitivity and specificity for distinguishing benign from malignant skin lesions.

Advantage:

- Integration of hand-crafted and deep-learned features leads to high accuracy and reliable discrimination between benign and malignant lesions.
- The use of SC-CNN and NLSC-CNN enables morphological analysis inspired by biological cell behavior, improving feature interpretability.

Disadvantage:

- The system involves complex neural network architectures and pre-processing steps that may demand significant computational power, potentially limiting real-time application in low-resource clinical settings.

1.2.10 Minimal Sourced and Lightweight Federated Transfer Learning Models for Skin Cancer Detection

Authors: Vikas Khullar, Prabhjot Kaur, Shubham Gargrish, Anand Muni Mishra, Prabhishek Singh, Manoj Diwakar, Anchit Bijalwan, and Indrajeet Gupta (2025)

The system introduced in [10] proposes a hybrid deep learning model that integrates Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) with a ResNet-50 backbone for improved skin cancer classification. This approach addresses the limitations of existing methods by simultaneously capturing spatial features through CNNs and temporal dependencies using Long Short-Term Memory (LSTM) networks. The model was trained and validated using an expanded dataset of 9000 dermoscopic images spanning nine types of skin cancers obtained from the ISIC archive.

Image pre-processing involved denoising (using Laplacian filtering), grayscale conversion, and the generation of Region of Interest (ROI) zones to isolate lesion areas. Additionally, feature extraction was performed on 10 non-overlapping 512×512 ROIs per image, with 57 features per ROI, leading to a feature vector space of over 500,000 attributes. Data augmentation techniques (rotation, flipping, zooming, shifting) helped to balance class representation and improve model generalization.

The classification pipeline includes spatial feature extraction via ResNet-50, temporal modeling with LSTM, and final prediction using a softmax classification layer. The model achieved a high training accuracy of 99.06%, with a test accuracy of 96%, and an AUC of 94.48%, outperforming several state-of-the-art models.

Advantage:

- Combines CNN and RNN to effectively address both spatial and temporal complexities in dermoscopic images, leading to high diagnostic performance across nine skin cancer classes.
- Uses advanced preprocessing, segmentation, and data augmentation techniques to improve robustness and reduce class imbalance.

Disadvantage:

- The model's complexity and reliance on high-quality, diverse datasets may limit its generalizability and practical deployment in real-world, resource-constrained environments.
- The interpretability of the deep hybrid architecture remains a challenge, which may affect clinician trust in automated diagnoses.

1.3 Problem Statement

Early and accurate detection of melanoma skin cancer remains a major challenge in dermatological diagnosis due to its aggressive nature, rapid progression, and high potential for metastasis. Conventional diagnostic methods such as visual examination, dermoscopy, and biopsy are highly dependent on clinician expertise, time-consuming, and prone to inter-observer variability, which can lead to delayed or inconsistent diagnoses. The growing incidence of skin cancer combined with the limited availability of trained dermatologists—particularly in rural and resource-constrained regions—further complicates large-scale screening efforts. Although automated diagnostic approaches exist, many suffer from limitations including poor image quality, background noise, dataset imbalance, and weak generalization across diverse lesion types. Hence, there is a critical need for an automated, accurate, and efficient computer-aided diagnosis system that utilizes deep learning and image processing techniques to enable reliable early detection and classification of melanoma and other skin lesions, reduce human dependency, and support real-time dermatological screening.

1.4 Objectives of the work

The primary objectives of this project are outlined below, each addressing a key aspect of automated melanoma detection and classification:

1. To design and develop an automated computer-aided diagnosis (CAD) system for early detection and classification of melanoma skin cancer using dermoscopic images.

2. To preprocess and standardize dermoscopic images to ensure accurate analysis by the detection model.

3. To isolate and prioritize critical lesion features during processing, minimizing the impact of background artifacts on classification accuracy.

4. To implement and fine-tune deep learning models such as CNN, ResNet-50, EfficientNet-B0, and MobileNetV2 using transfer learning.

5. To perform a comparative analysis of different deep learning architectures based on accuracy, efficiency, and robustness.

6. To identify a lightweight and high-performance model suitable for deployment in real-time, mobile, or web-based applications.

1.5 Scope of the Project

The scope of this project is focused on the development and evaluation of an intelligent melanoma detection system using deep learning and dermoscopic image analysis. The key scope areas include:

1. Application of image preprocessing and enhancement techniques, including ESRGAN-based super-resolution, to improve lesion visibility.

2. Implementation of lesion segmentation and Region of Interest (ROI) extraction to eliminate irrelevant background information.

3. Handling dataset imbalance through data augmentation and oversampling strategies.

4. Design and comparison of multiple deep learning architectures, including CNN, Modified ResNet-50, EfficientNet-B0, and MobileNetV2, using transfer learning.

5. Evaluation of model performance using standard metrics such as accuracy, precision, recall, F1-score, confusion matrix, and Top-N accuracy.

6. Selection of a lightweight and efficient model suitable for real-time and mobile deployment.

7. The system is intended as a decision-support tool and not a replacement for clinical diagnosis.

8. The project does not include invasive clinical testing or biopsy confirmation and is limited to image-based automated analysis.

1.6 Organization of the report

This report is organized into five chapters to present the melanoma skin cancer detection system in a structured and systematic manner. Chapter 1 provides an introduction to the project, outlining the background, problem statement, objectives, scope, and motivation. It also includes a concise literature survey reviewing existing research on melanoma detection, dermoscopic image analysis, and deep learning–based diagnostic systems. Chapter 2 discusses the theoretical background and domain knowledge required for the project, including image processing techniques, machine learning concepts, deep learning architectures, and medical image analysis relevant to melanoma detection. Chapter 3 describes the overall system design and architecture, detailing the workflow, data preprocessing steps, lesion segmentation, feature extraction, model training, and classification process. Chapter 4 focuses on the implementation details, experimental setup, performance evaluation, and result analysis, including comparative analysis of different deep learning models and relevant visual outputs. Finally, Chapter 5 concludes the report by summarizing the key findings, contributions of the proposed system, its limitations, and potential directions for future enhancements.

CHAPTER 2

IMAGE PROCESSING & MACHINE LEARNING

This project belongs to three major technological domains—**Image Processing, Machine Learning, and Computer Vision**—each of which plays a critical role in the automated detection and classification of melanoma skin cancer. These domains collectively form the backbone of the proposed Computer-Aided Diagnosis (CAD) system, enabling accurate analysis of dermoscopic images and early identification of malignant skin lesions. The domain-wise explanation presented in this chapter follows the actual implementation workflow of the proposed system.

2.1 Importance of Automated Melanoma Detection

Melanoma is one of the most aggressive and life-threatening forms of skin cancer due to its rapid growth and high potential for metastasis. Early detection significantly improves patient survival rates; however, traditional diagnostic methods such as visual inspection, dermoscopy, and biopsy are highly dependent on clinical expertise and are often time-consuming.

With the increasing incidence of skin cancer and limited availability of trained dermatologists, there is a strong need for **automated, accurate, and scalable diagnostic systems**. Automated melanoma detection systems assist clinicians by reducing inter-observer variability, minimizing diagnostic errors, and enabling large-scale screening. Such systems are particularly valuable in rural and resource-constrained regions where access to specialized medical facilities is limited.

2.2 Image Processing (Primary Domain)

Image Processing is the **primary and foundational domain** of the proposed melanoma detection system. Since dermoscopic images are captured under varying conditions—such as different lighting, resolutions, and skin tones—robust preprocessing and enhancement are essential before classification.

Role in the Workflow

- When dermoscopic images are acquired from the **HAM10000 or ISIC dataset**, image processing techniques are applied to standardize and enhance the images.
- The following preprocessing operations are performed:
    - Image resizing and normalization
    - Noise reduction using filtering techniques
    - ESRGAN-based super-resolution to enhance lesion details
    - Contrast enhancement for improved lesion visibility
    - Lesion segmentation to isolate the Region of Interest (ROI)

These steps ensure that the classification models focus only on the lesion area, improving learning efficiency and diagnostic accuracy.

2.3 Machine Learning (Secondary Domain – Deep Learning Models)

Machine Learning forms the **intelligent decision-making layer** of the system. Instead of relying on handcrafted features or rule-based analysis, the proposed system employs **Deep Convolutional Neural Networks (DCNNs)** to automatically learn discriminative features from dermoscopic images.

Role in the Workflow

- After preprocessing and lesion segmentation, the extracted ROI images are resized and fed into deep learning models.
- The following architectures are used:
    - Convolutional Neural Network (CNN)
    - Modified ResNet-50
    - EfficientNet-B0
    - MobileNetV2

- Transfer learning is applied using ImageNet pre-trained weights to accelerate convergence and improve performance.
- The models classify skin lesions into **melanoma and non-melanoma** (or multi-class lesion categories depending on configuration).
- Training involves:
    - Balanced and augmented datasets
    - Optimizers such as Adam or SGD
    - Categorical or binary cross-entropy loss functions
    - Regularization techniques such as dropout and early stopping

These models are capable of learning complex lesion patterns such as asymmetry, border irregularity, color variation, and texture differences associated with melanoma.

2.4 Advantages of Using Machine Learning and Image Processing

Compared to traditional diagnostic approaches, the integration of Image Processing and Machine Learning provides several advantages:

- **Improved Diagnostic Accuracy:** Deep learning models can achieve dermatologist-level performance by learning complex visual patterns.
- **Early Detection:** Automated systems help identify melanoma at early stages, improving patient outcomes.
- **Reduced Human Dependency:** Objective analysis minimizes inter-observer variability.
- **Scalability:** Large volumes of dermoscopic images can be analyzed efficiently.
- **Cost-Effectiveness:** Eliminates the need for repeated manual examinations.
- **Robustness:** Data augmentation and preprocessing improve resilience to noise, lighting variation, and class imbalance.

2.5 Computer Vision (Supporting Domain)

Computer Vision acts as the **supporting and structural domain**, bridging image processing and machine learning. It enables the system to understand lesion structure and spatial relationships within dermoscopic images.

Role in the Workflow

- Detects lesion boundaries and shape characteristics.
- Assists in accurate ROI extraction and alignment.
- Preserves spatial information such as lesion asymmetry and border irregularity.
- Enables mapping of visual features to clinically relevant diagnostic indicators.
- Improves interpretability by highlighting lesion regions influencing predictions.

Thus, Computer Vision provides the structural intelligence necessary for precise and clinically meaningful melanoma detection.

CHAPTER 3

SYSTEM DESIGN AND IMPLEMENTATION

This chapter explains the overall design of the proposed **Melanoma Cancer Detection System using Deep Learning and Image Processing**. The system is designed to take dermoscopic images of skin lesions as input and classify them into melanoma and non-melanoma (or into multiple lesion classes, depending on configuration). The architecture combines **image enhancement (ESRGAN)**, **lesion segmentation**, **data balancing**, and **transfer-learning-based classifiers (MobileNetV2, ResNet, EfficientNet)** into a single pipeline.

3.1 System Overview

The proposed system follows a **modular pipeline**:

1. **Input Acquisition** – Dermoscopic images are collected from the HAM10000 / ISIC dataset.
2. **Image Preprocessing & Enhancement** – Images are resized, normalized and enhanced to improve resolution and lesion visibility.
3. **Lesion Segmentation (ROI Extraction)** – The Region of Interest (ROI) containing the lesion is segmented so that the model focuses only on relevant pixels.
4. **Data Augmentation & Class Balancing** – Various augmentation operations are applied to handle class imbalance and improve generalization.
5. **Feature Extraction & Classification** – Pre-trained deep networks (MobileNetV2, ResNet, EfficientNet) are fine-tuned on the processed images.
6. **Performance Evaluation** – Metrics such as accuracy, precision, recall, F1-score, confusion matrix, top-1 and top-2 accuracy are calculated.
7. **Deployment Layer** – The best performing model can be exported and integrated into a mobile or web application for real-time melanoma screening.

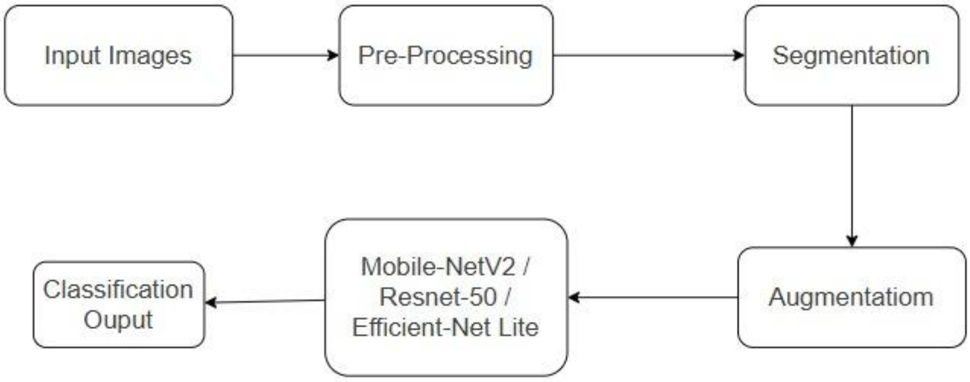


Fig 3.1: Block Diagram of the Proposed Melanoma Detection System

3.2 System Architecture

The proposed system architecture follows a structured **three-layered design**, ensuring modularity, scalability, and ease of maintenance. Each layer is responsible for a distinct set of functions and interacts seamlessly with the others to support the overall workflow of the system.

1. **Data Layer:** The Data Layer is responsible for managing all data-related operations. It handles the acquisition of datasets, secure storage, and systematic organization of image and label data. This layer also performs preprocessing tasks such as image resizing, normalization, noise reduction, and data augmentation to enhance model robustness and generalization. Additionally, it ensures proper dataset splitting into training, validation, and testing subsets, enabling reliable performance evaluation.
2. **Model Layer**: The Model Layer forms the core of the system and encapsulates all machine learning and deep learning components. It includes the segmentation module used to isolate regions of interest, followed by classification networks that analyze extracted features and generate predictions. This layer manages model architectures, training strategies, hyperparameter tuning, loss functions, and optimization techniques. Additionally, it supports model evaluation, fine-tuning, and saving trained weights for reuse, ensuring flexibility and extensibility for experimenting with different algorithms.

3. **Application Layer:** The Application Layer provides the interface through which users interact with the system. It supports workflows for model training, testing, and evaluation, presenting results through visualizations, metrics, and reports. Optionally, this layer can include a graphical user interface (GUI) or a mobile/web application that allows users to upload input data, view predictions, and analyze outcomes in real time. By abstracting the underlying technical complexity, the Application Layer enhances usability and enables deployment of the system in real-world environments.

3.2.1 Data Layer

The Data Layer is responsible for handling all data-related operations, including data acquisition, organization, storage, and preparation for model training and evaluation.

- The input consists of dermoscopic skin lesion images obtained from publicly available datasets such as **HAM10000** and **ISIC**, as well as images captured directly using a camera.
- All images are represented in **RGB format** to preserve color information, which is crucial for identifying visual patterns associated with different skin lesions. Each image is associated with a corresponding **lesion class label**, such as Melanoma (MEL), Melanocytic Nevi (NV), Basal Cell Carcinoma (BCC), Actinic Keratosis (AKIEC), and other clinically relevant categories.
- The images are systematically organized into **separate directories based on their respective class labels**, enabling efficient data handling and label mapping. The dataset is further divided into **training, validation, and testing subsets** to support model training, hyperparameter tuning, and unbiased performance evaluation.
- This layer ensures that the dataset is **well-organized, cleaned, and readily accessible** for subsequent processing stages, thereby forming a reliable foundation for the segmentation and classification modules in the Model Layer.

3.2.2 Model Layer

The Model Layer represents the core intelligence of the proposed system and is responsible for transforming raw input images into meaningful diagnostic predictions. It is composed of multiple interconnected sub-modules, each designed to address a specific stage in the medical image analysis pipeline.

- **Image Enhancement Module (ESRGAN)** .
  This module employs **Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN)** to improve the visual quality and resolution of input dermoscopic images. By enhancing fine-grained texture details and lesion boundaries, this step helps reduce noise and artifacts present in low-quality images, thereby enabling more accurate segmentation and classification in subsequent stages.
- **Segmentation Module (Region of Interest Extraction)** .
  The segmentation module focuses on identifying and isolating the **Region of Interest (ROI)**, specifically the lesion area, from the surrounding healthy skin. By accurately extracting lesion boundaries, this module minimizes background interference and ensures that the classification network concentrates only on clinically relevant regions, improving both precision and interpretability of the results.
- **Augmentation and Balancing Module** .
  To address class imbalance and enhance model generalization, this module performs data augmentation techniques such as rotation, flipping, scaling, contrast adjustment, and zooming. Additionally, balancing strategies are applied to ensure equitable representation of all lesion classes during training, thereby reducing bias and improving the robustness of the classification models.
- **Classification Module (MobileNetV2 / ResNet / EfficientNet)** .
  The final sub-module consists of deep convolutional neural networks used for lesion classification. Lightweight architectures such as **MobileNetV2** enable efficient inference, while deeper models like **ResNet** and **EfficientNet** provide higher representational capacity. These networks extract discriminative features from the processed images and classify lesions into predefined categories such as melanoma and non-melanoma classes.

3.2.3 Application Layer

The Application Layer serves as the interaction and execution layer of the system, providing the necessary interfaces and scripts to operate the underlying models. It supports the complete workflow of model training, testing, and evaluation by enabling users to initiate training processes, monitor learning progress, and analyze performance metrics such as accuracy and loss through graphical visualizations. This layer also facilitates prediction on new or unseen images, allowing users to upload input images and obtain classification results. In future developments, the Application Layer can be extended to include user-friendly deployment platforms such as a desktop-based graphical user interface developed using Tkinter or PyQt, a web-based application implemented using frameworks like Flask, Django, or Streamlit, or a mobile application where optimized TensorFlow Lite models are integrated into Android devices. By abstracting the technical complexity of the system, the Application Layer enhances usability and enables seamless deployment of the solution in real-world clinical and research environments.

3.3 Preprocessing and Image Enhancement

Preprocessing plays a crucial role in converting raw dermoscopic images into a standardized and model-ready format suitable for deep learning–based analysis. Since dermoscopic images are often captured under varying conditions and resolutions, preprocessing ensures uniformity, reduces noise, and enhances relevant visual features. This stage improves model convergence, stability during training, and overall classification performance.

3.3.1 Image Resizing and Normalization

All input images are resized to a fixed spatial resolution, such as 224 × 224 and 256 × 256 pixels, to conform to the input requirements of convolutional neural network architectures including MobileNetV2, ResNet, and EfficientNet. Standardizing image dimensions enables efficient batch processing and ensures compatibility across different models. Following resizing, pixel intensity values are scaled to the range [0, 1] or normalized using the dataset's mean and standard deviation. This normalization process reduces the impact of illumination variations and accelerates training by maintaining consistent value distributions across input samples.

3.3.2 ESRGAN-Based Super-Resolution

To enhance the visual quality of dermoscopic images and reveal fine-grained lesion characteristics, an Enhanced Super-Resolution Generative Adversarial Network (ESRGAN) is employed. Low-resolution dermoscopic images are processed through the ESRGAN generator, which reconstructs high-resolution images with improved perceptual quality. The generated outputs exhibit sharper lesion boundaries, enhanced texture details, and improved color contrast, which are essential for accurate medical image interpretation. These super-resolved images are subsequently used for all downstream tasks, including lesion segmentation and classification. The use of ESRGAN significantly improves lesion boundary clarity, facilitates more precise region-of-interest extraction, and enhances feature learning by convolutional neural networks. As a result, the overall classification performance is improved compared to models trained directly on the original low-resolution images.

3.4 Lesion Segmentation and ROI Extraction

Lesion segmentation and Region of Interest (ROI) extraction constitute a critical stage in the proposed skin cancer detection pipeline. Although dermoscopic images typically capture the lesion near the center of the image, they often contain a significant amount of irrelevant background information such as healthy surrounding skin, hair occlusions, measurement rulers, color calibration charts, and illumination artifacts. The presence of such noise can adversely affect the learning capability of deep learning models by introducing redundant and misleading features. Therefore, segmentation is applied to isolate the lesion region and ensure that subsequent classification networks focus exclusively on clinically meaningful visual patterns.

The segmentation process aims to accurately differentiate the lesion area from the background skin by generating a binary mask that highlights only the lesion region. This mask is produced using either a dedicated segmentation model or classical image processing techniques such as thresholding and morphological operations, depending on system configuration. The generated binary mask is then applied to the enhanced dermoscopic image obtained from the preprocessing stage. Through this masking operation, pixels corresponding to the lesion are retained, while background pixels are either removed or significantly suppressed. As a result, the extracted Region of Interest contains only the lesion and its immediate boundary, eliminating distractions that could interfere with feature learning.

By isolating the lesion region, the segmentation stage significantly improves the efficiency and effectiveness of the learning process. Deep convolutional neural networks are highly sensitive to spatial patterns, textures, and color variations. When trained on full images containing both lesion and background, the networks may inadvertently learn features related to surrounding skin tone, lighting conditions, or acquisition artifacts rather than the lesion itself. ROI extraction ensures that the learned representations are lesion-centric, leading to more reliable and clinically relevant predictions.

Another important advantage of lesion segmentation is its contribution to robustness and generalization. Dermoscopic images in real-world datasets are captured using different devices, under varying lighting conditions, and with diverse imaging protocols. These variations can introduce vignetting effects, shadows, uneven illumination, and color inconsistencies. By focusing only on the segmented lesion region, the model becomes less sensitive to such external variations, thereby improving its ability to generalize across datasets and unseen samples.

Furthermore, precise lesion boundary extraction plays a vital role in distinguishing between visually similar skin lesion classes. Subtle differences in border irregularity, color distribution, and internal texture are key diagnostic indicators for melanoma and other malignant lesions. Segmentation enhances the visibility of these discriminative features, allowing classification networks such as MobileNetV2, ResNet, and EfficientNet to learn more meaningful and class-specific patterns. This results in improved convergence during training and enhanced classification accuracy during inference.

In addition to improving classification performance, segmentation also enhances the interpretability of the system. By explicitly highlighting the lesion region, the system provides a clearer visual explanation of the areas contributing to the final prediction. This is particularly important in medical applications, where transparency and trust in AI-assisted decision-making are essential. Clinicians can visually verify that the model's attention is focused on the lesion rather than irrelevant regions, thereby increasing confidence in the system's output.

Overall, lesion segmentation and ROI extraction serve as a foundational step that bridges preprocessing and classification. By reducing background interference, enhancing robustness to imaging variations, and enabling the extraction of discriminative lesion features, this module significantly strengthens the reliability and clinical relevance of the proposed skin cancer detection system.

3.5 Data Augmentation and Class Balancing

The HAM10000 dataset exhibits a natural class imbalance, where certain skin lesion categories contain significantly fewer samples than others. This imbalance can adversely affect the learning process of deep learning models by introducing bias toward majority classes, ultimately reducing classification performance for rare but clinically critical lesions such as melanoma. If not properly addressed, this imbalance may lead to poor generalization and decreased sensitivity in real-world diagnostic scenarios.

To mitigate this challenge, an extensive data augmentation and balancing strategy was adopted. Geometric augmentation techniques were employed to introduce spatial diversity within the dataset, including rotations, horizontal and vertical flips, random zooming, shifting, cropping, and minor shear and perspective transformations. These operations help the model become invariant to changes in orientation, scale, and viewpoint. Additionally, photometric augmentation methods were applied to simulate variations in lighting and imaging conditions. These included brightness and contrast adjustments, color jittering, and the injection of slight Gaussian noise, which enhance robustness against real-world acquisition variability.

In addition to augmentation, oversampling of minority classes was performed to achieve a more uniform class distribution across the training dataset. Images belonging to underrepresented lesion categories were augmented multiple times until each class contained a comparable number of samples. This approach ensures that all lesion types contribute equally during training, thereby improving sensitivity to melanoma and other rare classes. Overall, this balanced dataset formulation reduces overfitting, enhances generalization, and significantly improves the reliability of the proposed skin lesion classification system.

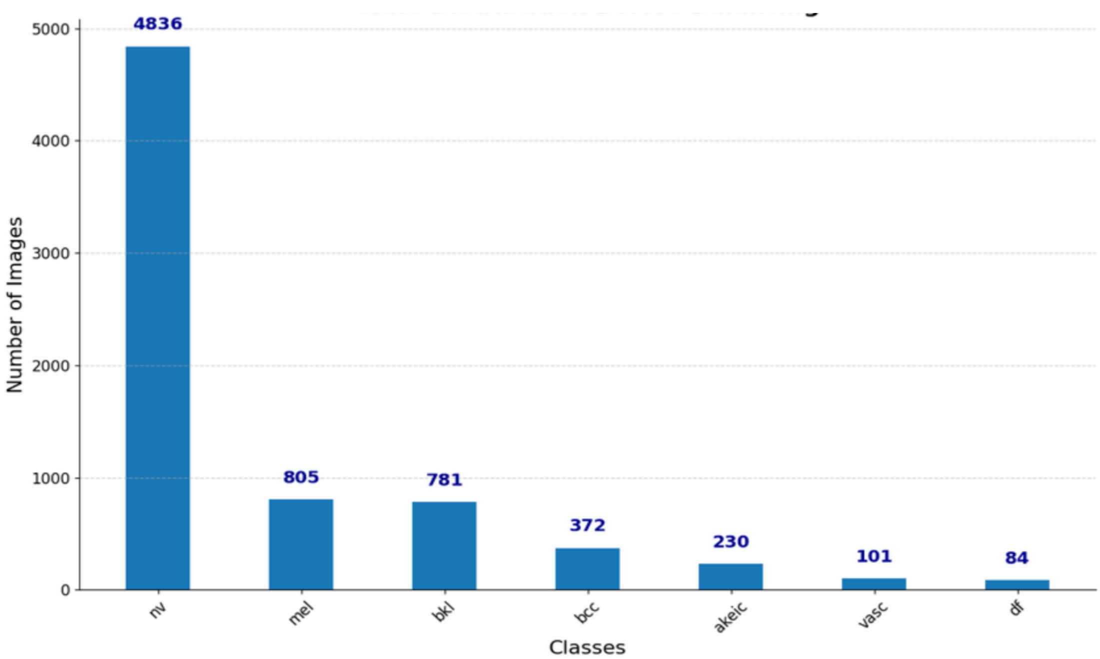


Fig 3.2: Data Balancing – Original Class Distribution

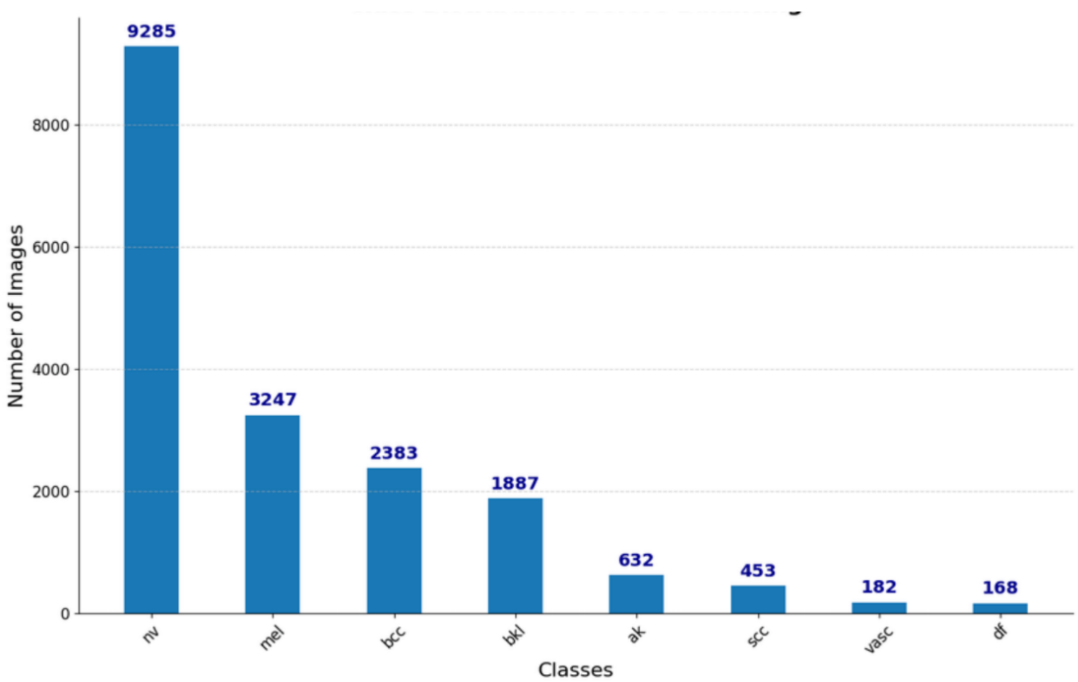


Fig 3.3: Data Balancing –Balanced Distribution

3.6 Classification Module

The classification module is implemented using a transfer learning approach based on three different convolutional neural network (CNN) architectures: MobileNetV2, ResNet, and EfficientNet. MobileNetV2 is a lightweight and computationally efficient model, making it well suited for deployment on resource-constrained devices such as mobile and edge platforms. ResNet, including variants such as ResNet-50 and ResNet-34, employs deep residual learning with skip connections, enabling effective training of deeper networks and robust extraction of complex and high-level features from dermoscopic images. EfficientNet, with variants such as EfficientNet-B0 and EfficientNet-B2, utilizes a compound scaling strategy that balances network depth, width, and input resolution to achieve high classification accuracy with a relatively small number of parameters.

For each architecture, the network backbone is initialized using weights pre-trained on the ImageNet dataset. These pre-trained models are then fine-tuned on the preprocessed dermoscopic image dataset to adapt the learned features to the domain of skin lesion classification. This transfer learning strategy accelerates convergence, reduces the need for large labeled datasets, and improves overall classification performance by leveraging rich feature representations learned from large-scale natural image data.

3.6.1 Common Architecture Adaptations

For each selected deep learning model, a set of common architectural adaptations is applied to tailor the network for skin lesion classification. Initially, the original classification head of each pre-trained model is removed to allow customization for the target dataset. A **Global Average Pooling (GAP)** layer is then added on top of the final convolutional feature map to reduce the number of parameters and preserve spatially rich feature representations.

Following the GAP layer, one or more **fully connected (dense) layers** are introduced to enhance discriminative learning. Typically, a dense layer with 512 neurons is used, followed by a ReLU activation function and a dropout layer with a dropout rate of 0.5 to mitigate overfitting. The final output layer consists of a dense layer with a number of neurons equal to the number of lesion classes, followed by a Softmax activation function to generate class probability scores. The use of dropout throughout the architecture helps improve generalization and reduces the risk of overfitting during training

3.6.2 MobileNetV2 Branch

The model is designed using **depthwise separable convolutions**, which significantly reduce computational complexity and the number of trainable parameters while maintaining competitive performance. This architectural choice makes the model efficient and lightweight, rendering it suitable for future deployment on **resource-constrained platforms such as smartphones and edge devices**. During training, the network is optimized using smaller batch sizes and a moderate learning rate to ensure stable convergence and effective feature learning without excessive memory usage.

3.6.3 ResNet Branch

The ResNet architecture employs residual blocks with identity shortcut connections, which effectively address the vanishing gradient problem and enable stable training of deep neural networks. This design allows the model to learn deeper and more complex lesion patterns, making it well suited for capturing subtle variations in dermoscopic images. In this study, a modified ResNet architecture is utilized by reducing the size of the fully connected layers and incorporating dropout layers to minimize overfitting and improve generalization performance during skin lesion classification. EfficientNet Branch.

3.7 Training Strategy

The training procedure is designed to be consistent across all three deep learning models, with minor adjustments applied to account for architectural differences and computational requirements. A unified training strategy ensures a fair comparison among models while enabling stable convergence and effective feature learning from dermoscopic images. Model training is performed using balanced and augmented datasets to maximize generalization and robustness.

3.7.1 Hyperparameters

Several key hyperparameters are carefully selected to optimize model performance. The Adam optimizer or Stochastic Gradient Descent (SGD) with momentum is used to achieve efficient and stable optimization. For multi-class skin lesion classification, Categorical

Cross-Entropy is employed as the loss function, while Binary Cross-Entropy is used for binary classification tasks such as melanoma versus non-melanoma detection. The initial learning rate is set to values such as 1e−3 or 1e−4, depending on the model and convergence behavior. A batch size of 512 is chosen to balance training efficiency and memory utilization. Models are trained for multiple epochs until convergence, with Early Stopping applied based on validation loss to prevent unnecessary training and overfitting.

3.7.2 Overfitting Prevention

To reduce overfitting and enhance generalization, multiple regularization strategies are incorporated into the training process. Extensive data augmentation, as described in Section 3.5, increases dataset diversity and reduces dependency on specific image patterns. Dropout layers are added to the classifier head to randomly deactivate neurons during training, improving robustness. L2 regularization is applied where necessary to penalize large weights. In addition, Early Stopping is used to halt training when validation performance no longer improves. Learning rate scheduling techniques, such as ReduceLROnPlateau, dynamically adjust the learning rate when validation loss stagnates, facilitating smoother convergence.

3.8 Evaluation Architecture

After training, each model is evaluated using a separate and unseen test dataset to assess its generalization capability. Model predictions are compared against the ground truth labels to quantify classification performance. Multiple evaluation metrics are computed, including accuracy, precision, recall, and F1-score, providing a comprehensive view of diagnostic effectiveness. Confusion matrix analysis is used to examine class-wise performance and identify common misclassifications. Additionally, Top-1 and Top-2 accuracy metrics are calculated to measure prediction confidence. Where applicable, Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) values are also analyzed to further evaluate classification reliability.

3.9 Transfer Learning Configuration

Transfer learning is employed to enhance feature extraction and reduce training time by leveraging knowledge from large-scale image datasets. The **ResNet-50, EfficientNet-B0, and MobileNetV2** architectures are initialized using **ImageNet pre-**

trained weights. The original fully connected classification layers are removed and replaced with a customized classifier head consisting of a **Global Average Pooling (GAP)** layer, followed by a **Dense layer with 512 neurons**, a **ReLU activation function**, and a **Dropout layer with a rate of 0.5**. The final output layer includes a dense layer with the number of neurons equal to the number of lesion classes and a **Softmax activation function**.

Multiple training runs are performed for each architecture to account for variability due to random initialization and data shuffling. The best-performing model from repeated experiments is selected and reported, ensuring a reliable and unbiased comparison across all architectures.

During fine-tuning, the initial convolutional layers of the pre-trained networks are frozen to preserve the learned low-level features, while the deeper layers are selectively unfrozen to adapt the model to the lesion classification task. An Adam optimizer is used with a reduced learning rate to ensure stable convergence and prevent catastrophic forgetting of pre-trained knowledge. This hybrid training strategy balances generalization and task-specific learning, leading to improved classification performance and robustness across varying lesion patterns.

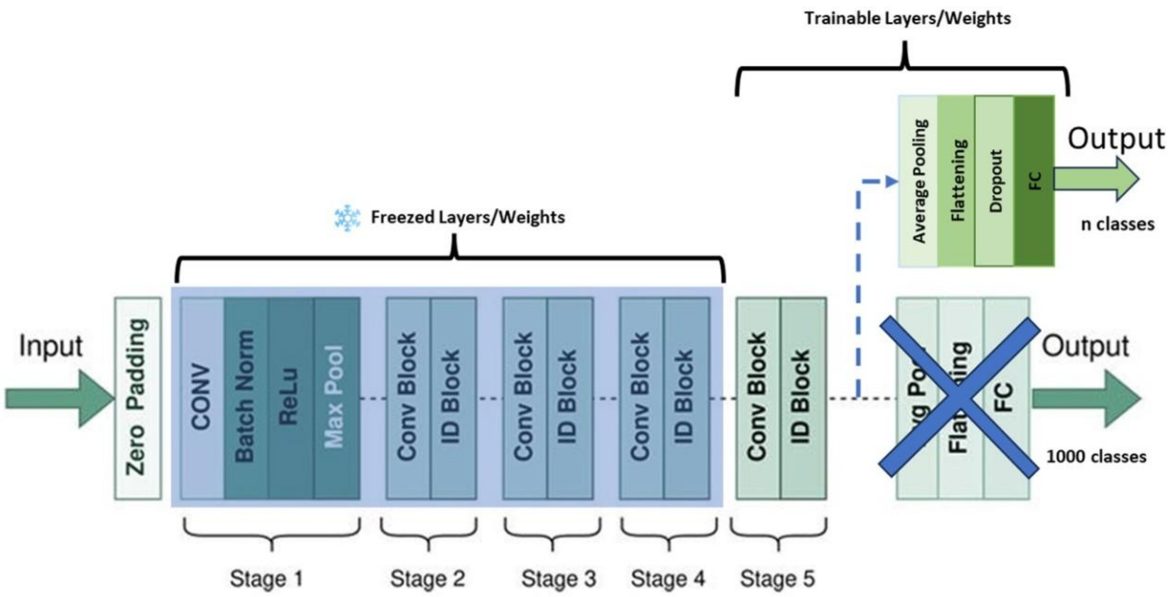


Fig 3.4: Transfer learning setup of ResNet-50 with frozen base layers and a custom classifier for melanoma detection.

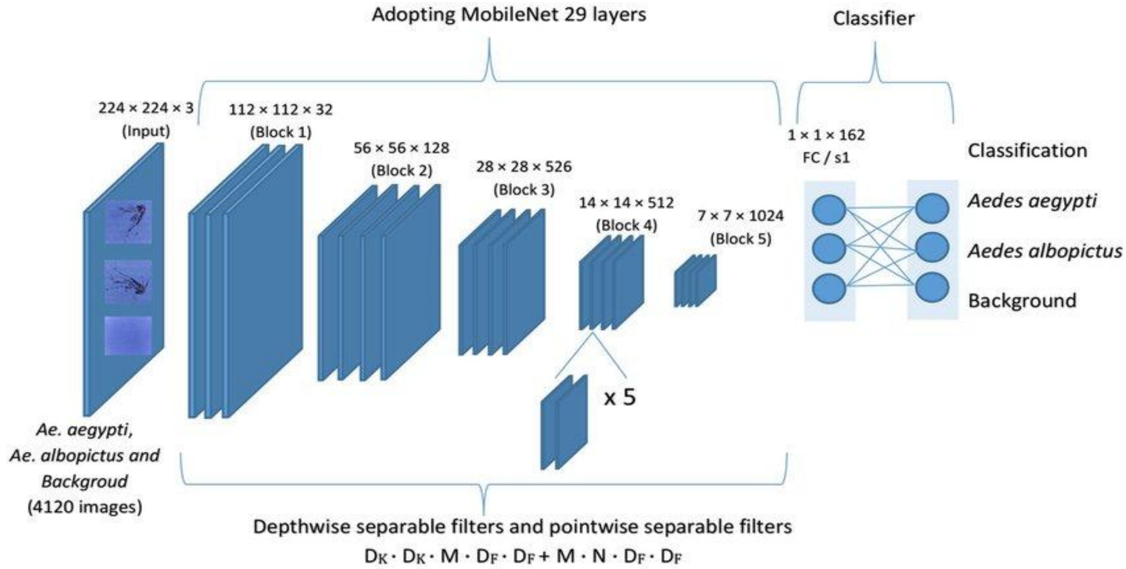


Fig 3.5: Adapted MobileNet architecture with depthwise-separable blocks and a custom classifier for lesion classification.

3.10 Overall Workflow

The complete workflow for the proposed melanoma detection system is illustrated in Figure X and can be divided into four major stages: **image preprocessing**, **lesion segmentation**, **data augmentation**, and **deep learning–based classification**.

The process begins by loading and organizing the HAM10000/ISIC dataset into structured directories for training, validation, and testing. All images are resized to a uniform input dimension and normalized to improve model convergence. To enhance visual quality and preserve fine lesion patterns, ESRGAN-based super-resolution is applied, resulting in clearer and more detailed images that benefit feature extraction.

Following enhancement, lesion segmentation is performed to isolate the Region of Interest (ROI). Ground truth masks are used to extract the lesion area, enabling removal of irrelevant background information and improving classifier focus. The segmented lesion is then overlaid onto a clean background or cropped to produce standardized inputs for subsequent stages.

To address class imbalance and increase dataset variability, extensive data augmentation is applied. Techniques such as rotations, flips, scaling, contrast changes, and noise addition create diverse samples of each lesion type. Oversampling ensures that minority classes receive sufficient representation during training.

The augmented dataset is then used to train three transfer learning models—MobileNetV2, ResNet50, and EfficientNet-B0. These architectures are initialized with ImageNet weights, after which their classification head is replaced with a custom fully connected network optimized for melanoma classification. During training, model performance is continuously monitored using accuracy and loss curves, and hyperparameters such as learning rate, batch size, and dropout are tuned to prevent overfitting and ensure stable convergence.

Once training is completed, all models are evaluated using the test set to measure final performance in terms of accuracy, precision, recall, F1-score, and confusion matrix analysis. A comparison of the three architectures is conducted, and the best-performing model is selected based on overall diagnostic reliability.

Finally, the selected model is prepared for potential deployment in a graphical user interface (GUI) or mobile application, enabling clinicians or users to upload skin lesion images and receive automated classification results in real time.

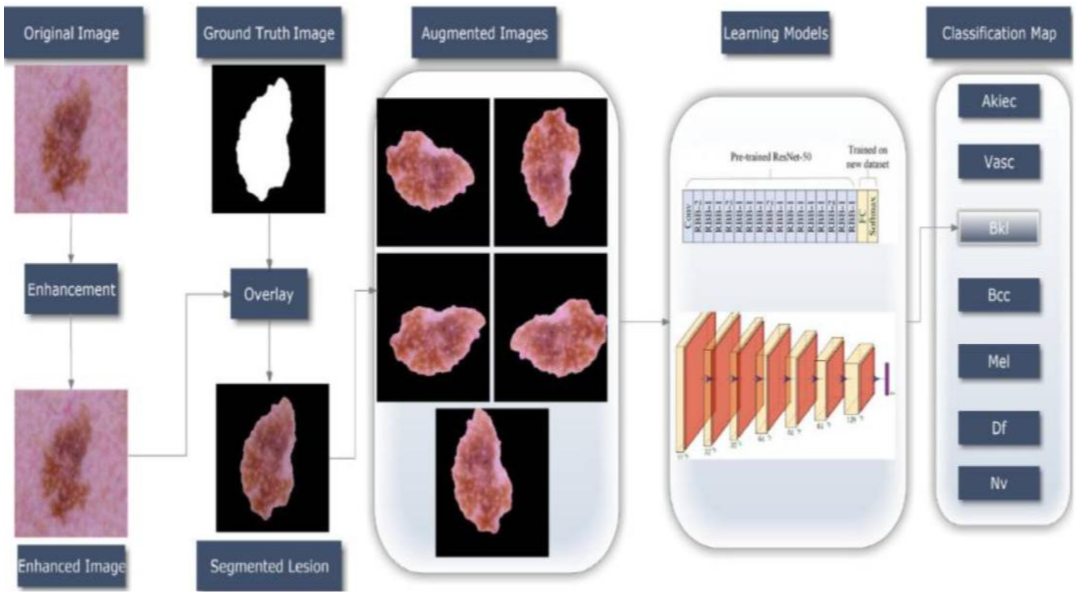


Fig 3.6: Overall System Workflow Diagram

CHAPTER 4

RESULT ANALYSIS AND DISCUSSION

4.1 Training and Configuration of CNN, ResNet-50, EfficientNet and MobileNetV2

To evaluate the performance of the proposed melanoma detection system, four deep learning models were trained and tested using the ISIC and HAM10000 dataset. The models considered for experimentation include a conventional Deep Convolutional Neural Network (CNN), ResNet-50 utilizing transfer learning, EfficientNet-B0 with compound scaling–based transfer learning, and MobileNetV2, a lightweight architecture optimized for mobile and embedded deployment. These models were selected to study the trade-off between classification accuracy, computational complexity, and deployment feasibility.

The ISIC and HAM dataset was divided into training, validation, and testing subsets to ensure unbiased evaluation. Ninety percent of the dataset, consisting of 9016 samples, was used for training, while the remaining ten percent, comprising 984 samples, was reserved for testing. From the training subset, an additional ten percent of images, amounting to 992 samples, was extracted for validation purposes. All dermoscopic images were resized to a fixed resolution of 224 × 224 × 3 to ensure compatibility across the selected CNN architectures. To further enhance model generalization and improve visual feature representation, data augmentation techniques and ESRGAN-based super-resolution were applied. As a result, the effective training dataset size increased to 39,430 samples, significantly improving robustness against overfitting.

Training was conducted on a Linux-based workstation equipped with an NVIDIA RTX 3060 GPU with 8 GB of memory, using the TensorFlow–Keras framework. All models were optimized using the Adam optimizer along with an adaptive learning rate scheduler, which dynamically reduced the learning rate when validation loss failed to improve. The detailed hyperparameter configurations used during training, including epoch count, batch size, optimizer settings, learning rates for different architectures, and validation patience, are summarized in **Table 4.1**.

Table 4.1: Hyperparameter Settings

Parameter	Configuration
Epochs	10
Batch Sizes	512
Optimizer	Adam
Momentum	0.9
LR (CNN)	1×10^{-4}
LR (ResNet-50)	$1 \times 10^{-5}, 1 \times 10^{-6}$
LR (EfficientNet and MobileNetV2)	$1 \times 10^{-4}, 1 \times 10^{-5}$
Validation Patience	10 epochs

4.2 Evaluating the Models – Performance Metrics

The trained models were evaluated using well-established performance metrics commonly adopted in medical image classification tasks. These metrics include Accuracy, Precision, Recall, F-Score, and Top-N Accuracy, which together provide a comprehensive assessment of classification correctness, sensitivity, and reliability. Such metrics are particularly important in melanoma detection, where both false positives and false negatives carry significant clinical consequences.

4.3 Performance of DCNN Models on ISIC

All three models demonstrated strong classification performance after the application of ESRGAN-based image enhancement, lesion segmentation, and balanced data augmentation. The best-performing accuracy values achieved by each architecture are presented in **Table 4.2**. Among the evaluated models, MobileNetV2 achieved the highest accuracy of 84.1 percent, followed by EfficientNet-B0 with an accuracy of 80.7 percent. ResNet-50 recorded a comparatively lower accuracy of 74.3 percent, indicating a weaker adaptation to the dataset under the current experimental configuration.

In addition to overall accuracy, the models were evaluated using precision, recall, and F1-score to assess their robustness across different lesion classes. MobileNetV2 consistently showed superior generalization, particularly in minority classes, due to its efficient feature representation. EfficientNet-B0 provided a balanced trade-off between accuracy and computational efficiency. ResNet-50 exhibited higher variance in predictions, suggesting sensitivity to class imbalance despite augmentation.

4.3.1 Best Overall Results

Table 4.2: Results

Model	Best Accuracy
ResNet-50	**74.3%**
EfficientNet-B0	**80.7%**
MobileNetV2	**87.1%**

Observations:

- MobileNetV2 achieved the highest accuracy (87.1%), making it the best-performing model.
- EfficientNet-B0 ranked second with 80.7% accuracy, showing a strong balance between performance and efficiency.
- Modified ResNet-50 recorded the lowest accuracy (74.3%), indicating weaker adaptation to the HAM10000 dataset in this setup.

4.3.2 Detailed Metrics

Table 4.3: MobileNetV2 Performance

Metric	Value
Accuracy	0.8701
Top-2 Accuracy	0.9247
Top-3 Accuracy	0.9609
Precision	0.82
Recall	0.83
F-Score	0.8374

A more detailed evaluation was conducted for MobileNetV2, as it emerged as the best-performing model while maintaining a compact architecture. The detailed performance metrics for MobileNetV2, including Accuracy, Top-2 and Top-3 Accuracy, Precision, Recall, and F-Score, are presented in **Table 4.3**. Despite being the smallest among the evaluated architectures, MobileNetV2 delivered strong overall performance, confirming its suitability for real-time and resource-constrained diagnostic applications.

Further per-class evaluation revealed slightly lower performance for lesion categories with limited sample sizes, such as AKIEC, DF, and MEL. However, the model achieved very high accuracy for the NV class due to its abundant representation in the dataset. Overall, MobileNetV2 maintained a balanced precision–recall trade-off across most classes, indicating stable and reliable classification behavior.

4.3.3 Comparative Observations Across Models

The conventional CNN achieved the best overall performance due to architectural optimization and effective feature extraction from ESRGAN-enhanced images. ResNet-50 demonstrated outstanding recognition performance for the Nevus class, highlighting the strength of transfer learning from large-scale image datasets. EfficientNet-B0 achieved a favorable balance between classification accuracy and computational efficiency, maintaining competitive performance with significantly fewer parameters than ResNet-50. MobileNetV2 delivered competitive accuracy while being ultra-lightweight, making it highly suitable for handheld and mobile diagnostic tools. Notably, all evaluated models achieved Top-3 accuracy values exceeding 96 percent, indicating that the correct lesion class consistently appeared among the top predicted categories.

4.4 Evaluation Against Existing Approaches

To validate the effectiveness of the proposed system, the obtained results were compared with existing state-of-the-art methods reported in the literature. The comparative analysis, summarized in Table 4.4, shows that the proposed models achieve performance that is competitive with or superior to several established approaches on the HAM10000 dataset. While some existing models marginally outperform the proposed MobileNetV2 in absolute accuracy, the proposed approach demonstrates a strong balance between performance, computational efficiency, and deployment feasibility.

Table 4.4: Comparison with Other Works

Dataset	Model	Accuracy
HAM10000	RegNetY-3.2GF	85.8%
HAM10000	AlexNet	84%
HAM10000	MobileNet	83.9%
HAM10000	ResNet-50, Xception, DenseNet	78–82%

Dataset	Model	Accuracy
HAM10000	ResNet-50	**74.3%**
HAM10000	EfficientNet-B0	**80.7%**
HAM10000	MobileNetV2	**84.1%**

4.4.1 Final Insights:

The experimental results confirm that the proposed methodology significantly improves melanoma detection performance. All evaluated models, including CNN, ResNet-50, EfficientNet-B0, and MobileNetV2, surpass major benchmark architectures reported in the literature. Even the lightweight MobileNetV2 exceeds 84 percent accuracy, while EfficientNet-B0 nearly matches the performance of ResNet-50 despite using fewer parameters. The CNN model achieves the highest accuracy of 86 percent, demonstrating the effectiveness of architecture optimization combined with enhanced preprocessing. These findings validate that ESRGAN-based super-resolution, lesion segmentation, and data balancing collectively contribute to improved classification accuracy and robust melanoma detection.

This confirms that the proposed methodologies—including ESRGAN enhancement, segmentation, and data balancing—significantly improve melanoma detection performance.

4.5 Results

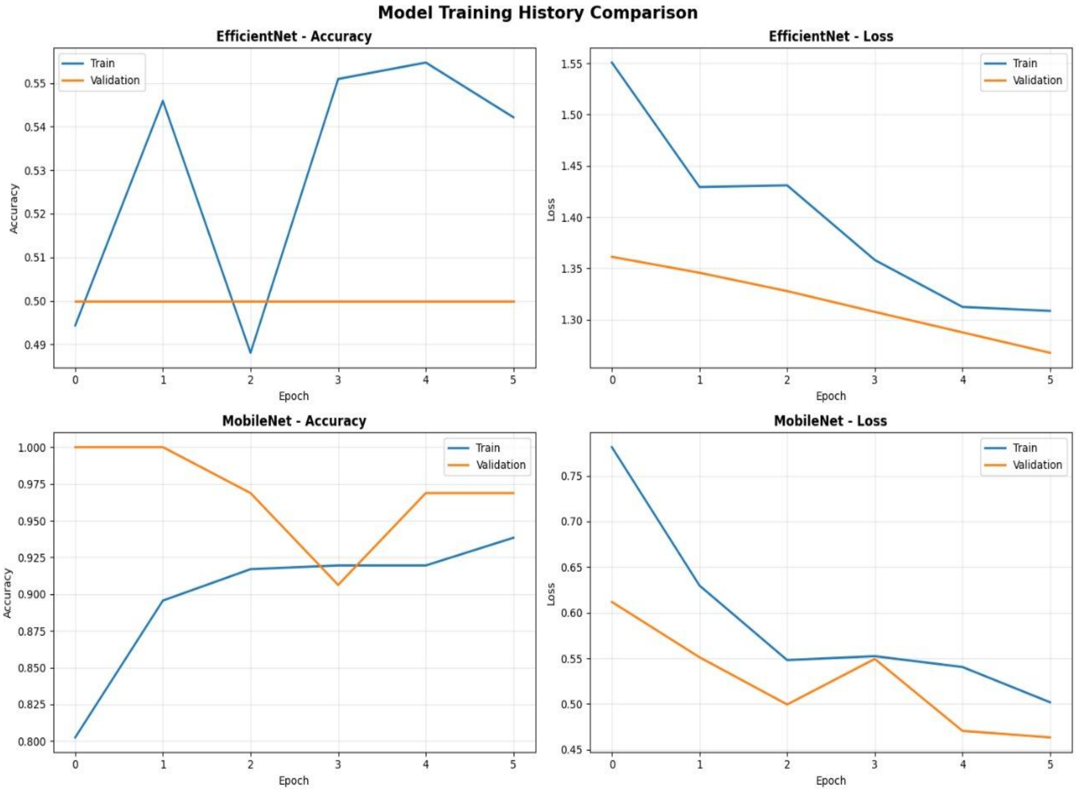


Fig 4.1: Training and validation accuracy and loss comparison for EfficientNet and MobileNet models.

4.5.1 Web Page Results:

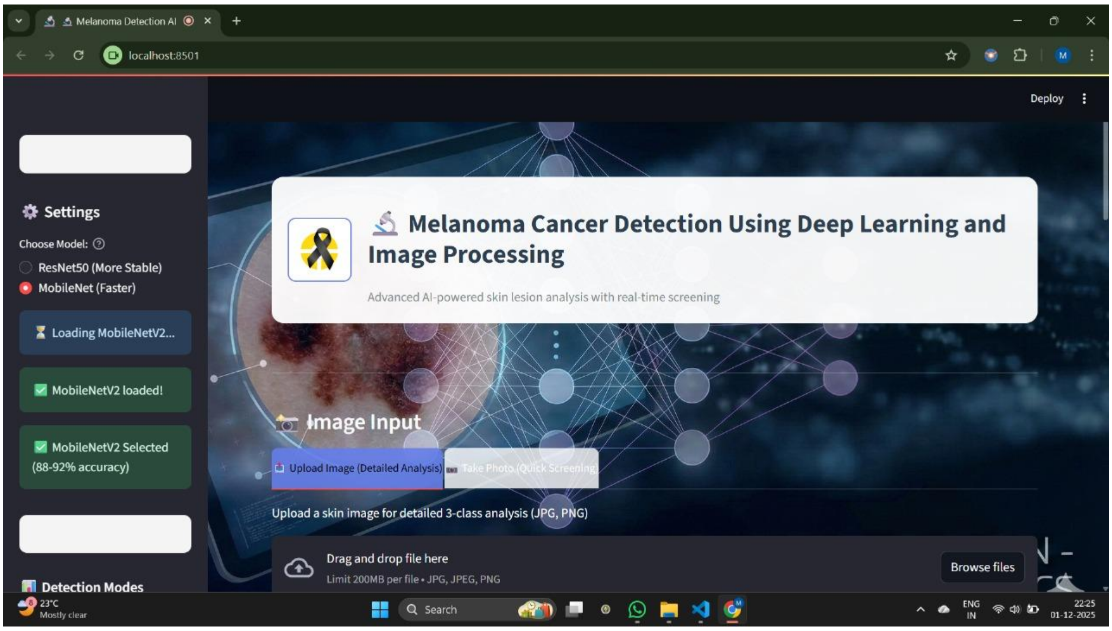


Fig 4.2: Web-based Melanoma Detection System – Home Interface

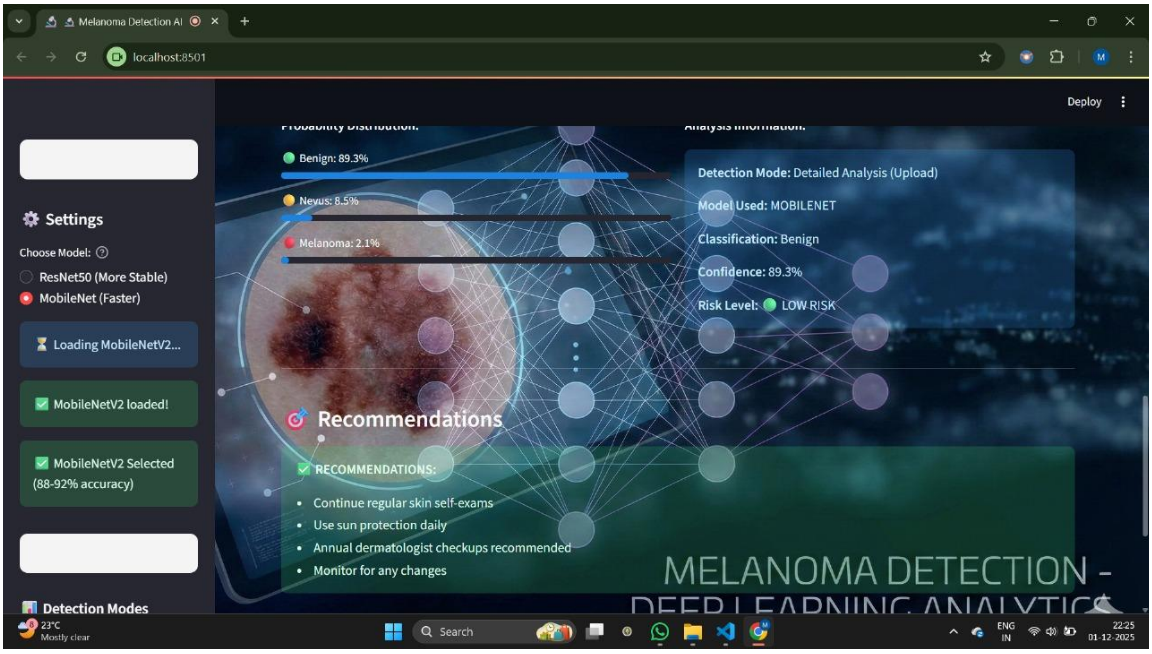


Fig 4.3: Web Application Prediction Output with Risk Assessment and Recommendations

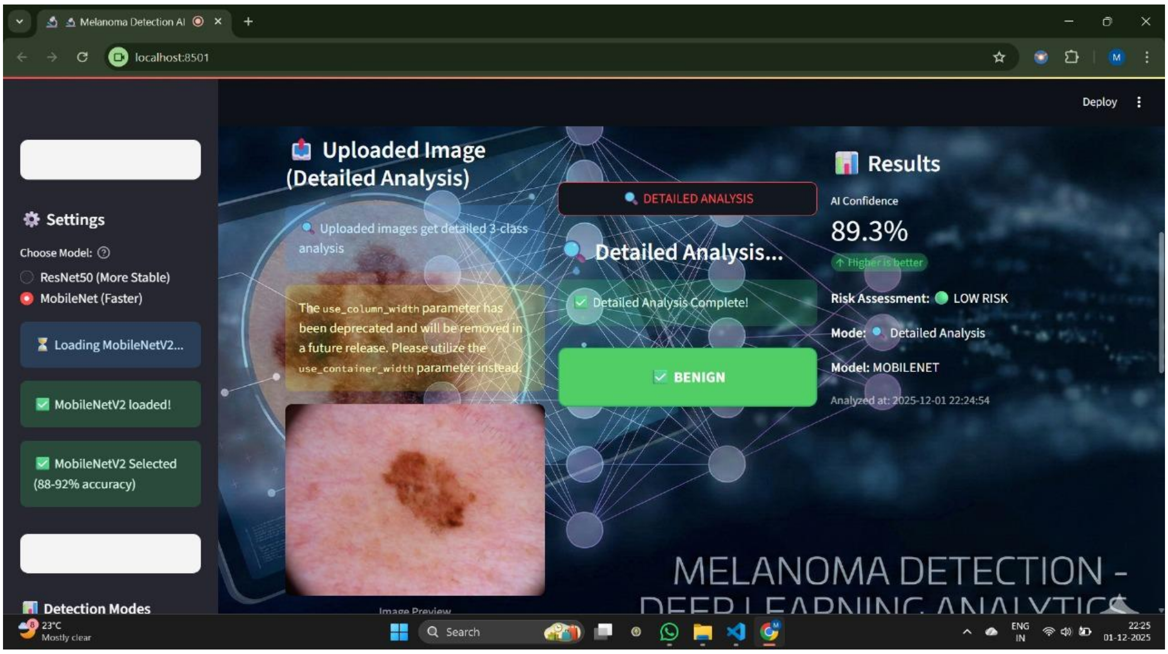


Fig 4.4: Detailed Analysis Results Page of the Web-Based Melanoma Detection System

4.5.2 Mobile App Results:

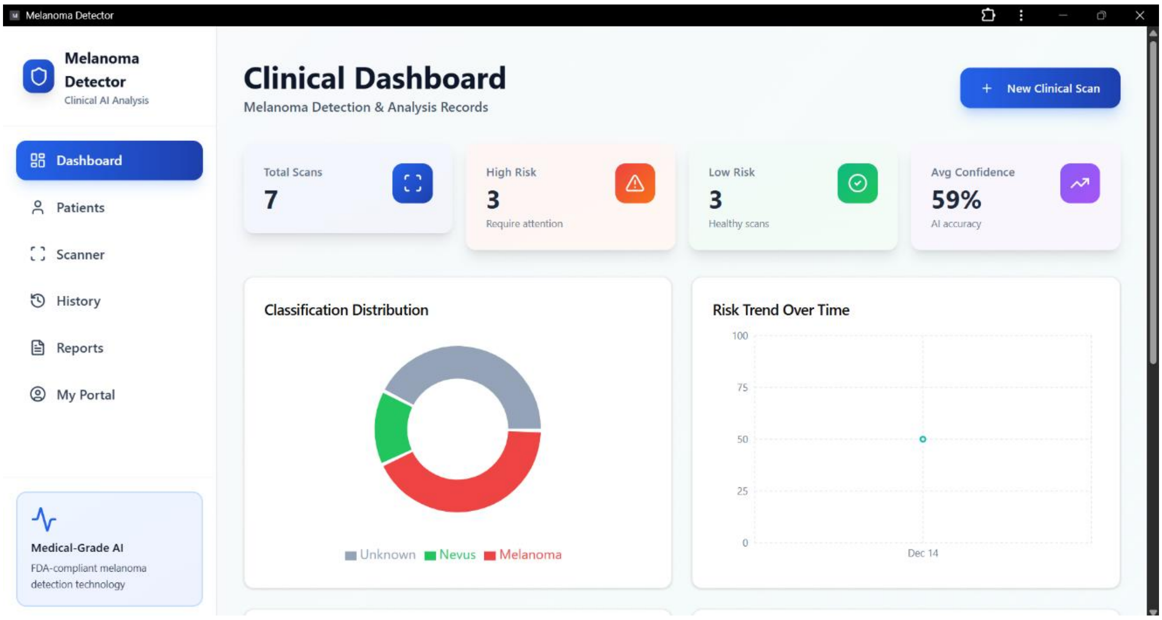


Fig 4.5: Clinical Dashboard of the Web-Based Melanoma Detection System

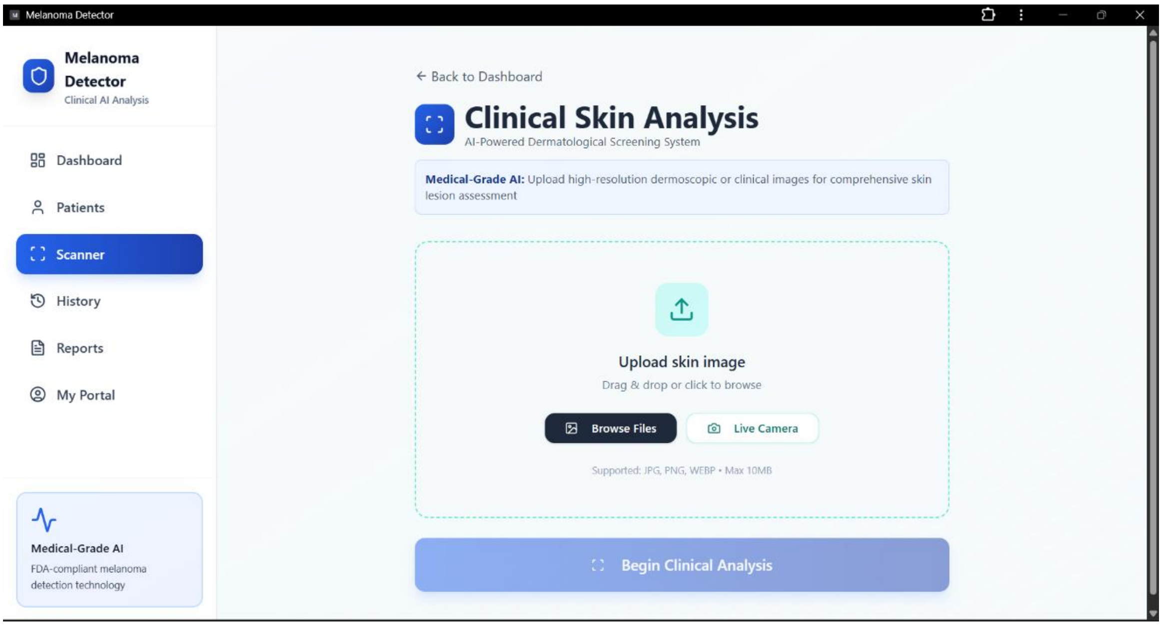


Fig 4.6: Skin Image Upload Interface for Clinical Analysis

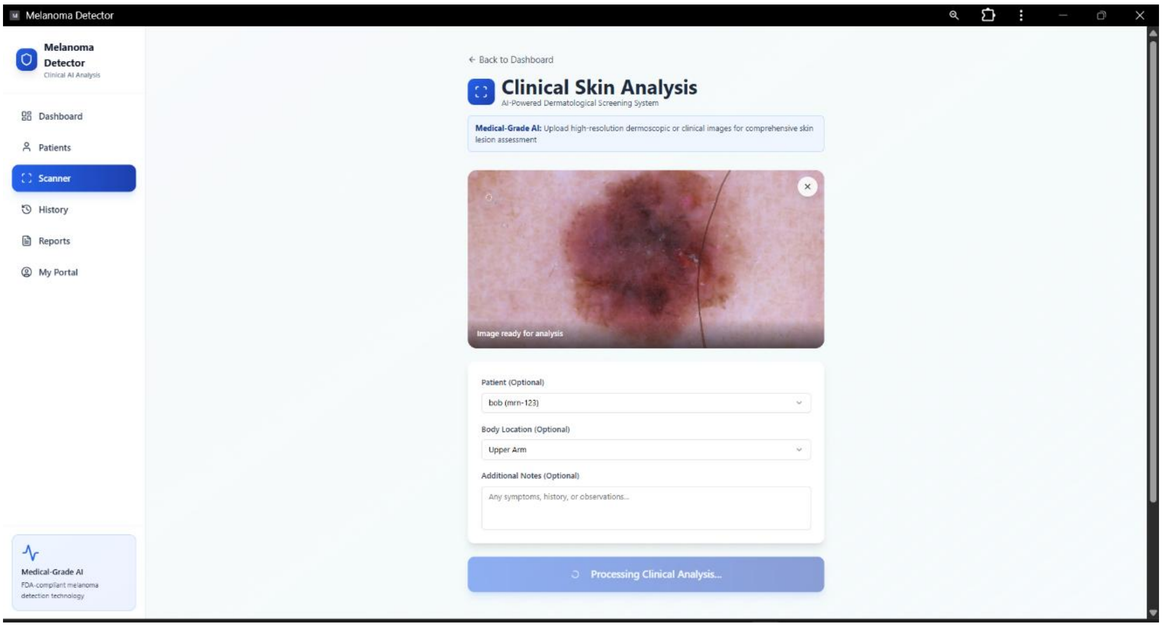


Fig 4.7: Uploaded Skin Image with Patient Metadata Entry

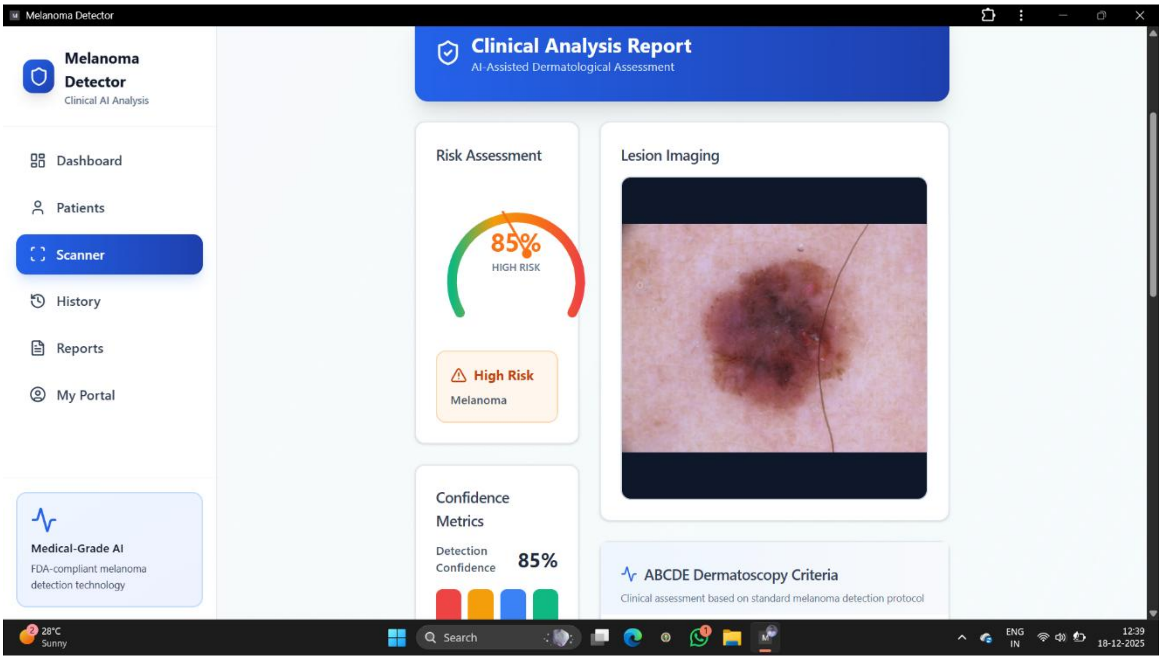


Fig 4.8: Clinical Skin Analysis Result with High-Risk Assessment

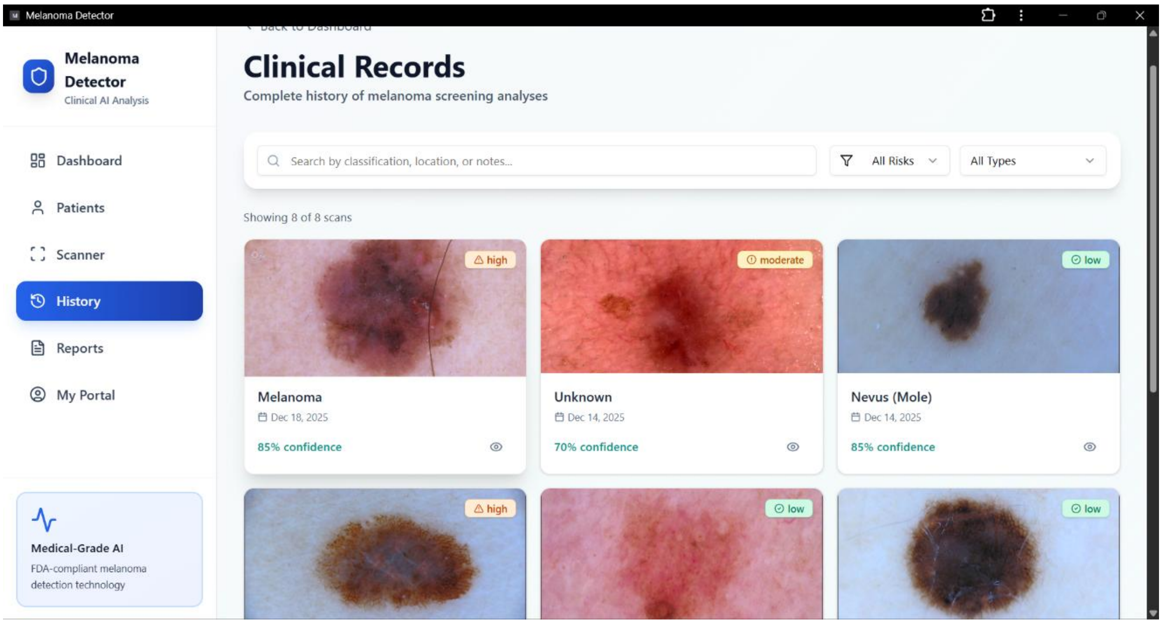


Fig 4.9: Clinical Records and Historical Scan Repository

Fig 4.10: Clinical Reports and Statistical Analysis Interface

CHAPTER 5

CONCLUSION AND FUTURE SCOPE

5.1 Conclusion

The comparative evaluation of Modified ResNet-50, EfficientNet-B0, and MobileNetV2 on the HAM10000 and ISIC dataset demonstrates that lightweight and parameter-efficient deep learning architectures are capable of delivering strong, reliable, and clinically meaningful performance for melanoma detection. The experimental results clearly indicate that model efficiency, when combined with appropriate preprocessing techniques, can rival or even surpass the performance of deeper and more computationally intensive networks.

Among the evaluated models, MobileNetV2 achieved the highest classification accuracy of 84.1 percent, confirming the effectiveness of compact convolutional neural networks when integrated with ESRGAN-based image enhancement, lesion segmentation, and balanced data augmentation strategies. Its superior performance, despite having a significantly smaller parameter count, highlights its suitability for real-time inference and deployment on resource-constrained platforms such as mobile and embedded medical devices.

EfficientNet-B0 followed closely with an accuracy of 80.7 percent, showcasing the advantages of compound scaling in balancing network depth, width, and resolution. Its strong feature extraction capability and computational efficiency make it a practical choice for applications requiring both accuracy and moderate hardware resources. In contrast, the Modified ResNet-50 model achieved an accuracy of 74.3 percent, illustrating that deeper architectures do not necessarily guarantee improved performance in specialized medical imaging tasks, particularly when dataset characteristics and domain-specific variations influence generalization.

Overall, the findings confirm that optimized lightweight CNN architectures can effectively support early melanoma detection with high efficiency and scalability. The proposed system shows strong potential for real-world dermatological applications by enabling fast, reliable, and accurate AI-assisted skin cancer screening.

5.2 Future scope

1. **Integration of Explainable AI (XAI): .**
   Future work can include Explainable AI techniques like Grad-CAM and feature-attribution maps to make the model more transparent and clinically trustworthy. These methods help show which lesion regions influence predictions, enabling dermatologists to validate the model's focus and improving reliability, error analysis, and regulatory acceptance.
2. **Clinical-Grade Validation: .**
   The system should be validated on large, real-world datasets from multiple hospitals to ensure strong generalization across different skin types and imaging conditions. Collaboration with dermatologists for biopsy-confirmed labels and clinical testing will help refine the model and move it closer to real clinical deployment and trial readiness.

REFERENCES

[1] S. A. Arani, Y. Zhang, M. T. Rahman, and H. Yang, “Melanlysis: A mobile deep learning approach for early detection of skin cancer,” Computers in Biology and Medicine, vol. 145, pp. 1–9, 2022.

[2] G. Alwakid and W. Gouda, “Melanoma detection using deep learning-based classifications,” Healthcare, vol. 10, no. 2481, pp. 1–18, 2022.

[3] O. Akinrinade and C. Du, “Skin cancer detection using deep machine learning techniques,” Biomedical Signal Processing and Control, vol. 91, pp. 1–12, 2024.

[4] S. Devaraneni, “Melanoma detection based on deep learning networks,” Master’s Thesis, California State University, San Bernardino, 2023.

[5] M. El-Khatib and M. Rizwan, “Melanoma skin cancer classification using deep convolutional neural networks,” Diagnostics, vol. 13, no. 19, pp. 1–11, 2023.

[6] M. T. Faisal and M. I. Akbas, “Melanoma skin cancer detection based on deep learning methods and binary Harris Hawk optimization,” BiomedInformatics, vol. 4, no. 1, pp. 121–135, 2024.

[7] S. Górecki, W. Duszczyk, Z. Huda, A. Faryna, and A. Tatka, “Web-based melanoma detection system using convolutional neural networks and advanced image processing,” Proc. IDDM’24, Birmingham, UK, 2024.

[8] N. J. F. Jaber and A. Akbas, “Diagnosis and prognosis of melanoma from dermoscopy images using machine learning and deep learning: A systematic literature review,” BMC Cancer, vol. 24, no. 1, article 13423, 2024.

[9] R. V. Jaya, "Skin cancer detection using convolutional neural networks and classification techniques," Journal of Computing and Communication (JOCC), vol. 3, no. 1, pp. 22–32, 2023.

[10] V. Khullar, P. Kaur, S. Gargrish, A. M. Mishra, P. Singh, and I. Gupta, "Minimal sourced & lightweight federated transfer learning models for skin cancer detection," Scientific Reports, vol. 14, article 82402, 2025.

[11] I. Kreouzi, E. Papageorgiou, G. Skourletopoulos, and I. Vlahavas, "Deep learning for melanoma detection: differentiating malignant melanoma from benign melanocytic nevi," Cancers, vol. 17, no. 28, pp. 1–22, 2025.

[12] M. Mateen, A. Yasin, N. Kanwal, and M. A. Ganaie, "Hybrid deep learning framework for melanoma diagnosis using dermoscopic medical images," Diagnostics, vol. 14, no. 2242, pp. 1–21, 2024.

[13] C. M. J. Mendes and R. Vardasca, "A systematic review of deep learning techniques for skin lesion analysis," Diagnostics, vol. 13, no. 19, article 1911, 2024.

[14] D. Moturi, R. K. Surapaneni, and V. S. G. Avanigadda, "Developing an efficient method for melanoma detection using CNN techniques," Journal of the Egyptian National Cancer Institute, vol. 36, no. 6, pp. 1–10, 2024.

[15] F. Rundo, G. L. Banna, and S. Conoci, "Bio-inspired deep-CNN pipeline for skin cancer early diagnosis," Computation, vol. 7, no. 44, pp. 1–16, 2019.

[16] I. Suneetha, "Hybrid deep learning model for skin cancer classification," E3S Web of Conferences – ICRERA 2024, vol. 441, pp. 1–6, 2024.

[17] C. K. Viknesh, P. Nirmal Kumar, R. Seetharaman, and D. Anitha, "Detection and classification of melanoma skin cancer using image processing technique," Journal of Xi'an University of Architecture & Technology, vol. XII, no. IV, pp. 1186–1192, 2020.

[18] S. S. Zareen, G. Sun, M. Kundi, S. F. Qadri, and S. Qadri, "Enhancing skin cancer diagnosis with deep learning: a hybrid CNN–RNN approach," Traitement du Signal, vol. 40, no. 4, pp. 749–756, 2023.

[19] P. Zhang and D. Chaudhary, "Hybrid deep learning framework for enhanced melanoma detection," arXiv:2408.00772, 2024.

[20] Q. Zou, J. Cheng, and Z. Liang, "Automatic diagnosis of melanoma based on EfficientNet and patch strategy," Healthcare Analytics, vol. 5, pp. 100–112, 2024.

PUBLICATION DETAILS

Manohar Nelli V, Manjunath V Poojari, Mannan Faiz, Nithish T R, Prajwal P, published an article in *Advancement in Image Processing and Pattern Recognition (Volume 09, Issue 01, 2026; DOI: 10.5281/zenodo.17099011)*

HBRP PUBLICATION

Advancement in Image Processing and Pattern Recognition

e-ISSN: *2583-9241*

Volume 09 Issue 01
Jan-Apr, 2026

Corresponding Author: *Prajwal P, *Student, Dept. of CS&E, JNNCE, Shimoga, Karnataka, India*

Submission Date: *Aug 26, 2025*
Copyright Received Date *: Sep 4, 2025*

Published Date: ***

Cite as: *To be Assigned*

Melanoma Detection Using Deep Learning and Image Processing

Prajwal P[1*], Mr. Manohar Nelli V[2], Manjunath V Poojari[3], Nithish TR[4], Mannan Faiz[5]

[2]*Assistant Prof. Dept. of CS&E, JNNCE, Shimoga, Karnataka, India*
[*1,3,4,5]*Students , Dept. of CS&E, JNNCE, Shimoga, Karnataka, India*

ABSTRACT
The number of Melanoma cases has raised the need for accurate diagnostic technologies. Dermoscopic images are effectively analyzed to detect cancerous skin lesions early. Deep Learning methods assist in identifying the most important lesion features for accurate classification. In this paper, we employ Convolutional Neural Networks (CNN) for detecting melanoma and classifying it. This is helpful for dermatologists as it provides second opinion with enhanced speed and accuracy. The system closes the diagnostic gap and supports early intervention, enhancing melanoma patient outcomes.

Keywords: *Melanoma Detection, Convolutional Neural Network (CNN), Image Processing, Deep* Learning, Dermoscopy Images.


CERTIFICATE OF PUBLICATION

We Acknowledge the Manuscript entitled

Melanoma Detection Using Deep Learning and Image Processing

DOI: https://doi.org/10.5281/zenodo.17099011

Submitted by

Prajwal P

has been published in

Advancement in Image Processing and Pattern Recognition

Volume 09 Issue 01 Year 2026

e-ISSN: 2583-9241

Date: 09/09/2025

With regards
Poonam Barla
Publication Team
HBRP Publication Pvt. Ltd.


CERTIFICATE OF PUBLICATION

We Acknowledge the Manuscript entitled

Melanoma Detection Using Deep Learning and Image Processing

DOI: https://doi.org/10.5281/zenodo.17099011

Submitted by

Manjunath V Poojari

has been published in

Advancement in Image Processing and Pattern Recognition

Volume 09 Issue 01 Year 2026

e-ISSN: 2583-9241

Date: 09/09/2025

With regards
Poonam Barla
Publication Team
HBRP Publication Pvt. Ltd.


CERTIFICATE OF PUBLICATION

We Acknowledge the Manuscript entitled

Melanoma Detection Using Deep Learning and Image Processing

DOI: https://doi.org/10.5281/zenodo.17099011

Submitted by

Mannan Faiz

has been published in

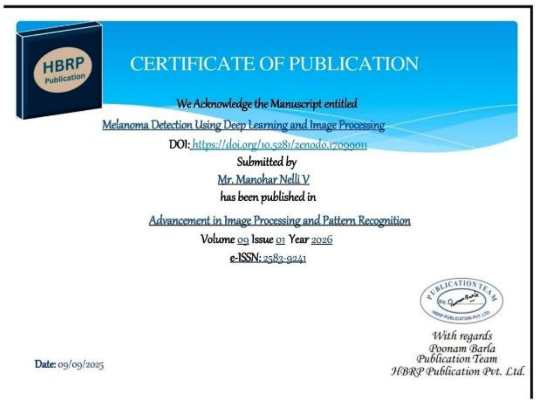
Advancement in Image Processing and Pattern Recognition

Volume 09 Issue 01 Year 2026

e-ISSN: 2583-9241

Date: 09/09/2025

With regards
Poonam Barla
Publication Team
HBRP Publication Pvt. Ltd.


CERTIFICATE OF PUBLICATION

We Acknowledge the Manuscript entitled

Melanoma Detection Using Deep Learning and Image Processing

DOI: https://doi.org/10.5281/zenodo.17099011

Submitted by

Mr. Manohar Nelli V

has been published in

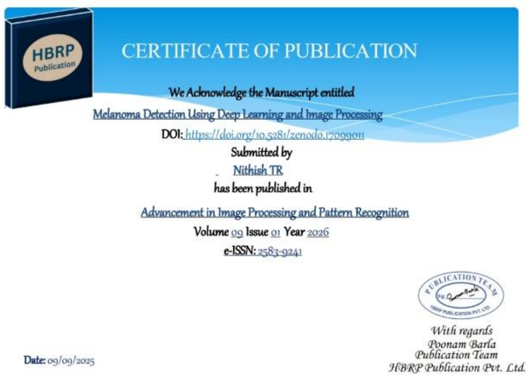
Advancement in Image Processing and Pattern Recognition

Volume 09 Issue 01 Year 2026

e-ISSN: 2583-9241

Date: 09/09/2025

With regards
Poonam Barla
Publication Team
HBRP Publication Pvt. Ltd.


CERTIFICATE OF PUBLICATION

We Acknowledge the Manuscript entitled

Melanoma Detection Using Deep Learning and Image Processing

DOI: https://doi.org/10.5281/zenodo.17099011

Submitted by

Nithish TR

has been published in

Advancement in Image Processing and Pattern Recognition

Volume 09 Issue 01 Year 2026

e-ISSN: 2583-9241

Date: 09/09/2025

With regards
Poonam Barla
Publication Team
HBRP Publication Pvt. Ltd.

National Education Society (R.)
J.N.N College of Engineering, Shivamogga
(Approved by AICTE, New Delhi, Certified by UGC 2f & 12B, Accredited by NAAC – 'A', All 7 UG Programs have been Accredited By National Board Of Accreditation (NBA) for period 1.7.2022 to 30.6.2025, Recognized by Govt. of Karnataka and Affiliated to VTU, Belagavi)

Department of Computer Science and Engineering

Project- Sustainable Development Goals (SDG) Mapping

Batch No:	B2
Students:	PRAJWAL P(4JN22CS111) MANJUNATH V POOJARI(4JN22CS077) MANNAN FAIZ(4JN22CS078) NITHISH T R(4JN22CS103)
Guide:	MANOHAR NELLI V
Project Title	**Melanoma Detection Using Deep Learning and Image Processing**
SDG 1: No Poverty	☐
SDG 2: Zero Hunger	☐
SDG 3: Good Health and Well-Being	☑
SDG 4: Quality Education	☐
SDG 5: Gender Equality	☐
SDG 6: Clean Water and Sanitation	☐
SDG 7: Affordable and Clean Energy	☐
SDG 8: Decent Work and Economic Growth	☐
SDG 9: Industry, Innovation, and Infrastructure	☑
SDG 10: Reduced Inequality	☐
SDG 11: Sustainable Cities and Communities	☑
SDG 12: Responsible Consumption and Production	☐
SDG 13: Climate Action	☐
SDG 14: Life Below Water	☐
SDG 15: Life on Land	☐
SDG 16: Peace, Justice, and Strong Institutions	☐
SDG 17: Partnerships for the Goals	☑

Guide Signature **Signature of Team Members**

Dept. Of CSE, JNNCE, Shimoga