DERMATOLOGY AI

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2024-2025

Final documentation

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1. Abstract

The importance of the project lies in the widespread prevalence of skin diseases, Skin diseases affect over 3 billion people globally, with annual treatment costs reaching $53 billion in the US alone. Many conditions can be effectively treated if detected early, highlighting the importance of accessible and accurate diagnostic tools. This project aims to develop a mobile application that leverages AI-powered dermatological analysis to assist users in diagnosing skin conditions through image-based assessment.

System Overview:

The proposed mobile application integrates computer vision and deep learning techniques to classify skin diseases based on images uploaded by users. The system consists of the following key stages:

1. Image Upload & Preprocessing
2. Feature Extraction & Clustering
3. AI-Based Image Classification
4. Diagnosis & Recommendations

Significance & Impact:

- Early Detection: Timely diagnosis increases survival rates and prevents complications.
- Accessibility: The offline functionality ensures availability in regions with limited internet access.
- Cost Reduction: Helps reduce unnecessary medical visits and treatment delays.
- Global Reach: Addresses the high prevalence of skin diseases worldwide

2. Introduction

2.1 What is this project?

This project focuses on developing an AI-powered dermatology model capable of diagnosing skin diseases through visual examination of affected areas. Integrated within a mobile application, the system allows users to capture or upload images of their skin conditions. Before analysis, images undergo preprocessing to enhance clarity and ensure accurate results. The system then extracts features and applies clustering techniques to streamline the classification process, making it suitable for offline use.

Once processed, the image is analyzed using a deep learning-based classification model, which identifies potential skin diseases. The application promptly delivers diagnostic results, along with detailed information about the identified condition, including its severity, contagiousness, and necessary precautions. By leveraging AI, this solution aims to enhance early detection, accessibility, and affordability of dermatological care, ultimately improving patient outcomes.

2.2 Why this project?

This project specifically aims to present a set of crucial numbers and statistics. For instance, there are 1.8 billion people worldwide who are affected by various skin diseases, with varying degrees of severity and types. Imagine the amount of money spent annually on treating these diseases, specifically in terms of medication alone. The annual cost of treating skin cancer in America is $8 billion. [2] Additionally, 58 million American citizens are diagnosed with some form of skin cancer, including benign types, [3] which are the most prevalent. However, these types need to be monitored and treated as they can progress to malignant forms over time, leading to fatalities. In America, 9,500 individuals are screened for skin cancer daily. Skin cancer causes the death of two individuals every hour worldwide. Early detection is a key focus of this application, as it significantly increases the chances of recovery and survival from skin cancer, reaching up to 97%. However, if detected in later stages, the recovery rate drops to 14%.

Key Reasons for Developing This Project:

1. **Prevalence of Skin Diseases:**

   Prevalence of any skin disease: 26.98% of the population.

   Total affected population: 84,524,194 individuals.

   Average number of skin diseases per affected person: 1.6.

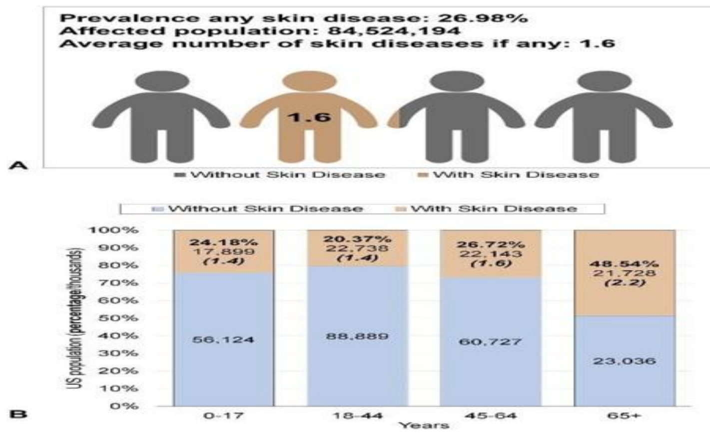


Figure 1: prevalence of skin diseases

Age Group Distribution of Skin Diseases (Figure 1): The bar chart shows the percentage of people with and without skin diseases across different age groups:

Age Group	% with Skin Disease	Affected Population (in thousands)	Avg. Skin Diseases per Person
0-17	24.18%	17,899	1.4
18-44	20.37%	22,738	1.4
45-64	26.72%	22,143	1.6
65+	48.54%	21,728	2.2

Key Insights:

The prevalence of skin diseases **increases with age**, with the highest percentage found in the **65+ age group (48.54%)**.

The **youngest age group (0-17 years)** has a relatively lower prevalence (**24.18%**).

The **average number of skin diseases per affected individual** increases with age, peaking at **2.2 diseases per person** in the **65+ group**.

Relevance to the Project:

Age Factor in Skin Disease Classification: Since skin disease prevalence increases with age, the model should consider **age as a potential feature** for classification.

Multiple Skin Diseases Per Person: The presence of **more than one skin disease per individual** suggests the need for a model capable of **multi-label classification** rather than single-label classification.

Balancing Data for Model Training: Given the varying prevalence rates across age groups, ensuring a **balanced dataset** across age ranges can improve model accuracy.

2-**The image contains four pie charts** representing the distribution of age groups across different healthcare coverage populations in the United States.

The age groups are categorized as follows:

0-17 years (blue)

18-44 years (orange)

45-64 years (gray)

65+ years (yellow)

Population Groups Covered in the Analysis:

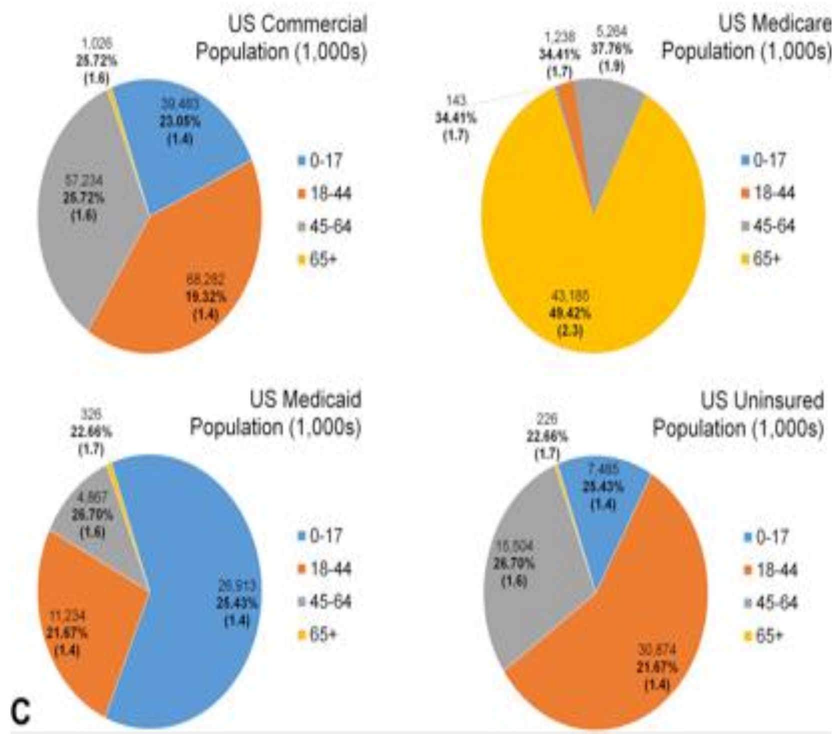


Figure 2: Distribution of age groups across US healthcare

US Commercial Population: Individuals with commercial health insurance.

US Medicare Population: Individuals covered by Medicare (mainly elderly people aged 65+).

US Medicaid Population: Individuals covered by Medicaid (typically low-income individuals and families).

US Uninsured Population: Individuals without health insurance coverage.

Age Group Distribution Insights:

The Medicare Population is predominantly composed of individuals aged 65+, as expected since Medicare is designed primarily for senior citizens.

The Commercial Population has a more balanced age distribution, with a significant portion in the

18-44 and 45-64 age groups.

The Medicaid Population includes a high proportion of children (0-17 years) and younger adults (18-44 years).

The Uninsured Population is largely made up of young adults (18-44 years), indicating that this group has the highest rate of individuals without health coverage.

3-The bar chart illustrates the 5-year relative survival rates for skin cancer based on different stages at diagnosis. The x-axis represents the stage of skin cancer:

Localized: Cancer is confined to the primary site.

Regional: Cancer has spread to nearby lymph nodes or tissues. Distant: Cancer has spread to distant parts of the body (metastatic cancer). The y-axis represents the percentage of survival rates over five years.

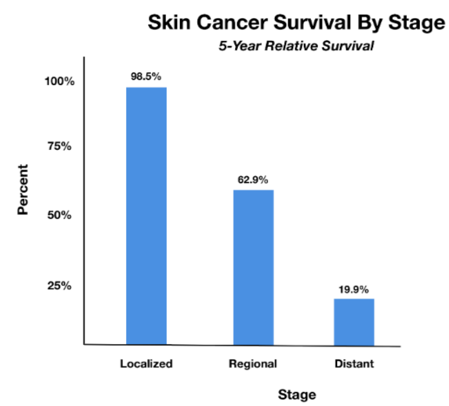


Figure 3: Skin Cancer By Stage

Key Observations:

Localized Stage: Shows the **highest survival rate of 98.5%**, indicating that early detection significantly improves prognosis.

Regional Stage: The survival rate drops to **62.9%**, highlighting the impact of cancer spreading beyond the original site.

Distant Stage: The survival rate is significantly lower at **19.9%**, reflecting the severe impact of metastasis on patient outcomes.

Implications for the Project:

Importance of Early Detection: The sharp decline in survival rates from localized to distant stages emphasizes the need for early and accurate diagnosis.

Potential Applications in Image Processing:

Developing models that can classify skin cancer based on severity or stage.

Using image-based features such as **color, texture, and size** to improve diagnostic accuracy.

Relevance to Data Analysis: These survival rates could be used to correlate skin cancer characteristics with patient outcomes, potentially enhancing predictive models.

2. Limited Access to Dermatological Services:

Many individuals, particularly in **rural and developing regions**, lack access to **dermatologists or specialized healthcare facilities**.

This mobile application offers **offline functionality**, ensuring that even users in **low-connectivity areas** can benefit from **AI-driven skin disease detection** without needing an internet connection.

3. Early Detection and Intervention:

Skin diseases, particularly **skin cancer**, can have severe health consequences if not diagnosed early. Studies show that **early detection can increase survival rates up to 97%**, while late-stage diagnosis drops survival chances to **just 14%**.

This project provides an **AI-powered mobile solution** that enables users to **detect potential skin conditions in their early stages**, allowing for **timely medical intervention and better treatment outcome**

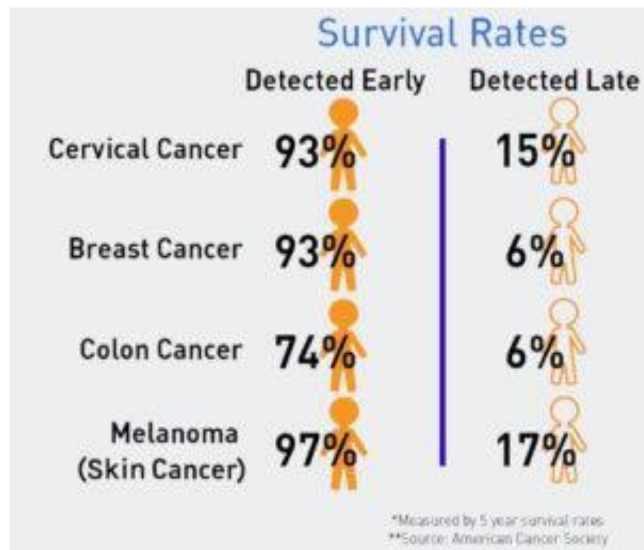


Figure 4: Early Detection Effect

4. **Reducing Healthcare Costs & Overburdened Medical Systems:**

The financial burden of **skin disease treatments** is enormous, with the **U.S. alone spending $8 billion annually on skin cancer treatment**.

Many people avoid dermatological consultations due to **high medical costs**, leading to **delayed diagnoses and more expensive treatments** in advanced stages.

An **AI-powered mobile application** allows individuals to **self-screen for early warning signs**, potentially reducing **unnecessary hospital visits** and alleviating strain on healthcare systems.

5. **Improving Awareness and Education:** In addition to diagnosis, educational resources about skin diseases, including their causes and prevention methods, can also be provided by the app. By increasing awareness and education about these issues, the spread of diseases can be reduced, and preventive health practices can be promoted.
6. Providing Support and Guidance for Patients:

   A significant role in providing psychological support and guidance for patients dealing with skin problems can be played by the app. By offering reliable information and supportive resources, patients can feel reassured and confident in facing their health challenges.
7. Advancing AI in Healthcare & Personalized Medicine:

   The integration of deep learning, image processing, and clustering techniques enables highly accurate and efficient disease classification.

   AI-powered diagnostics can continuously improve with larger datasets, making the system smarter and more reliable over time.

   By personalizing disease detection and risk assessment, the project empowers users to take control of their health and seek medical attention when necessary.

2.3 How to do the project?

A goal exists within our project to develop a mobile application. This application enables the user to take a picture using the camera of the affected part of their body. Based on this, the type of skin disease the user is suffering from is displayed by the application. This will be accomplished according to a set of steps, which will be mentioned in the following points:

1. Data Collection & Dataset Preparation:

The AI model needs to be trained on a **large dataset of skin disease images** for accurate classification.

- Gather **dermatology image datasets** like:
    - **ISIC Archive** (International Skin Imaging Collaboration)
    - **DermNet NZ**
    - **HAM10000 Dataset** (Harvard Dataset for Skin Cancer)
- Ensure the dataset includes **various skin conditions** (benign, malignant, infections, etc.).
- Preprocess images by:
    - **Resizing** for consistency.
    - **Augmentation** (rotation, brightness adjustment) to improve AI performance.
    - **Labelling & annotation** of each image with disease type.

2. Image Preprocessing:
    - Convert to gray scale
    - Apply **contrast enhancement, noise reduction, and feature extraction** techniques.
    - **Clustering for Offline Optimization**
    - Use **K-Means or hierarchical clustering** to group similar skin conditions.
    - Reduces complexity for **faster processing in offline mode**.

3. Image Classification:

   In this step, we classify the disease and determine its type using a deep learning model. We input the cropped part of the image, which contains the affected skin area, to determine the type of disease. We work on Ham10000 Skin Disease Dataset that is dermatoscopic images.

4. Explanation with Database:

   In this part, the goal is to provide the patient with some information about the disease they are suffering from, such as its severity, prevalence, and whether it is contagious. Additionally, advice is provided, such as the necessity of consulting a doctor for treatment. Furthermore, appropriate treatment for this disease can be recommended by keeping suitable treatments for each disease in our database.

5. Flutter Application:

   This application makes it easier for anyone to use a mobile phone to open the app, take a picture of the affected area, and the disease is classified by the app to determine its type. After the type of disease is determined, an explanation including the severity of the disease and the actions the patient should take will be provided by the app.

3. Literature Review

The work here is divided into two parts: the first part focuses on research papers that address the classification problem of skin diseases, while the second part deals with competing applications on the Google Play Store.

3.1 Papers:

1- Huang Paper

The paper "Skin Lesion Segmentation Using Recurrent Attentional Convolutional Networks" focuses on improving the accuracy of skin lesion segmentation in medical imaging, which is a crucial step in early skin cancer diagnosis. The authors introduce a deep learning model called Recurrent Attentional Convolutional Network (O-Net), which enhances segmentation performance by iteratively refining the segmentation results through an attention mechanism.

O-Net is designed with a recurrent unit that processes attention feature maps, enabling a coarse-to-fine segmentation approach. It incorporates an Attentional Class Feature Module (AFFM) to capture contextual information and improve accuracy. The model is evaluated using two widely recognized datasets, ISIC-2017 and PH2, demonstrating its effectiveness in identifying skin lesions.

Compared to existing models such as Recurrent U-Net and Attentional Class Feature Network (ACFNet), O-Net

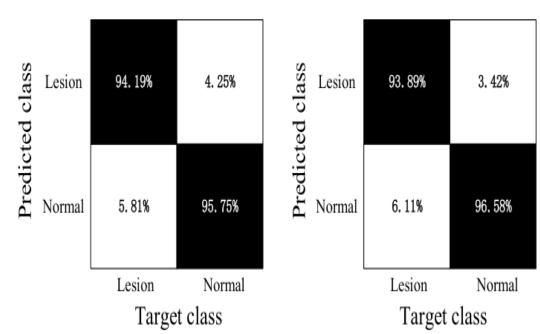


Figure 5: Confusion matrix of Huang Paper

shows superior performance, particularly in handling low-contrast lesion images. The model achieved a Dice coefficient of 87.04% on ISIC-2017 and 92.12% on PH2, with corresponding Jaccard indices of 80.36% and 86.15%. These results indicate that O-Net captures finer details and enhances segmentation accuracy.

The study concludes that O-Net is a valuable contribution to Computer-Aided Diagnosis (CAD) systems in dermatology, offering a reliable approach for segmenting skin lesions. Future work may focus on further optimizing the model and extending its application to other areas of medical image processing.

2- Snowber & Omker

Image Processing Techniques Used:

The study applies various image processing techniques to enhance skin cancer images before feeding them into the deep learning model. The techniques include:

1. Hair Removal (DullRazor Technique)
   - Removes hair artifacts from dermoscopic images using morphological operations and adaptive median filtering.
2. Gaussian Blur
   - Applies a Gaussian filter to smooth the image and reduce noise, improving feature extraction.
3. Median Filtering
   - A nonlinear filter that reduces noise while preserving edges.
4. Color Image Filtering
   - Enhances image quality by improving contrast and reducing artifacts.
5. Image Resizing
   - Resizes all images to a standard size (224x244 pixels) for consistency in CNN processing.

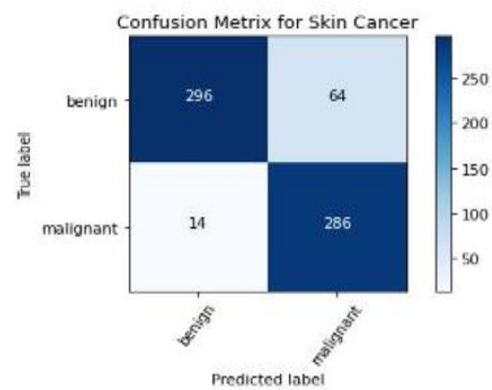


Figure 6: Confusion matrix of Snowber Paper

Deep Learning Model Used:

The study uses a Convolutional Neural Network (CNN) for skin cancer classification. The CNN model consists of:

1. Convolutional Layers
    - Extracts key features from images using learned filters.
2. Pooling Layers
    - Reduces dimensionality while retaining essential features.
3. Fully Connected Layers
    - Classifies the processed features into benign or malignant categories.

Comparison of Performance:

The study compares different image processing techniques combined with CNN. The best performance was achieved when using Hair Removal + Median Filtering + Gaussian Filtering + CNN, resulting in an AUC of 0.888.

3- Gunjan & Shashank & Gopal & Santosh:

Image Processing Techniques Used:

The paper applies several image processing and augmentation techniques to enhance the HAM10000 dataset before feeding it into the CNN model:

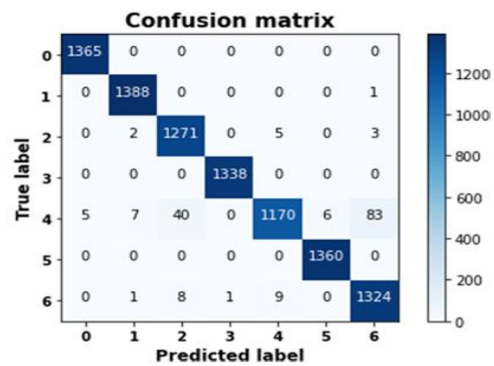


Figure 7: Confusion matrix of Gunjan Paper

1. Data Augmentation
    - Due to dataset imbalance, synthetic data generation techniques (SMOTE) were applied.
    - Augmentation techniques include cropping, padding, and horizontal flipping to increase variability.
2. Resampling Techniques
    - Oversampling minority classes and undersampling majority classes to balance the dataset.
3. Preprocessing Steps
    - Standard image resizing (28×28×3) before feeding into the CNN.
    - Normalization to scale pixel values between 0 and 1.

Deep Learning Model Used: The study proposes a Customized AlexNet CNN Model for skin cancer classification with an improved activation function. Key components include:

1. Convolutional Layers

- Extracts spatial features from the images using 3×3 kernels.

2. Pooling Layers
   - Max-pooling layers (Stride=2) reduce dimensionality while retaining important features.
3. Custom Activation Function
   - A new activation function is proposed to overcome the vanishing gradient problem, improving performance over traditional ReLU, Sigmoid, and Tanh.
4. Fully Connected Layers
   - The final layers use Softmax Activation for classifying skin conditions into 7 categories.

Performance Comparison:

- Customized AlexNet achieved 98.20% accuracy on the HAM10000 dataset.
- It outperformed models like VGG-16, ResNet, MobileNet, and EfficientNet in accuracy, precision, recall, and F1-score.

4- Pratiwi et al.: Deep Ensemble Learning for Skin Lesions Classification

Image Processing Techniques Used

To enhance the quality and diversity of the HAM10000 dataset, specific preprocessing and augmentation methods were applied:

Data Augmentation

Real-time data augmentation was used to increase the number of training samples and reduce overfitting. The following techniques were implemented:

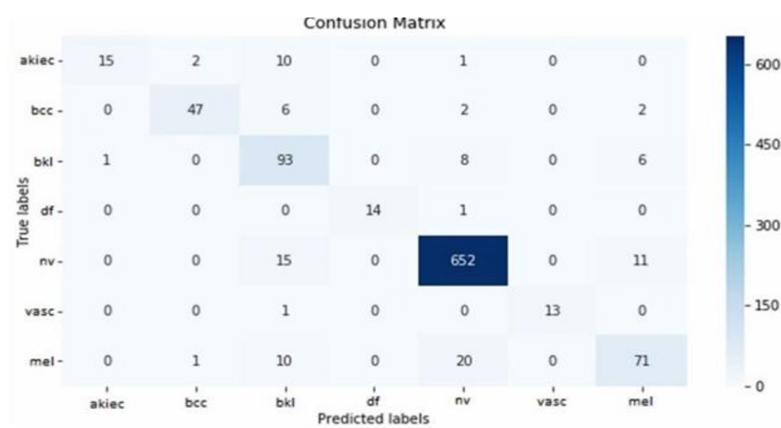


Figure 8: Confusion matrix of Pratiwi paper

- Rotation (up to 60°)
- Shear transformations
- Zoom
- Width and height shifts (each with a 0.2 probability)

Preprocessing Steps

- Resizing: Dermoscopy images were resized from 450×600 to 192×256 pixels.
- Normalization: Pixel values were scaled to the [0, 1] range by dividing by 255.
- Stratified Splitting:
    - **Training Set:** 8111 images
    - **Validation Set:** 902 images
    - **Test Set**: 1002 images

Deep Learning Model Used

The study implements an Ensemble Learning strategy, combining three fine-tuned deep CNN architectures to classify skin lesions into seven categories.

CNN Architectures Utilized

- **Inception V3:** Incorporates inception modules with varying filter sizes for feature extraction.
- **Inception ResNet V2:** Merges inception modules with residual connections for improved depth and feature representation.
- **DenseNet201**: Uses dense connectivity between layers to enhance gradient flow and encourage feature reuse**.**

Model Customization

For each architecture, the original classification layers were replaced with:

- Global Max Pooling layer
- Dense layer with 512 neurons (ReLU activation)
- Dropout layer with 0.5 rate
- Dense output layer with Softmax activation for 7-class classification

Note: Pre-trained ImageNet weights were used, followed by fine-tuning either the top or all layers.

3.2 Applications

1. Medgic Application

Figure 9: Medgic Application

In this application, a picture of the skin is uploaded by the user, where the affected area is in the center of the image. Then, the user is allowed to manually draw the boundaries of the affected area, which is considered segmentation. After that, the user requests a diagnosis of the disease present in the image and waits for approximately fifteen minutes to obtain the result. After receiving the result, the user can obtain some information about the disease through the application by answering some questions provided to choose from. This application is very distinctive, but it has a serious drawback, which is the time it takes for diagnosis, which is approximately fifteen minutes, and sometimes the result is not available even after this time. [11]

2. Ai Dermatologist

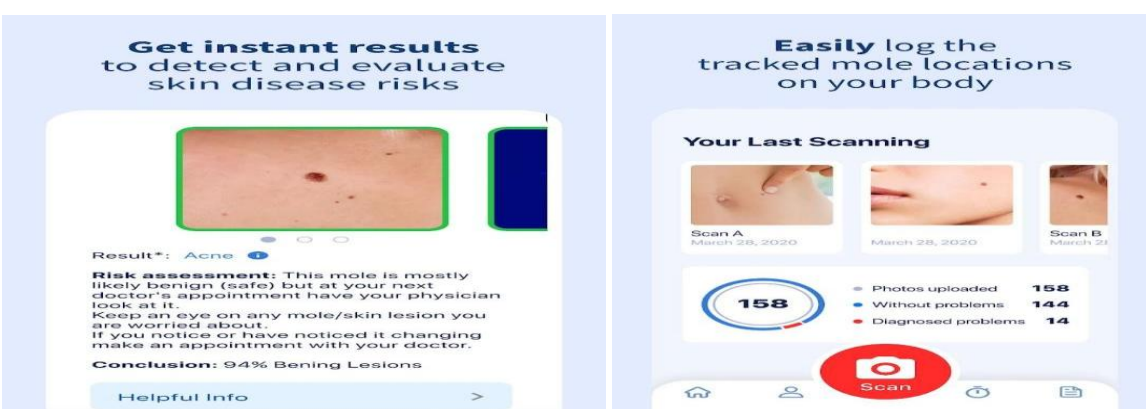


Figure 10: Ai Dermatologist Application Interface

In this application a picture of the skin is uploaded by the user, with the affected area positioned at the center of the image. Then, A diagnosis is requested by the user, and the result is waited for about a minute. Twenty-nine different skin diseases, including serious ones like skin cancer, as well as benign conditions, can be diagnosed by users of this application. This application has been used by 950,000 users, resulting in 3 million diagnostic procedures. With a cost of $1.47 per procedure, the application has generated revenue equivalent to

$4.5 million. Additionally, it has identified 35,000 cases of confirmed skin diseases.

3. All Skin Diseases and Treatment:

This application represents another type of application that is not responsible for the diagnostic process of the disease but rather focuses on treatment methods for each disease. It serves as a database, providing an image of the disease and its corresponding treatment

Figure 11: All Skin Application

4. Methodology

The methodology followed in this project consists of several key stages, organized within an application framework. The process is structured as follows:

4.1 Upload All Images

- The system starts by collecting and uploading all relevant images of skin diseases. These images serve as the dataset for further processing and analysis.

4.2 Preprocessing Images

- Uploaded images undergo preprocessing to enhance quality and extract meaningful features. This step includes tasks such as resizing, normalization, noise reduction, and contrast adjustment to ensure consistency in image analysis.

4.4 Image Classification

- **The images are then classified based on predefined skin disease categories. deep learning models are applied to label images accurately, aiding in disease identification.**

4.5 Explanation

- The final stage involves providing explanations for the classification results. This may include highlighting key visual features that contributed to the classification, ensuring transparency and interpretability of the model's decisions.

4.6 Data

Addressing Unbalanced Data: After thorough analysis, we identified a significant issue contributing to our low accuracy and overfitting: the imbalance in our dataset. Unbalanced data occurs when the distribution of classes within a dataset is skewed, with some classes having far fewer

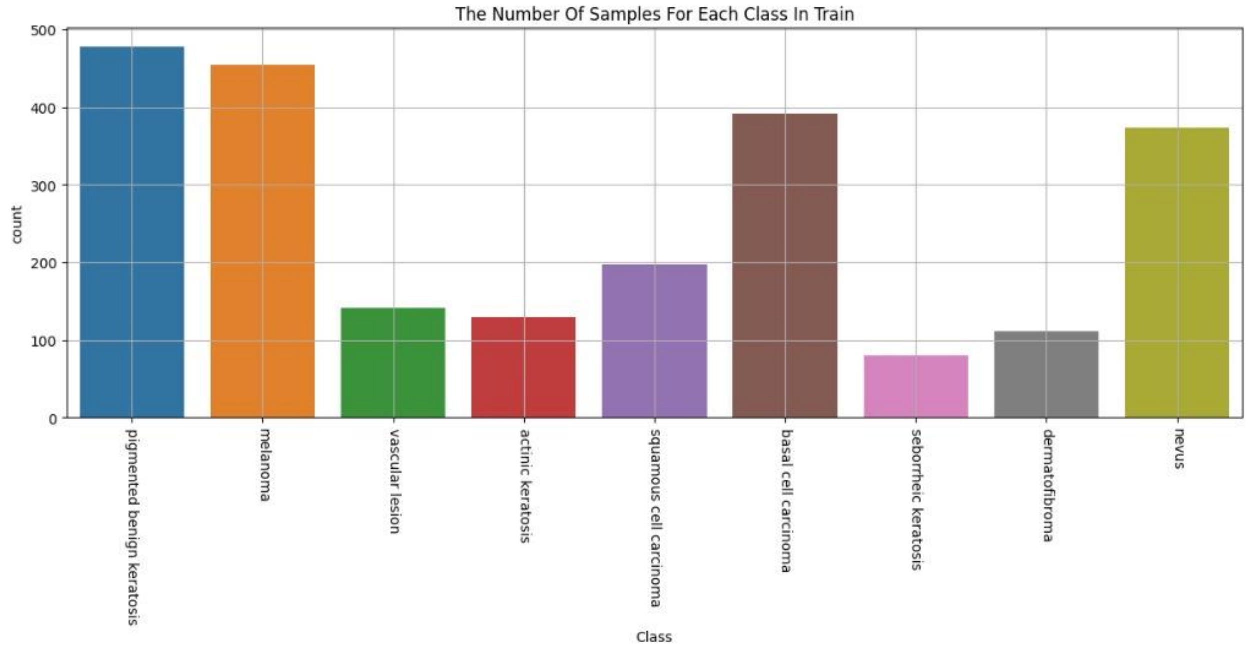


Figure 12: Addressing unbalanced data

instances than others. In our case, certain skin disease classes were underrepresented compared to others, leading to biases in our model's training process. This figure shows that:

4.7 Techniques for Handling Unbalanced Data

To mitigate the effects of unbalanced data, we explored several techniques commonly employed in machine learning:

4.7.1 Resampling Techniques: Resampling involves either oversampling the minority class or Undersampling the majority class to achieve a more balanced distribution.

4.7.2 Oversampling: Oversampling involves increasing the number of instances in the minority class by generating synthetic samples or replicating existing ones.

4.7.3 Under sampling: Under sampling involves reducing the number of instances in the majority class by randomly selecting a subset of samples.

4.7.4 Data Augmentation: Data augmentation techniques involve generating new samples by applying transformations such as rotation, scaling, and flipping to existing data points.

4.7.5 Class Weighting: Class weighting assigns higher weights to minority class samples during training to give them more importance in the model's optimization process.

4.7.6 Synthetic Minority Over-sampling Technique (SMOTE): SMOTE is a popular oversampling technique that synthesizes new minority class samples by interpolating existing minority class instances.

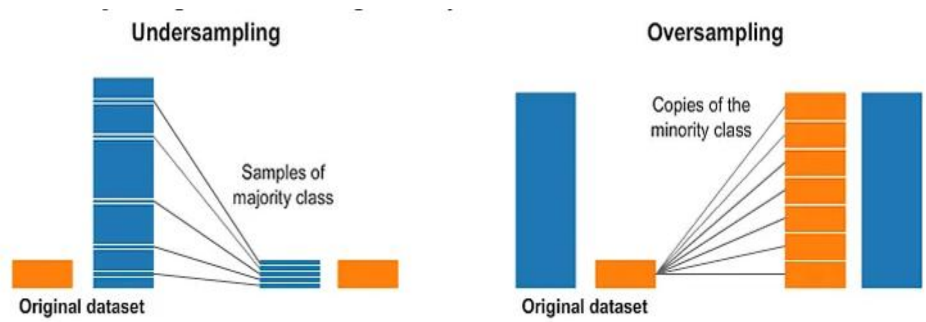


Figure 13: Undersampling and Oversampling

4.7.7 Choosing the Best Approach Without SMOTE

In this project, the Synthetic Minority Over-sampling Technique (SMOTE) was not applied due to the image-based nature of the dataset and the selected preprocessing pipeline. SMOTE is typically designed for generating synthetic samples for structured, tabular data to address class imbalance. Instead of SMOTE, the project leveraged the ImageDataGenerator in TensorFlow/Keras to perform real-time data augmentation, which generates diverse image variations while preserving the true characteristics of skin lesion images. This approach is more suitable for medical image classification tasks, where realistic transformations (like rotation, flipping, and zoom) effectively increase dataset diversity without altering the clinical meaning of the images. In addition to augmentation, clustering and fine-tuning of pretrained CNN models were used to further improve classification performance.

4.7.8 Choosing the Best Approach: Using ImageDataGenerator for Data Augmentation

Definition:

ImageDataGenerator is a powerful tool provided by TensorFlow/Keras for performing data augmentation in image-based deep learning workflows. It automatically applies a wide range of transformations — such as rotation, scaling, shifting, shearing, zooming, flipping, and brightness adjustments — to the training images in real time while feeding them into the model. By introducing these controlled variations, ImageDataGenerator helps increase the effective size and diversity of the dataset, which enhances the model's generalization capability and reduces the risk of overfitting, especially when working with limited or imbalanced medical image datasets.

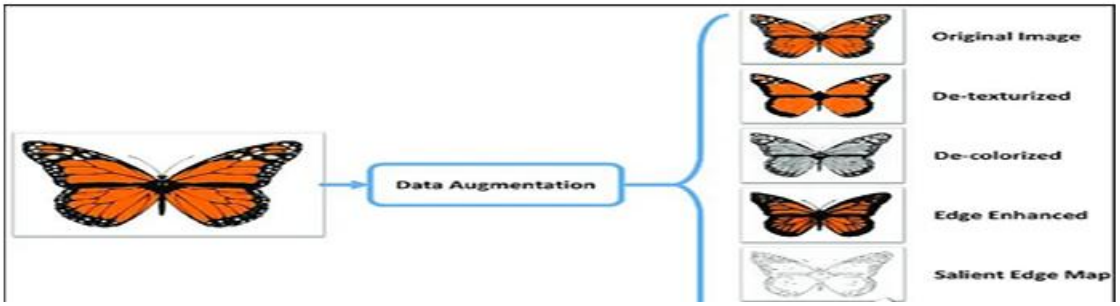


Figure 14: Data Augmentation EX.1

This ImageDataGenerator configuration defines advanced data augmentation strategies to improve the diversity of the training images and help prevent overfitting in the CNN model.

Key Settings:

- Rescaling:
  - All pixel values are scaled to the range [0, 1] by dividing by 255.
- Rotation:
  - Images are randomly rotated up to 40 degrees.
- Width & Height Shift:
  - Images can be shifted horizontally and vertically by up to 20% of their size.

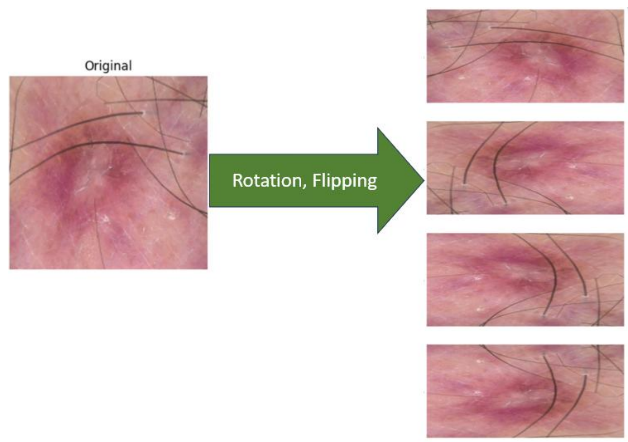


Figure 15: Data Augmentation EX.2

- Shear:
  - Shearing transformations are applied with a range of 0.2.
- Zoom:
  - Images can be randomly zoomed in/out by up to 30%.
- Horizontal Flip:
  - Images can be flipped horizontally for more variation.
- Brightness Adjustment:
  - Randomly adjusts brightness within the range 0.8 to 1.2.
- Fill Mode:

- Newly created pixels during transformations are filled using the 'nearest' method.

- Validation Split:
  - 20% of the data is automatically reserved for validation during training.

Purpose:

These augmentation operations expand the dataset by generating realistic image variations, improving the model's ability to generalize to unseen skin lesion images.

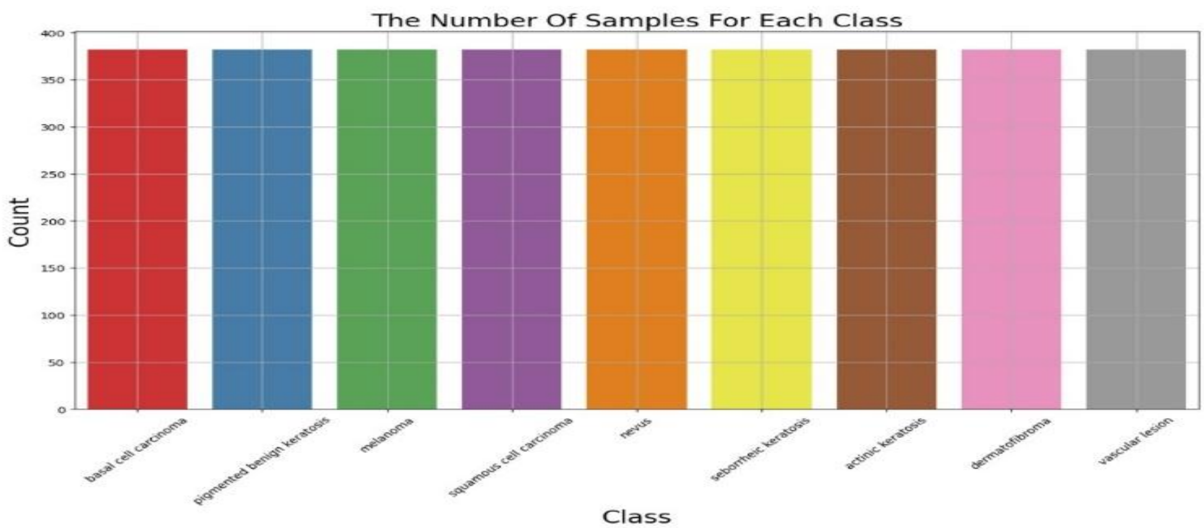


Figure 16: Balanced Data after Augmentation

Despite the benefits of using **ImageDataGenerator** for data augmentation — which helps enhance the model's robustness and reduce overfitting — we observed that it did not significantly improve the overall accuracy compared to using advanced oversampling techniques. However, **ImageDataGenerator** remains an effective tool, especially when generating synthetic samples is not feasible or when additional real-time diversity is needed to enrich the training data and simulate real-world variations.

4.8 Image Processing

- Black Border Removal
  - Objective: Remove black borders from images to focus on the lesion area.
  - Process: The original image contains black borders that can interfere with analysis. The processed image eliminates these borders, providing a clearer view of the affected skin.

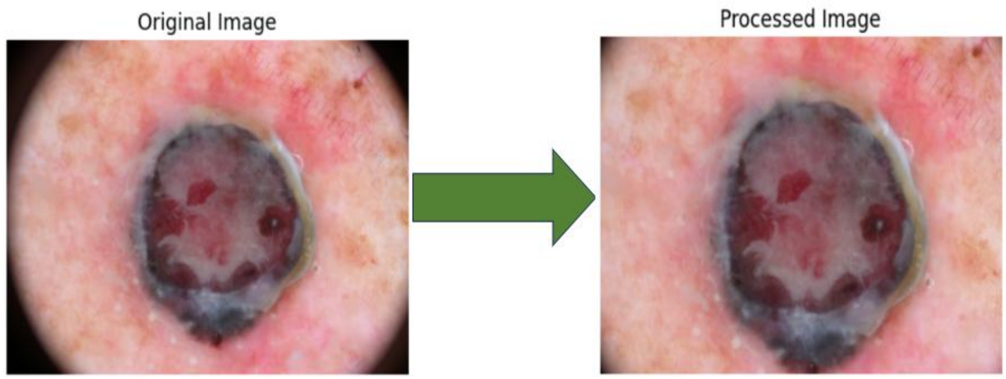


Figure 17: Image before and after removing borders

2. Gray Scale Conversion

- Objective: Convert images to grayscale for further processing.
- Process: The original-colored image is transformed into a grayscale image, emphasizing intensity variations and aiding in texture analysis.

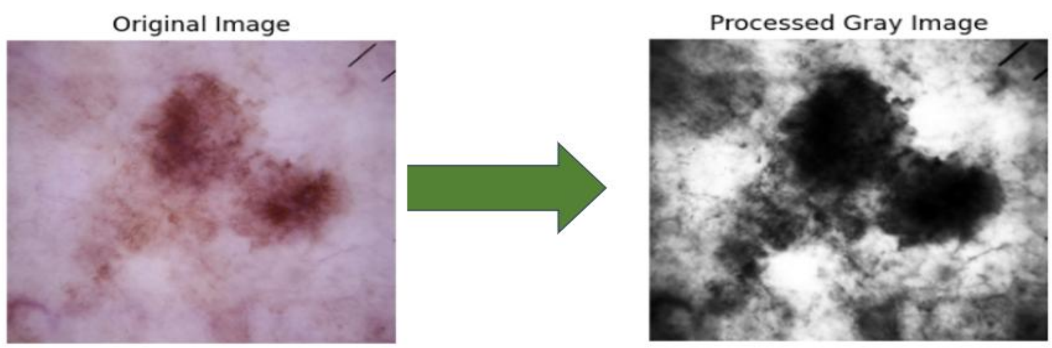


Figure 18: Image after applying gray scale

3. Gaussian Blur

- Objective: Apply Gaussian blur to smooth the image and reduce noise.
- Process: A Gaussian filter is applied, reducing high-frequency noise and making features more distinct for further processing.

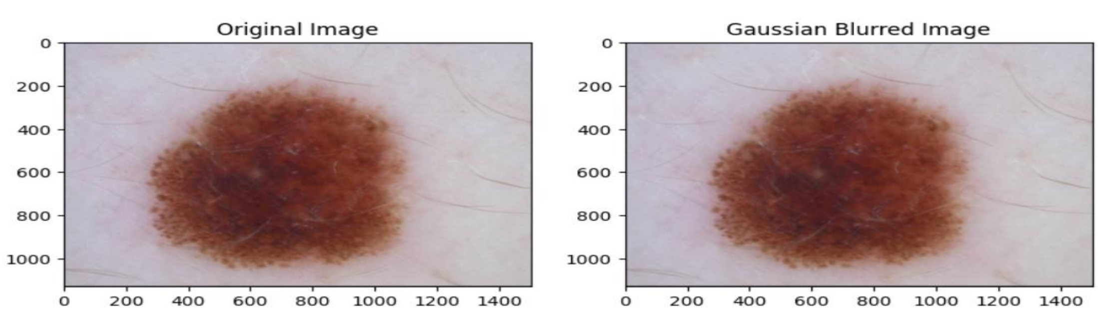


Figure 19: Image after applying Gaussian blur

4. Gray Area Highlighting

- Objective: Highlight gray regions in the lesion to enhance feature extraction.
- Process: The image is processed to emphasize gray areas, which may indicate abnormal skin conditions.

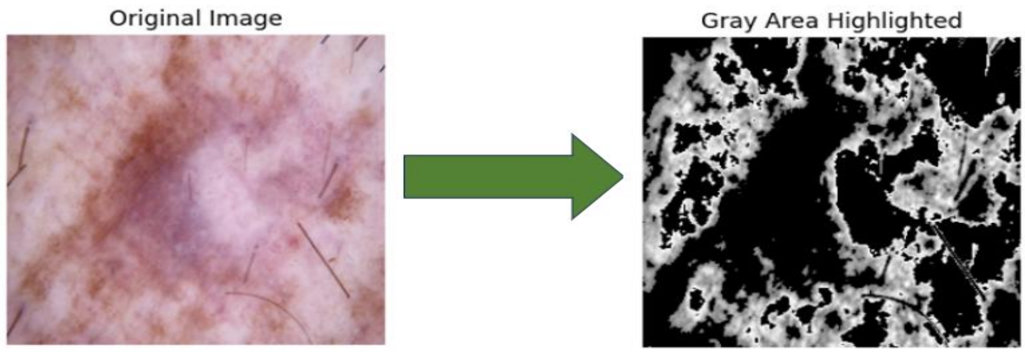


Figure 20: Original Image vs Image with gray highlights

5. Mask and Contour Detection

- Objective: Extract contours and highlight affected regions.
- Process:
    - Color Image with Contours: Detects and highlights contours in the original image.
    - Gray Image with Contours: Converts the image to grayscale and extracts contours for detailed analysis.
    - Merged Image with Contours: Combines color and contour information to enhance visualization.

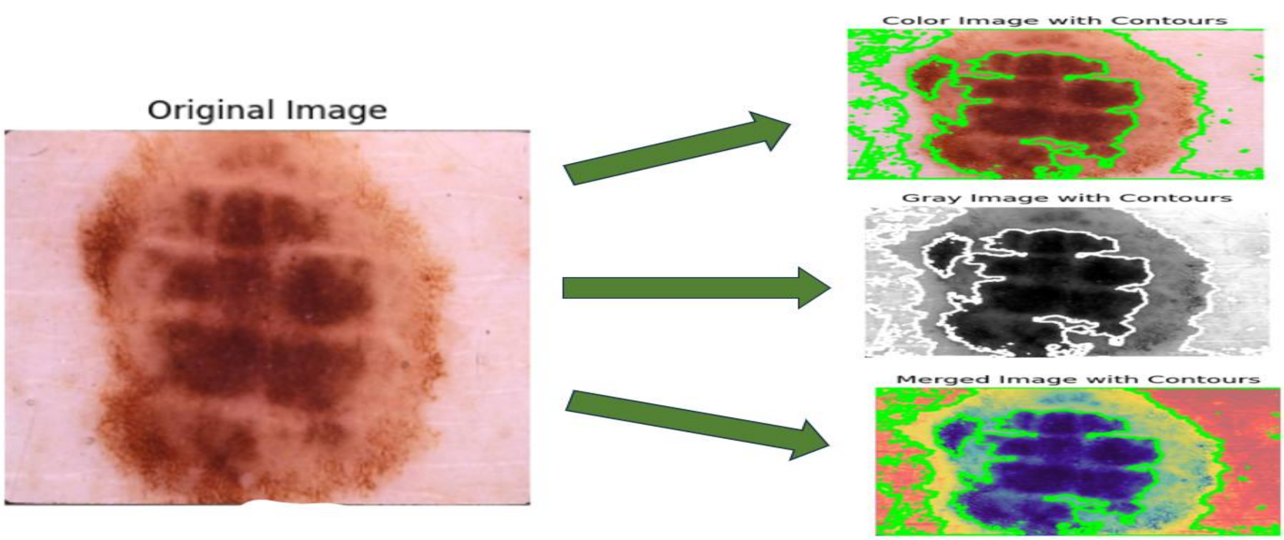


Figure 21: Three different ways of viewing Images with Contours

6. Clustering

1. Image Processing

In this step, various image processing techniques are applied to enhance and preprocess the images for further analysis. The preprocessing techniques include:

- Grayscale conversion: Converting the image to grayscale to simplify the data.
- Noise reduction: Using Gaussian Blur or other filtering techniques to remove noise.
- Edge detection: Applying edge detection methods to highlight the boundaries of lesions.
- Segmentation: Identifying and isolating regions of interest from the background.

2. Feature Extraction

After processing the images, important features are extracted to facilitate clustering. These features include:

- Shape features: The contour, area, and perimeter of the lesion.
- Texture features: Contrast, correlation, and smoothness of the skin.
- Color features: RGB and HSV color distributions to differentiate between lesion types.

3. Clustering

Using the extracted features, clustering algorithms are applied to group similar images together. This step helps in identifying patterns within the dataset and categorizing skin conditions into different clusters for further analysis.

Figure 22: Simple roadmap for clustering

Examples from Cluster Make:

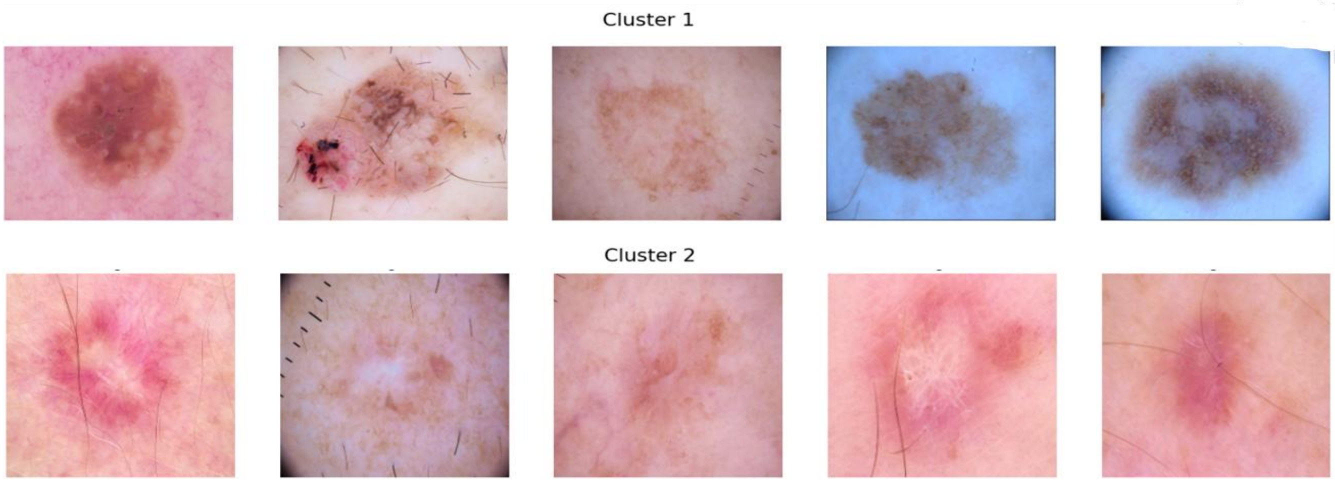


Figure 23: Samples after Clustering

4.9 Introduction to Convolutional Neural Networks (CNNs):

Convolutional Neural Networks (CNNs) are a class of deep neural networks primarily designed to process and analyze visual data, such as images. Unlike traditional neural networks, CNNs use a specialized architecture that enables them to efficiently capture spatial hierarchies and patterns within images. CNNs consist of multiple layers, including convolutional layers, pooling layers, and fully connected layers.

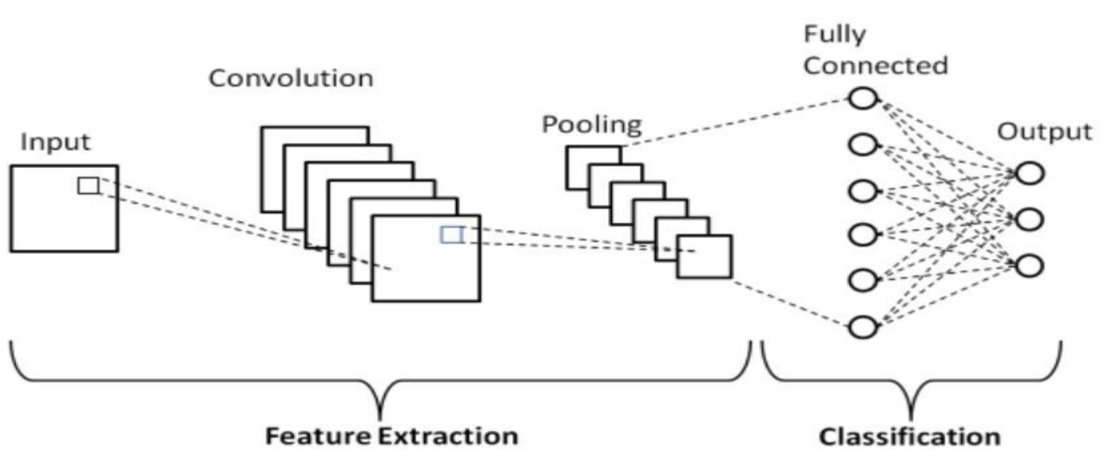


Figure 24: Explanation of CNN Architecture

4.10 Application of CNNs in Skin Disease Classification

In our project, we utilize CNNs for the classification of skin diseases. The dataset used for this task is the Ham10000 Skin Disease dataset, which contains images categorized into Seven different classes of skin diseases. By leveraging the power of CNNs, we aim to automatically classify these images into their respective disease categories.

4.11 Challenges and Solutions:

Despite the effectiveness of CNNs, we encountered challenges in achieving satisfactory accuracy. One common issue we faced was overfitting, wherein the model performed well on the training data but failed to generalize to unseen data. To address this challenge, we explored the use of pre-trained models and transfer learning.

4.12 Pre-trained Models and Transfer Learning

Pre-trained models are neural network architectures that have been trained on large- scale datasets, such as ImageNet, to solve generic image classification tasks. These models have learned rich feature representations that can be transferred to new tasks with minimal retraining. Transfer learning involves fine-tuning these pre-trained models on a new dataset, such as the Ham10000 Skin Disease dataset, to adapt them for specific classification tasks.

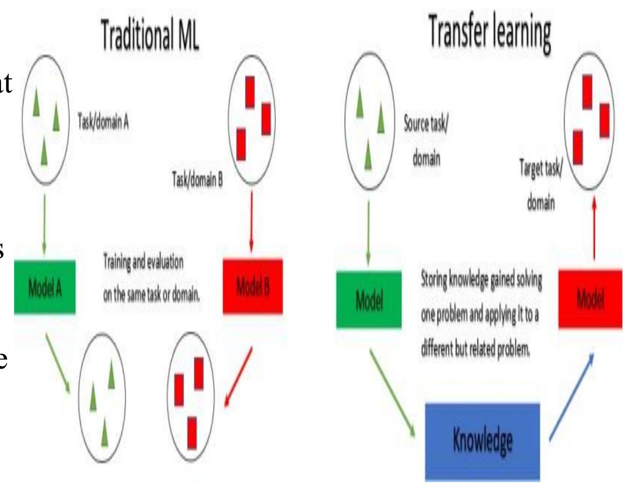


Figure 25: Transfer Learning Architecture

Despite the advantages of using pre-trained models and transfer learning, we encountered challenges in achieving high accuracy and combating overfitting. Overfitting occurs when the model learns to memorize the training data too well, leading to poor performance on unseen data. This can be particularly problematic when working with limited datasets, such as medical image datasets like Ham10000 skin Disease. The complex nature of skin diseases and the subtle variations in their visual representations make it challenging for the model to generalize effectively. In our experiments, we employed various pre-trained models, including InceptionV3, InceptionResNetV2, DenseNet201, MobileNet and VGG16 as the base architectures for transfer learning. Despite the diverse architecture and capabilities of These models, we observed that simply fine-tuning them on the Ham10000 Skin dataset did not yield the desired level of accuracy. The models struggled to generalize to unseen examples, resulting in suboptimal performance. Additionally, we encountered instances of overfitting, where the models performed exceptionally well on the training data but failed to generalize to new images.

Ensemble models:

The diagram illustrates the ensemble learning architecture used in this project for skin lesion classification:

1. Input Dataset:
   - The HAM10000 dermoscopy dataset serves as the input source, providing 10,000+ labeled skin lesion images.
2. Base Models:
   - Three different pre-trained Convolutional Neural Network (CNN) architectures are used:
     - Inception V3
     - Inception ResNet V2
     - DenseNet 201
   - Each model is fine-tuned to extract features and predict the probability distribution for the seven skin lesion classes.
3. Individual Predictions:
   - Each CNN produces a class probability prediction: r_1, r_2, and r_3.
4. Ensemble Strategy:
   - The outputs from the three models are combined in an ensemble module.
   - The ensemble calculates the average probability across the three predictions.
5. Final Output:
   - The combined average probability is used to make the final classification prediction, which improves overall accuracy, robustness, and generalization compared to any single model alone.

In summary, CNNs offer a powerful approach for skin disease classification. By leveraging pre-trained models and transfer learning techniques and using Ensemble Model, we aim to overcome challenges such as overfitting and improving the accuracy of our classification model. Through this project, we contribute to the advancement of automated diagnosis and treatment of skin diseases.

5. Results and Analysis

5.1 Data Augmentation

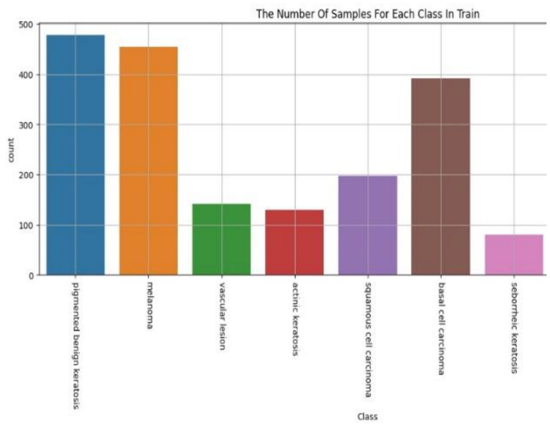


Figure 26: Data before Augmentation (Unbalanced)

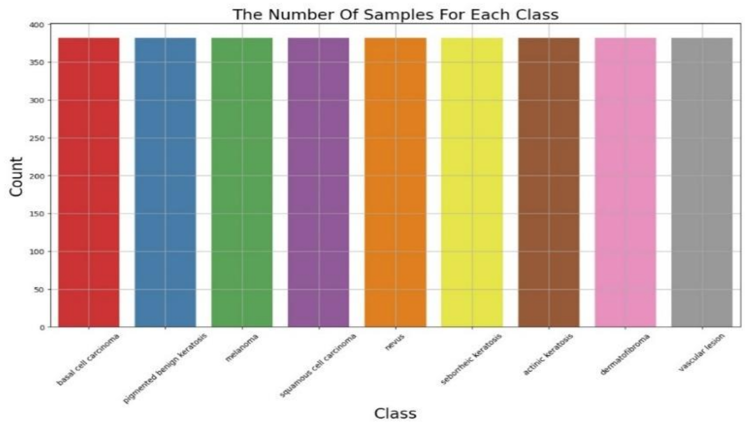


Figure 27: Data after Augmentation (balanced)

5.2 Models

Pre-Trained Model:

- DenseNet Result

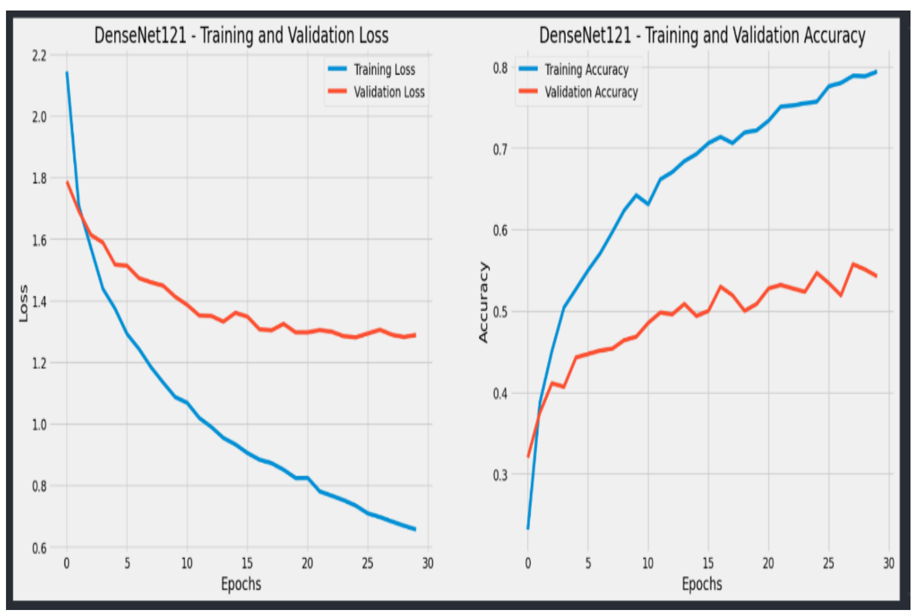


Figure 28: Graphing Accuracy and loss for DenseNet21

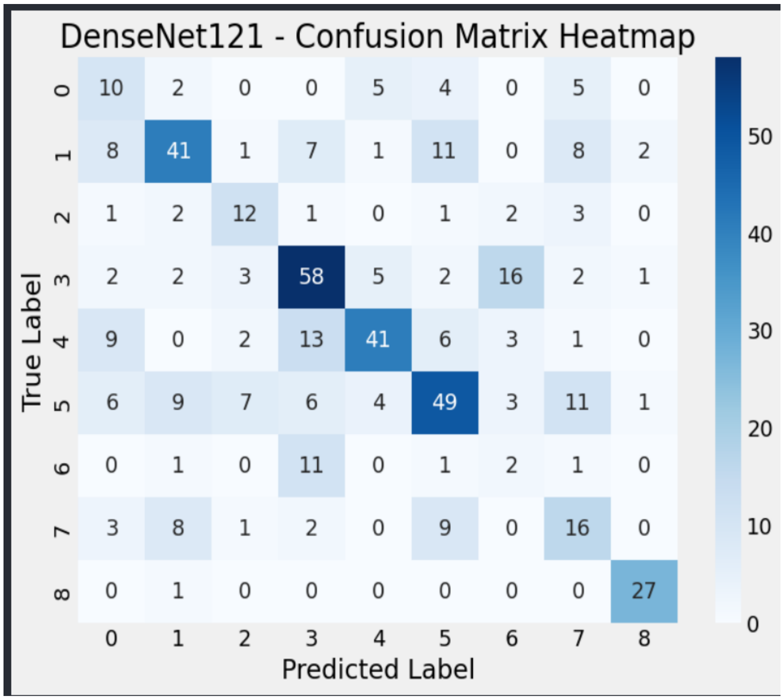


Figure 29: DenseNet21's Confusion Matrix

📌 Model: DenseNet121

	precision	recall	f1-score	support
0	0.26	0.38	0.31	26
1	0.62	0.52	0.57	79
2	0.46	0.55	0.50	22
3	0.59	0.64	0.61	91
4	0.73	0.55	0.63	75
5	0.59	0.51	0.55	96
6	0.08	0.12	0.10	16
7	0.34	0.41	0.37	39
8	0.87	0.96	0.92	28
accuracy			0.54	472
macro avg	0.50	0.52	0.50	472
weighted avg	0.57	0.54	0.55	472

Figure 30: DenseNet121 Classification Report

- CNN Without Processing:

Layer (type)	Output Shape	Param #
conv2d (Conv2D)	(None, 126, 126, 32)	896
max_pooling2d (MaxPooling2D)	(None, 63, 63, 32)	0
conv2d_1 (Conv2D)	(None, 61, 61, 64)	18,496
max_pooling2d_1 (MaxPooling2D)	(None, 30, 30, 64)	0
conv2d_2 (Conv2D)	(None, 28, 28, 128)	73,856
max_pooling2d_2 (MaxPooling2D)	(None, 14, 14, 128)	0
flatten (Flatten)	(None, 25088)	0
dense (Dense)	(None, 256)	6,422,784
dropout (Dropout)	(None, 256)	0
dense_1 (Dense)	(None, 7)	1,799

Total params: 6,517,831 (24.86 MB)

Trainable params: 6,517,831 (24.86 MB)

Non-trainable params: 0 (0.00 B)

Figure 31: CNN Architecture

	precision	recall	f1-score	support
Actinic keratoses	0.30	0.25	0.27	65
Basal cell carcinoma	0.43	0.62	0.51	102
Benign keratosis-like lesions	0.55	0.44	0.49	219
Dermatofibroma	0.50	0.09	0.15	23
Melanocytic nevi	0.84	0.94	0.89	1341
Melanoma	0.68	0.32	0.44	222
Vascular lesions	0.76	0.68	0.72	28
accuracy			0.76	2000
macro avg	0.58	0.48	0.49	2000
weighted avg	0.75	0.76	0.74	2000

Figure 32: CNN Classification Report

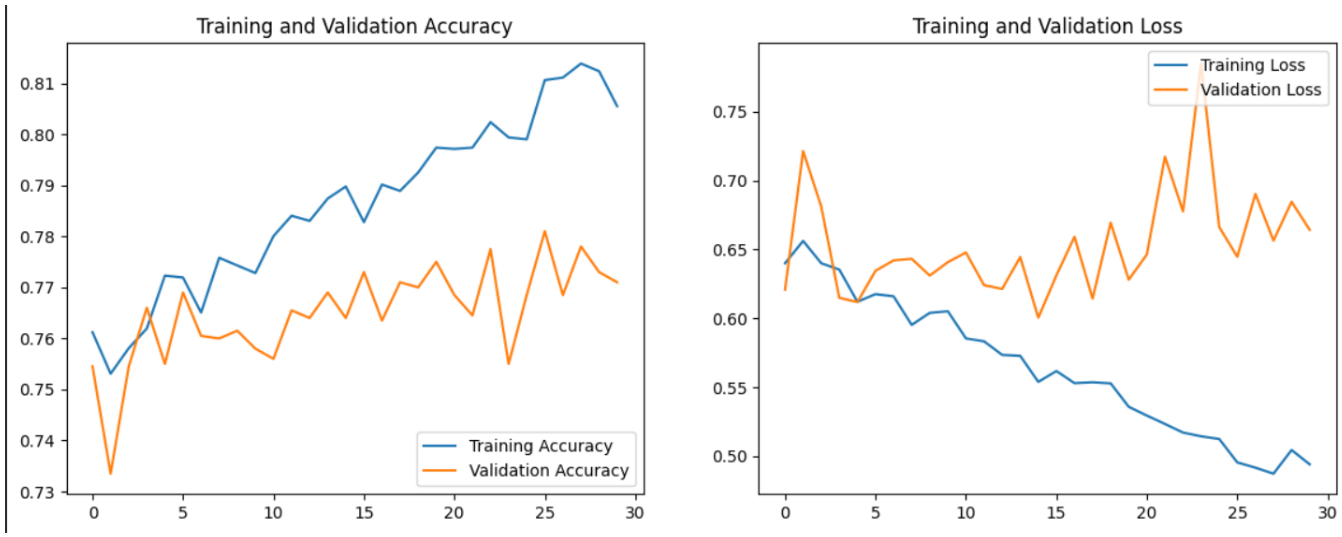


Figure 33: Accuracy For CNN

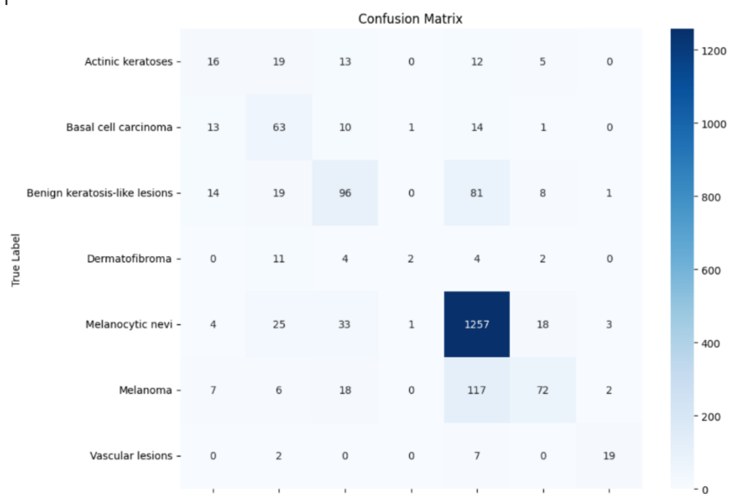


Figure 34: Confusion Matrix For CNN

- **Swin Transformer:**

(Validation Accuracy): 79.98%

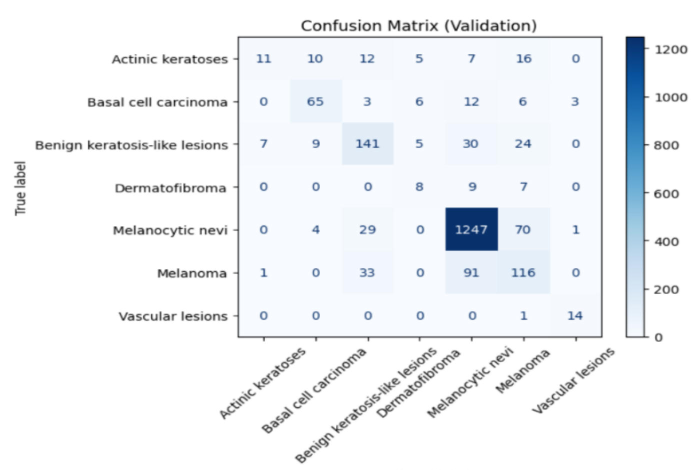


Figure 35: Confusion Matrix For Swin Transformer

- **Ensemble using InceptionV3, InceptionResNetV2, DenseNet201**

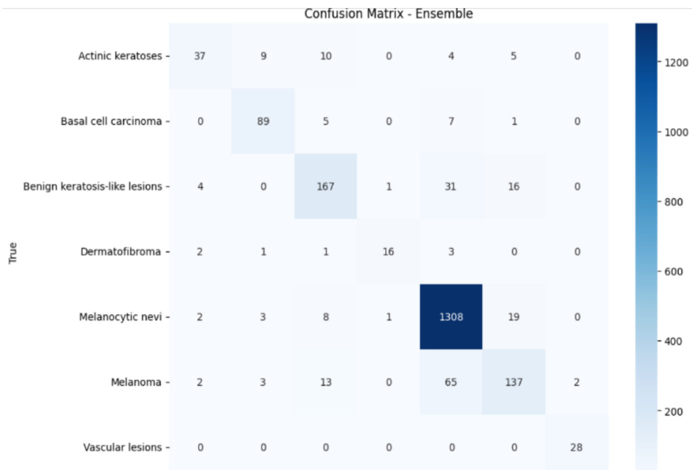
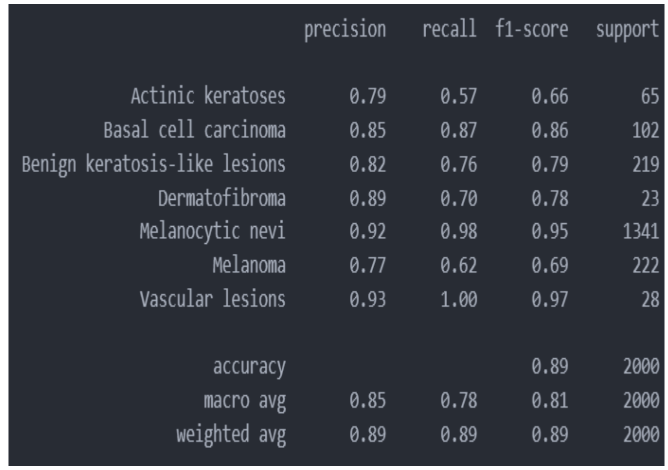


Figure 36: Confusion Matrix with ensemble



	precision	recall	f1-score	support
Actinic keratoses	0.79	0.57	0.66	65
Basal cell carcinoma	0.85	0.87	0.86	102
Benign keratosis-like lesions	0.82	0.76	0.79	219
Dermatofibroma	0.89	0.70	0.78	23
Melanocytic nevi	0.92	0.98	0.95	1341
Melanoma	0.77	0.62	0.69	222
Vascular lesions	0.93	1.00	0.97	28
accuracy			0.89	2000
macro avg	0.85	0.78	0.81	2000
weighted avg	0.89	0.89	0.89	2000

Figure 37: Classification Report with ensemble

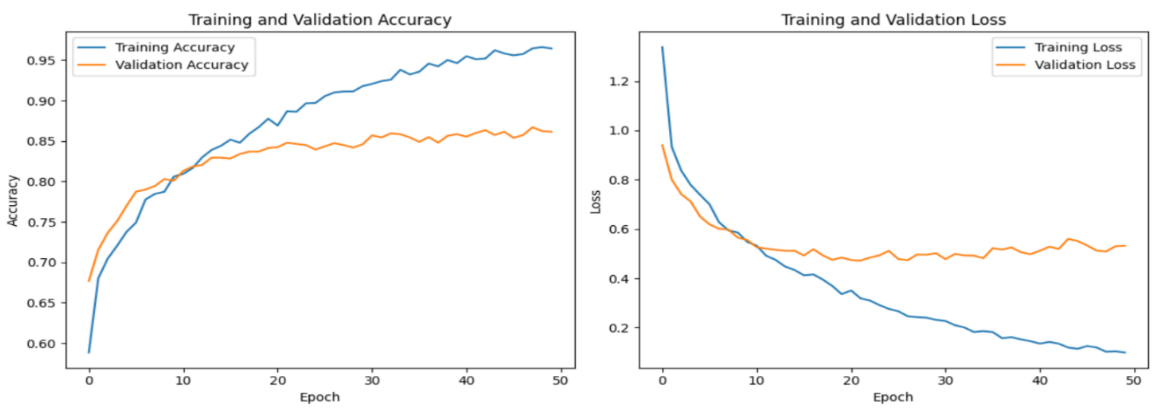


Figure 38: Accuracy with ensemble

- **5 Classes With contour CNNs:**

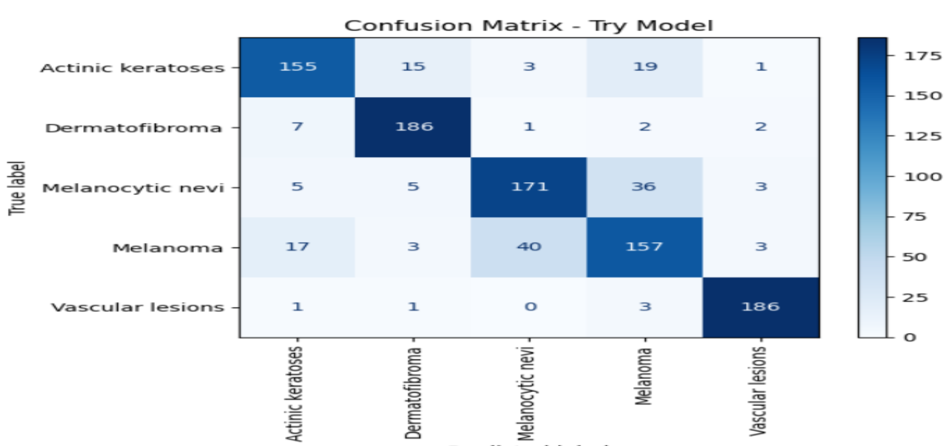


Figure 39: Confusion Matrix CNN Model

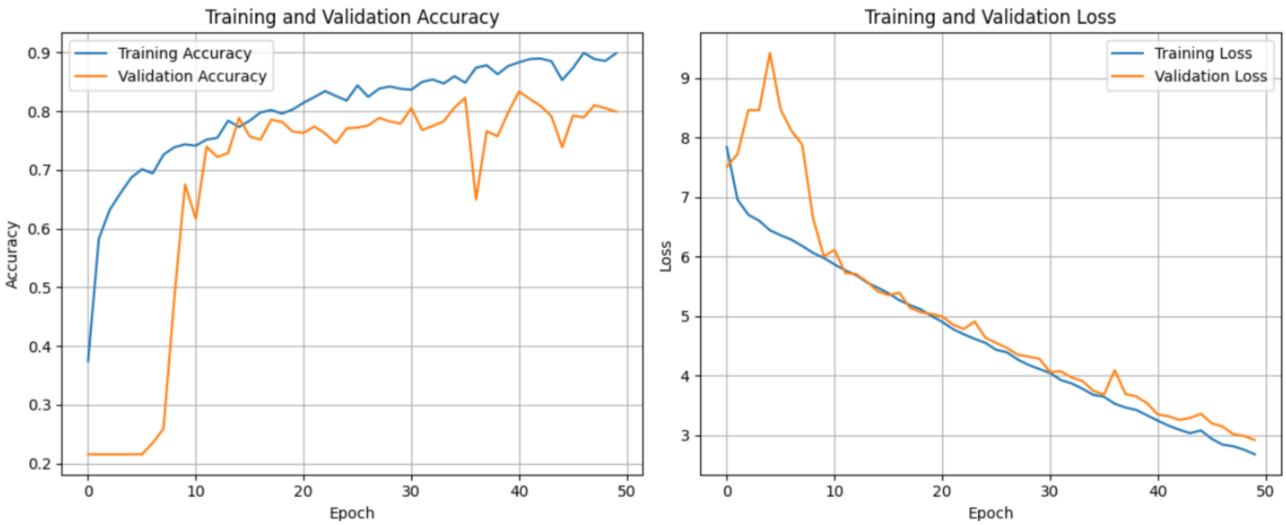


Figure 40: Accuracy CNN Model

- **MobileNet 5 Classes with Contour:**

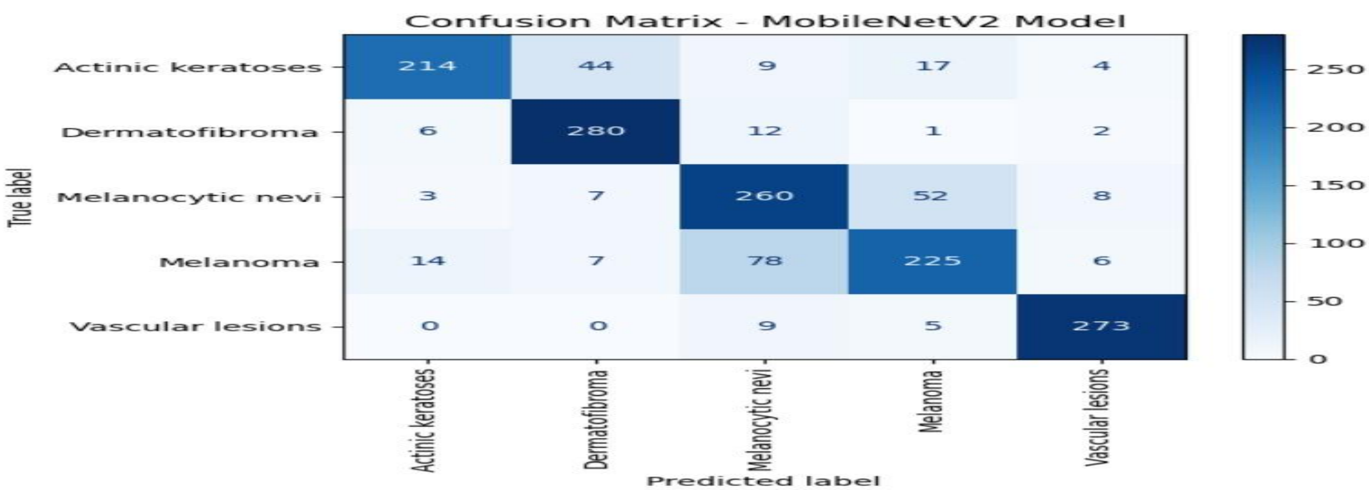


Figure 41: Confusion Matrix MobileNet

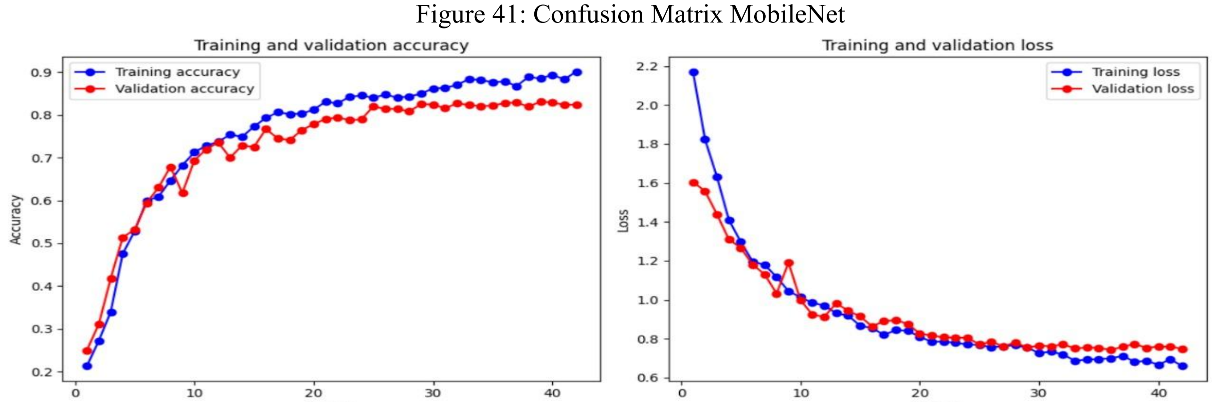


Figure 42: Confusion Matrix MobileNet

- Cluster Models :

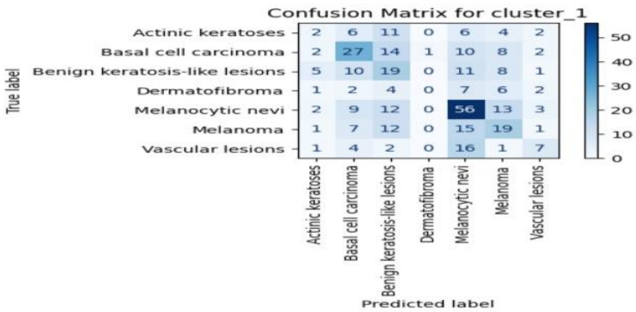


Figure 43: Confusion Matrix after Cluster

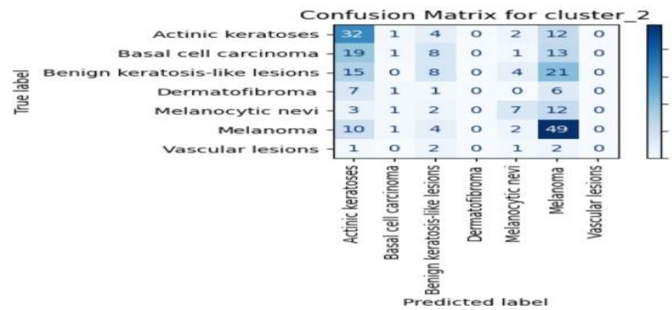


Figure 44: Confusion Matrix Cluster

- **CNN Color Contour 7 classes:**

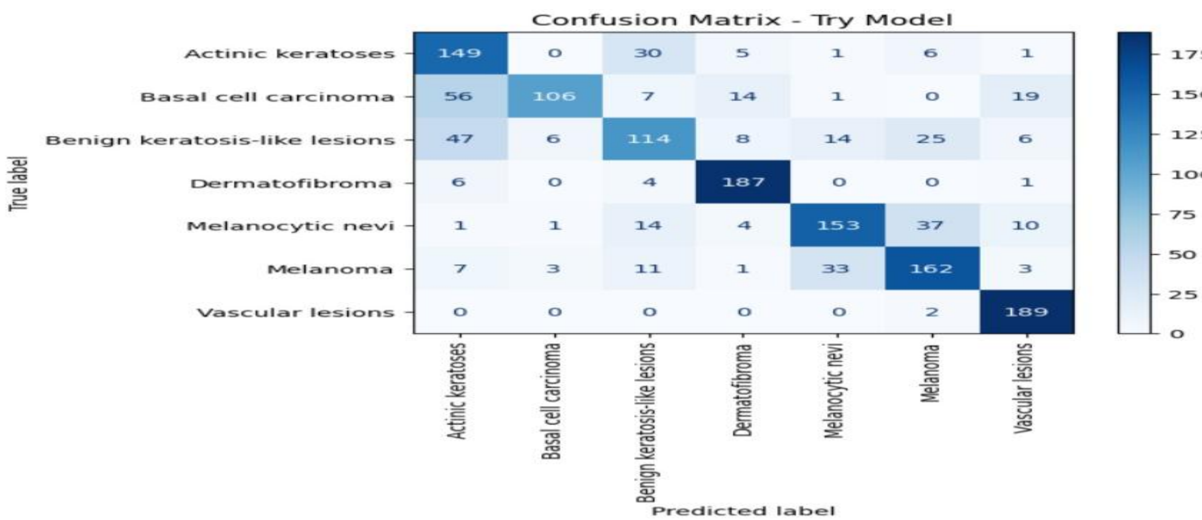


Figure 45: Confusion Matrix CNN with 7 Classes

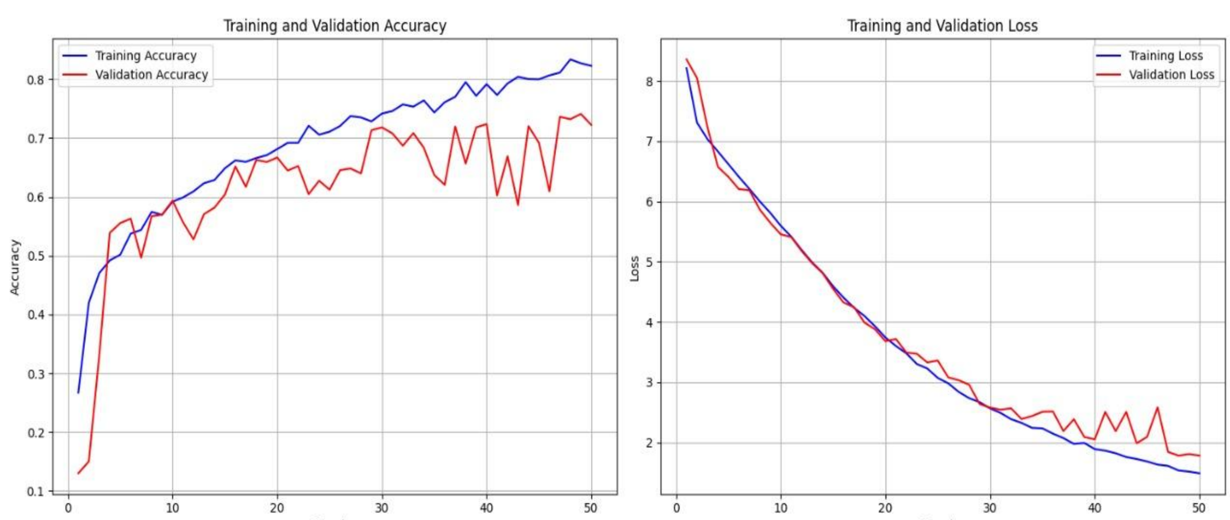


Figure 46: Accuracy CNN with 7 Classes

- **MobileNetV2 7 classes Color Contour:**

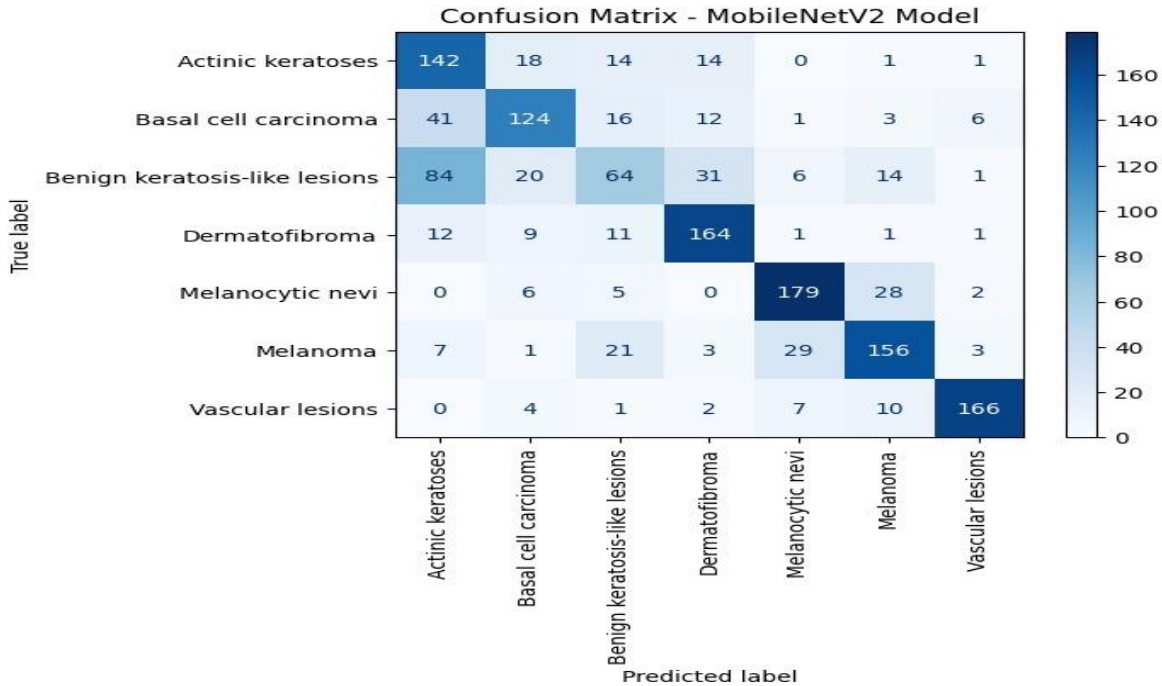


Figure 47: Confusion Matrix MobileNet with 7 Classes

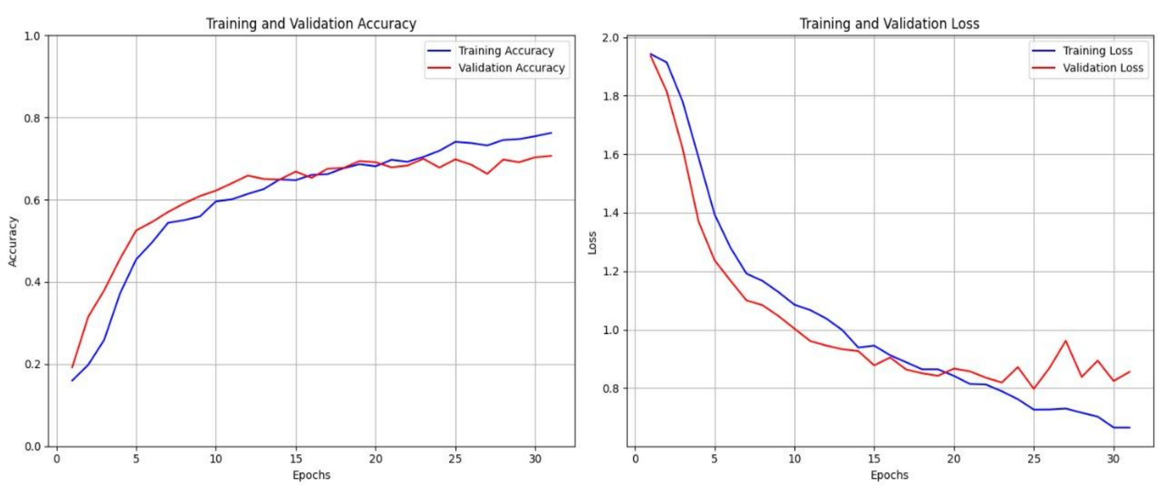


Figure 48: Accuracy MobileNet with 7 Classes

- DenseNet201(TOP_MODEL):

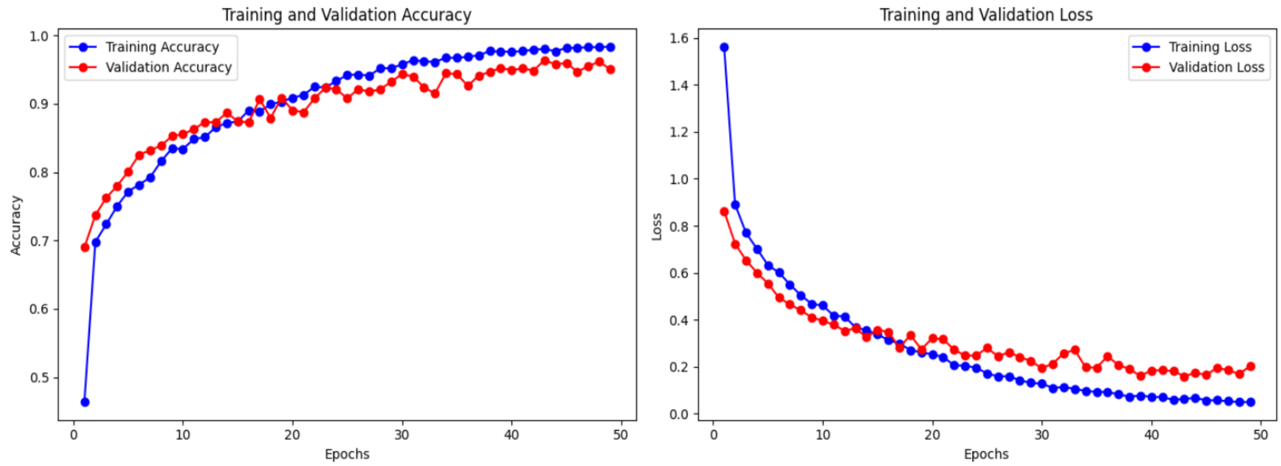


Figure 49: Accuracy Dense201 with 7 Classes

```
87/87 ━━━━━━━━━━━━━━━━━━━━ 51s 373ms/step
✅ Test Accuracy (Color Contour): 0.9456

✅ Classification Report (Color Contour):
                              precision    recall  f1-score   support

           Actinic keratoses       0.95      0.86      0.90        93
        Basal cell carcinoma       0.90      0.91      0.90       141
Benign keratosis-like lesions       0.85      0.94      0.89       307
              Dermatofibroma       1.00      0.91      0.95        32
            Melanocytic nevi       0.98      0.96      0.97      1858
                    Melanoma       0.84      0.91      0.88       305
            Vascular lesions       1.00      0.93      0.96        40

                    accuracy                           0.95      2776
                   macro avg       0.93      0.92      0.92      2776
                weighted avg       0.95      0.95      0.95      2776
```

Figure 50: Classification Report Dense201 with 7 Classes

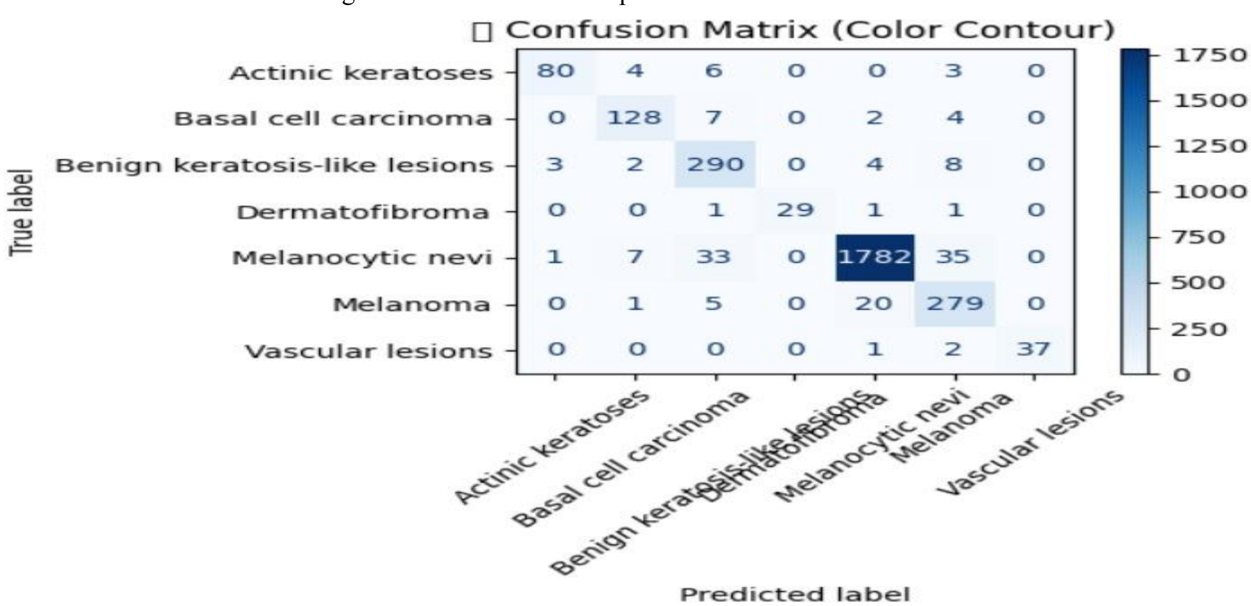


Figure 51: Confusion Matrix Dense201 with 7 Classes

This table shows Accuracy, Number of Classes, Number of Layers and Years and Reference Between our proposed Model and other models in different papers:

Papers	Accuracy	Number of Classes	Year	Reference
Snowber & Omker	**90%**	**2**	**2024**	ResearchGate
Gunjan & Shashank & Gopal & Santosh	**98.2%**	**7**	**2021**	Wiley
Rehab	**99%**	**2**	**2023**	IEEE
Huang	**95.8%**	**2**	**2022**	IEEE
Dilip & Upendra & Mohanan & Geetika	**97.53%**	**4**	**2024**	malque
Atyia & Syed & Habiba	**92%**	**7**	**2025**	ResearchGate

Table 1: Comparison Between Previous Models

Application: These are the results achieved in the application

Step 1: Login Page

To access the mobile app, open the application and enter your registered email address and password on the login screen.

- If you're a new user, tap **"Sign Up"** to create an account.
- Returning users can simply tap **"Log In"** after entering their credentials.
- If you’ve forgotten your password, use the **"Forgot Password"** link to reset it.

After a successful login, you’ll be redirected to the home screen where you can explore all app features.

Please ensure a stable internet connection for a smooth login experience.

Figure 52: Login Page

Step 2: Sign-Up Page

The Sign-Up page allows new users to easily create an account through a simple and user-friendly interface.

- It includes clearly labeled fields for entering a **username**, **email**, and **password**.
- For added convenience, users can also sign up quickly using their **Google** or **Facebook** accounts.
- The page is fully optimized for mobile devices, ensuring smooth performance across all screen sizes.
- Strong security measures are in place to protect your information during registration.

This page plays an important role in helping new users join the app easily and securely.

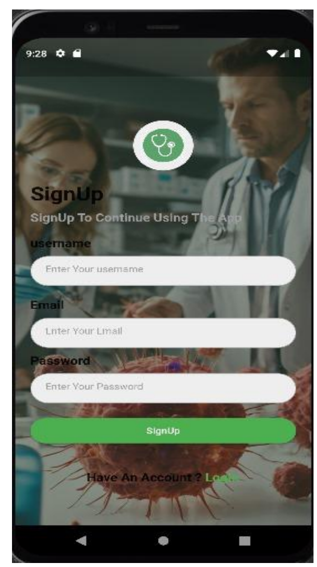


Figure 53: Sign Up Page

Step 3: Verify Warning

The Verify Warning feature helps ensure account security by confirming the user's identity during login.

- If your account hasn't been verified yet, a message will appear prompting you to check your email and complete the verification process.
- The dialog provides options to either **cancel** or **proceed** after reading the message.
- This step helps prevent unauthorized access and protects your account from misuse.

To continue using the app, follow the instructions in the verification email and complete the process.

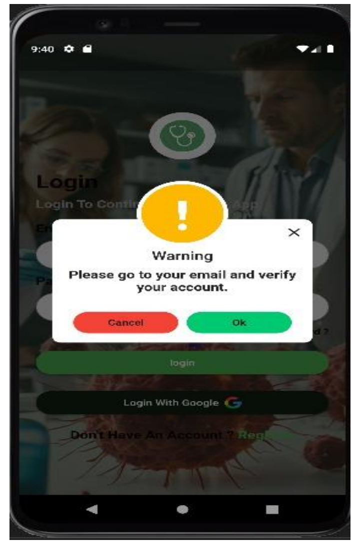


Figure 54: Verification error message

Step 4: Verification Email

This is the form of the verification email.

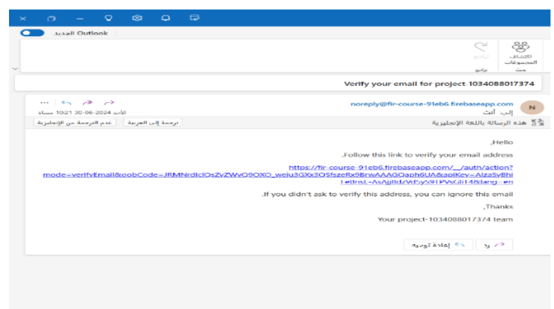


Figure 55: Verification email

Step 5: Email Verification Confirmation

After clicking the verification link sent via email, a confirmation page is displayed, indicating that the account has been successfully verified. This step completes the verification process and allows the user to proceed with accessing the app's features.

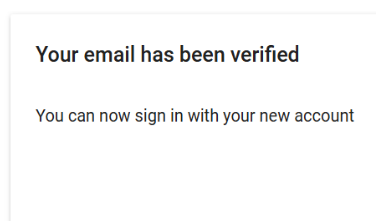


Figure 56: Verification confirmation

Step 6: Login Page

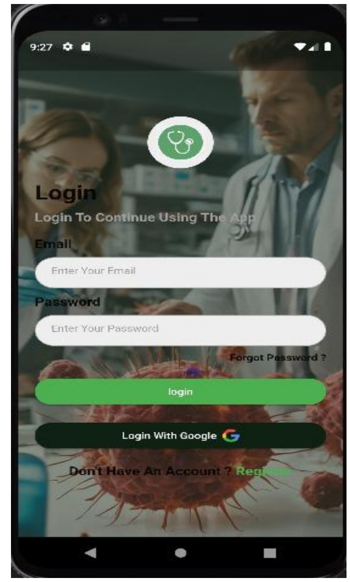


Figure 57: Login Page

To access the mobile app, users must enter their registered email address and password on the login screen.

- New users can select **"Sign Up"** to create an account.
- Returning users can proceed by clicking **"Log In"** after entering valid credentials.
- In case of forgotten passwords, the **"Forgot Password"** link allows users to reset their login details.

After successful authentication, users are redirected to the home screen to access the app's features. A stable internet connection is recommended for a smooth login experience.

Step 7: Home Page

Figure 58: Home page

The home page of the **SKIN Diseases App** offers multiple options for users to begin the skin disease analysis process.

- A default message, **"The model has not been predicted,"** is displayed when no image has been submitted.
- Users can choose to:
    - Select an image from the gallery
    - Capture a photo using the camera
    - Upload an image from the device storage

An additional **"Go to Info"** button redirects users to a list of skin diseases. Selecting any disease from the list opens a dedicated page with detailed information about the chosen condition.
The home page is designed to provide a straightforward and intuitive interface, helping users navigate the process with ease.

Step 8: Browsing Device

The browsing device feature enables users to access and select files directly from their mobile device.
When initiated, a file browser interface opens, displaying the device's folders and files. Users can navigate through their storage to locate and upload the desired image, document, or media file. This feature supports seamless file selection and is essential for submitting inputs within the app.

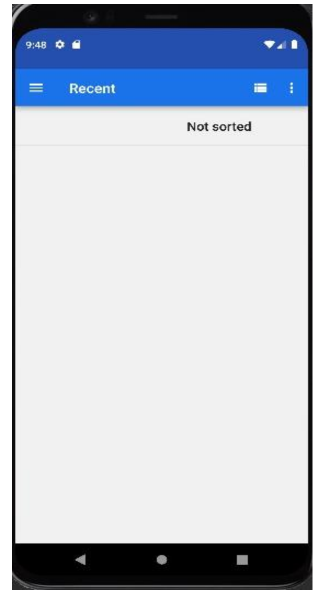


Figure 59: Browsing images

Step 9: Diseases Page

The Diseases page provides a list of skin conditions available within the app. Each item in the list can be selected to access a dedicated page containing detailed information about the chosen disease. This feature is designed to offer users clear and accurate medical insights to support better understanding and awareness.

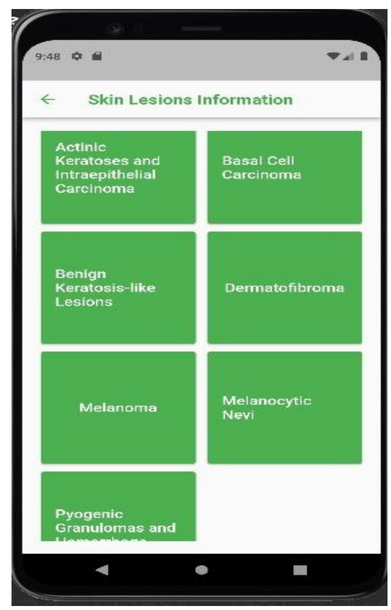


Figure 60: Disease page

Step 10: Information Page

Introducing our Information Page from the app, where users can access comprehensive details about specific diseases. This page is designed to provide in-depth insights, including symptoms, treatments, and preventive measures, ensuring users have the knowledge they need at their convenience. Check out how we're making health information accessible and informative!

Figure 61: Information Page 1

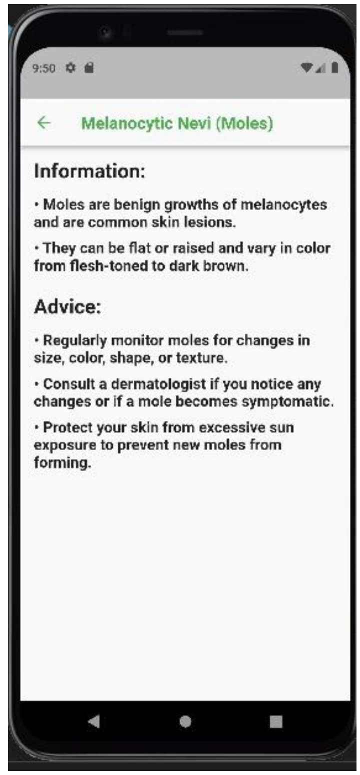


Figure 62: Information page 2

5.3 Application Development challenges:

First, our primary focus centered on the development of an application, prompting an exploration of existing applications for inspiration, additional features, and overall advancement. Following a comprehensive examination, two prevalent categories of applications in the market were identified. The first category comprises applications designed for the determination of skin diseases yet lacks the capability for scanning and classification. The second category, exemplified by Medgic, specializes in disease scanning and classification but falls short in the critical aspect of segmentation. Recognizing the strengths and limitations of these existing solutions, our objective is to integrate the optimal features of both categories. The envisioned application aims not only to accurately identify skin diseases but also to incorporate a comprehensive scanning and classification system, thereby bridging the existing gap in current applications. This dual functionality seeks to empower users with a holistic understanding of their skin health. Combining strengths for better skin disease diagnosis: A Novel Application Concept Envision an application seamlessly amalgamating the strengths of two existing skin disease detection tools: one excelling in identification through symptom analysis and user input, and another boasting powerful visual classification through advanced scanning technology. This innovative concept has the potential to revolutionize dermatology by offering a more comprehensive and user-friendly approach to skin disease diagnosis.

The proposed application aims to address the limitations of existing solutions. The first application, proficient in guiding users through symptom-based identification, lacks the accuracy and objectivity of scan-based analysis. Conversely, the second application, equipped with scanning technology, falls short in providing user-friendly symptom analysis and segmentation, crucial for refined diagnoses.

The novel application would bridge this gap by integrating both functionalities. Users would initiate the process by inputting symptoms and concerns, leveraging the expertise of the first application in symptom analysis to generate a shortlist of potential diagnoses. Subsequently, the application would seamlessly guide users through a scan process akin to the second application, utilizing acquired images to further refine the diagnosis and provide segmentation for detailed analysis. This dual approach harnesses the power of both methods, resulting in a more accurate and user-driven diagnostic experience.

-The benefits of this innovative app concept are numerous:

Enhanced accuracy: Combining symptom analysis with visual classification yields a more precise and reliable diagnosis compared to either method alone.

Improved user experience: The app guides users through a clear and intuitive process, ensuring accurate data collection and analysis.

Accessibility: By eliminating the need for specialized equipment, the app makes skin disease diagnosis readily available to a wider audience.

Early detection: Accurate and timely diagnosis empowers users to seek early treatment, potentially improving treatment outcomes.

This groundbreaking app concept has the potential to significantly transform skin disease diagnosis, bringing the power of advanced technology into the hands of individuals while maintaining a user-friendly experience. By bridging the gap between symptom analysis and visual classification, it paves the way for a future where accurate and accessible skin disease diagnosis becomes a reality for all.

Secondly, to implement the scanning feature for disease images, we integrated the TensorFlow Lite package. However, we encountered challenges as the scanning process failed. there are Several factors may cause this issue:

i. Limited Model Support: TF-Lite doesn't support all TensorFlow operations and functionalities. Complex models requiring more advanced operations might need workarounds or adaptation.

ii. Performance Trade-offs: TF-Lite prioritizes efficiency over flexibility. While highly optimized for mobile and embedded devices, it might not achieve the same performance as running the full TensorFlow on a powerful computer resource.

In our project, we utilized Flask, a micro web framework designed for Python, to develop a RESTful API endpoint. This API functions as an intermediary connecting our Flutter application with a machine learning model. By capitalizing on Flask's simplicity and adaptability, we seamlessly incorporated the model into our backend infrastructure.

Through this API, our Flutter frontend establishes communication with the model, enabling real-time predictions and data processing. This methodology not only guarantees scalability but also facilitates the integration of machine learning functionalities within our mobile application, thereby augmenting its overall functionality and enhancing the user experience.

6. Conclusion

This project presents a robust skin disease classification system developed using the HAM10000 dataset. Both traditional and deep learning approaches were explored to achieve accurate and efficient results. Initially, custom Convolutional Neural Network (CNN) architectures were implemented to extract and analyze important image features such as shape, texture, and color. These early models offered valuable insights into the dataset and the challenges of handling class imbalance and complex feature distributions in medical imaging.

To further improve model performance and reliability, the DenseNet201 architecture was adopted. This pretrained convolutional neural network leverages deep hierarchical feature extraction, enhancing the model's ability to generalize across varied inputs. The model utilized an image-based input pipeline and incorporated comprehensive data augmentation techniques—including rotation, flipping, zooming, and brightness adjustments—which contributed significantly to the system's robustness.

Training Configuration

The model was trained using the following setup:

- **Input Size:** 224 × 224
- **Batch Size:** 32
- **Data Augmentation:** Rotation, shift, shear, zoom, brightness adjustment, and horizontal flip
- **Validation Split:** 20%

Model Performance

The final model achieved the following results:

- **Training Accuracy:** 98%
- **Validation Accuracy:** 96.4%
- **Test Accuracy:** 94.6%

These outcomes reflect the effectiveness of the chosen preprocessing techniques, model architecture, and training strategy. The integration of data augmentation and transfer learning played a critical role in addressing class imbalance and improving the classification of all seven skin disease categories.

Future Work

To enhance the system further, several improvements are planned:

- Exploring hybrid architectures that combine multiple deep learning models
- Integrating advanced preprocessing methods such as lesion segmentation and color normalization
- Expanding the dataset to include a wider range of skin types and rare disease cases
- Deploying the model in a user-friendly web or mobile application for real-time diagnostic support

These future directions aim to increase accuracy, usability, and accessibility in clinical and remote healthcare settings.

Model Architecture and Fine-Tuning Strategy

Model Overview

DenseNet201, a high-performance CNN pretrained on the ImageNet dataset, was used as the base model. To tailor it for the HAM10000 dataset, transfer learning was applied by adding custom layers on top of the base architecture.

Architecture Components

- **Base Model:** DenseNet201
- **include_top=False:** Removes the original classification head
- **weights='imagenet':** Loads pretrained ImageNet weights
- **input_shape=(224, 224, 3):** Supports RGB images resized to 224×224 pixels

Custom Classification Head:

- **GlobalAveragePooling2D:** Reduces spatial dimensions by averaging feature maps
- **Dense(512, activation='relu'):** Learns complex feature representations
- **Dropout(0.5):** Applies regularization to prevent overfitting
- **Dense(num_classes, activation='softmax'):** Outputs class probabilities for seven disease categories

Fine-Tuning and Training Setup

Fine-Tuning Strategy:

- Initially, only the custom classification layers were trained while keeping DenseNet201's layers frozen
- DenseNet201 layers were later optionally unfrozen for full fine-tuning
- Transfer learning was configured using include_top=False and weights='imagenet'

Training Configuration:

- **Optimizer:** Adam, with a learning rate of 1e-5 for gradual weight updates
- **Loss Function:** categorical_crossentropy, suitable for multi-class classification
- **Metric:** Accuracy, used for both training and validation evaluation

Model Checkpointing:

- A ModelCheckpoint callback was used to monitor val_accuracy and automatically save the best-performing model to

  best_densenet201_color_contour.h5

```
Total params: 19,309,127 (73.66 MB)
Trainable params: 19,080,071 (72.78 MB)
Non-trainable params: 229,056 (894.75 KB)
```

Figure 63: Model Parameters Summary

7. References

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