SKIN DISEASE DETECTION USING DEEP LEARNING

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FINAL YEAR DESIGN PROJECT REPORT

This Report Presented in Partial Fulfillment of the Requirements for the Degree of Bachelor of Science in Computer Science and Engineering

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APPROVAL

This Project titled "Skin Disease Detection Using Deep Learning", submitted by Md Tarikul Islam Selim and Md Moinul Islam to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 13-07-2024.

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We hereby declare that this project has been done by us under the supervision of **Dr. Md Monzur Morshed, Professor, Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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ABSTRACT

For successful treatment and better patient outcomes, skin disorders must be identified early and accurately. Conventional diagnostic techniques, which mostly depend on dermatologists' visual inspection, are frequently arbitrary and based on the expertise of the practitioner. The application of deep learning models such as CNN, VGG16, MobilenetV2, and Densenet121 for automated skin disease identification from dermatoscopic pictures is investigated in this work. Our methodology allows the models to recognize complex patterns and characteristics typical of different skin disorders. We overcome the difficulties caused by sparse and unbalanced datasets by applying transfer learning and data augmentation strategies, guaranteeing strong model performance across several skin disease categories. When tested on a small picture dataset, the suggested CNN-based system outperforms conventional machine learning techniques in terms of accuracy, sensitivity, and specificity. Furthermore, the model offers graphical explanations to support its predictions, improving interpretability and building medical experts' confidence. According to the findings, deep learning may greatly enhance the early diagnosis and screening of skin conditions, providing a trustworthy instrument for initial screening and diagnosis. Because it makes fast and accurate therapeutic interventions possible, this development has the potential to save healthcare expenditures while also improving patient care. We demonstrate the efficiency of our technique by correctly and robustly classifying a broad spectrum of skin illnesses through a comprehensive performance evaluation.

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CHAPTER 1

Introduction

1.1 Overview

Skin diseases are such conditions that affect our skin. Any substance that affects the skin's texture such as swelling, itching, irritation, and redness is addressed as Skin disease. Infection from bacteria or disease can also be a cause of skin changes. Skin diseases can cause blisters, lumps, rashes, increased or decreased skin pigmentation, sensitivity, or scaling.

1.2 Background and Present State

Deep learning-based skin disease detection is a fascinating and quickly developing topic with great potential to advance dermatological diagnosis. Conventional skin problem diagnosis techniques mostly rely on dermatologists' knowledge, which may be laborious and subjective. However recent developments in deep learning—especially with convolutional neural networks (CNNs)—have demonstrated that AI models are capable of diagnosing a wide range of skin illnesses with a high degree of sensitivity and accuracy. Large, annotated datasets of skin imaging data are used to train these models, which helps them recognize and understand patterns that might not be immediately obvious to the human eye. A rising number of commercial programs and technologies are available that provide automated skin disease diagnosis via cellphones and internet platforms, expanding the public that may access these sophisticated diagnostics. Furthermore, dermatologists are able to identify patients more quickly and accurately because to the incorporation of deep learning models into clinical processes, which enhances patient outcomes. Deep learning is set to transform dermatology and provide fresh hope for the early and accurate diagnosis of skin illnesses as research advances and regulatory frameworks change to ensure the safe and ethical use of AI in healthcare.

1.3 Problem Statement

Cutaneous complications are one of the conditions of Skin disease that occur when the body's integumentary systems which include the skin, hair, nails, and related muscles including glands that cover the human body become affected or contaminated. The following factors may contribute to the study of skin disease: A weakened immune system with genetic illnesses impacts the kidneys, thyroid, immunological system, and other bodily systems chemicals that cause allergies or diseases. In this situation, various issues such as rash, headache, and muscle soreness may manifest in various body parts. Due to a variety of factors, people with allergies or skin conditions have various issues, including skin rashes. Skin conditions can alter the skin's color or texture.

1.4 Objectives

Motivated by the constraints of existing approaches and the immense potential of deep learning, this research delves into the exciting intersection of artificial intelligence and dermatology. Our goal is to use cutting-edge methods such as convolutional neural networks, also known as CNNs, to improve and automate the diagnosis and categorization of skin diseases.

1.5 Scope and Limitations

The system will make use of a dataset that includes pictures of several skin disorders, such as melanoma, psoriasis, and eczema, among others. With great accuracy, the deep learning model can identify and categorize common skin conditions. Here, In order to create and train deep learning models for the diagnosis and classification of skin disorders, we employ the collected dataset. These models include CNN architectures and a few convolutional layers.

1.6 Report Organization

The report will be divided into multiple important sections. By going over the significance of identifying skin diseases and the function of deep learning, the introduction will set the scene. After that, an extensive study of the literature will look at current approaches and new developments in the subject. The dataset's acquisition and preparation, as well as the deep learning architectures and training techniques used, are all covered in detail in the methods section.

1.7 Summary

Deep learning-based skin disease diagnosis is a major development for the fields of dermatology and medical imaging. This method, which makes use of deep learning algorithms, has the ability to diagnose a variety of skin problems quickly, automatically, and accurately. By utilizing convolutional neural networks (CNNs), other deep learning architectures, scholars and medical practitioners can examine extensive collections of skin photos to detect trends and characteristics suggestive of various medical conditions. Skin illnesses like melanoma, eczema, psoriasis, and acne can now be accurately detected and classified thanks to the development of robust models trained on a variety of datasets.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

Deep learning-based skin disease detection has garnered significant attention in the medical community, as seen by the diverse spectrum of research and methodologies presented in the literature. Many academics have looked at the automated diagnosis and classification of different skin disorders using deep learning techniques, especially convolutional neural networks (CNNs). Research has employed a variety of datasets, from publically accessible archives to carefully selected sets of clinical photos, to train and assess deep learning models for the identification of skin diseases.

2.2 Related Works

To develop an automated dermatological screening system Nawal Soliman ALKolifi ALEnezi et al.[1] performed image processing techniques. Here the approach works on pre-trained convolutional neural networks and after that uses Multiclass SVM. The approach used is 100% accurate in detecting three distinct forms of skin disorders.

Without any constraints Jainesh Rathod et al.[2] propose an automated image-based system that can diagnose skin diseases. Based on several properties of the photos, the system processes, analyses, and assigns the image data using machine learning categorization. The image is then classified using a CNN (Convolutional Neural Network) utilising the softmax classifier technique to get a more accurate predicted result.

A model was proposed by ZHE WU et al.[3] that studies the effectiveness of several convolutional neural network (also known as CNN) algorithms for the clinical image-based categorization of skin disorders on the face. The authors experimented with five different CNN architectures. The best model obtained mean recall and accuracy of 77.0% and 70.8% for BCC and SK, respectively, and recalls of 92.9%, 89.2%, and 84.3% for the LE.

A web-based method is proposed by author Samuel Akyeramfo-Sam et al.[4] for the identification of skin problems. The system relies on an CNN model (convolutional neural network) named Medilab-Plus to identify skin illnesses such as scabies, acne vulgaris, and atopic dermatitis. Three different skin conditions were successfully classified by the algorithm with an 88% accuracy rate: scabies, acne vulgaris, and atopic dermatitis. In this study, two kinds of sounds and a random offset are added.

Deep CNN model was utilised by Xioyu Fan et al. [5]. The author using the image which images taken by smartphones and then added both Gaussian noise with deviation of 25 to 35 and impulse noise with 0.02 to 0.04 proportion. Classification accuracy increases to the high value and training converges to zero near the 2000th step three evaluation methods t-SNE,ROC and saliency maps. The accuracy and overall performance of the CNN models improved on clear, noise-free images but gradually declined as the amount of noise grew. Higher noise levels caused a more obvious decline in classification accuracy, proving that noise has a detrimental effect on models' capacity to correctly classify skin lesions.

The work illustrates the effectiveness of transfer learning in differentiating between benign and malignant lesions by training a CNN on a broad dataset of skin lesion photos S.R.Guha et al.[6] findings highlight the value of using computer-aided technologies to improve dermatological diagnoses. Their dataset included 10015 photos in total for the analysis of Melanoma Detection.VGG16 transfer learning model and CNN were employed. The greatest model they utilized was the VGG16. And they got better accuracy when using the VGG16 model.

This study compares the various CNN models' working methods in order to learn which produces the best outcomes Hsan et al.[7] Sequential models are used to examine how CNN models are created. With 6594 pictures, they obtained accurate VGG16(93.18%) and SVM(83.48%) findings. so here final highest accuracy of 93.18%. The dataset utilized in this study came from Kaggle. Used six different model neural networks (SVM,VGG16,ResNet50,sequential 1/2/3). The purpose is to identify skin cancer.

The study provides a novel approach to deep learning-based lightweight variable kernel Convolutional Neural Networks (for the classification of skin lesions into many categories Aldyani et al. [8] Through filter modifications in convolutional layers, the proposed model enhances the ability to extract many types of information from pictures of skin lesions. They achieved an accuracy of 97.89%.HAM1000 dataset used for experimentation. Python 3.8.8 was used to implement the suggested model, and the Keras API 2.7.0 library was used. They classified melanoma (MEL) using the support vector machine (SVM) and parenchymal (PL) approaches utilized by the author. Finally, good results have been obtained in the diagnosis of skin disorders utilizing this approach in conjunction with the CNN method. And it was taken by smartphone and digital camera, which was difficult for CNN models and wasn't scaled. As a result, They suggested an effective CNN-based model that makes use of kernels and activation functions.

In this study, Xiaoyu He [9] suggested an evolutionary method with a simple encoding method (SEECNN) for the developing Easy-Encoded convolutional neural network (CNN) and its application to skin disease picture classification challenges. The authors evaluated SEECNN on nine benchmark datasets and a taxonomy of images of skin diseases in real-life datasets. The results demonstrated that SEECNN was able to achieve state-of-the-art results on most of the datasets. A real-world example of image categorization for a skin illness is used to test the suggested algorithm SEECNN.

The paper proposes an efficient solution by Sadik [10] to identify skin diseases by the use of Convolutional neural network, also known as CNN, architectures. To construct an expert system, the authors used two CNN architectures, MobileNet and Xception, and a transfer learning method. Five different categories of skin problems were identified using the data that was gathered from two different data sources. They employed a variety of performance assessment metrics, including as accuracy, precision, recall, and F1-score, to confirm the efficacy of their method. In this case, the Xception model obtained 97.00% classification accuracy, whereas MobileNet achieved 96.00%.

In this paper, the author Nigat [11] explores the use of Convolutional Neural Networks

(CNNs) for classifying four common fungal skin diseases:tinea pedis, tinea capitis, tinea corporis, and tinea unguium. A collection of 407 fungal lesions of the skin were gathered from Jimma, Ethiopia's Dr. Gerbi Medium Clinic to create the dataset. Images were normalized to three different dimensions. Additionally, augmentation techniques were applied to enhance the diversity of the dataset. The authors propose a CNN model achieving an accuracy of 93.3%, which is promising for early detection and potentially improving patient outcomes.

A smartphone-based skin disease classification system was introduced by the author Velasco [12] using MobileNet convolutional neural network (CNN). An Android application was developed using a skin illness categorization method based on the MobileNet model applied to the seven skin diseases. Here the dataset contains a total of 3,406 images and, using data augmentation and oversampling techniques during the preprocessing of the raw data yields an accuracy of 94.4%. This paradigm was implemented in the Android application that was developed.

An ensemble method combining deep learning networks is proposed by the author Kalaivani [13] for accurately classifying skin diseases. Using the publicly accessible ISIC2019 dataset, which contains pictures of seven distinct skin conditions, the method investigates several data mining techniques to classify the skin condition. With an accuracy of 96.1%, the ensemble approach outperformed the individual models (VGG16: 93.7%, InceptionV3: 94.5%, Naive Bayes: 88.2%).

To achieve the best outcome when categorizing psoriasis and atopic dermatitis the author Sari [14] proposed 10 convolutional neural networks (CNNs) architecture. The dataset contains 480 images (240 each for atopic dermatitis and psoriasis) collected from online databases. For both training and unseen data, InceptionV3 achieved the best accuracy (84%) and F1-score (0.83). The performance of other models varied, with some models, such as VGG16 and ResNet50, attaining reasonable accuracy (around 80%).

Using deep learning in this model Zhang et al [15] image classification and important features can be automatically obtained. They employed a brand-new dataset of 129450 clinical photos divided into 2032 categories, labeled by dermatologists. This experiment focuses on the skin condition melanoma. It is of the worst types of skin cancer. About 70% of skin cancer-related fatalities globally. Here used the different models, ZFNet, VGG, GoogLeNet , and ResNet. Used the CNN Algorithm.

In this paper, skin protects the body and takes in sensory input from the environment et al [16] used deep learning in this model. CNNs, or convolutional neural networks, are used to identify skin issues. The majority of picture values are 1-D converted and also converted to RGB format for these pre-enhanced photos. A total of 12288 images were used. Here Used the CNN, KNN, and DCNN algorithms. Skin conditions with 98.4% accuracy, 96.3% precision, 97.2% recall, and a 10000 ms detection time.

2.3 Comparison between existing works

Skin disease diagnosis has undergone a revolution thanks to deep learning, which significantly outperforms more conventional techniques that depend on manually created features and less complex classifiers like Support Vector Machines (SVM) and k-nearest Neighbours (k-NN). Convolutional Neural Networks (CNNs) attain superior accuracy and greater generalization to unknown input by automatically extracting and learning features from big datasets. Deep learning algorithms simplify the whole process, from picture input to illness classification, while older approaches frequently struggle with large datasets and require extensive domain expertise for feature extraction. Deep learning models perform better and are more adaptive when they use techniques like data augmentation and transfer learning, even if they need large amounts of labeled data and have greater processing demands. Despite the fact that these models are generally regarded as "black boxes," new interpretability strategies are beginning to appear that shed light on how they make decisions. Deep learning provides a strong and scalable method for precisely identifying and treating skin diseases, greatly assisting with early diagnosis and therapy.

Table 2.3.1: Comparative Analysis Table

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
1.	ALEnezi, N.S.A. et al. [1]	SVM	SVM=100%
2.	Rathod, J. et al. [2]	CNN	CNN= 70%
3.	Wu,Z.H.E. et al. [3]	CNN	CNN=77.0%
4.	Akyeramfo-Sam, S. et al. [4]	CNN, Decision tree (DT), Artificial neural network(ANN), SVM, Naïve Bayes	CNN=88%
5.	Fan, X. et al. [5]	CNN	CNN=96.50%
6.	Guha, S.R. et al. [6]	CNN, VGG16	VGG16=95%
7.	Hasan, M.R. et al. [7]	CNN, SVM, VGG16	VGG16 = 93.18%
8.	AlDhyani, T.H. et al. [8]	SVM, CNN, ANN	CNN=97.85%
9.	Kalaivani, A. et al. [9]	Random Forest, CNN	Random forest=96.1%
10.	Sadik, R. et al. [10]	CNN	CNN=97.00%
11.	Nigat, T.D. et al. [11]	CNN	CNN=93.3%
12.	Velasco, J. et al. [12]	SVM, CNN,ANN	CNN=94.4%

2.4 Open Issues

Even with deep learning's advances in skin disease diagnosis, there are still a number of obstacles to overcome. Since many datasets do not cover a wide range of skin tones and demographics, ensuring data diversity is essential to preventing biased predictions. Establishing confidence between patients and healthcare professionals requires improving the interpretability and openness of models. It is necessary to take into account ethical issues and regulatory permission, especially with regard to patient data protection. For dependable performance, models must be robust and generalizable across many clinical situations and technologies. In addition, widespread use and fair healthcare depend on these tools being easily incorporated into clinical processes and made affordable and accessible.

2.5 Summary

A major advancement in dermatology and medical imaging is indicated by the literature review, which shows growing interest in using deep learning algorithms for skin disease identification and categorization. Convolutional neural networks (CNNs) have been a popular option among researchers investigating a range of deep learning architectures because of their capacity to process and interpret complicated picture input. A wide range of datasets, both publicly accessible repositories and carefully chosen sets of clinical photos, have been used to train and assess deep learning models. One notable development is the creation of specialized preparation methods to improve the diversity and quality of datasets. Future research endeavors focused on resolving certain obstacles and enhancing deep learning models have the potential to transform dermatological diagnosis, thereby enhancing patient outcomes and progress.

CHAPTER 3
METHODOLOGY

3.1 Overview

Deep learning-based skin disease detection is a revolutionary method for accurately and efficiently identifying dermatological disorders. In order to identify and categorize a variety of skin illnesses, such as melanoma, psoriasis, eczema, and more, this study topic intends to investigate the creation and use of sophisticated deep learning models, such as CNN, VGG16, MobilenetV2, and Densenet121. The goal of the project is to train these algorithms to identify tiny patterns and abnormalities that may be difficult for human eyes to pick up on by using big datasets of dermoscopic and clinical pictures.

3.2 Proposed Methodology

Here's a more thorough breakdown of the deep learning approach's classification step for identifying skin diseases:

1. Preprocessing:

Resizing, cropping, and maybe using noise reduction methods are steps in the preparation of images for analysis.

2. Feature Extraction:

The preprocessed photos are scanned by the deep learning model, which is usually a Convolutional Neural Network (CNN). In the convolutional phase, the CNN gathers information about the pictures' features. These qualities and patterns are what CNN considers significant for categorization.

3. Classifier and Evaluation:

After analyzing features, the classifier—typically CNN or a different deep learning architecture like VGG16, MobilenetV2, and Densenet121 —assigns a class label to the picture. following an assessment of the model's performance. By contrasting the predicted labels (assigned class labels) of the model with the actual labels of the pictures in the test dataset, the accuracy of the model is determined. Finally, the accuracy is evaluated.

The following figure 7 shows the whole idea of our project.

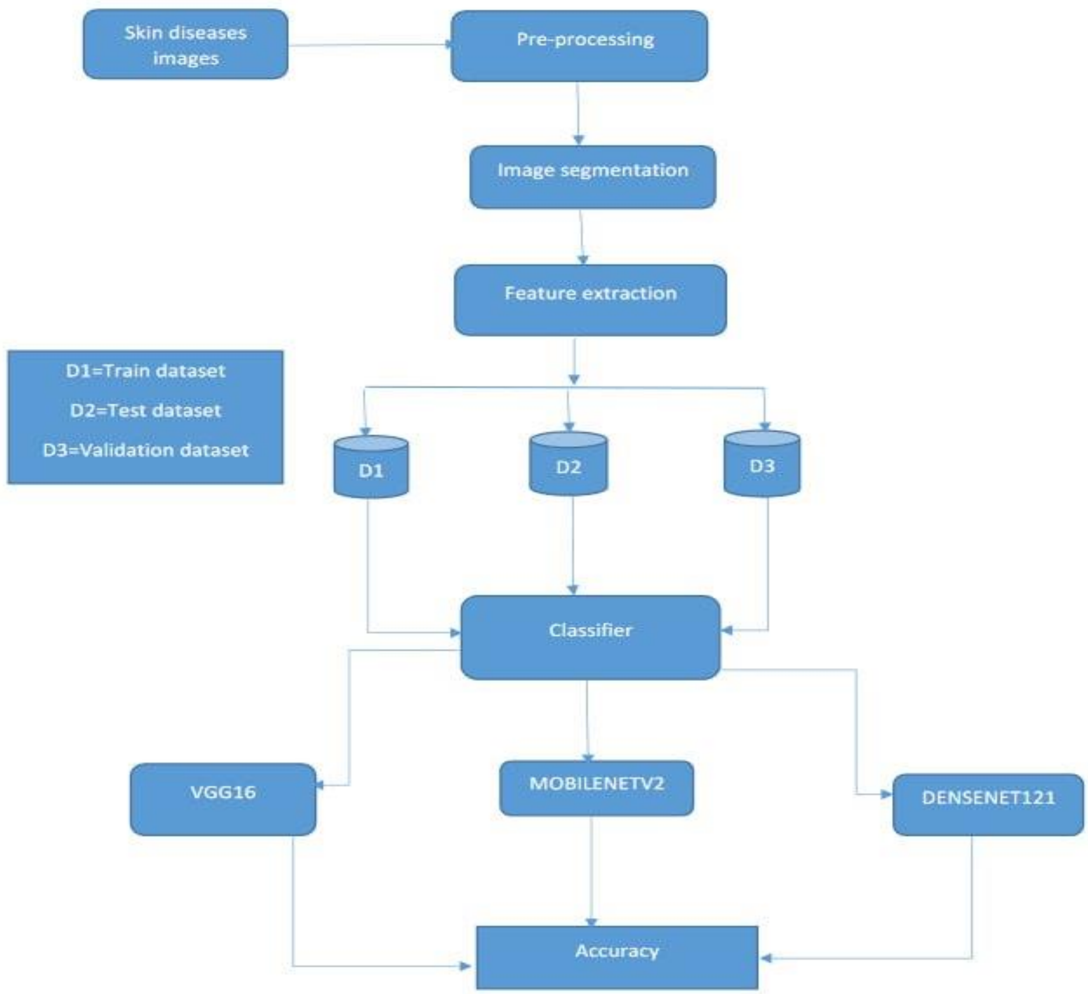

Figure 3.2.1: Proposed Design

3.3 Hardware/ Software Requirement

There are several prerequisites that must be met in order for the research project on "Skin Disease Detection Using Deep Learning" to be implemented successfully. These implementation requirements cover aspects like data gathering and model assessment in addition to hardware and software components.

A. Equipment and Tools:

A. Desktop PCs with high speed can handle activities like processing images and machine learning and have enough RAM and processing power.
B. core i5 laptop served as the workstation for this study.
C. For these systems, Jupiter Notebook has functioned as an IDE.
D. The Jupiter Notebook's inbuilt RAM and GPU are utilized instead of the laptop's integrated graphics (2 GB) and RAM (8 GB).
E. The dataset was aided in storage by Hardware.

B. Software and Technologies:

A. Python is a popular programming language that's utilized to create deep learning algorithms.
B. Deep learning frameworks that provide tools and libraries for building and deploying deep learning models, including convolutional neural networks (CNNs).
C. OS that is compatible with x64 architecture.

3.4 Project Management and Financial Analysis

Project Management

Project Objectives:

A. Through the use of algorithms based on deep learning, like convolutional neuronal networks (CNN), VGG16, MobilenetV2, and Densenet121 the research seeks to develop a model that can accurately and quickly assess skin pictures.
B. The ultimate objective is to help dermatologists and other medical professionals diagnose skin disorders more quickly and accurately, which will enable the early diagnosis, management, and treatment of skin illnesses.

Project Timeline:

A. Phase 1: Planning and Data Collection (2-4 weeks)
B. Phase 2: Data Pre-processing (4-6 weeks)
C. Phase 3: Selection (2-4 weeks)
D. Phase 4: Model Training & Testing (Ongoing)
E. Phase 5: Documentation (3-6 weeks)

Risk Management:

SWOT analysis involves assessing the Strengths, Weaknesses, Opportunities, and Threats of a project. Here's a SWOT analysis for the skin diseases project:

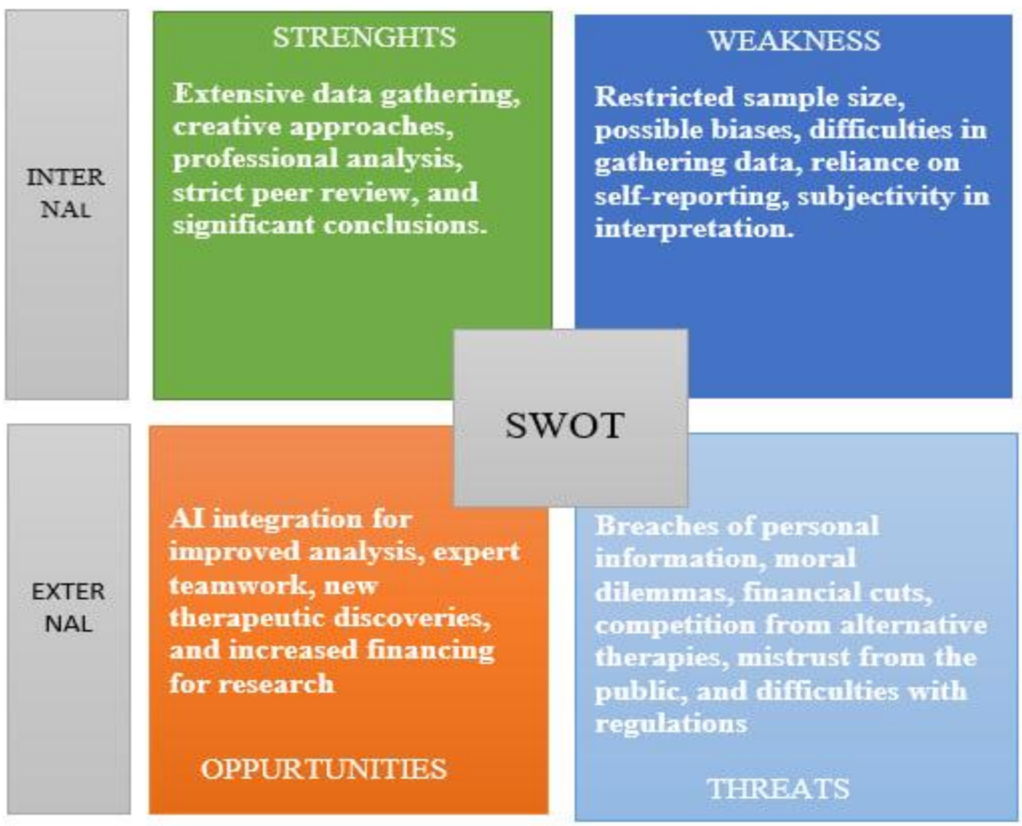

Figure 3.4.1: SWOT analysis for skin diseases

Communication Plan:

A. Stakeholder Meetings:

Purpose: Update stakeholders on project requirements gathering progress and gathering feedback.

Participants: Team members, and stakeholders.

Frequency: Bi-weekly or as specified in the Project plan.

B. Change Control Meetings:

Purpose: Discuss and approve any changes to the project scope or requirements.

Participants: Supervisor, and team members.

Frequency: As needed when change requests arise.

Financial Analysis:

For the skin disease detection project to be successful, effective management is essential. The development process will be guided by assembling a team with pertinent experience and making use of project management tools. Selecting the right approach guarantees the clarity and adaptability we need to do the job. In the first stage, we need some financial.

Table 3.4.1: Estimated Cost Table

SN	Components	Estimated Cost (BDT)
01.	Hardware/Infrastructure	6000-7000
02.	Visiting Stakeholders	0.0
03.	Software and Tools	3500-4000

04.	Data Collection and Processing	0.0
06.	Documentation and Report Writing	2000-2500
07.	Miscellaneous (e.g., licenses, tools)	0.0
08.	Contingency (10% of total)	1500-2000
	Total Estimated Cost	13000-15500

3.5 Summary

The process of creating reliable and accurate diagnostic models is a crucial part of the deep learning approach for the identification of skin diseases. usually begin with gathering and preprocessing a broad collection of skin photos to guarantee sufficient representation of different skin types and demographic variables. Next, to acquire discriminative characteristics for illness identification, deep learning architectures—like convolutional neural networks (CNN), VGG16, MobilenetV2, and Densenet121 are put into practice and trained on the dataset. In general, in order to ensure the reliability and effectiveness of the diagnostic system, careful data preparation, model training, and evaluation are crucial, as demonstrated by the deep learning technique for skin disease diagnosis.

CHAPTER 4
IMPLEMENTATION

4.1 Overview

There are several prerequisites that must be met in order for the research project on "Skin Disease Detection Using Deep Learning" to be implemented successfully. These implementation requirements cover aspects like data gathering and model assessment in addition to hardware and software components.

4.2 Train Model

A. Datasets

We collected the dataset from Kaggle. A total of 1157 images have been worked on in the dataset. Here through pre-processing, we have identified the images of the train set and test-test. There are 924 images and 8 classes in the train set. The test has 233 images and 8 classes. We are working on sophisticated deep learning models, such as Convolutional Neural Networks (CNNs), VGG16, and resnet50 to find out the accuracy and we hope to get good accuracy.

Figure 4.2.1: Some Raw Images of Dataset

Table 4.2.1: Images Used in the Train and Test Sets.

	Train	**Test**
Raw Dataset	924	233

B. Process of Experiments

Deep learning-based skin disease identification uses sophisticated neural network architectures to identify and categorize a range of skin problems from pictures. This procedure usually consists of many important steps, each of which adds to the model's overall accuracy and performance. The experiment was planned to go as follows:

Image Augmentation and Preprocessing:

Several crucial processes are involved in the data augmentation and preprocessing methods for deep learning-based skin disease diagnosis in order to improve model performance and generalizability. Using the ImageDataGenerator class from TensorFlow Keras, augmentation of data is carried out. To create a varied collection of training examples, transformations including rotation, width and height shifts, shearing, zooming, and horizontal flipping are used. This procedure aids in making the model invariant to changes in the magnitude, direction, and location of the skin lesions. To make sure that the training and testing pictures are compatible with the activation functions of the neural network, pixel values are also normalized. The flow_from_directory method is then used to load the augmented and preprocessed photos in batches from their appropriate directories while keeping batch processing settings and image size constant. The enhanced photos are visualized using the display_image_batch utility function, which confirms that the augmentation procedure was successful. All of these procedures work together to provide a solid dataset that is needed to train a deep-learning model that correctly diagnoses and categorizes skin conditions.

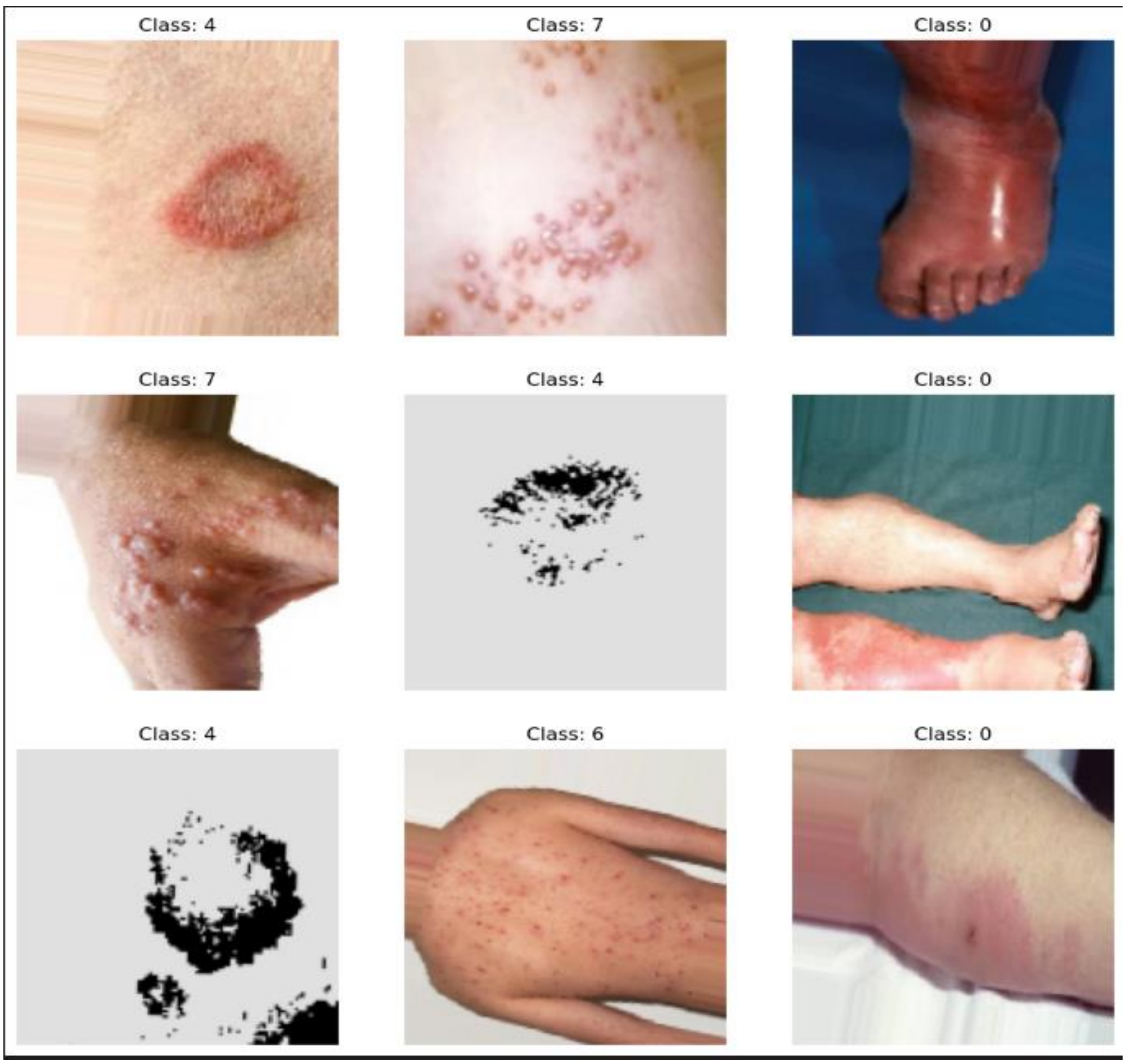

Figure 4.2.2: Augmented and Preprocessed Image

Training:

A portion of the training photos are visualized in this technique step to give a general idea of the contents and organization of the dataset. The process of picking and presenting a few photographs at random from every class aids in confirming the accuracy and variety of the data. The code carries out the following actions for every class: Assuming the photos are in JPEG format, it uses Path.glob("*.jpg") to display all the image file paths in the class's directory. Using random.choices, it chooses a certain number of photos (NUM_IMAGES) at random from the image paths list. Since matplotlib requires pictures in RGB format, each selected image is first read in BGR format using cv2.imread and then transformed from BGR format to RGB format using cv2.cvtColor. The relevant subplot displays the chosen photographs. Each subplot's title contains the picture form and the class name, and for a more aesthetically pleasing visualization, the axis is disabled.

Figure 4.2.3: Visualize Training Image

Mask and Annotation:

There are numerous important phases in the mask and annotation process for object detection visualization. To represent areas of interest (ROIs) inside a picture, a binary mask is first constructed. To guarantee correct alignment, the mask is then scaled to match the image dimensions. Annotations include comprehensive details about things that have been identified, such as labels identifying the objects that have been detected, bounding boxes defined by coordinates, and confidence ratings showing the correctness of the detection. Using a colormap, distinct colors are allocated to each mask during visualization. The ROIs are then highlighted by blending the masks with the matching picture areas. Detected items are surrounded by bounding boxes, with labels and scores shown next to the boxes for clarification. An annotation and masking tool such as matplotlib is then used to show this image. This procedure is essential for verifying how well object detection models work since it gives a clear visual depiction of how the models recognize and categorize various areas inside photos.

Figure 4.2.4: Mask and Annotation Images

Segmentation:

Using a number of stages, skin disease photos are converted to binary images as part of the segmentation approach. To make the data simpler, each image is first read and converted to grayscale. Next, binary thresholding is used to create a binary picture by setting pixel values above a threshold to their highest value and those below to zero. For clarity, this segmented image is saved with a changed filename. Using matplotlib, the original and binary segmented pictures are shown side by side for visualization. By iterating over a list of picture paths, applying the segmentation function to each, and managing errors to guarantee robust processing, the method is expanded to handle multiple photos. To ensure that all pertinent photos are handled, image paths are collected from designated folders. This technology facilitates the visualization and study of skin disease areas by efficiently producing binary representations of pictures.

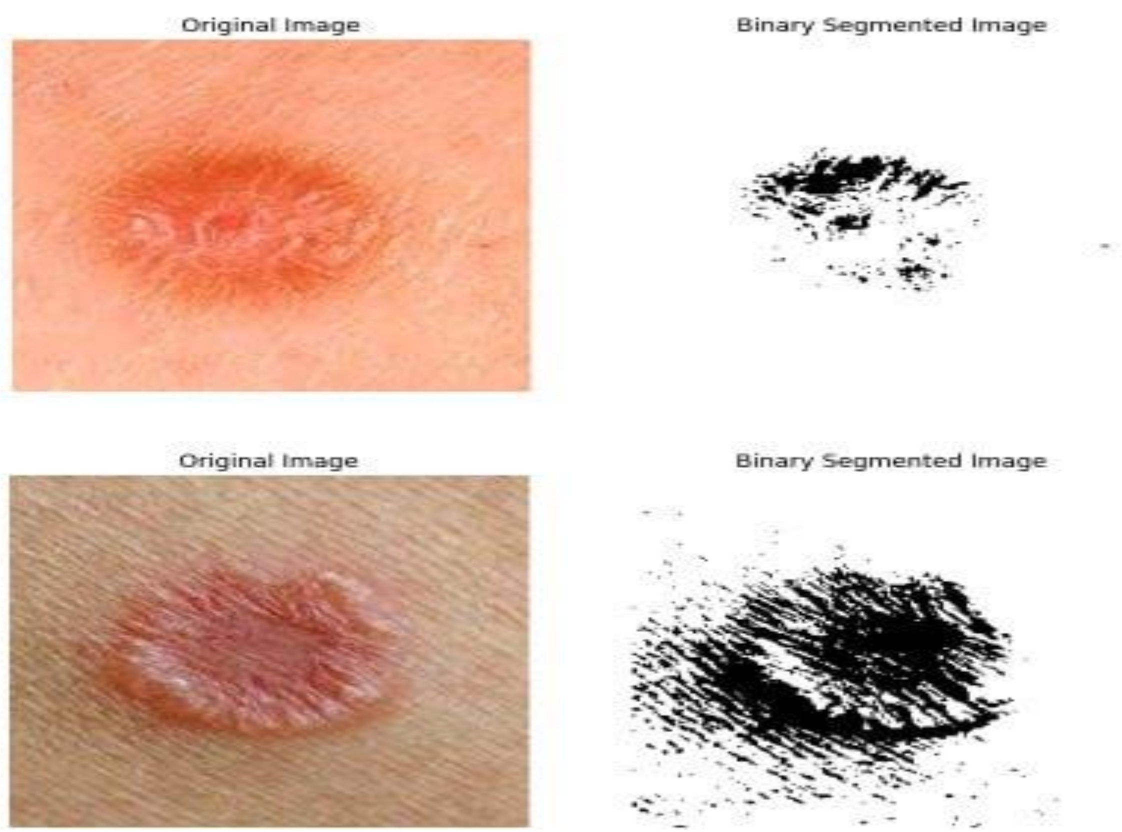

Figure 4.2.5: Segmented Images

4.3 Model Evaluation

To thoroughly evaluate the model's performance, there are many crucial elements in the deep learning model assessment process for skin disease detection. First, the test data is produced using the same preprocessing methods as the training data, and the trained model is loaded. To make sure that a deep learning model for skin disease detection works effectively and consistently in identifying different skin disorders, there are a few essential elements in the assessment process. This is a thorough explanation of the Model Evaluation section:

1. Performance Metrics

The predictive models are evaluated using common performance criteria including accuracy, precision, recall, and F1-score. These metrics offer quantifiable information on how successfully the algorithms use input data to categorize patients into hemorrhoid and non-hemorrhoid groups.

2. Confusion Matrix

Make a confusion matrix to see how well the model performs in various classes. For every class, this matrix displays the true positives, true negatives, false positives, and false negatives.

3. Generalization Performance

Plot the loss/accuracy curves for training and validation to look for indications of overfitting or underfitting. A model that is well-generalized will exhibit training and validation curves that are nearly aligned.

4. Ensemble Methods

Integrate forecasts from many models to enhance overall effectiveness and resilience.

5. Reporting and Documentation

Keep thorough records of all assessment measures, confusion matrices, and performance curves.

These procedures will allow us to properly evaluate the model and make sure that the deep learning system for skin disease detection is accurate, dependable, and prepared for use in clinical settings.

4.4 Summary

Skin disease detection is seeing a surge in the use of deep learning. This has the potential to greatly enhance patient outcomes. Still, performance might differ from sickness to disease, and large, high-quality datasets are essential to the models' optimal functioning. All things considered, deep learning has enormous potential for the field of dermatology.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

Three deep learning models were compared in the research: a Convolutional Neural Network (CNN), VGG16, MobilenetV2, and Densenet121. The analysis and experimental findings were presented. These models were assessed using an annotated dataset of dermatological photos to determine how well they could detect different types of skin illnesses.

5.2 Experimental Result

Several critical measures were used to evaluate each model's performance, including accuracy, precision, recall, and F1-score. These metrics offer a thorough assessment of the model's accuracy in categorizing skin conditions.

Accuracy: One metric is the categorization model's accuracy. The accuracy of the model is its predicted percentage. Accuracy is defined as the ratio of accurately classified pictures to total samples. Equation of accuracy.

$$\text{Accuracy}=(TP+TN)/(TP+TN+FP+FN)$$

Precision: the percentage of actual positive cases that match the total number of cases that were projected to be positive. This equation represents it mathematically:

$$\text{Precision}=TP/(TP+FP)$$

Recall: Recall or sensitivity quantifies the quantity of positively predicted occurrences that are accurately classified. When recall is higher than FP, it is a valuable metric. The F1-score is an additional classification accuracy measure that takes recall and precision into consideration. Recall and accuracy are harmonic means, hence the F1 score can provide a comprehensive understanding of these two measures. It functions best when Precision and Recall are equal. Utilize the following equation to calculate it:

Recall=TP/(TP+FN)

F1-score: A recall-precision measure of classification accuracy is the F1 score. The F1-score provides a comprehensive view as it is the harmonic mean of Precision and Recall.

F-1 Score=2*(Precision*Recall)/(Precision+Recall)

Specificity is defined as the proportion of individuals with a negative test result who do not have the illness. A very particular test works well for ruling out most people who don't have the illness. This is why a positive result on an extremely specialized test might rule out the disease for a particular individual. The following is the equation:

Specificity = (TN+FP) ⁄ (TN)

Results Summary

Table 5.2.1: Accuracy, Precision, Recall, and F1-Score's table

	Accuracy	**Precision**	**Recall**	**F1-Score**
Densenet121	0.93	0.93	0.93	0.93
CNN	0.83	0.83	0.83	0.81
VGG16	0.91	0.91	0.90	0.90
Mobilenetv2	0.82	0.82	0.82	0.80

5.3 Comparative Analysis

The performance of four deep learning models—DenseNet121, a custom CNN, VGG16, and MobileNetV2—used for skin disease detection is compared in this section. The main comparison metric is accuracy, where DenseNet121 achieves the highest accuracy of 0.93, followed by VGG16 at 0.91, custom CNN at 0.83, and MobileNetV2 at 0.82. Here, the custom CNN model's accuracy is higher than that of other optimizers since we utilized Adamax as the optimizer. The models are thoroughly analyzed and compared here:

1. **Accuracy**:
    - DenseNet121 demonstrated the highest accuracy (93%), indicating its superior capability in correctly classifying skin disease images. With an accuracy of 91%, VGG16 closely trails, demonstrating good generalization and great performance.
    - Custom CNN balanced computational economy and performance to reach a reasonable accuracy of 83%, while MobileNetV2 also achieved 82%.
2. **Precision and Recall**:
    - Densenet121 exhibited the best precision (93%) and recall (93%), reflecting its strong performance in identifying true positives and minimizing false positives, whereas VGG16 performed well with (91%) and (90%).
    - Custom CNN also performed balanced in terms of precision (83%) and recall (83%), outperforming the MobileNetV2 in both metrics.
3. **F1-score**:
    - The F1-score of Densenet121 (93%) was the highest, balancing both precision and recall effectively, whereas VGG16 closely follows with (90%).
    - Custom CNN achieved an F1-score of 81%, while the MobileNetV2 had an F1-score of 80%.

In conclusion, DenseNet121 is the best performer and has the greatest accuracy (0.93), which makes it ideal for clinical contexts where skin disease identification has to be precise and dependable. While Custom CNN offers an excellent mix of accuracy (0.83) and computational efficiency, making it perfect for mobile applications, VGG16 also exhibits great performance (0.91). Given its lower accuracy (0.82), the MobileNetV2 underscores the significance of model complexity and architecture in attaining optimal performance, hence indicating the necessity for more improvement. Every model has distinct advantages and disadvantages, and the best model to choose will depend on the particular needs of the application and the available resources.

Training and Validation Accuracy and Loss:

The research's training and validation accuracy and loss show how the original models performed throughout a number of epochs. Metrics are monitored in order to track the progress of learning and spot any problems like overfitting. The graphs' y-axis shows the accuracy and loss percentages, while the x-axis represents the number of epochs.

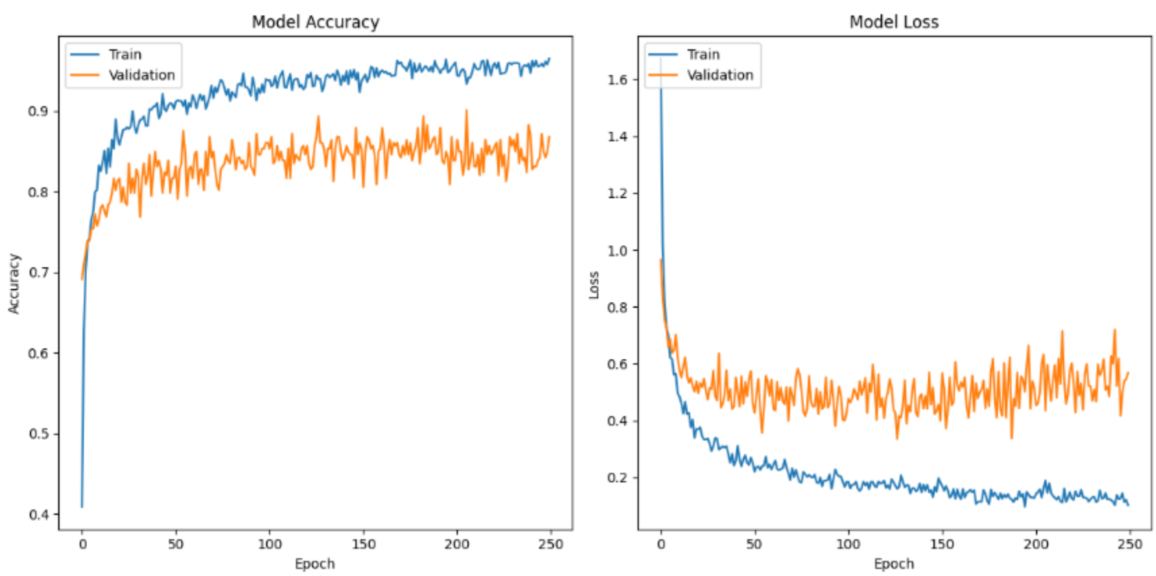

Figure 5.3.1: Training and validation accuracy and loss over the epochs (DenseNet121)

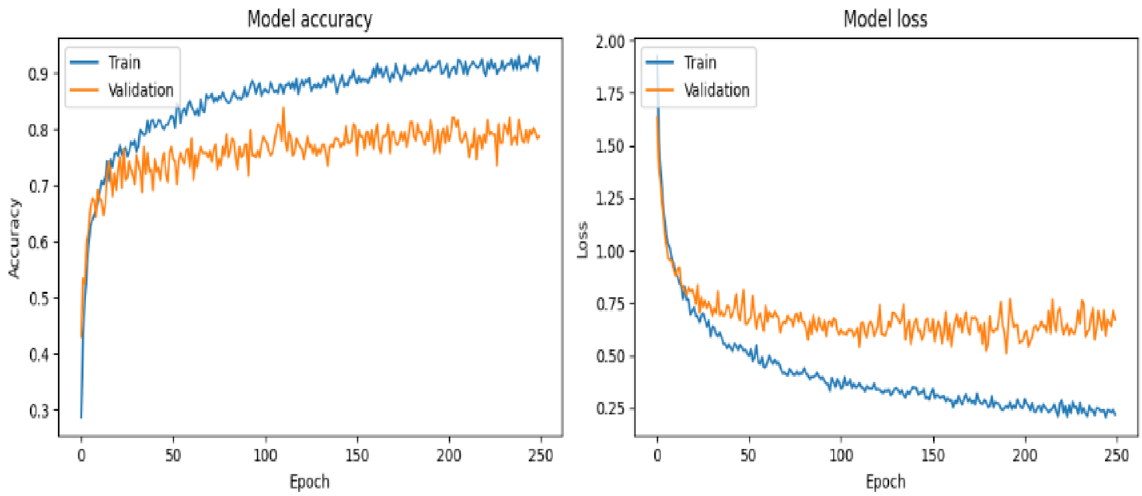

Figure 5.3.2: Training and validation accuracy and loss over the epochs (VGG16).

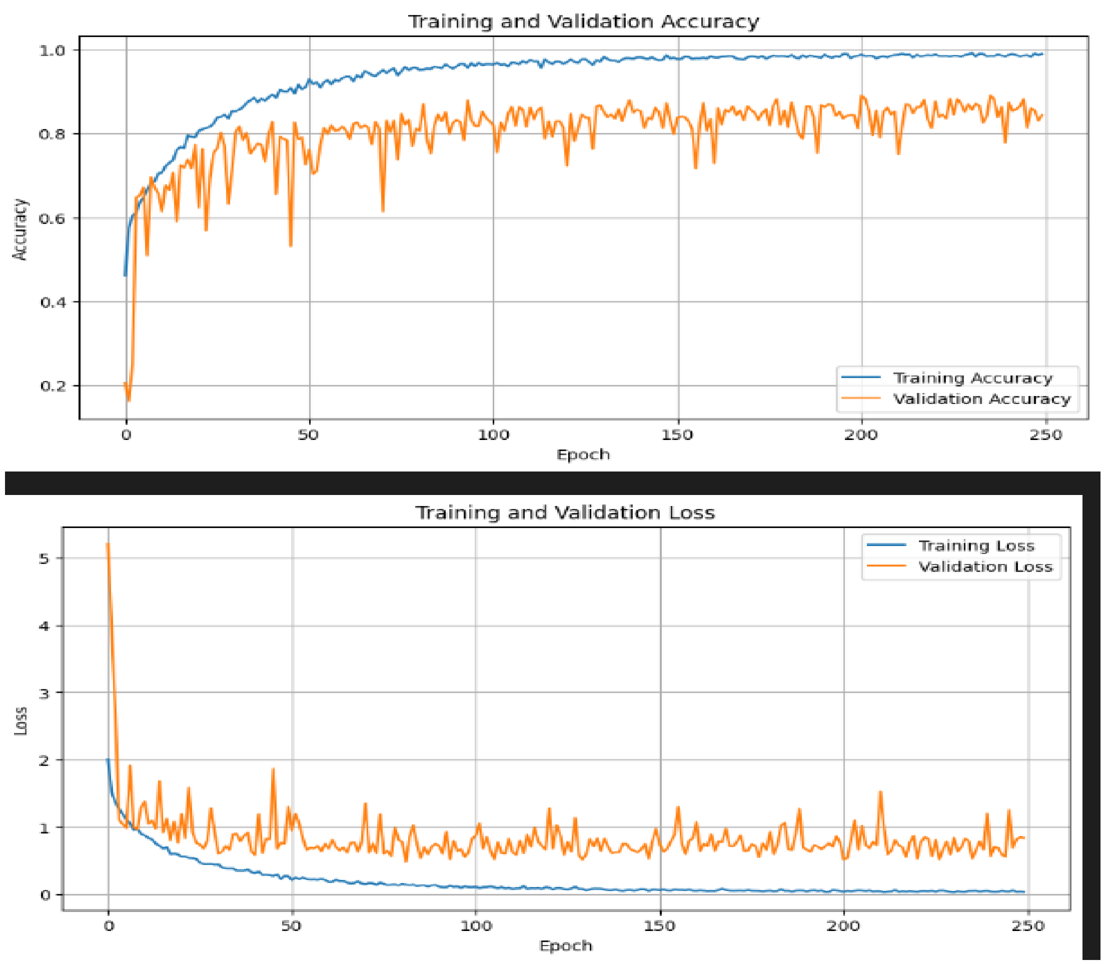

Figure 5.3.3: Training and validation accuracy and loss over the epochs (CNN).

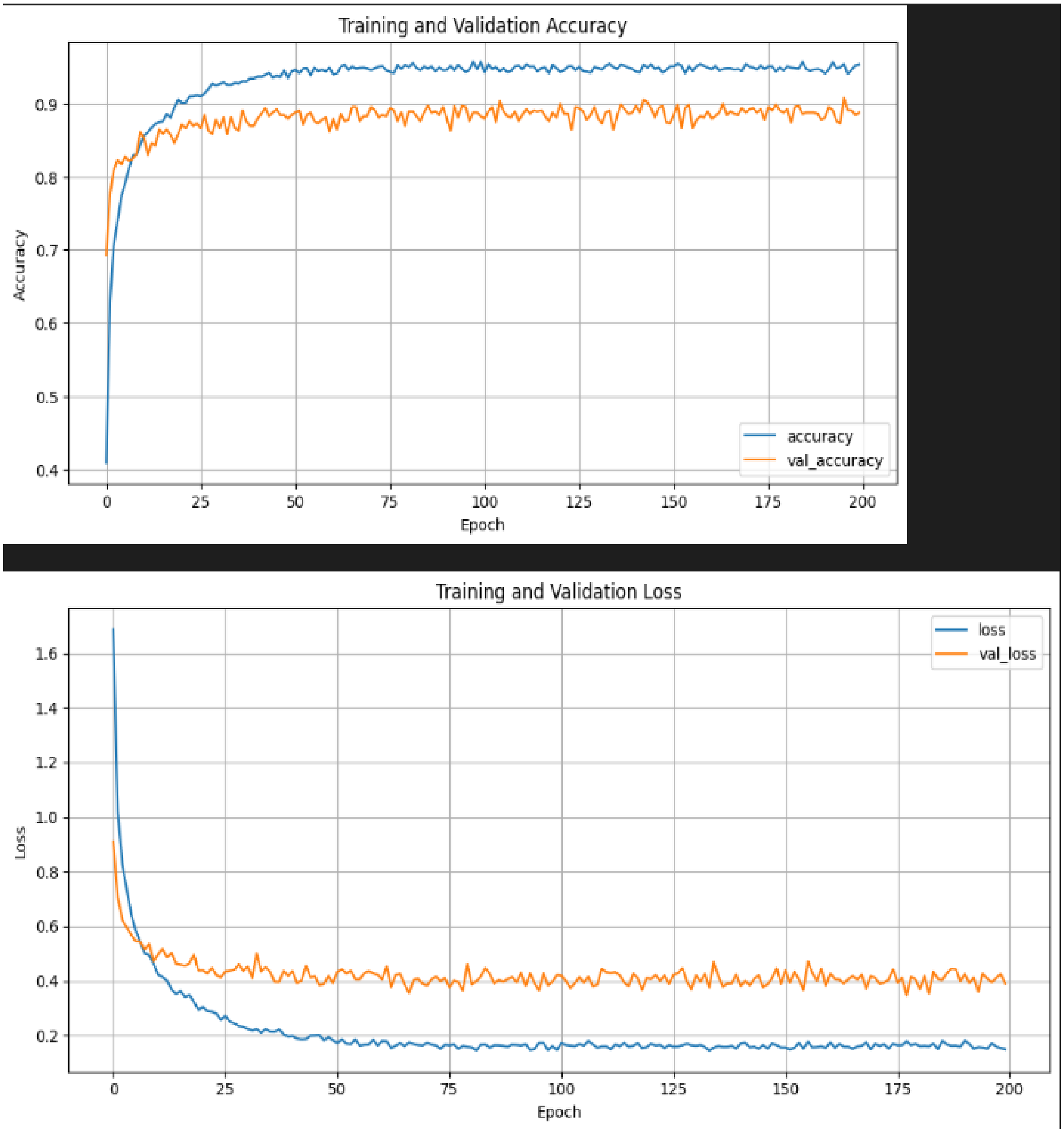

Figure 5.3.4: Training and validation accuracy and loss over the epochs (MobileNetV2).

Confusion Matrix:

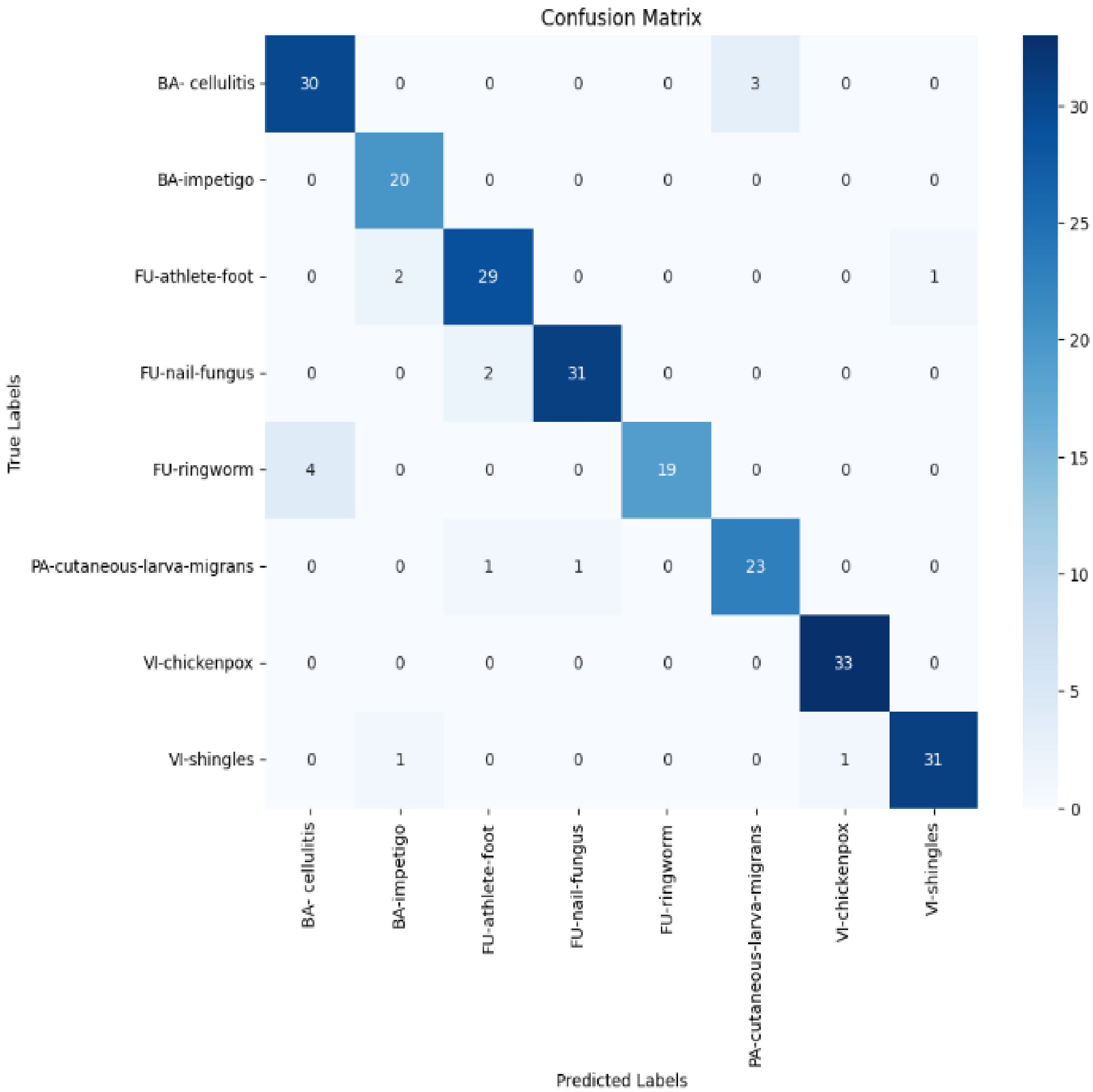

Figure 5.3.5: CM after DenseNet121

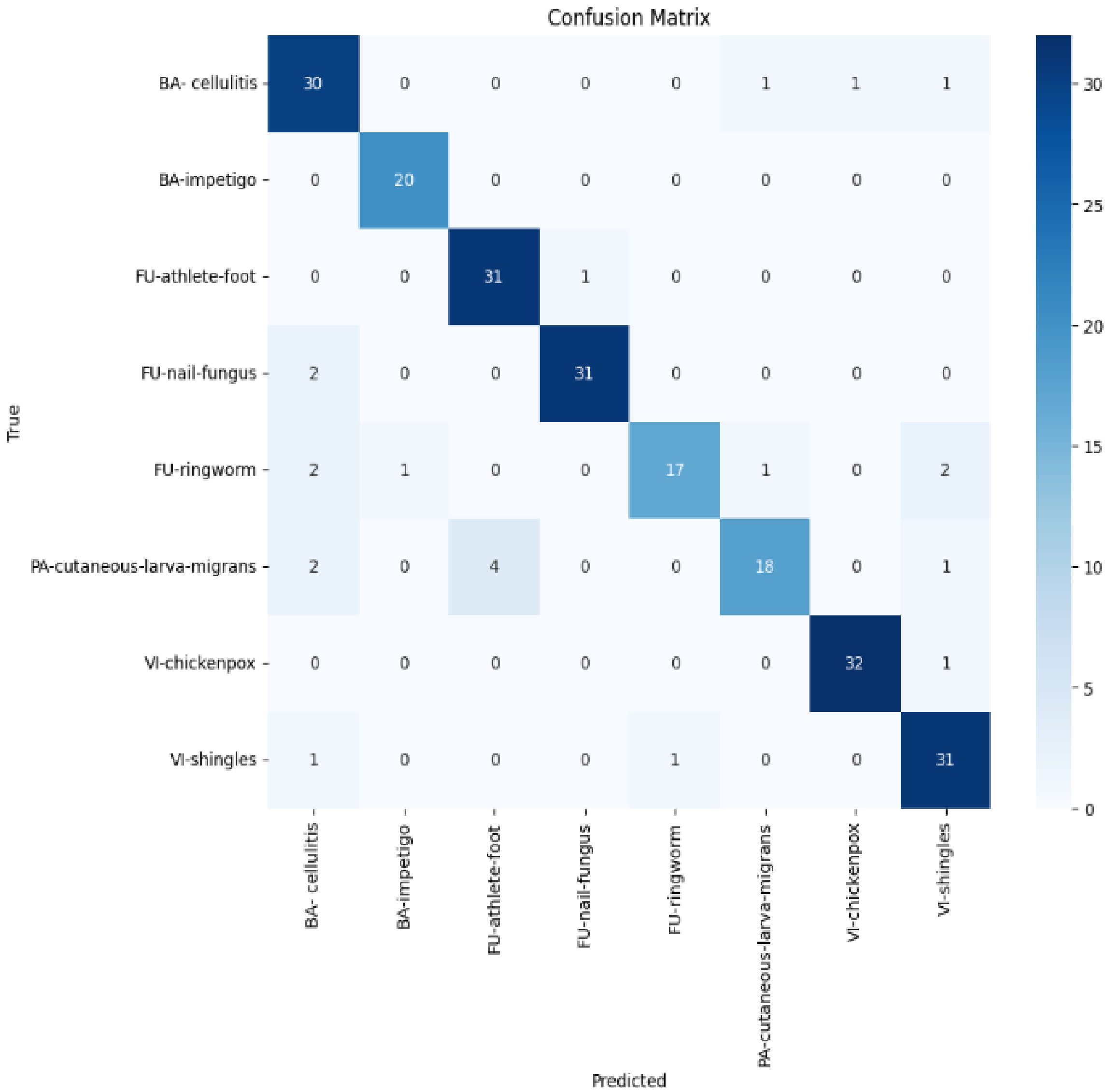

Figure 5.3.6: CM after VGG16

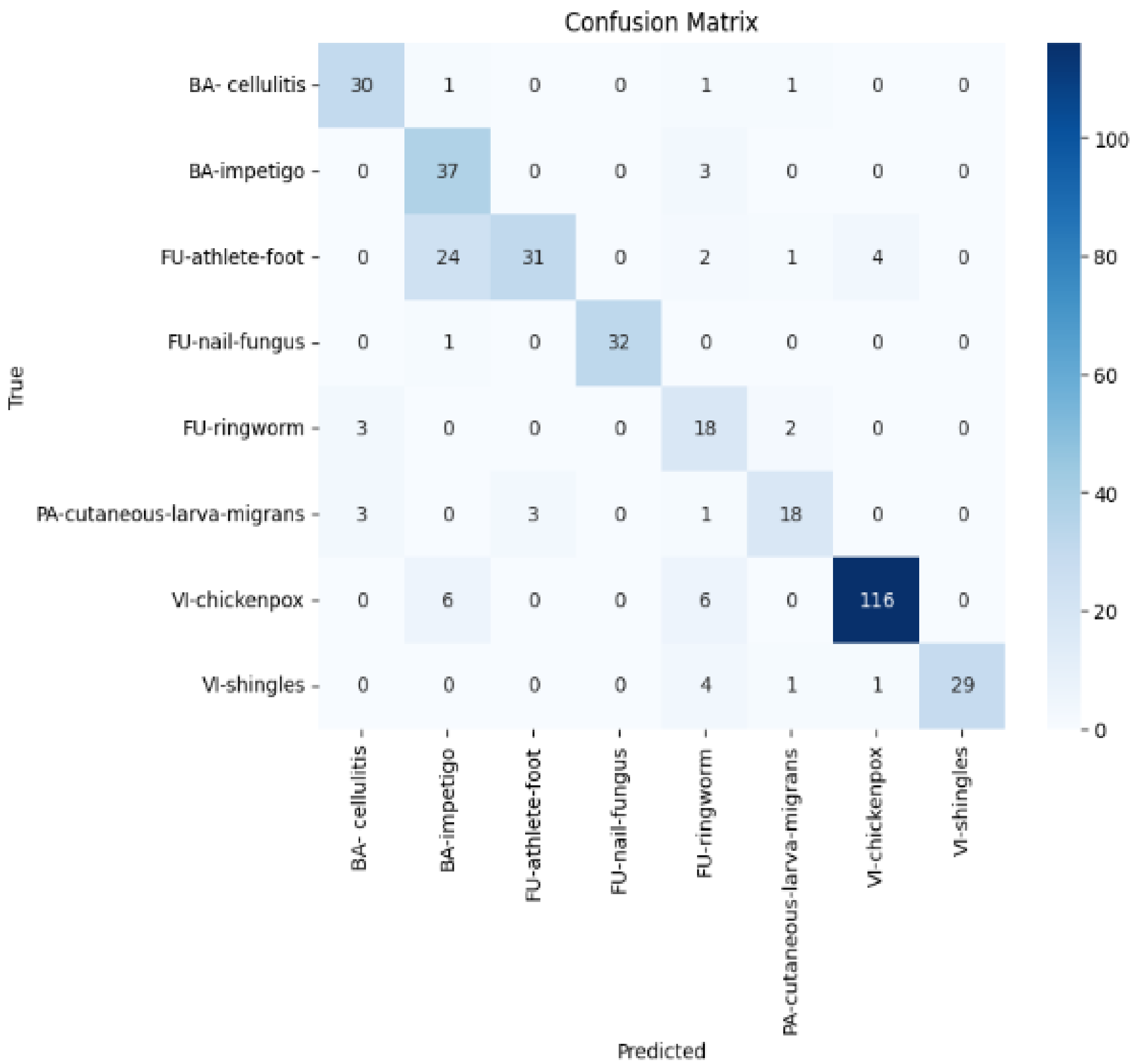

Figure 5.3.7: CM after MobileNetV2

Figure 5.3.8: CM after CNN

For the CNN, VGG16, MobilenetV2, and Densenet121 models, the training and validation accuracy and loss measures showed high generalization and efficient learning without appreciable overfitting. Densenet121 outperformed VGG16, MobilenetV2, and CNN in terms of accuracy and loss. Because the training and validation sets of data were sufficiently separated, the models were able to learn from a variety of instances and perform well when applied to new sets of data.

5.4 Summary

This thorough investigation explores how well deep convolutional neural networks (CNNs) identify and categorize different skin conditions from dermatological photos. Making use of a sizable dataset, the study applies advanced augmentation methods to improve the diversity and resilience of the training set. The work investigates the use of original CNNs, possible advantages of ensemble models, and transfer learning approaches using models like VGG16, MobilenetV2, and Densenet121. Specifically, the study examines how well these models perform in terms of memory, accuracy, precision, and F1-score.

CHAPTER 6
IMPACT ON SOCIETY

6.1 Impact on Life

Deep learning in skin disease detection has the potential to completely transform healthcare by enabling early and precise diagnosis, prompt treatment, and better patient outcomes. These solutions can improve productivity and lessen the strain on healthcare professionals, freeing up dermatologists to concentrate on challenging patients. Furthermore, these technologies' accessibility through the internet and smartphone platforms democratizes healthcare by offering top-notch diagnostics to underprivileged and distant places. Deep learning in the diagnosis of skin diseases, taken as a whole, has the potential of a more effective, fair, and efficient healthcare system that will benefit people as well as society.

6.2 Impact on Society & Environment

The environment and society stand to gain much from the use of deep learning to the diagnosis of skin diseases. It guarantees prompt diagnosis for marginalized people and lessens healthcare inequities by democratizing access to high-quality dermatological treatment. Improved disease prevention and resource allocation may be achieved through data-driven initiatives and enhanced public health monitoring. AI-driven diagnostics have a positive environmental impact by reducing the need for physical consultations and travel, hence supporting more efficient healthcare procedures and lowering carbon footprints. In general, this technology promotes a healthcare system that is more sustainable, efficient, and egalitarian.

6.3 Ethical Aspects

In order to guarantee appropriate deployment, a number of significant ethical issues are brought up by the application of deep learning in the diagnosis of skin diseases. Patient data privacy and confidentiality are crucial, thus strong security measures are needed to keep private information safe from breaches and unwanted access. Patients must be made aware of the possible consequences and the manner in which their data will be used in order to provide their informed permission. In addition, there's a chance that algorithmic bias will exacerbate existing health inequities by producing diagnostic results with varying degrees of accuracy depending on the demographic group receiving the training data. To keep people's faith in the technology, these algorithms must be transparent about their decision-making process and take responsibility for any mistakes. Furthermore, worries regarding the devaluation of professional knowledge and the necessity of maintaining a balanced integration where technology helps rather than replaces doctors are raised by the possibility that deep learning algorithms would replace human judgement. For deep learning to be applied in dermatology in a way that is equitable, secure, and productive, these ethical issues must be addressed.

6.4 Sustainability Plan

To achieve long-term viability and good effect, a thorough sustainability strategy for deep learning-based skin disease detection must include many essential components. Initially, continuous investment in R&D is necessary to enhance algorithm accuracy and adjust to novel dermatological discoveries. To reduce prejudices and guarantee fair healthcare, the models should be updated often and trained using a variety of inclusive and varied datasets. The environmental effect of data processing and storage can be reduced by using renewable energy sources and energy-efficient computing techniques. In order to ensure that these technologies are effectively integrated into clinical workflows and that they enhance current practices rather than replace them, collaboration with stakeholders and healthcare professionals is essential. In addition, defining precise policies for data security and privacy will support upholding patient confidentiality and legal requirements. Future generations can benefit from deep learning applications in skin disease diagnosis, provided that an ecosystem of ethical usage, environmental responsibility, and continual development is fostered.

6.5 Summary

In an effort to improve diagnostic accessibility and accuracy, this work investigates the use of deep learning techniques for the diagnosis of skin disorders. By using sophisticated neural networks that have been trained on large datasets of dermatological photos, the study shows how deep learning algorithms can accurately diagnose a variety of skin disorders, including malignant melanoma. The study emphasizes the potential advantages of early diagnosis made possible by these technologies, which might result in better patient outcomes and lower medical expenses.

CHAPTER 7
CONCLUSION AND FUTURE WORK

7.1 Conclusions

This study on deep learning-based skin disease identification shows that sophisticated neural networks may greatly improve the precision and effectiveness of dermatological diagnoses. The results show that deep learning systems, trained on large and varied datasets, can accurately diagnose a variety of skin ailments, including serious illnesses like melanoma. These developments in technology have the potential to improve patient outcomes by enabling earlier and more accurate diagnoses, as well as perhaps saving lives through prompt action.

Furthermore, the availability of these deep learning tools—especially on mobile platforms—indicates a bright future for the provision of egalitarian healthcare. This technology can fill up large gaps in the availability of dermatological treatment by offering dependable diagnostic capabilities to underprivileged and rural populations.

The study also emphasizes how deep learning might save healthcare expenses by eliminating pointless procedures and maximizing the use of available resources. To guarantee impartial and equitable healthcare delivery, the study does, however, highlight the need to give ethical issues—such as patient data protection, algorithmic transparency, and bias mitigation—through careful thought.

In conclusion, deep learning's incorporation into the diagnosis of skin diseases is a revolutionary development for dermatology, even though issues with its ethical application and ongoing algorithmic development still need to be resolved. The entire potential of this technology will require ongoing study, development, and ethical supervision, which will ultimately result in more efficient, affordable, and long-lasting healthcare solutions.

7.2 Further Suggested Works

The study's encouraging findings regarding the use of deep learning to detect skin diseases open up new research directions. To increase algorithmic accuracy across all age groups, skin tones, and demographic groupings, it is imperative to first diversify the training datasets. This will address any biases and provide equal diagnostic capabilities. The main goal of future research should be to gather and curate extensive datasets that accurately represent the variety of the world's population.

Second, researching the integration of multimodal data—for example, merging genetic and medical history with imaging data—could improve the accuracy of diagnoses and offer more comprehensive understanding of skin disorders. Understanding the fundamental causes of these disorders and how they develop may also be aided by this method.

Furthermore, to confirm the effectiveness and dependability of these deep learning models in diverse healthcare environments, real-world clinical trials are crucial. Working together with dermatologists and medical facilities will improve these technologies for routine clinical usage and offer vital insights into the real-world difficulties.

Additionally, it is critical to do research into enhancing the interpretability of deep learning models. Creating techniques to elucidate the algorithms' decision-making procedures would foster confidence between medical professionals and patients, guaranteeing the technology is applied sensibly and openly.

The ethical and legal frameworks required for the secure application of deep learning in dermatology should also be the subject of future research. The wider adoption and integration of these technologies depend on resolving data privacy issues, setting guidelines for algorithmic openness, and guaranteeing adherence to healthcare laws.

Ultimately, investigating the long-term environmental effects of implementing deep learning in healthcare—that is, the data center's carbon footprint and the diagnostic gadget lifecycle—will help to advance sustainable medical technology practices.

In summary, while the current study demonstrates the revolutionary potential of deep learning in the diagnosis of skin diseases, further research is necessary to properly solve the obstacles and reap the rewards of this technology in terms of bettering healthcare outcomes throughout the world.

7.3 Limitations

While there are many advantages to using deep learning for skin disease diagnosis, there are drawbacks and possible conflicts as well. Insufficient variety in training datasets may result in biased models that impair diagnostic accuracy in various populations. Profitability may take precedence over patient care in commercial interests, which raises questions about overdiagnosis and needless therapies. To reduce these dangers and foster confidence, strict regulatory supervision and transparency in algorithm development are crucial. Furthermore, supporting open-source projects can guarantee the ethical application of AI in dermatology and enable independent evaluation. Harnessing the full potential of deep learning while preserving patient welfare and healthcare integrity requires striking a balance between innovation and ethical issues.

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Appendix A

Course Outcomes, Complex Engineering Problems (EP) and Complex Engineering Activities (EA) Addressing

Title: SKIN DISEASE DETECTION USING DEEP LEARNING

Student ID: [202-15-3806 & 202-15-3786]

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	Integrate recently gained and previously acquired knowledge to identify a Skin Disease Detection problem for the Final Year Design Project (FYDP)	**PO1**
CO2	Analyze different aspects of the goals in designing a solution for this FYDP	**PO2**
CO3	Explore diverse problem domains through a literature review, delineate the issues, and establish this goal for the FYDP	**PO4**
CO4	Perform economic evaluation and cost estimation and employ suitable project management procedures throughout the development life cycle of the FYDP	**PO11**
Phase -II		
CO5	Design and develop technical solutions and system components or processes that meet specified requirements, ensuring compliance with public health and safety standards, as well as considering cultural, socioeconomic, and environmental factors in this FYDP	**PO3**
CO6	Choose and apply appropriate methodologies, resources, and contemporary engineering and IT technologies to address complex engineering processes, encompassing prediction and modeling, while adhering to relevant constraints in this FYDP	**PO5**
CO7	Analyze societal, health, safety, legal, and cultural considerations, along with associated responsibilities, in the context of professional engineering practice and the resolution of this problem, employing logical reasoning guided by contextual understanding.	**PO6**
CO8	Comprehend and evaluate the enduring sustainability and impact of professional engineering endeavors in addressing intricate engineering challenges within social and environmental frameworks.	**PO7**
CO9	Implement ethical principles and adhere to professional standards and norms in this FYDP	**PO8**
CO10	Capable of operating proficiently both individually and as a team member or leader across diverse teams and interdisciplinary settings in this FYDP.	**PO9**

CO11	Proficiently communicate with the engineering community and broader society regarding complex engineering endeavors, including the ability to comprehend and generate comprehensive reports and design documentation, as well as provide and receive clear instructions throughout this FYDP.	**PO10**
CO12	Acknowledge the importance of self-directed and life-long learning within the evolving landscape of technology, and possess the readiness and capability to engage in lifelong learning endeavors.	**PO12**

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP), and Attainment of Complex Engineering Activities (EA)

Addressing CO (1 to 8), Knowledge Profile (K), Attainment of Complex Engineering Problems (EP):

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	Through the use of deep learning, data augmentation methods, and several CNN designs for image processing, this research illustrates fundamental engineering (K3) concepts. Through the evaluation of deep learning models like resnet50, VGG16, and convolutional neural networks (CNNs), the project exhibits specialized knowledge (K4).	**Page no:** [17-22] **Section:** [4.2] **Page no:** [23] **Section:** [4.3]
				Through methodical experiment preparation and execution, including data pretreatment, model training, and assessment, this project uses engineering practice and design (K5). It also uses the resnet50 and vgg16 Convolutional Neural Network (CNN) models to address	**Page no:** [11-12] **Section:** [3.2] **Page no:** [17-22]

				Engineering Practice and Technology (K6).	**Section:** [4.2]
				This study uses deep learning to enhance skin disease identification by synthesizing ideas from current studies, thereby ensuring adherence to Research Literature (K8).	**Page no:** [4-8] **Section:** [2.2]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	In order to solve EP-2, this study acknowledges the challenges associated with skin disease identification, such as the shortcomings of conventional techniques and the difficulties in combining deep CNNs with transfer learning.	**Page no:** [2] **Section:** [1.5]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This work tackles EP-3 by carefully contrasting trial results in order to improve skin disease identification among several possible methods.	**Page no:** [25-26] **Section:** [5.2]

4.	**EP4: Familiarity of Issues**	Yes	CO8	The multidisciplinary nature of this study affects dermatological medical diagnoses in addition to computer science and engineering. Through improving the identification of skin conditions, it advances public health and medical procedures. This points to EP-4 as the project not only expands the possibilities of technology but also has a big impact on patient outcomes and the standard of dermatological treatment.	**Page no:** [8-9] **Section:** [2.3]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and**	No	CO8	N/A	N/A

7.	**EP7: Interdependence**	Yes	CO5	The holistic approach of this project integrates many components related to data gathering, statistical analysis, and recommended techniques in order to address high-level challenges. It guarantees EP-7 by guaranteeing a comprehensive response to intricate problems in medical diagnostics. In the end, this integration helps to enhance dermatological healthcare practices by enabling more precise and dependable skin disease identification.	**Page no:** [11-12] **Section:** [3.2]

Addressing CO11 with Complex Engineering Activities (EA) [Some or all of the following]:

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	In order to ensure methodical research, our project makes use of a variety of resources, including GPUs, deep learning frameworks, annotated datasets, and high-performance computing infrastructure. Through the use of deep learning models, the research advances the field of skin disease diagnosis by using these resources.	**Page no:** [12-13] **Section:** [3.3]
2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	No		N/A	N/A

4.	**EA4: Consequences for society and the environment**	Yes		This initiative benefits society by advancing healthcare through the use of cutting-edge techniques for identifying skin diseases. Additionally, by using effective computational resources and abiding by moral standards for patient data protection, it supports environmental sustainability. The initiative offers better patient outcomes while assuring appropriate use of technology and protecting sensitive medical data by improving diagnostic accuracy and efficiency in dermatology.	**Page no:** [36-37] **Section:** [6.2, 6.3]
5.	**EA-5: Familiarity**	Yes		By using deep learning models to investigate a potential method for skin disease identification, this project builds on previous studies. It provides fresh perspectives on the topic, as evidenced by an extensive comparative study and preliminary terminology.	**Page no:** [8-9] **Section:** [2.3]

Addressing CO (4, 9, 10, and 12):

SN	COs	Attainment	Justification	References
1	CO4	Yes	Through the integration of efficient project management and financial control, this project tackles CO4 by guaranteeing careful planning, resource allocation, and budget estimate for the best possible resource utilization throughout the dermatological research lifecycle.	**Page no:** [3] **Section:** [1.6]
2	CO9	Yes	By protecting patient privacy, getting participants' informed consent before collecting data, and openly reporting the dermatological research process, the initiative exemplifies adherence to ethical norms. The study conforms with CO9 by guaranteeing responsible information distribution and social well-being through the moral use of cutting-edge healthcare technology.	**Page no:** [36-37] **Section:** [6.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's extensive data gathering from many dermatological databases demonstrates its commitment to continuous learning (CO12) and adaptability within the ever-changing technological context. Robustness in the identification of skin diseases by deep learning approaches is ensured by diligent methodological development and rigorous statistical analysis.	**Page no:** [11-16, 17-22] **Section:** [3.2, 3.3, 3.4, 4.2]

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