Detection of Skin Diseases using Deep Learning

by

Masuk Ur Rahman Shodoy
19101177
Raitah Binte Khusru
18101331
Silma Binta Shoeb
19101083

A thesis submitted to the Department of Computer Science and Engineering
in partial fulfillment of the requirements for the degree of
B.Sc. in Computer Science

Department of Computer Science and Engineering
School of Data and Sciences
Brac University
September 2023

Declaration

It is hereby declared that

1. The thesis submitted is my/our own original work while completing degree at Brac University.
2. The thesis does not contain material previously published or written by a third party, except where this is appropriately cited through full and accurate referencing.
3. The thesis does not contain material which has been accepted, or submitted, for any other degree or diploma at a university or other institution.
4. We have acknowledged all main sources of help.

Student's Full Name & Signature:

Masuk Ur Rahman Shodoy

19101177

Raitah Binte Khusru

18101331

Silma Binta Shoeb

19101083

Approval

The thesis/project titled "Detection of Skin Diseases using Deep Learning" submitted by

1. Masuk Ur Rahman Shodoy (19101177)
2. Raitah Binte Khusru (18101331)
3. Silma Binta Shoeb (19101083)

Of Summer, 2023 has been accepted as satisfactory in partial fulfillment of the requirement for the degree of B.Sc. in Computer Science on September 17, 2029.

Examining Committee:

Supervisor:
(Member)

Amitabha Chakrabarty, PhD

Professor
Computer Science Engineering
Brac University

Program Coordinator:
(Member)

Md. Golam Rabiul Alam, PhD

Professor
Department of Computer Science and Engineering
Brac University

Head of Department:
(Chair)

Sadia Hamid Kazi, PhD

Chairperson and Associate Professor
Department of Computer Science and Engineering
Brac University

Abstract

As a topic of global health importance, skin diseases must be quickly identified and accurately diagnosed to allow for effective treatment. Specifically for the classification of skin diseases, the use of deep learning models in the analysis of medical images has shown remarkable promise. To improve accuracy and predictability when classifying skin diseases, this paper suggests using an ensemble model composed of the ResNet-50, EfficientNet, Inception V3, MobileNet, NASNetMobile, DenseNet201 and Xception architectures. The first step of the investigation is to examine the existing research on deep learning models used for skin disease diagnosis and categorisation. ResNet-50, EfficientNet, MobileNet, Inception V3, DenseNet201, NASNetMobile and Xception have demonstrated their efficacy in several medical imaging applications, such as the identification and categorization of skin diseases. The utilization of diagnostic and classification methods in the context of skin illnesses serves as illustrative instances of such applications. It is important to note, however, that every construction possesses inherent imperfections. The present study is further enhanced by the use of a novel notion referred to as a "ensemble," which amalgamates the most advantageous attributes of many models. To ensure proper functioning, the ensemble model must initially extract and subsequently aggregate information. The comprehensive set of fundamental models underwent training utilizing a vast dataset of dermatological information. The objective of this training session was to acquire the knowledge and skills necessary to identify and discern the distinguishing features of skin lesions via the analysis of photographic representations. The ensemble model incorporates feature-level fusion to aggregate information obtained from many base models. When many data types are merged in this manner, it results in the creation of a cohesive representation. In order to improve the process of classification and generalization, the model utilizes the varied members of the ensemble. The efficacy of the ensemble model is assessed by a wide array of experiments. These research utilize a meticulously collected and standardized dataset encompassing many skin-related disorders. The ensemble model demonstrates superiority over the individual models in terms of accuracy, precision, recall, and F1-score. The fusion methodology, which leverages several sources, holds the potential to extract supplementary data from diverse systems. The utilization of gradient rendering techniques enables the comprehensive evaluation of a model's readability. This study examines the decision-making process of an ensemble in determining the salient features of a picture for the purpose of labeling. This thesis presents an ensemble architecture for identifying skin issues by utilizing ResNet-50, EfficientNet, Inception V3, MobileNet, NASNetMobile, DenseNet201, and Xception models. When compared to the gold standard dataset, the proposed model demonstrates superior performance, indicating its potential to assist dermatologists in making more accurate diagnoses in real-world clinical scenarios.

Keywords: CNNs, Xception, Psoriasis, NASNetMobile, Melanoma, Inception V3, Skin disease, ResNet-50, Eczema, EfficientNet, Acne, DenseNet201, MobileNet, Solar lentigo, Dermatofibroma, Scabies.

Acknowledgement

All glory be to the Great Allah for allowing us to conclude our thesis without any significant setbacks.

We owe a tremendous debt of appreciation to Dr. Amitabha Chakrabarty, PhD, our thesis supervisor, for his invaluable advice, assistance, and moral support during the duration of this study. His professionalism, insight, and commitment to our progress have been indispensable.

We'd also want to express our heartfelt appreciation to Md.Fahim-Ul-Islam, the Research Assistant of BRAC University, for his insightful comments and ideas, which substantially enhanced the quality of our final paper.

We are grateful to our beloved BRAC University and the CSE Department for facilitating this study and giving us access to the tools we needed to complete it.

Finally, our deepest gratitude to the members of our immediate and extended families, in addition to our family members and friends, for their unending love and support, and encouragement during all of our academic endeavours.

Table of Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Motivation

Skin diseases have a significant global impact due to their widespread prevalence, resulting in discomfort, agony, and, in certain instances, posing a potential threat to individuals' lives. The prompt emphasizes the significance of promptly and precisely identifying these disorders in order to facilitate effective treatment and management. In recent times, the utilization of deep learning techniques has significantly impacted the methodologies employed for medical picture analysis and classification tasks. This paper presents a novel ensemble model that integrates two individual models with three cutting-edge convolutional neural networks (CNNs), namely ResNet-50, EfficientNet, and Inception V3. The specific models employed in this study are MobileNet, NASNetMobile, DenseNet201, and Xception. The objective is to facilitate the categorization of skin disorders with enhanced ease and precision.

1.2 History of Diseases

1.2.1 Acne

The field of acne categorization utilising Convolutional Neural Network (CNN) models is a relatively nascent domain of investigation. The subsequent search results furnish insights into the historical development of acne classification through the utilisation of Convolutional Neural Network (CNN) models.The employment of computer vision techniques is involved in the process of detecting acne using deep learning. This procedure involves autonomously discerning and categorising acne lesions based on pictures of the skin. Adolescents and young individuals demonstrate an increased vulnerability to the onset of acne. The aetiology of this cutaneous condition is ascribed to the occlusion of pilosebaceous units by a confluence of sebum and cornified epidermal cells. The manifestation of this phenomena is predominantly found in the facial region, forehead, dorsal area, and thoracic region. Acne is a multifactorial dermatological condition that can be ascribed to several etiological reasons, such as the proliferation of bacteria, inflammatory processes, and the occlusion of pilosebaceous units. The ongoing epidemic is the ninth occurrence of its kind and is projected to impact around 9.4% of the worldwide populace. The current study identified and categorised acne on various skin types using a variety of pre-existing convolutional neural network (CNN) models, including Inception

V3, VGG16, and VGG19.Additionally, a comprehensive analysis of acne detection was conducted using machine learning classifiers. An impressive 99.5% accuracy is achieved by combining the Inception v3 model with a logistic regression classifier.It is important to recognise that the creation of a comprehensive model for detecting acne requires a substantial amount of annotated data and expertise in the domains of deep learning and computer vision. Furthermore, it is crucial to thoroughly analyse the ethical considerations, privacy concerns, and compliance with legal frameworks throughout the process of designing and deploying such a system, specifically in relation to the utilisation of patient data within a healthcare environment. The inclusion of dermatologists and medical specialists is essential to ensure the accuracy and dependability of the model for actual implementations.[25]
AcneNet is a classification approach for acne classes that utilises a deep convolutional neural network (CNN).[6]
Using a Deep Residual Neural Network model, this study presents a novel approach to classifying five distinct types of acne.Examining how interpretable convolutional neural network (CNN) models can be used in the context of acne diagnosis and severity evaluation is the primary goal of this research.[49]
In this research, we want to construct and compare different deep learning models that can identify acne lesions in photos of the face. In addition, these models attempt to assess facial acne severity according to medical standards.The major goal of this research is to develop and test a deep learning model that can reliably diagnose acne vulgaris by analysing pictures taken in clinical settings.[32]
Acne sufferers are sorted into one of seven groups using the 16-layer Visual Geometry Group (VGG16) model in the current investigation.The purpose of this research is to perform a methodical and comparative examination of several approaches to the segmentation of photographs displaying acne vulgaris.[55] The research presented here presents a method for automatically segmenting and labelling images of acne lesions using convolutional neural networks.
In general, the findings from the search indicate that the field of acne classification using convolutional neural network (CNN) models is now in its nascent phase. Researchers are actively proposing innovative methodologies and constructing deep learning models to effectively identify acne lesions and categorise them into distinct classes.

1.2.2 Melanoma

Melanoma is hypothesised to originate from melanocytes, which are specialist cells responsible for the production of melanin, the pigment that determines skin colour. The aforementioned sickness, if not properly addressed, has been widely acknowledged to be associated with aggressive conduct and can provide a substantial risk to an individual's overall welfare.The significant advancements of deep learning (DL) algorithms across many domains have resulted in a substantial increase in the adoption of automated diagnostic systems within the healthcare sector. The main aim of this work is to examine the potential of deep learning (DL) as a method for accurately identifying and demarcating the target region of a lesion. Enhanced Super-Resolution Generative Adversarial Networks (ESRGAN) are employed in the preliminary phase to enhance the quality of the image. The subsequent procedure involves employing segmentation techniques to effectively delineate the Regions of

Interest (ROIs) from the surrounding areas within the image. To address the disparity observed in the existing dataset, the researchers employed data augmentation techniques. Following the preliminary examination of the image, a convolutional neural network (CNN) that has been trained using a modified variant of Resnet-50 is employed to classify skin lesions. The present investigation utilised a heterogeneous dataset consisting of seven distinct types of skin cancer obtained from the HAM10000 database. This research paper introduces a new optimisation approach for achieving precise categorisation of skin lesions. The approach involves combining a Convolutional Neural Network (CNN) architecture with transfer learning.The original design of Resnet-50 underwent modifications in order to enhance the pretraining process of the model's weights prior to its deployment.[38]

In recent times, there has been a growing utility of Convolutional Neural Network (CNN) models in the process of categorising melanoma. The provided references provide insights into the evolution of Convolutional Neural Network (CNN) models for the purpose of melanoma categorisation across the years.The primary objective of this study is to use a newly built deep convolutional neural network (CNN) model to the task of melanoma classification. Dermoscopic images are employed for the purposes of educating and assessing a Convolutional Neural Network (CNN) model. These photos are widely regarded as the benchmark for accurately representing skin lesions.[41]

This work presents a novel methodology for the categorisation of melanoma through the analysis of microscopic images. The method reported in this study utilises a deep convolutional neural network (DCNN) to perform automated classification of melanoma lesions into malignant or benign categories. Previous research has demonstrated that DCNNs exhibit a notable degree of accuracy in this task.This study aims to explore the capabilities of deep learning algorithms in the context of melanoma detection and classification.[39]

This research presents a new optimisation approach for the precise identification and categorisation of different skin lesions. The approach involves the integration of a Convolutional Neural Network (CNN) structure with a transfer learning model. This research conducts a comprehensive analysis by means of a systematic review, focusing on the utilisation of convolutional neural networks (CNNs) for the purpose of accurately classifying skin cancer.[2]

This study offers an extensive examination of the existing body of literature pertaining to Convolutional Neural Networks (CNNs) in the context of skin lesion classification. The study conducted by researchers yielded a categorisation accuracy of 93.1% for distinguishing between melanoma and nonmelanoma cases. The sensitivity of the categorisation was determined to be 94.9%, indicating the ability to correctly identify melanoma cases, while the specificity was calculated to be 92.8%, reflecting the accuracy in correctly classifying nonmelanoma cases. The main aim of this study was to employ deep learning techniques in order to address the issue of melanoma categorisation. In order to accomplish this objective, it will be imperative to undertake a comprehensive examination of multiple datasets, assessment criteria, challenges encountered, and prospective avenues for progress within this field.[15]

This article provides an overview of the current research on the application of Convolutional Neural Networks (CNNs) in the categorisation of melanoma.The objective of this study is to examine the utilisation of deep convolutional neural networks in the automated categorisation of melanoma skin cancer.[37]

The present investigation employed convolutional neural networks (CNNs) for the purpose of detecting and diagnosing melanoma skin cancer. The primary objective was to perform binary classification of dermatological images.The primary objective of this project is to investigate the application of Convolutional Neural Networks (CNNs) in the development of a comprehensive autonomous system capable of accurately classifying skin cancer.[10]
The main aim of this study was to create an automated method utilising Convolutional Neural Network (CNN) for the precise identification and distinction of skin cancer and benign tumour lesions.
The use of Convolutional Neural Network (CNN) models for melanoma categorisation has seen a significant uptick in recent years of research activity. Researchers in academia have devised cutting-edge methods and produced complex deep learning models that can reliably differentiate between malignant and benign melanoma. The models rely heavily on dermoscopic images and skin images to make their classifications.

1.2.3 Solar Lentigo

Convolutional neural network (CNN) models for solar lentigo classification is an emerging field of study. The references supplied provide helpful context for understanding how Convolutional Neural Network (CNN) models have been used to classify solar lentigos over time.Solar lentigo, also known as age spots or liver spots, is a common skin condition characterised by the development of small, uniform, brown or deeply pigmented patches, most often on the face, hands, and other sun-exposed areas of the body. Excessive melanin production occurs locally due to prolonged sun exposure, which is widely believed to be the primary cause of these pigmented patches.In addition to traditional methods like MRI and X-ray imaging, reflectance confocal microscopy (RCM) is becoming increasingly used in the field of medical imaging. Today, Reflectance Confocal Microscopy (RCM) is the gold standard for diagnosing lentigo. The study of skin can be performed quickly and with a high degree of spatial resolution using Reflectance Confocal Microscopy (RCM). In this study, we used a deep convolutional neural network (CNN) to classify reflectance confocal microscopy (RCM) images with a focus on lentigo detection and identification. The InceptionV3 architecture was used as the research's methodology of choice, which allowed for the incorporation of techniques like data augmentation and transfer learning. Using RCM data, the proposed method was tested for its utility and found to be highly effective in its detection of anomalies.[18]
This research proposes a unique method for image categorisation using reflectance confocal microscopy (RCM) pictures and a deep convolutional neural network (CNN). The strategy's primary goal is to identify and confirm the condition of lentigo.In this paper, we give a systematic assessment of the literature on the application of Convolutional Neural Networks (CNNs) to the problem of skin cancer classification.[19]
In this paper, we provide a comprehensive review of work done to date on the topic of employing Convolutional Neural Networks (CNNs) to classify skin lesions. Whether a Convolutional Neural Network (CNN) is utilised solely as a feature extractor or for end-to-end learning can be used to classify the revealed methods.To better understand how Vision Transformer Networks (VTNs) and pre-trained models utilising Convolutional Neural Networks (CNNs) can be used for multi-class skin cancer clas-

sification, this study aims to examine these methods.[3]
The purpose of this research is to analyse solar lentigo classification problems, such as class imbalance within the dataset.In the field of radiology in particular, convolutional neural networks (CNNs) have emerged as a fundamental deep learning technique. This research provides a comprehensive look into Convolutional Neural Networks (CNNs), including an investigation of their fundamental concepts, architectural design, and training procedure. This research also looks at the application of Convolutional Neural Networks (CNNs) in radiology, highlighting its ability to improve diagnostic accuracy, boost productivity, and provide automated medical image interpretation. The final results of the study are in.This article gives a comprehensive evaluation of convolutional neural networks (CNNs) in radiography, with a special emphasis on its application to the classification of skin lesions. This article provides a comprehensive look of deep learning, discussing its foundational ideas, convolutional neural network (CNN) designs, existing obstacles, real-world applications, and future research directions.[52]
This research provides an in-depth understanding of deep learning's foundational concepts, with a focus on convolutional neural network (CNN) architectures and their application to medical image analysis, particularly skin lesion categorisation. In order to classify facial and scalp skin lesions, we compared a convolutional neural network with commercial validation against a panel of 64 domain experts.[4]
The purpose of this study is to evaluate a commercially validated Convolutional Neural Network (CNN) and a panel of 64 dermatologists for their ability to correctly categorise solar lentigo and other skin diseases.[20]
According to the above sources, classifying solar lentigo by the application of CNN models is a relatively new area of research. The identification of solar lentigo has come a long way thanks to the unique methods developed by researchers and the use of deep learning models.[23]

1.2.4 Dermatofibroma

The use of Convolutional Neural Network (CNN) models in the classification of skin lesions, particularly in the context of dermatofibroma, is widely discussed and several search results provide relevant material. The literature cited here is drawn from several scholarly publications. A benign skin condition, dermatofibroma is characterised by the development of a tiny, firm nodule or protrusion on the skin's surface. Lesions are often found to have a wide spectrum of colours, from shades of brown to crimson. Furthermore, the size of these lesions varies widely, from a few millimetres to as much as one centimetre. Although dermatofibromas are most commonly found in the limbs, they can appear in other locations of the body.In this groundbreaking study, the authors present a novel deep learning model trained to identify skin cancer from photographs of moles. The current research made use of a dataset of 3,400 images called the HAM10000 dermoscopy picture collection. Melanoma and non-melanoma lesions were both included in the dataset. 860 cases of melanoma, 327 cases of actinic keratoses and intraepithelial carcinoma (AKIEC), 513 cases of basal cell carcinoma (BCC), 795 cases of melanocytic nevi, 790 cases of benign keratosis, and 115 cases of dermatofibroma were included in the dataset. In order to accurately categorise images as either benign or malignant, a highly sophisticated convolutional neural network (CNN) was created. By using the already-trained

AlexNet model, the researchers used a transfer learning approach. The suggested model takes the original image as input and chooses relevant features from it autonomously to speed up the labelling process. Because of this, segmenting lesions and extracting relevant characteristics can be done with less effort.[7] The authors suggested using a deep convolutional neural network (CNN) model for accurate and efficient lesion boundary detection in photos. After initial training, a more refined and improved dataset was used to further fine-tune the ResNet-50 model. Dermoscopy pictures were then classified into melanoma, seborrheic keratosis (SK), and nevus using the enhanced model.[22] The CNN model achieved the greatest accuracy of 95.18% in the suggested method for classifying dermoscopic pictures of skin lesions.[47] Researchers used a GoogleNet Inception v3 Convolutional Neural Network (CNN) model that has been pre-trained using data from the 2014 ImageNet Large Scale Visual Recognition Challenge's dataset of roughly 1.28 million images. Using the dataset as a basis, the model was trained exhaustively via transfer learning methods. A dataset of 129,450 dermatologist-annotated clinical pictures was used for the study. A total of 33,740 images were examined, and it was determined that 3,374 of these were suitable for dermoscopy. The data set was split in half to create two groups. The original dataset used for training and validation included 127,463 images. There were 1,942 pictures in the second set, all of which had biopsy labels attached to them. These pictures were used for trials only. The research used a cross-validation technique with nine iterations.Researchers have effectively classified images of skin lesions using ensembles of deep learning models. In its research, the team used a variety of publicly available data sources. The authors used the ISIC 2018 competition dataset, which included 10,015 dermoscopy images, for their research. This data set is the one that was chosen to be used in the contest proper. The ISIC Archive1, a comprehensive collection of about 13,000 dermoscopic pictures, was also incorporated into the study. Researchers were able to gain access to more than a thousand additional clinical cases thanks to the Interactive Atlas of Extreme Learning, which they added into their dataset. There were dermoscopy and close-up clinical pictures to back up every claim. In addition, the PH2 Dataset, which contains 200 dermoscopic images, and the Dermofit Image Library, which contains 1300 photographs, were added into the study.Researchers used a Convolutional Neural Network (CNN), specifically the Microsoft ResNet-152 model, to categorise skin lesions like dermatofibroma.[42].Deep learning architectures have demonstrated outstanding performance in the classification of photos across various domains, including the field of dermatology.[21]Researchers have proposed using a model based on weighted average ensemble learning to categorise different types of skin lesions, including dermatofibroma. Five different deep neural network models were used in the research. [26]Convolutional neural network (CNN) models have been used for the aim of classifying skin lesions, including dermatofibroma, according to the cited works. Additional research is needed to fully comprehend the evolution of dermatofibroma classification through the application of Convolutional Neural Network (CNN) models.

1.2.5 Eczema

Scholarly interest is expanding in the potential of Convolutional Neural Network (CNN) models for use in the classification of eczema. The below cited works shed

light on the development of Convolutional Neural Network (CNN) models for eczema categorisation over time.One of the most common skin disorders, eczema has gained widespread attention in recent years. In order to improve the standard of care for patients, it is crucial that a treatment for this medical issue be found as soon as possible. Eczema is normally diagnosed after a thorough physical examination by a medical practitioner, such as a doctor or a dermatologist. Because of their same symptoms, it can be difficult to distinguish between the many forms of eczema. Multiple efforts have been made recently to automate the identification of skin diseases to a high degree of accuracy.Another obvious shortcoming is the lack of specific details about eczema's varied symptoms and clinical manifestations in the dataset. In this study, we introduce a unique approach to eczema classification using deep convolutional neural networks (CNNs). The data utilised in this study was gathered by the authors themselves. Data augmentation is a method used to improve the quality of images by the use of various adjustments. It has been shown that regularisation strategies, such as batch normalisation and dropout, can successfully alleviate the issue of overfitting.[12]In this article, we introduce a convolutional neural network (CNN) model trained on photos from clinical settings to detect and diagnose inflammatory skin disorders like eczema automatically. In order to categorise the many forms of eczema, this research presents the EczemaNet framework, which makes use of deep convolutional neural networks.[16]This study introduces a novel approach to categorising five different forms of eczema using a deep convolutional neural network (CNN). The task of assigning classes is carried out by means of a separate dataset that has been carefully selected and organised for this purpose. This study delves at how far artificial intelligence (AI) has come in the field of dermatology image analysis, and where it may go in the future. This paper gives a comprehensive examination of current and future trends in the application of AI to the interpretation of dermatology pictures. In this paper, we focus on how to use convolutional neural network (CNN) models for eczema classification.The use of AI in the field of multiphoton tomography with the aim of identifying cases of atopic dermatitis.[13]This paper introduces a novel approach for categorising eczema conditions into five groups using deep convolutional neural networks (CNNs). The task of assigning classes is carried out by means of a separate dataset that has been meticulously created for this function. In this investigation, we examine the state of the art and potential future directions of AI in dermatology image processing.[44]This academic essay presents a thorough analysis of the current state of artificial intelligence (AI) in the dermatology field and its potential future applications. The fundamental goal of this research is to analyse how convolutional neural network (CNN) models might be used to classify eczema.Multiphoton tomography for the diagnosis of atopic dermatitis using artificial intelligence.[11]In this work, multiphoton tomography images were analysed to see whether or not artificial intelligence might be used to detect atopic dermatitis. It is also emphasised that this technology has the potential to be used in the diagnosis of other skin disorders including eczema. Collectively, the preceding citations suggest that study into CNN models' potential utility in the context of eczema classification is blossoming. The appropriate categorisation of different eczema problems is currently the focus of academic experts who are actively presenting novel techniques and developing deep learning models. Analysing clinical images and multiphoton tomography images allows for the classification to be completed.

1.2.6 Psoriasis

Psoriasis classification using Convolutional Neural Network (CNN) models is an active area of study. The subsequently referenced articles shed light on the evolution of psoriasis classification using CNN models and offer essential historical context.Psoriasis is an autoimmune disease that causes abnormal and excessive growth of the skin's outermost layer, the epidermis. This condition is clinically manifested by the appearance of erythematous, raised, and desquamating patches or plaques, which can appear anywhere on the body but most commonly do so on the elbows, knees, scalp, and lumbosacral area. The symptoms of any of the patches mentioned above may include itching, soreness, cracking, or even bleeding. Psoriasis is a skin disorder characterised by an overactive immune system that leads to the inappropriate destruction of healthy skin cells and rapid turnover of these cells.The primary aim of this research was to create an advanced deep-learning network that could correctly and quickly classify dermoscopic images of psoriasis and other papulosquamous illnesses. The research was conducted to better diagnose psoriasis.The EfficientNet-B4 architecture was trained using a database of 7033 dermoscopy images collected from a total of 1166 people. The aforementioned photographs were obtained from the Dermatology Clinic of China's Peking Union Medical College Hospital. Five-fold cross-validation was used on the training dataset to evaluate EfficientNet-B4 and compare its classification performance to that of other widely used networks in previous studies. Ninety images were taken from the test dataset and used to compare the performance of a four-class model and trained dermatologists. An online poll was used to gather demographic data, including the ages and specialities of the dermatologists who provided the diagnoses.[31]Using 5241 photos of psoriasis lesions, this research developed a CNN model for the detection of different forms of psoriasis.[36] The primary objective of this study was to compare and contrast Convolutional Neural Network (CNN) deep learning models for automated psoriasis identification and categorisation. Psoriasis was one of nine common skin conditions used in this standardised dermatological collection comprising 8021 clinical photos.There was no user-provided content for scholarly revision.[17]The aforementioned research evaluated Convolutional Neural Network (CNN) models for classifying psoriasis, a skin disorder. There was cause for optimism in the results of these experiments, with accuracy rates ranging from 72.4% to 82.9%.[27][9] This systematic review aims to examine the increasing amount of research conducted on computer-aided systems utilised in the diagnosis of skin lesions, with a particular focus on the categorization of psoriasis through the application of convolutional neural network (CNN) models.[24] This comprehensive study of deep learning applications in dermatology examines the many approaches taken, results obtained, and restrictions placed on these applications. Psoriasis classification using convolutional neural network (CNN) models is the primary focus of this investigation.[54] Collectively, the aforementioned articles point to a new area of study concerned with the development and use of Convolutional Neural Network (CNN) models for the categorisation of psoriasis. In order to accurately detect different psoriasis symptoms through the analysis of clinical pictures, researchers are currently engaged in the development of novel approaches and the construction of deep learning architectures.

1.2.7 Scabies

The microscopic arthropods called Sarcoptes scabiei are the infectious cause of the skin disease known as scabies. The relevant mites can penetrate the stratum corneum of the skin and lay eggs there. Intense itching and the appearance of a rash with redness and raised bumps are the results of this procedure. Nighttime itching is caused by an allergic reaction to the mite's saliva and excretory secretions.The fundamental objective of this study is to analyse in depth the effectiveness of a deep learning system trained with a VGG-16 model in the timely detection of scabies. Examining deep learning approaches, gathering quantitative data, employing the VGG-16 model for training and testing, and assessing the results were the primary goals of this investigation. The research strategy included reevaluating a dataset obtained for the study's aims and making use of an advanced computational system that enhances the efficacy of results. Two distinct sets of data were used for training and testing the VGG-16 model. Emerging deep learning-based categorisation algorithms, along with improvements in hardware technology and computing capacity, have greatly enhanced the significance of dermatological applications. These courses are equipped to handle issues such limited access due to geographical isolation, physical difficulties, a lack of dermatologists, employment constraints, schedule conflicts, and others. They also help doctors make objective and quick diagnoses.[61]

1.3 Researched Problem

Numerous people throughout the world suffer from skin diseases, each of which can have serious consequences for their health and well being. Rapid and accurate diagnosis of skin conditions is critical for starting effective therapy as soon as possible and minimizing adverse effects. Medical image analysis, and more specifically the diagnosis of skin diseases, is an area where deep learning, and more specifically Convolutional Neural Networks (CNNs), has shown promising results. The fundamental goal of this study is to devise an accurate and automated approach to classifying dermatological images into discrete categories according to different skin conditions. The following important points will next be discussed and dissected:

1.3.1 Dataset Collection and Preparation

- Gathering a diverse and comprehensive dataset of dermatological images containing various skin disease classes with appropriate annotations.
- Data Augmentation is done.
- Preprocessing the dataset to standardize image size, enhance image quality, and address class imbalance if present.

1.3.2 Model Selection and Implementation

- Investigate the suitability of CNN models like- Xception NasNetMobile, MobileNet and DenseNet201, for the detection and classification tasks of skin diseases.

- Implement the ensemble model comprising Inception V3, ResNet-50, and EfficientNet to leverage their collective strengths.

1.3.3 Model Training and Optimization

- Train the individual CNN models and the ensemble model using transfer learning with appropriate hyperparameter tuning and optimization techniques.
- Validate the models on separate test datasets to assess their generalization capabilities.

1.4 Aims and Objectives

The study's major objective is to develop a reliable and efficient method for identifying skin disorders. To accomplish this, we'll use many distinct CNN models, including Xception, NasNetMobile, MobileNet, and DenseNet201. In addition, we'll use a model consisting of multiple neural networks (an "ensemble"), including Inception V3, ResNet-50, and EfficientNet. The application of deep learning methods shows great potential for accurately diagnosing skin issues with a high degree of precision. The aims and purposes of utilising deep learning for the diagnosis of skin problems include:

1. **Automated diagnosis:**The purpose of this research is to create and implement a computerised system for the diagnosis of dermatological disorders using clinical photographs and patient data. [45].
2. **Classification:**Using convolutional neural networks and recurrent neural networks, more specifically MobileNet V2 and Long Short-Term Memory (LSTM) models, to categorise skin diseases. [30].
3. **Prognosis:**The development of automatic information systems that can efficiently gather information for analysis is crucial to the field's further development. [43].
4. **Review and analysis:**The primary aim of this research was to review extensively the application of deep learning methods to the classification of skin diseases. The primary purpose of this research was to provide a thorough review of the fundamental properties of various imaging technologies as they relate to skin lesions and to assess the current state of this field. Research analyses that rely on datasets can only be accurate if they make use of a variety of data processing methods, categorisation models, and evaluation criteria.[33]
5. **Construction of a novel framework:**The focus of this research is on developing a novel framework for clinical skin disease diagnosis using deep learning methods. [34].

Thanks to advancements in deep learning methods, the field of skin disease identification has made significant strides. Nonetheless, there are a few problems that need fixing before this area can truly flourish. There is a pressing need to improve the properties of datasets and fine-tune deep learning algorithms, as well as to construct

publicly-acceptable skin disease picture datasets and address racial and geographical biases in existing public datasets. [58].

Chapter 2

Literature Review

The group of researchers conducted an extensive analysis of deep learning and machine learning applications in the diagnosis of skin diseases. In order to enhance the diagnostic procedure for skin diseases, this study paper provides a comprehensive review of deep learning techniques and their use within the field of dermatology. The datasets used for testing and training algorithms were the primary topic of discussion. The study team reviewed numerous scholarly works on the topic of using deep learning algorithms to the problem of diagnosing and classifying skin disorders. This project's overarching goal is to conduct a thorough review of recent scholarly works that apply deep learning methods to the diagnosis of skin disorders.The first part of the lecture was a detailed explanation of the techniques used in the field of dermatology for photographing skin lesions and identifying their causes. The presentation's primary focus was on freely accessible skin datasets that can be used in the creation and evaluation of algorithms. Therefore, a comprehensive study was executed to analyse various viewpoints on the application of deep learning algorithms to the diagnosis of skin disorders. The primary purpose of this research was to examine deep learning and machine learning algorithms and their applicability to image processing in the context of diagnostic accuracy. The accuracy of the deep learning and machine learning algorithms was very high.The presentation began with a detailed explanation of the procedures now used in the field of dermatology for capturing visual evidence of skin conditions. The debate centred largely on freely available skin datasets that can be used to evaluate and optimise algorithms. Therefore, a comprehensive study was executed to analyse various viewpoints on the application of deep learning algorithms to the diagnosis and classification of skin disorders. The authors set out to investigate the diagnostic value of image processing methods. They also compared the outcomes of deep learning and machine learning algorithms. Accuracy is not an issue for either deep learning or machine learning algorithms.According to the study's findings, using deep learning and machine learning algorithms significantly improved the accuracy of identifying and classifying skin diseases by 99.04%. There is a wide range of precision between image processing methods.When comparing image processing approaches with deep learning and machine learning methods, there is a clear gap in the degree of diagnostic precision.There are unique difficulties involved in collecting data on dermatological diseases for the aim of algorithmic evaluation and education.There is a lack of specific information on the datasets used in the study in the reviewed research articles. The purpose of this research is to investigate if deep learning models can be used to accurately diagnose a wide range

of skin disorders. Physical examination and biopsy can be time-consuming and imprecise methods for diagnosing dermatological conditions. The current difficulties in the diagnosis of dermatological disorders can be overcome with more research and analysis of deep learning and machine learning methods.[46]
The study evaluated several Convolutional Neural Network (CNN) models for their ability to categorise 23 distinct skin disorders.The purpose of the study was to investigate the efficacy of using Deep Learning methods, specifically those that had been trained on the "DermNet" dataset, for the diagnosis of skin disorders. In addition, many more advanced architectures for Convolutional Neural Networks (CNNs) were presented.To determine which convolutional neural network (CNN) architecture is superior, a comparative study was performed.Numerous convolutional neural network architectures were used to train on the DermNet dataset, with impressive results. These included InceptionV4, InceptionV3, DenseNet-201, MobilenetV3, ResNet50, VGG19, ResNext50, NASNetLarge, GoogleNet, and InceptionResNetV2.The researchers used the DermNet dataset, which included 19,434 photos of various skin conditions. The images were further classified, and the process yielded 23 separate categories.In order to train the model, we used a dataset consisting of 12,368 images. There were a total of 3,085 photos set aside for verification, and another 4,002 were used for pilot testing.The DermNet dataset was used to classify skin diseases, and it was found that the DenseNet architecture provided the highest accuracy. Top-1 accuracy for the DenseNet design was 68.97%, while Top-5 accuracy was 89.05%.[35]
This work unveils an all-encompassing diagnostic system that uses deep learning methods to identify different types of skin lesions and precisely map their boundaries. When used, the integrated diagnostic system significantly boosts Inception-ResNet-v2's classification accuracy. In the ISIC 2016 test dataset, an improvement in classification performance of 2.72% was seen for benign patients while 4.71% was seen for malignant patients. The F1-score is used as a quantitative measure of improvement. The results of the study show that ResNet-50 performs more well as a classifier for identifying various skin lesion situations. In this context, however, Inception-ResNet-v2 is regarded as the second-most effective classifier.There are just two types of skin lesions included in the ISIC 2016 dataset: benign lesions and melanoma. The results cannot be extrapolated to cover other types of skin lesions because of the small sample size. Lacking comparative analyses of recognised methodology or models, it is difficult to determine how effective the proposed integrated diagnostic framework is in relation to other approaches. The study does not offer a comprehensive evaluation of key aspects connected to the deep learning model's interpretability and explainability. Establishing credibility and encouraging acceptance of the model within the field of clinical practise depends critically on meeting the aforementioned criteria.[14]
In order to detect melanomas, this study suggests using well-established architectures like AlexNet, ResNet50, Inception V3, and GoogleNet. Overall, the InceptionV3 model performed exceptionally well in melanoma detection across all included datasets, including MedNode, PH2, and HAM10000 Kaggle.The results of this study show that there was an absence of inclusivity in the reporting of details on the size and composition of the datasets that were analysed. Pre-trained architectures are used, but any potential biases or limits of these models are not adequately acknowledged or explored. In particular, the approach does not do enough

to recognise and counteract the biases that present within the ImageNet database, the primary dataset used to train the models.[40]
On the basis of observed data, it is clear that the proposed structures function better than anticipated. The behaviour observed is a result of the measurement parameters being pushed to their limits. When applied to the ISIC2017 dataset, the best results have been obtained using ResNet50 and SVM models. The accuracy of the above-described procedure is 99.19%, the AUC is 99.32%, the sensitivity is 98.98%, the precision is 98.78%, the F1 score is 98.88%, and the computation time is 2.6988 seconds.The research does not provide a thorough explanation of the specific difficulties and restrictions experienced in the course of applying the suggested deep learning models and preprocessing methods. A comparison of the proposed strategy's efficacy to that of other sophisticated methodologies or algorithms utilised for skin lesion classification is lacking from the study. Without this knowledge, determining its true efficacy is difficult.[28]
The major goal of this research is to study how convolutional neural networks (CNNs) and deep learning (DL) methods can be applied to the study and understanding of dermatology-related medical pictures. Three common dermatological problems are described in the Middle Eastern region, and the efficacy of six convolutional neural network (CNN) models is examined in this study. These models are VGG16, EfficientNet, InceptionV3, MobileNet, NasNet, and ResNet50.The study sheds insight on the underrepresentation of other dermatological conditions, as most recent efforts in the fields of dermatology and deep learning concentrate on the identification of skin cancer. Data for this study came from Dermnet and the University of Iowa's Department of Dermatology, among other well-established institutions that are cited in the text. However, the details provided fall short of providing a complete picture of the scope and depth of the dataset. Based on the results of this research, it is clear that the need for comprehensive databases relating to dermatological disorders does not receive the attention it deserves. Furthermore, it highlights the need of protecting patient anonymity. In addition, it doesn't account for the problem of protecting patients' privacy.[50]
The primary goal of this research was to improve the accuracy of skin condition identification and categorisation by using novel image processing models and deep learning methodologies. The study included a proprietary dataset of over 1450 images depicting nine different skin states, as well as three different neural models: MobileNetV2, InceptionV3, and ResNetV2. All of the above parts worked together to form a solid architectural basis. The MobileNetV2 model successfully distinguished between 96.77% of medical conditions. The prompt identification and diagnosis of dermatological diseases is the primary focus of this study because of the possible life-saving importance of this factor. The aforementioned finding demonstrates the need of encouraging interdisciplinary cooperation between the fields of computer science and medicine in the context of this particular topic.The research's capacity to be extrapolated to a larger population is hindered by the absence of details about the size and composition of the dataset used in the study. The research shows that not enough attention has been paid to thoroughly investigating the specific difficulties encountered during the initial phase of data gathering. The approaches and methods used to overcome these obstacles are not elaborated upon either. The study's failure to account for the model's crucial training and deployment features creates a realistic obstacle to its use in actual settings.[48]

The fundamental objective of this study is to create a hybrid deep learning approach for the automatic prediction of skin problems. An automated system for classifying skin conditions is now under development, and techniques like Deep Convolutional Neural Networks (DCNN) and the Binary Butterfly Optimisation Algorithm (BBOA) are being put to use in the process. The fundamental objective of this research is to improve the reliability and accuracy of forecasts for skin diseases. To improve performance by retaining state knowledge from previous image classification tasks, the proposed framework makes use of the Biogeography-Based Optimisation Algorithm (BBOA), and to accurately differentiate the specific type of skin condition, it makes use of the Deep Convolutional Neural Network (DCNN). Models are trained using image decomposition and feature abstraction methods, after which they are compared to a standard set of dermoscopy or clinical images. The various skin problems are then separated, extracted, and categorised using a wide variety of methods.Significant improvements in accuracy in the detection and classification of dermatological disorders have been demonstrated by the methods outlined in this study compared to earlier optimisation methodologies. This strategy also reduces the need for both computational and human resources.To better forecast skin illnesses, a hybrid deep learning framework is used. This framework integrates deep convolutional neural networks (DCNN) with the biogeography-based optimisation algorithm (BBOA). Reliable prognostic forecasts can be made thanks to this method's emphasis on preserving contextual data.When compared to conventional methods, the suggested model shows considerable improvements in computing efficiency, leading to more accurate categorisation and diagnosis of skin disorders. As a result, this model greatly reduces the need for a lot of time and effort spent on computing.Instead of completely replacing current disease diagnosis technology, the proposed strategy aims to supplement it. Visual symptom-based diagnoses typically have inferior diagnostic precision compared to those derived from laboratory approaches. Furthermore, it might be difficult to spot issues in their early stages when relying exclusively on visual inspection.Additional research and data collection are required to develop population-specific models that adequately address the limitations of existing risk prediction models.The strategy to integrating DCNN with BBOA is strengthened by incorporating historical timestamp data.[56]
The primary goal of this study is to compare fourteen different deep learning networks for their ability to categorise multiple skin lesions (MSLC) when presented with skewed data.The final fully connected layer of a set of fourteen deep learning networks is swapped out for FC7, softmax, and cross-entropy using transfer learning. This swap is performed to improve the sorting procedure.Ten thousand and fifteen dermoscopic images were used in the study. Scaling, normalising, and enhancing were just some of the pre-processing operations performed on the images.The evaluation of networks requires the use of fixed parameters such as batch size, number of iterations, and starting rate of learning. Accuracy, recall, precision, and the F1 score are just few of the performance metrics used in network analysis.The investigation's final step involves comparing and contrasting the results of the actual experiment.The purpose of this research is to compare fourteen different deep learning networks for their ability to correctly categorise a large variety of skin lesions. This study sheds light on the viability of such networks for classifying a wide range of dermatological conditions.Rather than spending time training on massive datasets from scratch, transfer learning can make use of already developed

models.Scaling, normalisation, and augmentation are examples of pre-processing techniques frequently used to improve classification task results.The study analyses and compares the performance of several networks using a variety of criteria, including accuracy, recall, precision, and F1 score.The limitations and shortcomings of the chosen methodology and approach are not thoroughly examined in the study. The difficulties in skin lesion categorisation could have been better understood if greater attention had been paid to the data set used or the constraints of deep learning networks.[51]

The fundamental objective of this study is to create a system for accurate skin disease diagnosis by combining optimal region growing segmentation with autoencoder-based classification techniques.When it comes to segmenting diseased regions, the Optimised Region Growing method coupled with the Grey Wolf Optimisation (GWO) algorithm produces the best results. Weber local descriptors (WLDs) and grey level co-occurrence matrices (GLCMs) are used to evaluate the segmented lesions' textures.Using an autoencoder and the resulting latent representation, a smaller collection of features can be built. This strategy makes it easier to reduce the feature vector's dimensionality.Pathological lesion classification is accomplished using a CNN and additional neural networks trained on the latent representation acquired from the autoencoder. The results of the empirical study show that the proposed classification model outperforms the more conventional deep classification techniques.The experimental results reported here lend credence to the claim that the suggested framework is superior to more traditional deep classification methods for spotting and diagnosing skin issues.Using the Optimised Region Growing with Grey Wolf Optimisation (GWO) method improves lesion segmentation precision.Autoencoder-based feature reduction is a technology that aims to lower the dimensionality of the feature vector, therefore improving the classification model's performance.The research does not thoroughly investigate the potential issues or constraints associated with the suggested architectural framework. It's important to remember that the framework's performance may vary depending on the quantity and variety of training data used to build the classification model.[57]

The primary goal of this research was to enhance the efficiency of skin cancer detection by combining the Sparrow Search Algorithm (SpaSA) with deep transfer learning approaches. The SpaSA optimizer was used as the method for optimising the hyperparameters in this study. Eight different pre-trained convolutional neural network (CNN) models and five unique U-Net models are used in the optimisation process. Improved skin cancer segmentation is the primary focus of this optimisation. The dataset used in this research is split into two subsets, one with 2 classes and the other with 10. Five different public resources were used in the compilation's acquisition. The presented method is based on the U-Net framework, namely DenseNet201. Publicly attested successes provide credence to the claim that the aforementioned approach is significantly effective in the field of skin cancer segmentation and classification.This research uses the Sparrow Search Algorithm (SpaSA) in conjunction with deep transfer learning methods to improve the identification and classification of skin cancer.Five distinct U-Net models are used to increase classification accuracy and resilience, and the SpaSA optimizer is utilised to improve hyperparameters.The Sparse Simulated Annealing (SpaSA) algorithm is one example of a meta-heuristic optimisation technique used to find optimal answers to difficult optimisation problems.The process entails collecting information from five

open-source resources to build a large-scale dataset that can be used for both evaluation and instruction.The study does not thoroughly investigate the performance indicators and outcomes linked to the proposed approach.In the absence of a comparative study involving established best practises or technology advances in the relevant field, it is difficult to determine whether the proposed technique is superior or effective.However, the work does not adequately discuss the drawbacks of using deep transfer learning and the SpaSA optimizer for skin cancer diagnosis.[53]
The primary goal of this research was to propose a comprehensive framework using deep neural networks (DNNs) for the reliable detection of skin cancer from the examination of dermoscopic images. This method was developed primarily to lessen the impact of human error in interpretation. The fundamental objective of this plan is to enhance early disease identification and guarantee delivery of services that meet exacting quality benchmarks.This work details a method for building such a knowledge base, which entails combining multiple dermoscopic datasets. In cases when there is insufficient data for a full training cycle, researchers have turned to transfer learning and fine-tuning techniques to speed up the model-building process. In order to make the model more accurate, data augmentation methods are used. The results show that the layered architecture of the model used in this work allows for binary categorisation of skin cancer. The performance of trained models is measured across a variety of multiclass and binary classification tasks. In comparison to other deep learning structures, the results imply that the Deep Neural Network (DNN) employing a modified version of EfficientNetV2-M is more effective.The improved EfficientNetV2-M deep neural network model outperforms state-of-the-art deep learning models developed specifically for multiclass classification tasks in the context of performance evaluation.Faster model training with a smaller training dataset is possible with the help of transfer learning and fine-tuning methods.In order to make the model more accurate, data augmentation methods are used. By including a wide variety of dermoscopy datasets, deep neural network (DNN) models can perform better, and a more complete body of information can be amassed.Regularisation of the model is made possible by the incorporation of the progressive learning technique within the EfficientNet models, which also helps to alleviate the problem of overfitting. There are no specific references to potential restrictions or limitations associated with the planned activity in the published materials.[60]
The primary aim of this research is to create a computerised classification approach using dermoscopic images for the rapid diagnosis of skin cancer.The fundamental objective of this study is to develop a better framework for the VGG-16 model in order to improve the accuracy of skin cancer detection.The primary aim of this study is to help dermatologists get better at analysing photographic evidence of skin cancer.To aid in the automatic diagnosis of melanoma, a particularly dangerous form of skin cancer, the current study employed the VGG-16 network, a model of convolutional neural network (CNN).The current research builds on previous work by using an improved VGG-16 architecture as the foundation for a model that can aid in the detection of skin cancer.The effectiveness of the model is evaluated by contrasting it to both benchmark datasets and existing methods for analysing skin images from the International Skin Image Collaboration.The outcomes indicate that the proposed model is more accurate than the competing alternatives.[59]
This research aims to further the state of the art in skin disease CAD through the im-

plementation of deep neural networks (DNNs).The focus of this study is on using disease taxonomy to correctly categorise skin diseases, with the ultimate goal of enhancing classification accuracy.In this research, two large skin image datasets—DermNet and the ISIC Archive—are used to train Deep Neural Networks (DNNs). The primary objective of the research was to properly classify the spectrum of skin diseases.Advanced deep neural networks (DNNs) were used in the study for training purposes, and the DermNet and ISIC Archive datasets were used for this purpose. Models' categorisation efficacy was boosted with the incorporation of a disease taxonomy.The study demonstrated substantial advancements in DermNet disease classification, with results that are cutting-edge in the profession. Additional proof of the effectiveness of the proposed methodology comes from the attained accuracy of 80% and the area under the curve (AUC) of 98%. When applied to the DermNet dataset, which contains 622 unique sub-classes, the accuracy rate and AUC value were determined to be 67% and 98%, respectively.The ISIC Archive dataset performed admirably, correctly diagnosing all seven diseases 93% of the time on average with an AUC of 99%.Based on the results of this study, it appears that deep learning has the potential to accurately classify different skin disorders with a degree of accuracy that is on par with human performance and that has improved reproducibility over previous methods. Therefore, this approach shows great promise for the rapid diagnosis of skin diseases in real-world settings. When used to the field of computer-assisted diagnosis (CAD), deep neural networks (DNNs) enable the precise classification of a wide variety of skin issues, on par with that achieved by human professionals. The study's findings were ground-breaking in that they successfully classified dermatological disorders with a high degree of accuracy and remarkable area under the curve (AUC) values.Disease taxonomy was incorporated to boost model accuracy in classification.By studying clinical or dermoscopy photos, deep learning approaches have the potential to greatly aid healthcare workers in making accurate diagnoses of skin disorders. The emerging technology offers a potentially game-changing chance for rapid and accurate skin disease diagnosis.The lack of standardisation among classification methods is acknowledged as a challenge in this research. Different train-test splits and numbers of classes across proprietary and publically available datasets cause this problem.Noise, low-resolution photos, and photographs with watermarks are just a few examples of the kinds of interference that could be present in publicly available datasets of large volume. There is a risk that crucial data needed for fine-grained object classification would be omitted due to these interferences.When used in real-world clinical situations as opposed to simulated ones for research purposes, the efficacy of artificial intelligence (AI) classifiers, in particular deep learning models, may show inconsistencies.[8]
The major objective of this study is to build a reliable system for melanoma detection in dermoscopy images using deep learning ensembles. The research team hopes that by creating automated methods for diagnosing melanoma, they can reduce costs, prevent unnecessary biopsies, and even save lives.The proposed approach uses a combination of recent advances in deep learning and traditional methods of machine learning to generate ensembles of algorithms. To aid in the detection of melanoma, these ensembles are used to segment skin lesions and analyse both the affected area and its surrounding tissue.The system uses a wide variety of low-level visual signals, such as edge histograms, colour histograms, and a multi-scale adaption of colour local binary patterns (LBPs), to perform photo classification

tasks.Classification and segmentation are the two key features of the system. The fully convolutional U-Net architecture is used to segment lesions, with the fully connected layer serving as a descriptor of the lesion's shape.Two independent sets of experiments, grid-search optimisation and an ensemble of ten networks, are used to evaluate the performance of the fully convolutional U-Net architecture. Semantic segmentation of dermoscopic lesions is the focus of these tests, with the hope of gauging the architecture's performance in this setting. Measures of performance excellence include improvements in sensitivity, specificity, and area under the receiver operating characteristic curve. The system's performance, as measured by its study of a set of test images, is superior to that of average dermatologists qualified by professional boards.The suggested method improves upon the accuracy of melanoma detection in dermoscopy images by combining deep learning techniques with traditional machine learning approaches. This leads to groundbreaking advances that set a new standard for the industry.When compared to prior art, the system shows notable advancements in the areas of receiver operating characteristic curve, average precision, and specificity.When compared to the performance of human dermatologists using the same test images, the system achieves higher levels of accuracy and specificity. There are two caveats that the paper recognises. The use of a preset dataset partition and the lack of software implementations for doing numerous n-fold assessments are to blame for the lack of statistical significance in the performance comparisons. In addition, healthcare practitioners' diagnostic accuracy in identifying skin lesions via dermoscopic pictures may demonstrate diversity in real-world settings due to the specifics of each lesion. [1]

This study's primary interest is in analysing and evaluating cutaneous lesions with the aim of detecting melanoma. In 2018, this project was carried out with the help and oversight of the International Skin Imaging Collaboration (ISIC).There were three separate goals in this competition: lesion segmentation, trait identification, and disease classification. A thresholded Jaccard index, a variant of the original Jaccard, was used to evaluate the segmentation task. To implement this change, a threshold was set, and if the Jaccard index was below that value, it was set to zero. The purpose of this investigation was to analyse pictures missing dermoscopic features. The criteria for success were modified as part of the study's design. Adjustments were made by adding a new segmentation metric to account for large variations in interobserver variability. Furthermore, decisions regarding classification were made using balanced accuracy as the criterion. Additionally, external test data was used to evaluate the algorithm's generalizability. The findings showed that the majority of the photographs, on average more than 10%, were improperly identified by the most common segmentation algorithms. Empirical studies have also shown that, despite equal performance on test data, algorithms might have varying degrees of generalisation capability. ISIC's 2018 competition was the most comprehensive skin image analysis challenge ever held because the dataset included more than 12,500 images. To better quantify segmentation errors and account for cases where dermoscopic properties are absent from images, we integrated the "Thresholded Jaccard" measure into the evaluation framework. The risk of overfitting due to inconsistencies in the dataset was effectively addressed through the use of balanced accuracy as the assessment parameter for classification decisions. Because of this methodology's efficacy, there were significant shifts in the participants' underlying social order. A more precise evaluation of the algorithm's generalizability was made

possible with the addition of test data from colleges that were not part of the initial training dataset.[5]

Table 2.1: Assessments of dataset durning study

Ref	Task	Classifier	Database	Accuracy
[1]	Skin disease diagnosis	Deep learning	N/A	99.04%
[2]	Skin disease classification	CNN	DermNet dataset	68.97%(Top-1), 89.05% (Top-5).
[3]	Enhanced automated skin lesion diagnosis	Inception-v3, ResNet-50, Inception-ResNet-v2, and DenseNet-201	ISIC datasets	77.04% to 89.28%
[4]	Melanoma classification	Inception-V3	Med Node, PH2, and HAM10000 Kaggle	97.1%, 97.2%, 96.2%.
[5]	Skin lesion classification	Support Vector Machine (SVM)	SIC 2017, MNIST-HAM10000, and ISBI 2016	99.19%
[6]	Early skin disease diagnosis	CND,CND Inception-V3	ISIC 2018, Xiangya Derm dataset	60% accuracy
[7]	Classifying common Middle Eastern dermatological disorders	CNN	N/A	95.7%
[8]	Automated skin disease prognosis	DCNN, BBOA	HAM10000	N/A
[9]	Skin lesion classification	Transfer learning on deep learning	ISIC 2018	N/A
[10]	Enhanced skin disease detection	CNN	N/A	N/A
[11]	Automatic approach for skin cancer detection	CNN	N/A	N/A
[12]	Skin Cancer Detection	DNN	Custom dataset	94.80%
[13]	Automated classification system for the early detection of skin cancer	N/A	(ISIC) dataset	N/A
[14]	Deep learning to improve the accuracy of skin disease classification	DNN	Dermnet,ISIC	93.06%
[15]	Advanced melanoma recognition system	Deep learning	N/A	76%
[16]	Analyze skin lesions for the purpose of melanoma detection	N/A	Skin Lesion Analysis Toward Melanoma Detection 2018	N/A

Chapter 3

Data Set

3.1 Data set Source

We used a data set that is available in Kaggle [29] had been used in research.During the course of our study project, we found that our data set is segmented to seven distinct portions. The sections of our data sets are: Acne, Melanoma, Solar Lentigo, Dermatofibroma , Eczema, Psoriasis and Scabies. We utilised picture augmentation strategies such rotation, shearing and scaling in order to expand the size of the of our data set as our inital size of the data set was small as you can see in the table **??**. After that the augmented data was gone through another processing that is we used clahe to make the images black and white.

Skin Disease	Number of Images before Augmentation	Number of Images after Augmentation
Acne	72	1080
Melanoma	73	1050
Solar Lentigo	45	1095
Dermatofibroma	50	1064
Eczema	90	1040
Psoriasis	56	1040
Scabies	40	1170

Table 3.1: Skin Disease initial Data Set

3.2 Data Augmentation

Data augmentation is a highly effective strategy that enhances the robustness and accuracy of machine learning models in their ability to handle changes seen in real-world scenarios. Data augmentation is a crucial technique for enhancing the efficacy of models, particularly in scenarios when the availability of training data is restricted. In our study, we employed the techniques of Histogram equalization and CLAHE (Contrast Limited Adaptive Histogram Equalization).
Histogram Equalization: Histogram equalization is a technique employed to improve the contrast of an image through the redistribution of pixel intensity values. The functionality of this process involves the manipulation of the intensity histogram

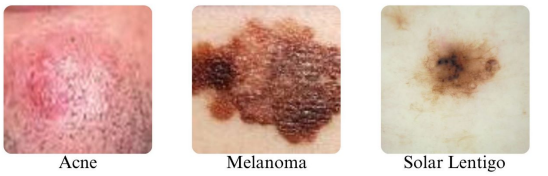

Figure 3.1: Images before Augmentation

Figure 3.2: Images after Augmentation

of the image in order to optimize the utilization of the complete range of intensities. This procedure efficiently amplifies the contrast of the image by intensifying the darkness of the darker regions and the brightness of the brighter regions.
Data augmentation using Histogram Equalization involves applying this technique to various images in a dataset. The process can be described as follows:

1. **Input Image:**Start with an original image that might have varying levels of contrast and illumination.

2. **Histogram Calculation:**Calculate the histogram of intensity values for the input image. This histogram represents the distribution of pixel intensities.

3. **Cumulative Distribution Function (CDF):**Compute the Cumulative Distribution Function from the histogram. The CDF provides a mapping from the original pixel intensities to the new, equalized intensities.

4. **Intensity Transformation:**Use the CDF to transform the pixel intensities of the original image. This transformation stretches the range of pixel intensities, resulting in improved contrast.

5. **Output Image:**The transformed image is the output of the data augmentation process using Histogram Equalization. It will have enhanced contrast compared to the original image.

CLAHE (Contrast Limited Adaptive Histogram Equalization):CLAHE is an extension of Histogram Equalization that aims to avoid over-enhancement in regions with large intensity variations. It divides the image into small tiles and applies Histogram Equalization to each tile independently. Additionally, it introduces a clipping mechanism to limit the amount of enhancement applied to each tile. This helps prevent noise amplification in uniform regions and ensures a more balanced enhancement.
Data augmentation using CLAHE can be summarised as follows:

1. **Input Image:**Start with the original image that may have both localized and global contrast variations.

2. **Image Division:**Divide the image into small non-overlapping tiles. The size of these tiles is a user-defined parameter.

3. **Histogram Calculation per Tile:**Calculate the histogram of intensity values for each tile individually.

4. **CDF Calculation per Tile:** Compute the Cumulative Distribution Function for each tile based on its local histogram.

5. **Clipping:**Apply a clipping mechanism to limit the amount of enhancement that can be applied to each tile. This prevents over-amplification of noise.

6. **Intensity Transformation per Tile:**Use the local CDF to transform the pixel intensities of each tile.

7. **Stitching:**Stitch the processed tiles back together to form the final output image.

8. **Output Image:**The final output of the data augmentation process using CLAHE will have enhanced contrast, both globally and locally, while maintaining a balance between enhancement and noise control.

Chapter 4

Methodology

4.1 Work Flow

our initial step was collecting the data set of different skin diseases. Further, we preprocessed the data and then performed image division. Additionally, we have done Histogram calculations per tile. Furthermore, we have also done a CDF calculation per tile. Then we did clipping as well as intensity transformations per tile and stitching. Further, we split the data set into test and train. We divided the data set 80-20. In detail, 80% is the training set where we trained the models, and 20% is the test set where we tested the models. We saved the models, and lastly, we used the best model.

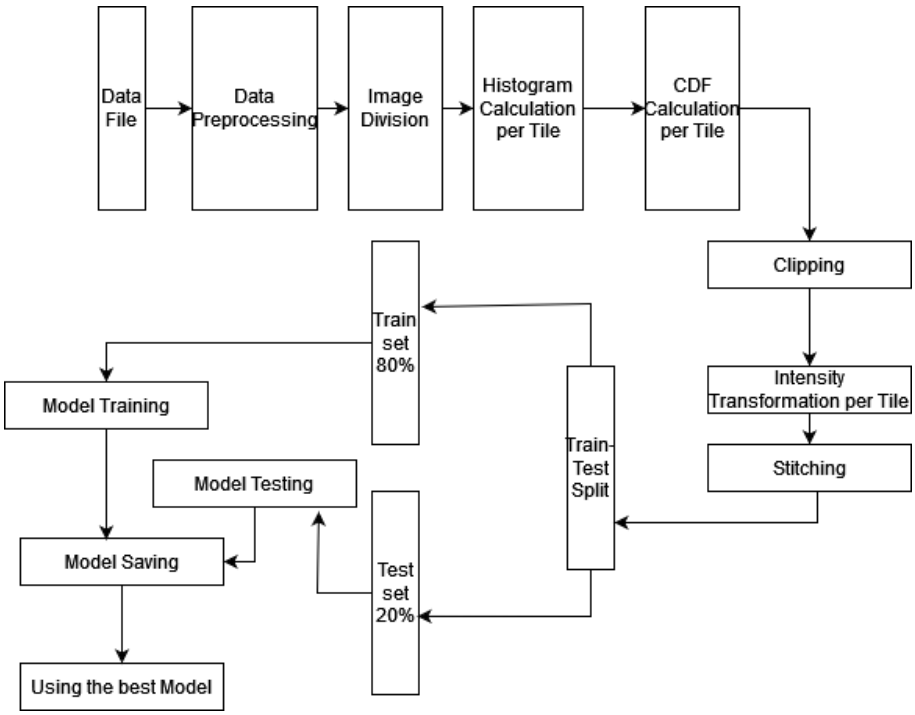

Figure 4.1: Work Flow of the research

4.2 Machine Learning Model Description

Skin diseases can manifest in various ways, posing challenges for accurate diagnosis by traditional methods. In contrast, CNN models possess a remarkable capability to detect subtle irregularities that might potentially indicate certain skin conditions, owing to their capacity to acquire intricate patterns and characteristics from photographic data.

4.2.1 InceptionV3

The architectural design of Inception V3, a deep learning model utilized for the purpose of image classification, has a diverse array of layers and components. Figure 4.2 presents a thorough examination of the architecture, as indicated by the search results obtained.The Inception V3 model is comprised of a total of 42 layers, which denotes a substantial augmentation in the number of layers as compared to its precursors, specifically Inception V1 and V2.The model incorporates many components, including convolutional layers, pooling layers, and auxiliary classifiers.The architectural design of Inception V3 places a strong emphasis on optimizing efficiency and minimizing the utilization of processing resources. By employing factorised convolutions, it is possible to reduce the total number of network parameters. The model incorporates regularization techniques such as dropout and batch normalization, along with the utilization of label smoothing.To facilitate the dissemination of information on labels at more intricate layers of the network, InceptionV3 employs an auxiliary classifier.The InceptionV3 architecture has been extensively employed in various academic fields.The model's performance on the ImageNet dataset exceeded that of human assessors by a substantial margin of more than 78.1%.

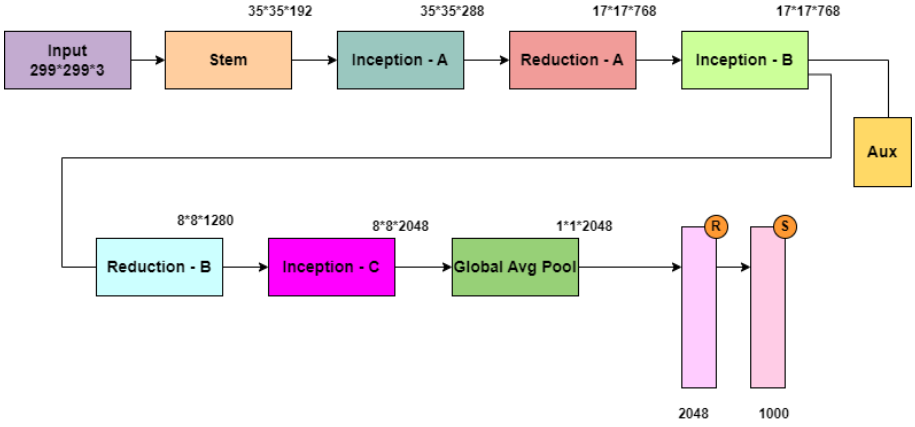

Figure 4.2: InceptionV3 Architecture

4.2.2 Xception

The Xception model utilizes a neural network design called Depthwise Separable convolutions, as depicted in Figure 4.3. This architecture belongs to the class of deep convolutional neural networks.The researchers at Google apply a distinct methodology in utilizing the Inception model.The Xception architecture consists of

a sequential arrangement of depth-separable convolution layers, which are interconnected through the use of residual connections.The model has a depth of 71 layers.The Xception architecture encompasses several notable characteristics. Firstly, it employs regular convolutions that effectively analyze both channel and spatial correlations simultaneously. Additionally, it utilizes the Depthwise Separable Convolution, a convolutional operation that evaluates channel and spatial correlations in a sequential manner, treating them as distinct entities. Lastly, the architecture incorporates residual connections, also referred to as shortcut connections, which aid in the seamless propagation of gradients during training and act as a preventive measure against the vanishing gradient problem.TThe Xception architecture has outperformed ResNet and Inception V3 in many classification benchmarks.In the domain of training, the issue of vanishing gradient can be addressed by incorporating Residual Connections. These connections act as efficient channels that aid in the transmission of gradients.The model comprises three distinct components, namely the input, the main, and the outflow.The impacts of batch normalisation are felt in both the convolutional layer and the separable convolutional layer.

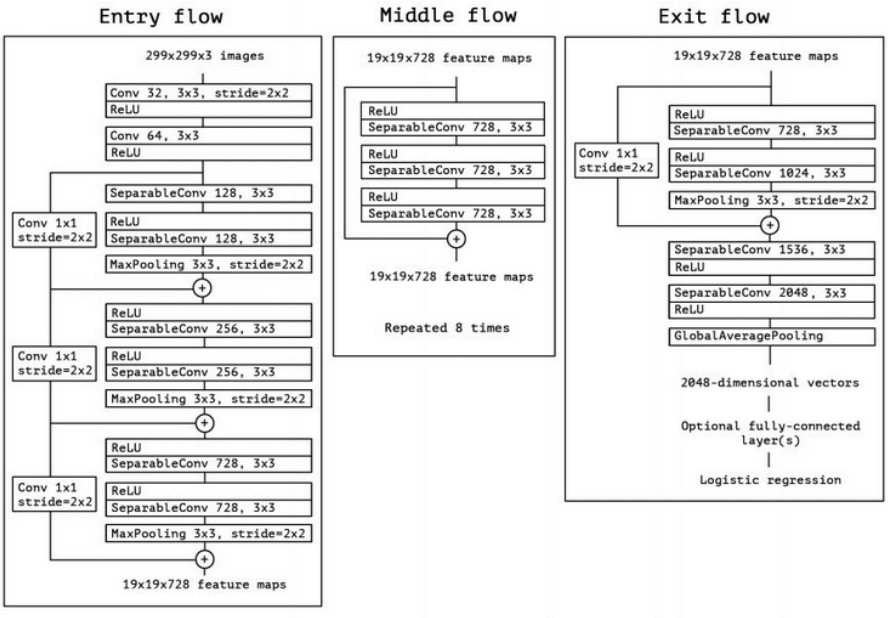

Figure 4.3: Xception Architecture

4.2.3 ResNet50

The graphic referred as 4.4 visually represents the ResNet50 architecture, showcasing the inclusion of 48 convolution layers, 1 maximum pool layer, and 1 average pool layer. The network under consideration is generally acknowledged for its significant level of activity and is held in high regard as an exemplary example within the ResNet network family. The use of convolutional neural networks (CNNs) has experienced substantial proliferation in the realm of deep learning, with the ResNet design receiving noteworthy acclaim in this particular discipline. In 2015, Microsoft Research presented a unique network design called Residual Network (ResNet), which has subsequently demonstrated significant improvements in

many performance benchmarks. The ResNet50 architecture has been specifically developed to effectively handle input images with dimensions that are evenly divisible by 32 in terms of height and width, and by 3 in terms of depth, within each of its four phases. In order to ensure clarity, it is assumed that the dimensions of the input are 224 × 224 x 3. In all ResNet topologies, the initial stage of convolution utilizes 7x7 kernels, while the succeeding step of max-pooling employs 3x3 kernels. The architecture of ResNet-50 consists of six unique components, which include input pre-processing, CFG blocks and a fully connected layer. There is noticeable variability observed among ResNet implementations regarding the total number of control flow graph (CFG) blocks utilized. The ResNet50 architecture is comprised of a maximum pooling layer, an average pooling layer, and a total of 48 convolution layers. The methodology consists of four independent stages and allows for efficient analysis of photos with dimensions that are divisible by both 32 and 3. The ResNet-50 architecture is comprised of six components, and the number of CFG blocks utilized in each stage may fluctuate among various implementations.

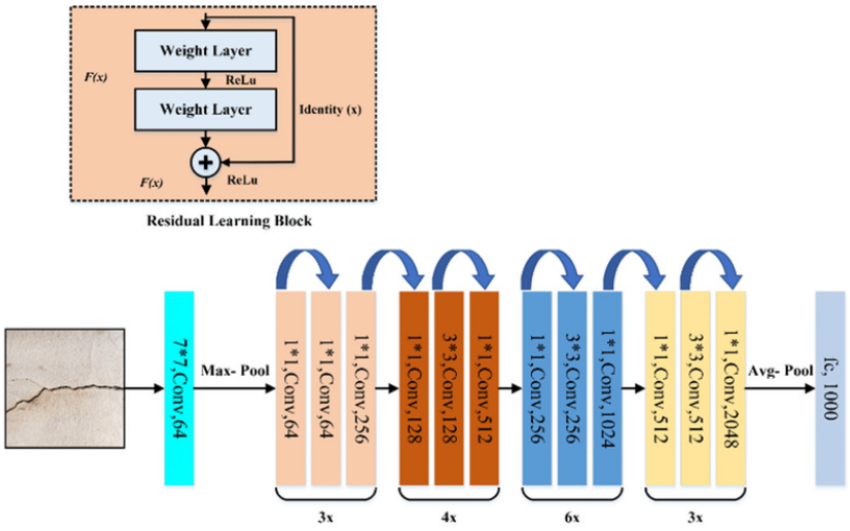

Figure 4.4: ResNet50 Architecture

4.2.4 NASNetMobile

The utilisation of convolutional neural networks is shown in the design of NASNetMobile in the figure 4.5, which is sometimes referred to as the Neural Architecture Search Network for Mobile. The subsequent elements encompass notable architectural features.The ImageNet database is employed as a training resource for instructing NASNetMobile in the task of object recognition.The neural network has the capability to accurately classify and distinguish up to 1000 unique categories of objects seen in an image.The NASNetMobile architecture is designed to process input photos of size 224x224.The architectural design of this system is specifically tailored to optimise performance on mobile devices such as smartphones and tablets.The technique known as Neural Architecture Search (NAS) was employed to develop NASNetMobile, a neural network architecture that leverages reinforcement learning to determine the most optimal architectural components.Instead of

prescribing a certain configuration for NASNetMobile, the authors adopt a more autonomous approach by allowing the NAS process to choose the optimal setup independently.The NASNetMobile architecture is a convolutional neural network that has undergone extensive training on a substantial dataset for the purpose of accurately categorising photographs into several object categories. Furthermore, it has been specifically tuned to operate efficiently on mobile devices.

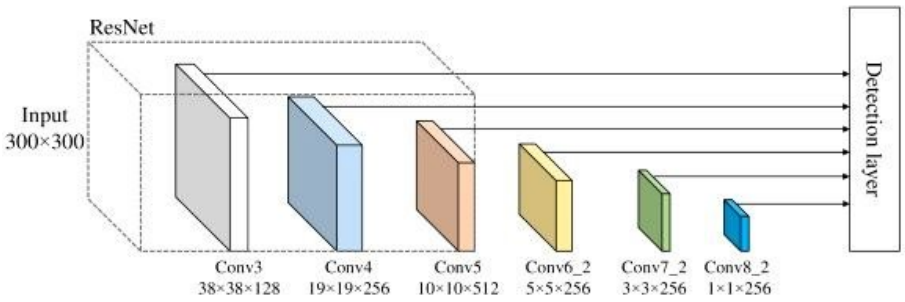

Figure 4.5: NASNetMobile Architecture

4.2.5 MobileNet

MobileNet is an ultra-lightweight convolutional neural network (CNN) model architecture that was developed primarily for mobile and embedded devices that have restricted access to computing resources. The underlying technique of MobileNet is built on depthwise separable convolutions, which are the main building block of the network. The pointwise convolution mixes the output channels of the depthwise convolution with numerous 1x1 convolutions, as opposed to the depthwise convolution, which applies a single convolutional filter to each input channel. Because it cuts down on the number of parameters and processes,this strategy brings the total computing cost down by a substantial amount. In most cases, MobileNet models are pre-trained on large-scale picture datasets like ImageNet. However, in addition to the initial MobileNet design, a number of pre-trained variations have been created in order to establish a balance between the level of accuracy and the size of the model. For instance, MobileNetV2 is an improvement over the first version of MobileNet. This is accomplished by incorporating inverted residual blocks and linear bottleneck layers. The end result is improved performance despite the model size being the same. The design is improved even more with the introduction of squeeze-and-excitation blocks as well as additional optimisations in MobileNetV3. MobileNet models have shown to have exceptional performance on mobile and embedded devices, which enables real-time inference and deployment on platforms with limited resources. Because it makes it possible to deploy deep learning models on devices with limited resources in an effective manner, MobileNet has made a significant contribution to the area of computer vision.The architecture of MobileNet is shown in the figure 4.6.

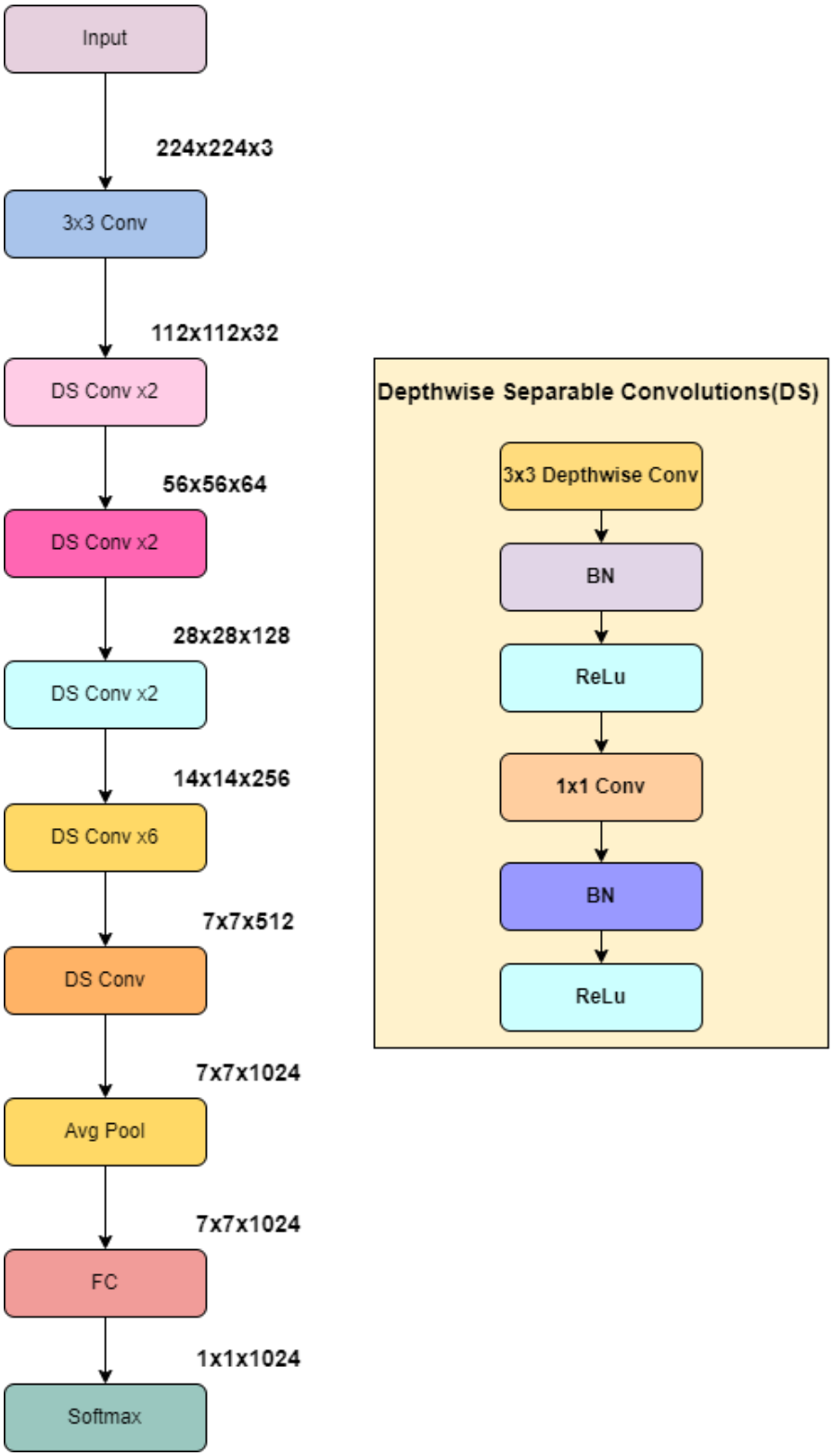

Figure 4.6: MobileNet architecture

4.2.6 DenseNet201

DenseNet201 is a convolutional neural network that is characterized by its depth, consisting of a total of 201 layers. The network design known as Dense Convolutional Network (DenseNet) enables the utilization of network features through the implementation of dense connections across layers. The architecture of DenseNet201 is outlined below. The arrival of dense blocks is prioritized. The DenseNet201 architecture consists of dense blocks, whereby numerous layers are tightly interconnected. In a thick block, every layer possesses the ability to access the feature maps of the layers positioned above it while concurrently transmitting its own feature maps to the layers situated below it. The subsequent levels to be discussed are the transitional layers. The thick slabs are interspersed with a transitional layer. The transition layer utilizes average pooling and 1x1 convolutional layers to effectively decrease the quantity of feature mappings and spatial dimensions. Subsequently, the global pooled average will be computed. The network culminates in a layer that aggregates information on a global scale. Through the process of aggregating over all feature maps within this particular layer, the input undergoes a transformation, resulting in the creation of a vector that possesses a predetermined length. After the global average pooling layer, there is an entirely linked layer with Softmax activation. In this particular stratum, the number of output categories is determined by the vector representation.Using TensorFlow, we instantiated the DenseNet201 architecture using the tf.keras.applications.densenet.DenseNet201 function. The architecture of Densenet201 is shown in the figure 4.7

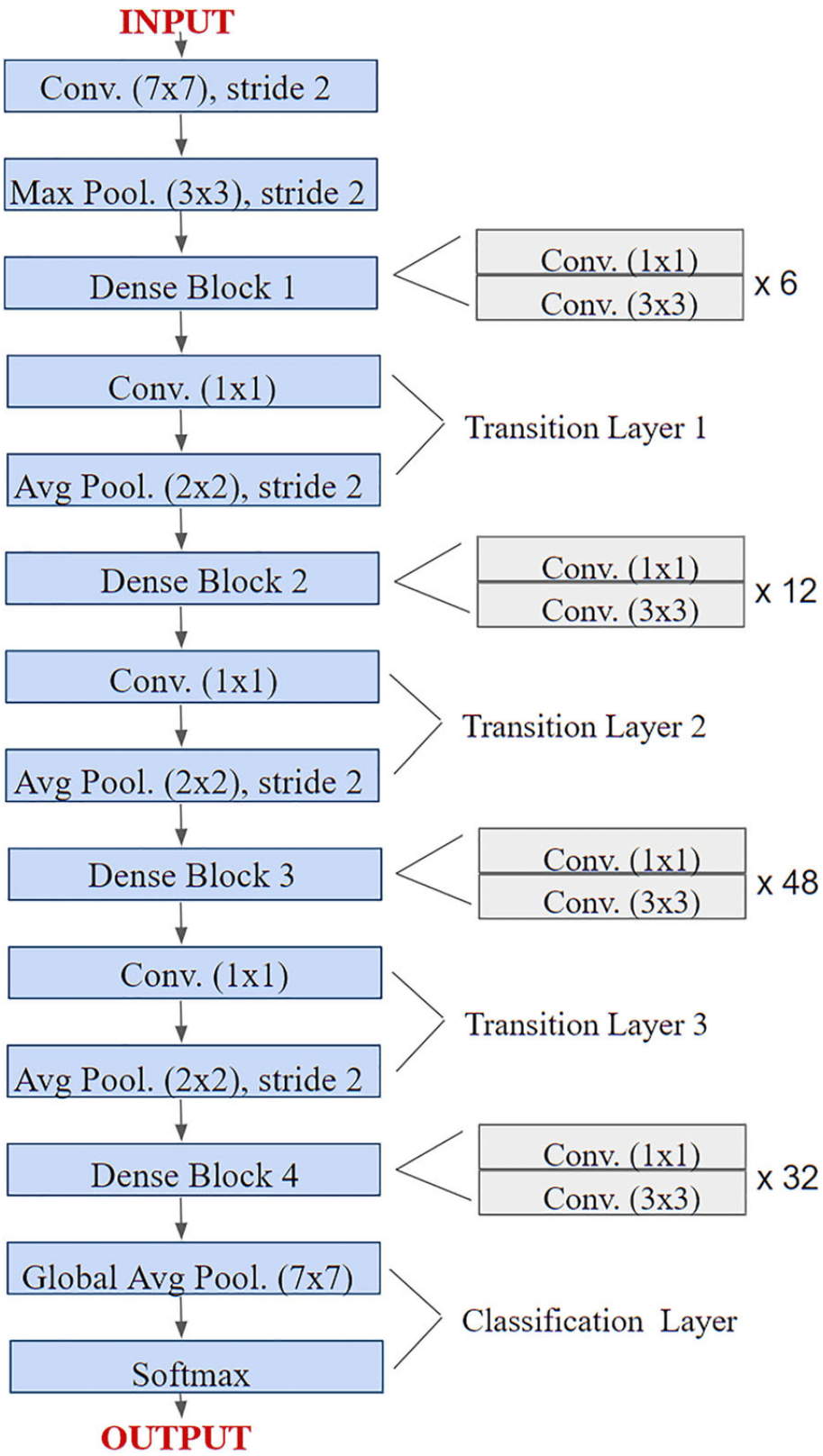

Figure 4.7: DenseNet201 Architecture

4.2.7 EfficientNetB0

The convolutional neural network design known as EfficientNetB0 is the most space-efficient in the EfficientNet family. Despite being smaller and faster to process, the 5.3-million-parameter model outperforms previous models in a variety of computer vision applications. The compound scaling technique used in EfficientNetB0's architectural design maintains uniform depth, width, and resolution as the network grows in size. To strike a good balance between the network's depth, width, and resolution, this method uses a simple yet incredibly efficient compound coefficient. In order to create models with more accuracy and efficiency than previous Convolutional Neural Networks (ConvNets), EfficientNetB0 uses neural architecture search (NAS) to design a revolutionary foundational network and then scale it up. Applications such as image classification, object recognition, and segmentation have found great success with the EfficientNetB0 model. In particular, it has shown considerable improvement in performance compared to baseline models developed in the past.The figure 4.8 shows the architecture of EfficientNetB0

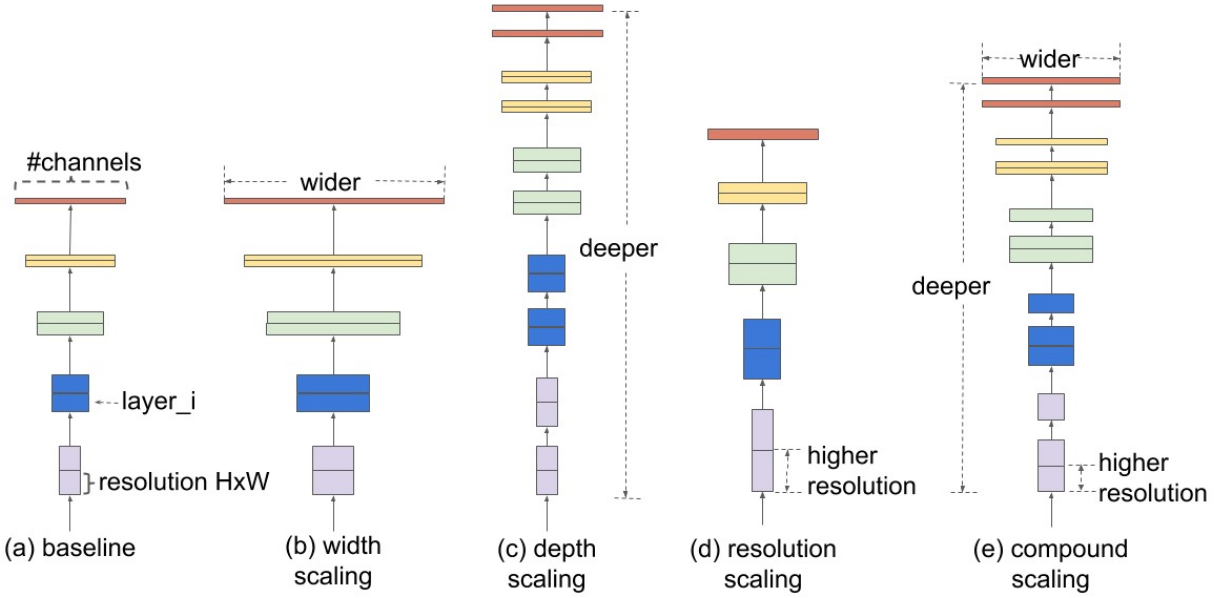

Figure 4.8: EfficientNetB0 Architecture

4.2.8 Ensemble Model-X1

To apply ensemble approach, firstly every single model is fine-tuned. As the dataset has 7 classes for that reason top layer is removed and after that 10 layers is freeze to Globalaveragepooling2D layer and Dense layer is added and it is used for every solo models. As for the ensemble approach when using pre-trained models in an ensemble or transfer learning situation, it is a good idea to freeze the top layers and add new layers like global average pooling. It lets you use the information stored in the pre-trained layers while changing the model to your unique task. This keeps the model from becoming too good at your task and gives the ensemble method more variety, which improves performance overall.The Figure below 4.9 shows the Architecture model. Model averaging is a type of ensemble method in which a lot of smaller models are put together to make a single guess.At a model-averaging ensemble, the

results of several learned models are averaged together. Since each model has its own pros and cons, it's usually best to make a few different ones that can pull out different traits before mixing the predictions of those models.The ensemble method could be used in many different ways, such as the simple average, the weighted average, and the weighted sum. One problem with the average method is that each model adds the same piece to the ensemble forecast. So, the execution doesn't get better and, in the worst case, may even get worse. Because of this, the best way to improve overall performance is with a weighted sum ensemble. It combines estimates from a lot of different models, giving each model's input a certain amount of weight based on how good it is. It can do better than any of the different types in every way.

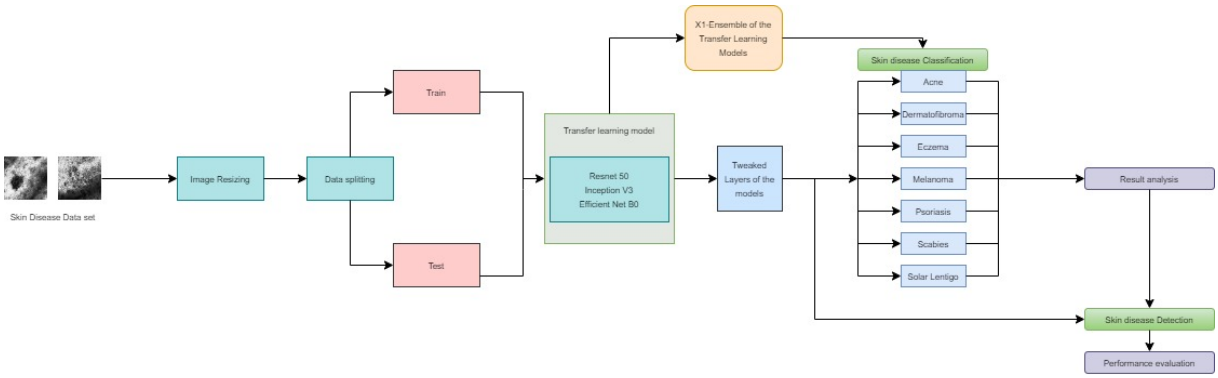

Figure 4.9: Ensemble Model-X1 Architecture

Chapter 5

Results and Discussion

5.1 Results

5.1.1 NasNetMobile

Model Accuracy

For the model NasNetMobile, we can see in the figure 5.1 initially the train accuracy shows approximately 0.98. The train accuracy almost reaches its optimal which is around 1.00 when the epoch is 15. After 40 epochs the training accuracy remains to approximately at 1.00.If we look at the validation accuracy at the initial stage, it shows 0.1 approximately, which fluctuates later on when the epoch increases.It reaches a highest value 0.99 approximately when the epoch is 40.After 40 epochs the validation accuracy comes to approximately at 0.99.

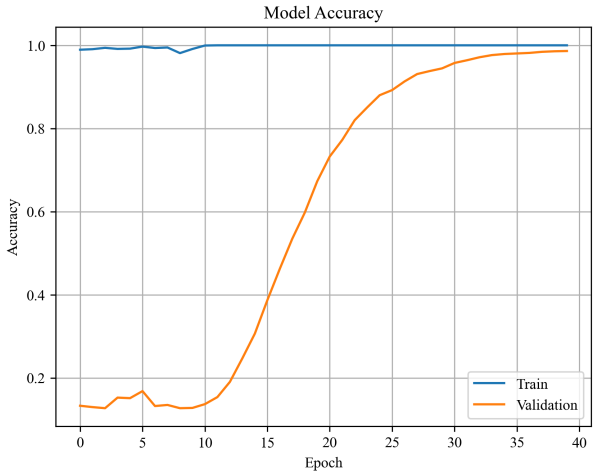

Figure 5.1: NasNetMobile Model Accuracy curve

Model Loss

For the model NasNetMobile, We can see in the figure 5.2 initially the train loss shows approximately 0. The train loss remains around approximately 0 with the increase in epoch. If we look at the validation loss at the initial stage, it shows 100 approximately, which increases and decreases when the epoch increases, but

the curve drastically shows a spike in which the validation loss increases to 1300 approximately after the 7th epoch, it was the highest validation loss. After the drastic increase, the validation loss curve drops to approximately 0 after the 14th epoch and remains the same throughout the 40th.

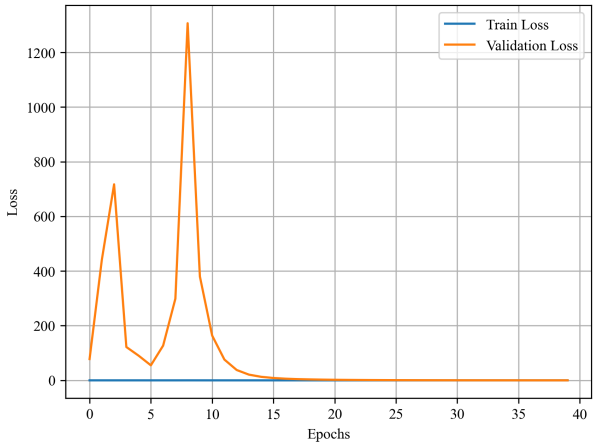

Figure 5.2: NasNetMobile Model Loss curve

Confusion Matrix

The Confusion Matrix for NasNetMobile shown in figure 5.3 describes- Acne: Out of 200 instances that truly belong to Acne, the model correctly predicted all 197 instances as Acne. There were no misclassifications for this class.Dermatofibroma: Among the 255 instances belonging to Dermatofibroma, the model accurately identified 239 as Dermatofibroma. It misclassified 3 instances as Acne, 2 instances as Eczema, 10 instances as Melanoma, and 1 instance as Solar Lentigo.Eczema: For the 221 instances of Eczema, the model correctly classified all of them as Eczema. There were no misclassifications for this class.Melanoma: Among the 223 instances of Melanoma, the model accurately predicted all 223 instances as Melanoma. There were no misclassifications for this class.Psoriasis: Out of 222 instances belonging to Psoriasis, the model correctly identified all 222 instances as Psoriasis. There were no misclassifications for this class.Scabies: For the 195 instances of Scabies, the model correctly predicted 193 as Scabies. It misclassified 1 instance as Psoriasis and 1 instance as Solar Lentigo.Solar Lentigo: Among the 217 instances of Solar Lentigo, the model accurately predicted all 217 instances as Solar Lentigo. There were no misclassifications for this class.

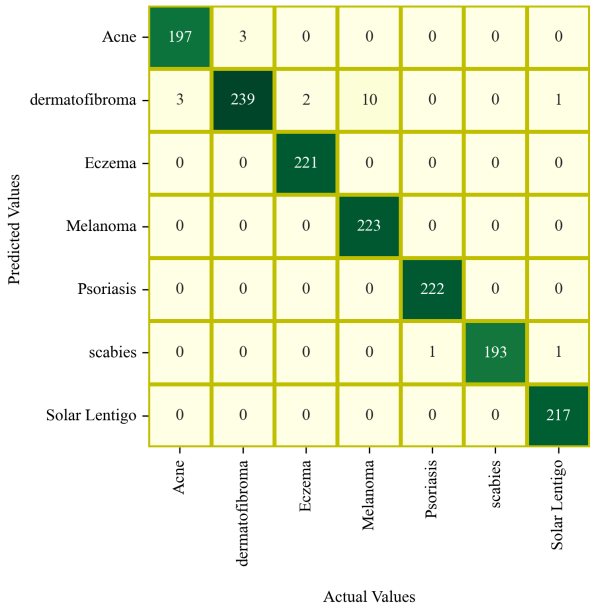

Figure 5.3: NasNetMobile Confusion Matrix

Receiver Operating Characteristic Curve

The ROC curves form the figure 5.4 for different skin conditions, including Acne, Dermatofibroma, Eczema, Melanoma, Psoriasis, Scabies, and Solar Lentigo, all exhibit perfect discrimination with an AUC of 1.00 each. These curves collectively signify that the classification model is exceptionally accurate in distinguishing between these specific skin conditions and non-condition cases. In essence, the model consistently achieves both high sensitivity and high specificity across these dermatological diagnoses, suggesting its robust performance and reliability in correctly identifying these skin conditions.

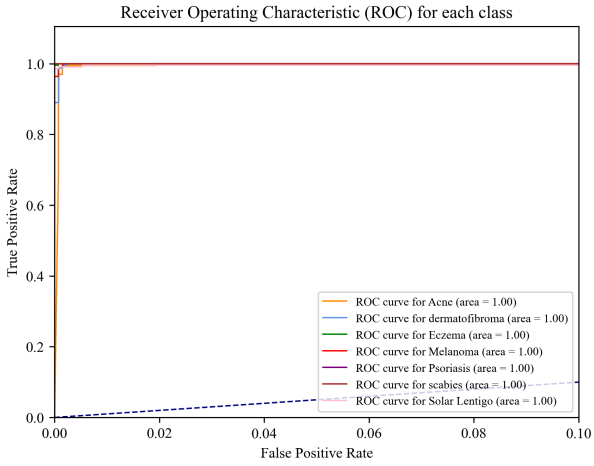

Figure 5.4: NasNetMobile ROC curve

5.1.2 MobileNet

Model Accuracy

For the model MobileNet, We can see in the figure 5.5 initially the train accuracy shows approximately 0.72. When the epoch reaches 15, the train accuracy almost reaches its optimal which is around 0.94. After 40 epochs the training accuracy increases and comes to approximately at 0.96.If we look at the validation accuracy at the initial stage, it shows 0.58 approximately, which fluctuates later on when the epoch increases.It reaches a highest value 0.97 approximately when the epoch is 38.After 40 epochs the validation accuracy comes to approximately at 0.96.

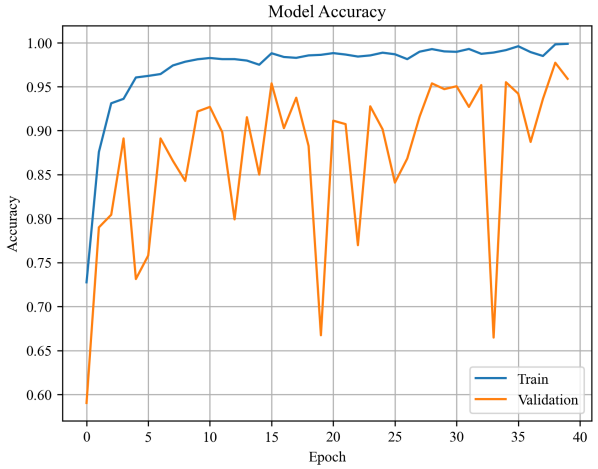

Figure 5.5: MobileNet Model Accuracy curve

Model Loss

For the model MobileNet, We can see in the figure 5.6 initially the train loss shows approximately .75. When the epoch is between 5 to 10 times, the train loss decreases to 0.1 and less and continues to decrease with the increase in epoch.After 40 epochs the train loss is approximately 0.05 If we look at the validation loss at the initial stage, it shows 1.7 approximately, which increases and decreases when the epoch increases, but the curve drastically increases to 3.9 approximately when the epoch is 33. After 40 epochs the validation loss drops and becomes around .25 approximately.

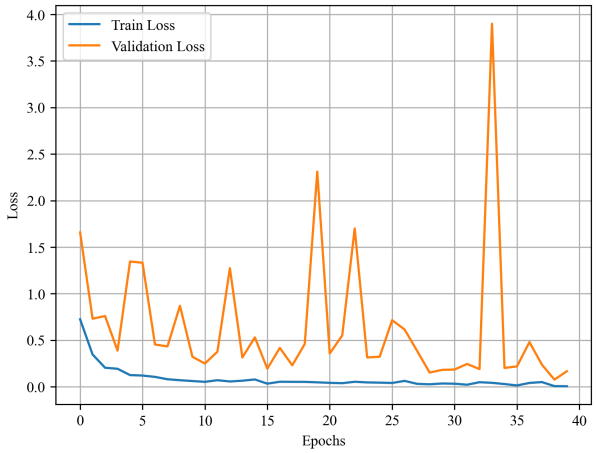

Figure 5.6: MobileNet Model Loss curve

Confusion Matrix

The Confusion Matrix for MobileNet shown in figure 5.7 describes- Acne: Out of 200 instances that truly belong to Acne, the model correctly predicted 184 instances as Acne. However, it misclassified 11 instances as Dermatofibroma, 1 instance as Eczema, 2 instances as Melanoma, and 2 instances as Psoriasis. There were no instances misclassified as Scabies or Solar Lentigo. Dermatofibroma: Among the 255 instances belonging to Dermatofibroma, the model accurately identified 240 as Dermatofibroma. It made mistakes by classifying 1 instance as Acne, 3 instances as Eczema, 8 instances as Melanoma, 2 instances as Psoriasis, and 1 instance as Solar Lentigo. There were no instances misclassified as Scabies. Eczema: For the 221 instances of Eczema, the model correctly classified 220 as Eczema. It misclassified 1 instance as Psoriasis. There were no instances misclassified into other classes. Melanoma: Among the 223 instances of Melanoma, the model accurately predicted 219 as Melanoma. It misclassified 2 instances as Dermatofibroma and 2 instances as Eczema. There were no instances misclassified into other classes. Psoriasis: Out of 222 instances belonging to Psoriasis, the model correctly identified 221 as Psoriasis. It misclassified 1 instance as Scabies. There were no instances misclassified into other classes. Scabies: For the 195 instances of Scabies, the model correctly predicted 192 as Scabies. It misclassified 3 instances as Psoriasis. There were no instances misclassified into other classes. Solar Lentigo: Among the 217 instances of Solar Lentigo, the model accurately predicted 194 as Solar Lentigo. It misclassified 5

instances as Eczema, 5 instances as Melanoma, and 12 instances as Psoriasis. There were no instances misclassified into other classes.

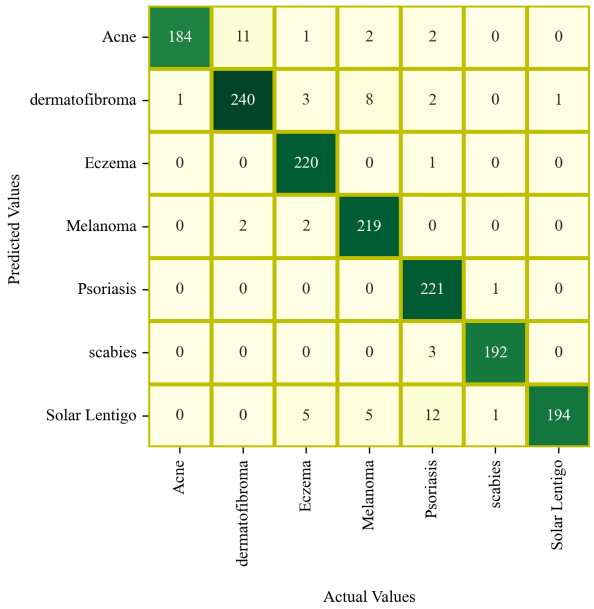

Figure 5.7: MobileNet Confusion Matrix

Receiver Operating Characteristic Curve

The ROC curves form the figure 5.8 for various skin conditions, such as Acne, Dermatofibroma, Eczema, Melanoma, Psoriasis, Scabies, and Solar Lentigo, depict strong discriminatory performance with AUC values ranging from 0.97 to 1.00. These curves collectively demonstrate that the classification model exhibits high accuracy in distinguishing these specific skin conditions from non-condition cases, as indicated by their AUC values close to 1.00. While Dermatofibroma and Psoriasis exhibit slightly lower AUC values, they still showcase effective discrimination capabilities. Overall, the model demonstrates its reliability in correctly identifying these skin conditions, making it a valuable tool in dermatological diagnoses.

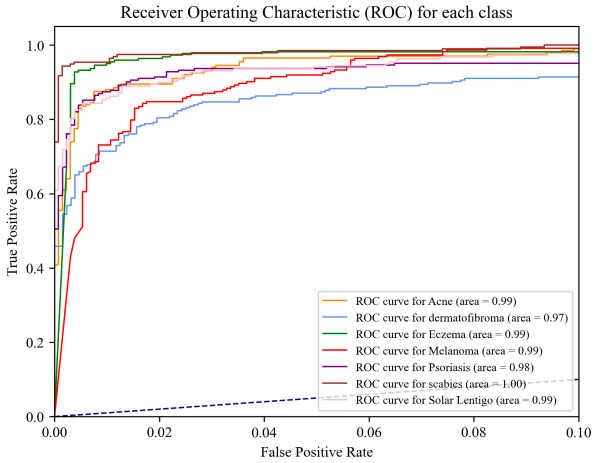

Figure 5.8: MobileNet ROC curve

5.1.3 DenseNet201

Model Accuracy

For the model DenseNet201 we can see in the figure 5.9, initially the train accuracy shows approximately 0.67. When the graph reaches to 15 epoch, the train accuracy almost reaches its optimal which is around 0.95. After 40 epochs the training accuracy increases and comes to approximately at 0.99.If we look at the validation accuracy at the initial stage, it shows 0.5 approximately, which fluctuates later on when the epoch increases.It reaches a highest value 0.94 approximately when the epoch is 35.After 40 epochs the validation accuracy comes to approximately at 0.87.

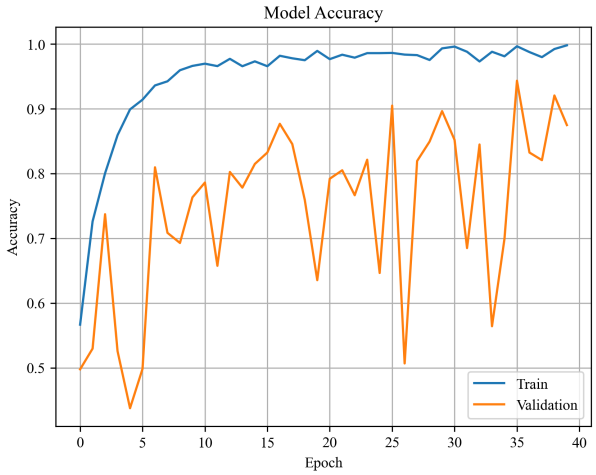

Figure 5.9: DenseNet201 Model Accuracy curve

Model Loss

For the model DenseNet201 we can see in the figure 5.10, initially the train loss shows approximately 1.1. When we epoch 5–10 times, the train loss decreases to 0.5 and less and continues to decrease with the increase in epoch. If we look at the validation loss at the initial stage, it shows 1.8 approximately, which increases and decreases when we epoch twice, but the curve drastically increases to 5.4 approximately after the third epoch. After the drastic increase, the validation loss curve drops to approximately 1.7 after the fifth epoch. With the increase in epoch, the validation loss curve has a considerable number of ups and downs.

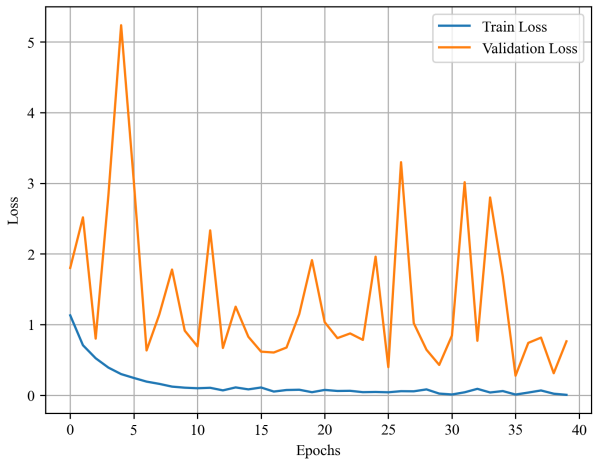

Figure 5.10: DenseNet201 Model Loss curve

Confusion Matrix

The Confusion Matrix for Densenet201 shown in figure 5.11 describes- Acne: Out of 200 instances that truly belong to Acne, the model correctly predicted 148 instances as Acne. However, it misclassified 11 instances as Dermatofibroma and 2 instances as Melanoma. Additionally, it incorrectly classified 39 instances as Solar Lentigo. Dermatofibroma: Among the 255 instances belonging to Dermatofibroma, the model accurately identified 215 as Dermatofibroma. It misclassified 6 instances as Acne, 2 instances as Melanoma, 2 instances as Psoriasis, and 1 instance as Scabies. Additionally, it incorrectly classified 29 instances as Solar Lentigo. Eczema: For the 221 instances of Eczema, the model correctly classified 210 as Eczema. It misclassified 1 instance as Acne, 4 instances as Dermatofibroma, and 1 instance as Psoriasis. Additionally, it incorrectly classified 2 instances as Scabies and 3 instances as Solar Lentigo. Melanoma: Among the 223 instances of Melanoma, the model accurately predicted 182 as Melanoma. It misclassified 4 instances as Acne and 9 instances as Dermatofibroma. Additionally, it incorrectly classified 28 instances as Solar Lentigo. Psoriasis: Out of 222 instances belonging to Psoriasis, the model correctly identified 177 as Psoriasis. However, it misclassified 33 instances as Scabies and 12 instances as Solar Lentigo. There were no instances misclassified into other classes. Scabies: For the 195 instances of Scabies, the model correctly predicted 193 as Scabies. It misclassified 1 instance as Melanoma and 1 instance as Solar Lentigo. There were no instances misclassified into other classes. Solar Lentigo: Among the 217 instances of Solar Lentigo, the model accurately predicted 216 as Solar Lentigo. It misclassified 1 instance as Dermatofibroma. There were no instances misclassified into other classes.

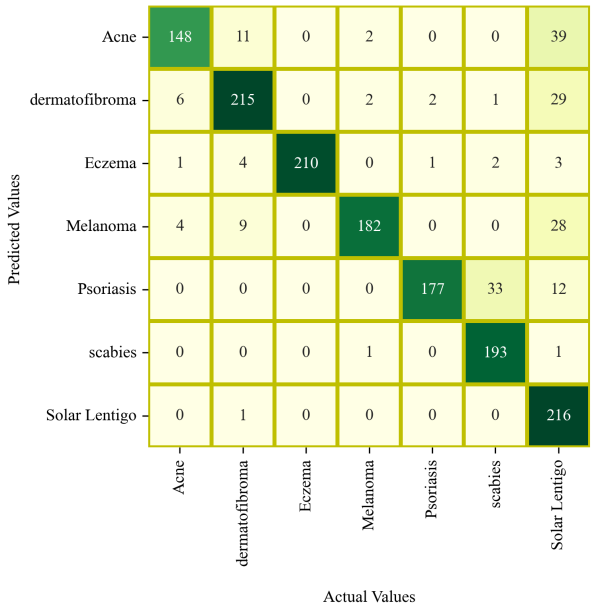

Figure 5.11: Densenet201 Confusion Matrix

Receiver Operating Characteristic Curve

The ROC curves form the figure 5.12 for various skin conditions, such as Acne, Dermatofibroma, Eczema, Melanoma, Psoriasis, Scabies, and Solar Lentigo, depict strong discriminatory performance with AUC values ranging from 0.97 to 1.00. These curves collectively demonstrate that the classification model exhibits high accuracy in distinguishing these specific skin conditions from non-condition cases, as indicated by their AUC values close to 1.00. While Dermatofibroma and Psoriasis exhibit slightly lower AUC values, they still showcase effective discrimination capabilities. Overall, the model demonstrates its reliability in correctly identifying these skin conditions, making it a valuable tool in dermatological diagnoses.

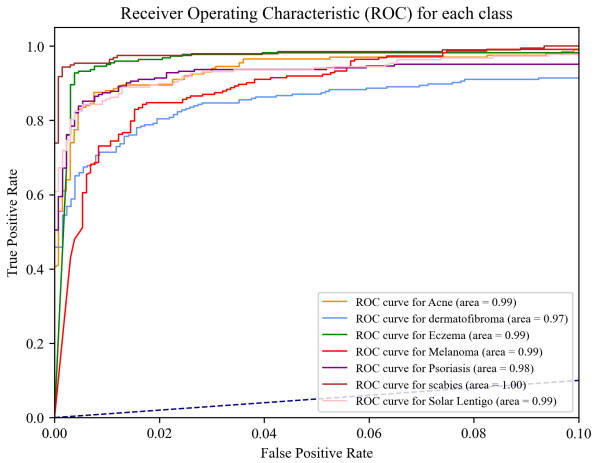

Figure 5.12: Densenet201 ROC curve

5.1.4 Xception

Model Accuracy

After running Extreme Inception (Xception) was capable of differentiating between different types of skin diseases with an accuracy of 86% in figure 5.13.Initially the train accuracy shows approximately 0.69. When the epoch 15 reaches, the train accuracy almost reaches its optimal which is around 0.95. After 40 epochs the training accuracy increases and comes to approximately at 0.97.If we look at the validation accuracy at the initial stage, it shows 0.67 approximately, which fluctuates later on when the epoch increases.It reaches a highest value 0.96 approximately when the epoch is 31.After 40 epochs the validation accuracy comes to approximately at 0.86.

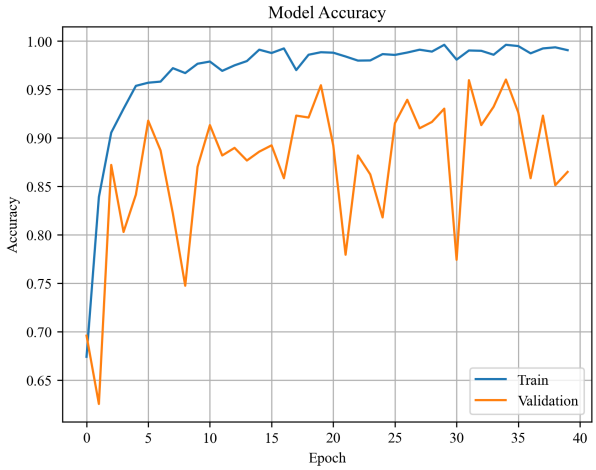

Figure 5.13: Xception Model Accuracy curve

Model Loss

In the figure 5.14 initially the train loss shows approximately 0.9. When the epoch increases to 5–10 times, the train loss decreases to 0.1 approximately and less and continues to decrease with the increase in epoch. If we look at the validation loss at the initial stage, it shows 2.6 approximately, which increases and decreases with increases with the epoch. Eventually it reaches to 0.95 when the epoch reaches to 40.

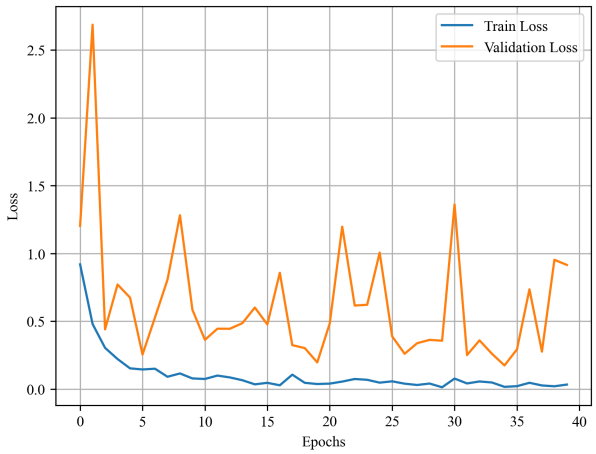

Figure 5.14: Xception Model Loss curve

Confusion Matrix

The Confusion Matrix for Xception shown in figure 5.15Acne:Out of 200 instances that truly belong to Acne, the model correctly predicted 189 instances as Acne. However, it misclassified 2 instances as Dermatofibroma, 1 instance as Eczema, 2 instances as Melanoma, 5 instances as Scabies, and 1 instance as Solar Lentigo. Dermatofibroma:Among the 255 instances belonging to Dermatofibroma, the model accurately identified 197 as Dermatofibroma. It made mistakes by classifying 13 instances as Acne, 14 instances as Melanoma, 2 instances as Psoriasis, 7 instances as Scabies, and 22 instances as Solar Lentigo.Eczema:For the 221 instances of Eczema, the model correctly classified 195 as Eczema. It misclassified 1 instance as Acne, 4 instances as Psoriasis, 17 instances as Scabies, and 3 instances as Solar Lentigo.Melanoma:Among the 223 instances of Melanoma, the model accurately predicted 193 as Melanoma. It misclassified 4 instances as Dermatofibroma, 9 instances as Scabies, and 17 instances as Solar Lentigo, while correctly classifying 193 instances.Psoriasis:Out of 222 instances belonging to Psoriasis, the model correctly identified 150 as Psoriasis. It incorrectly classified 1 instance each as Acne and Melanoma, and 64 instances as Scabies, while the remaining 7 instances were correctly classified as Solar Lentigo.Scabies:For the 195 instances of Scabies, the model correctly predicted all of them as Scabies. There were no misclassifications into other classes.Solar Lentigo:Among the 217 instances of Solar Lentigo, the model accurately predicted 207 as Solar Lentigo. It did misclassify 10 instances as Scabies, but did not misclassify any into the other classes.

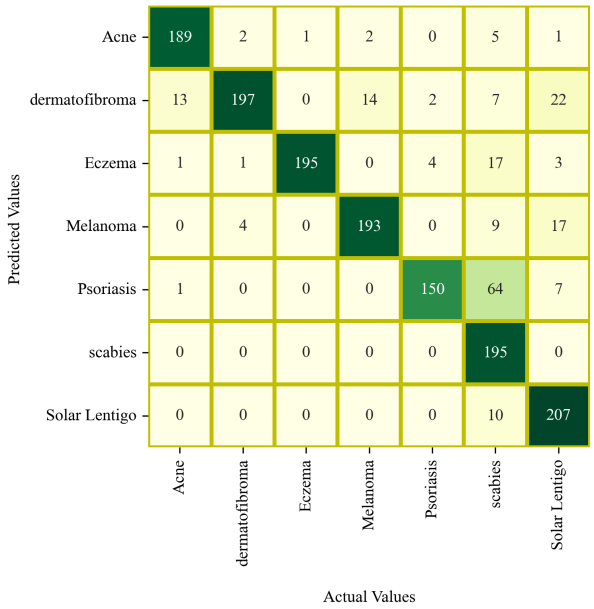

Figure 5.15: Xception Confusion Matrix

Receiver Operating Characteristic Curve

The ROC curve form the figure 5.16 for each skin conditions, including Acne, Dermatofibroma, Eczema, Melanoma, Psoriasis, Scabies, and Solar Lentigo, demonstrate strong discriminatory power with AUC values mostly exceeding 0.98. These curves collectively indicate that the classification model performs exceptionally well in distinguishing these specific skin conditions from non-condition cases. The near-perfect AUC values of 1.00 for Acne, Eczema, and Solar Lentigo, along with high AUC values for the others, underscore the model's remarkable accuracy in correctly identifying these dermatological conditions, making it a highly reliable tool for dermatological diagnoses.

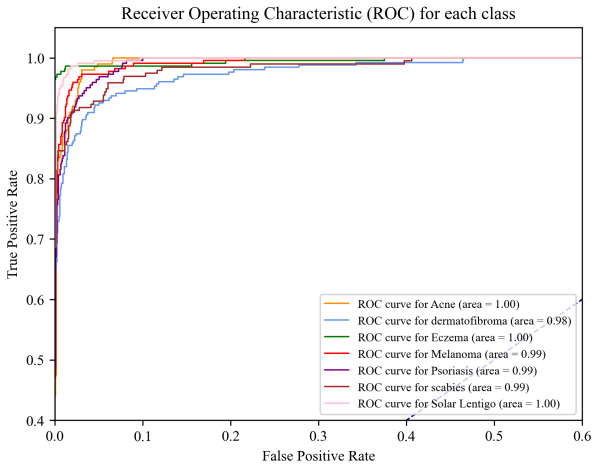

Figure 5.16: Xception ROC curve

5.1.5 EfficientNetB0

Model Accuracy

For the model EfficientNetB0, We can see in the figure 5.17 initially the train accuracy shows approximately 0.38. The train accuracy almost reaches its optimal which is around 0.97 when it is approximately 20 epoch. After 40 epochs the training accuracy increases and comes to approximately at 0.99.If we look at the validation accuracy at the initial stage, it shows 0.27 approximately, which fluctuates later on when the epoch increases.It reaches a highest value 0.92 approximately when the epoch is 34. After 40 epochs the validation accuracy comes to approximately at 0.606.

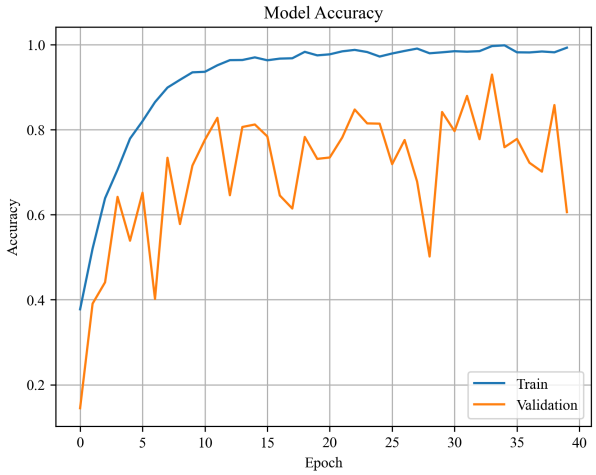

Figure 5.17: EfficientNetB0 Model Accuracy curve

Model Loss

For the model EfficientNetB0, We can see in the figure 5.18 initially the train loss shows approximately 1.5. When the epoch decreases to 5–10 times, the train loss decreases to 0.19 and less and continues to decrease with the increase in epoch.After 40 epochs the training loss decreases and comes to approximately at 0.02. If we look at the validation loss at the initial stage, it shows approximately 13.9, which increases and decreases when the epoch increases.With the increase in epoch, the validation loss curve has a considerable number of ups and downs.After 40 epochs the training loss decreases and comes to approximately at 0.60.

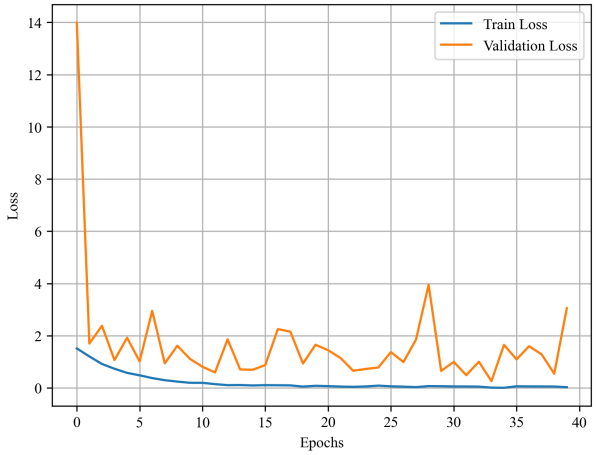

Figure 5.18: EfficientNetB0 Model Loss curve

Confusion Matrix

The Confusion Matrix for EfficientNetB0 shown in figure 5.19-Acne Out of 200 instances that truly belong to Acne, the model correctly predicted 133 instances as Acne. However, it misclassified 30 instances as Dermatofibroma, 10 instances as Eczema, 19 instances as Melanoma, and 8 instances as Solar Lentigo. There were no instances misclassified as Psoriasis or Scabies. Dermatofibroma Among the 255 instances belonging to Dermatofibroma, the model accurately identified 148 as Dermatofibroma. It made mistakes by classifying 48 instances as Acne, 2 instances as Eczema, 35 instances as Melanoma, and 22 instances as Solar Lentigo. There were no instances misclassified as Psoriasis or Scabies. Eczema For the 221 instances of Eczema, the model correctly classified 192 as Eczema. It misclassified 15 instances as Acne, 3 instances as Dermatofibroma, 6 instances as Melanoma, and 5 instances as Solar Lentigo. There were no instances misclassified as Psoriasis or Scabies. Melanoma Among the 223 instances of Melanoma, the model accurately predicted 128 as Melanoma. It misclassified 36 instances as Acne, 40 instances as Dermatofibroma, 2 instances as Eczema, 1 instance as Scabies, and 16 instances as Solar Lentigo. There were no instances misclassified as Psoriasis. Psoriasis Out of 222 instances belonging to Psoriasis, the model correctly identified 41 as Psoriasis. However, it misclassified 9 instances as Acne, 20 instances as Dermatofibroma, 67 instances as Eczema, 4 instances as Melanoma, 2 instances as Scabies, and 79 instances as Solar Lentigo. Scabies For the 195 instances of Scabies, the model correctly predicted 120 as Scabies. It misclassified 20 instances as Acne, 5 instances as Dermatofibroma, 8 instances as Eczema, 1 instance as Melanoma, and 41 instances as Solar Lentigo. There were no instances misclassified as Psoriasis. Solar Lentigo Among the 217 instances of Solar Lentigo, the model accurately predicted 167 as Solar Lentigo. It misclassified 21 instances as Acne, 18 instances as Dermatofibroma, 2 instances as Eczema, 9 instances as Melanoma, and no instances as Psoriasis or Scabies.

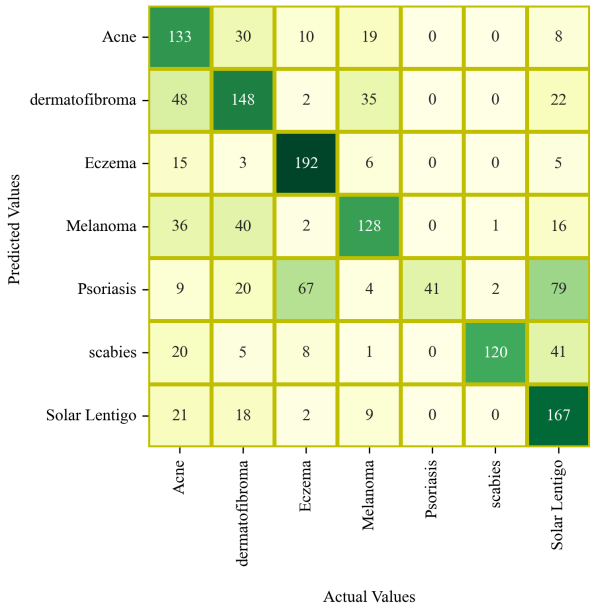

Figure 5.19: EfficientNetB0 Confusion Matrix

Receiver Operating Characteristic Curve

The ROC curves form the figure 5.20 for various skin conditions, including Acne, Dermatofibroma, Eczema, Melanoma, Psoriasis, Scabies, and Solar Lentigo, show good but varying discriminatory performance, with AUC values ranging from 0.79 to 0.95. While some conditions, such as Eczema, exhibit a higher AUC of 0.95, indicating strong discrimination, others like Psoriasis have a slightly lower AUC of 0.79. Overall, the model demonstrates reasonable accuracy in distinguishing these specific skin conditions from non-condition cases. However, it's important to note that there is room for improvement in the model's performance, particularly for Psoriasis, Dermatofibroma, and Acne, where the AUC values are comparatively lower. Further refinement of the model may enhance its reliability as a diagnostic tool for dermatological conditions.

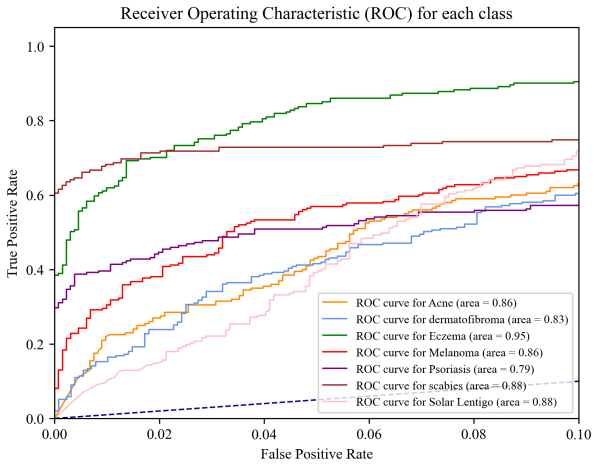

Figure 5.20: EfficientNetB0 ROC curve

5.1.6 InceptionV3

Model Accuracy

For the model InceptionV3, We can see in the figure 5.21 initially the train accuracy shows approximately 0.43. The train accuracy almost reaches its optimal which is around 0.97 when it is approximately 15 epoch. After 40 epochs the training accuracy increases and comes to approximately at 0.98.If we look at the validation accuracy at the initial stage, it shows 0.32 approximately, which fluctuates later on when the epoch increases.It reaches a highest value 0.88 approximately when the epoch is 37. After 40 epochs the validation accuracy comes to approximately 0.79.

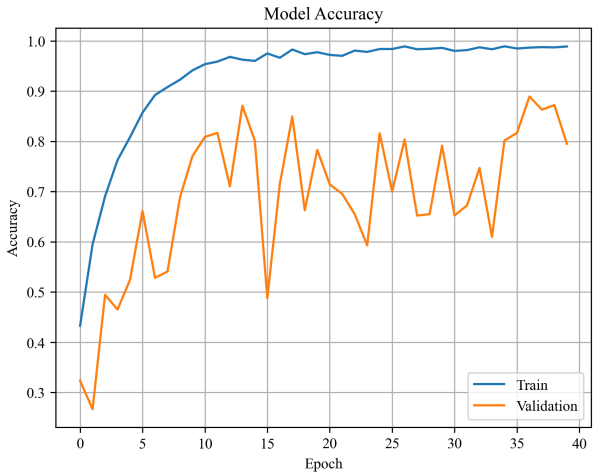

Figure 5.21: InceptionV3 Model Accuracy curve

Model Loss

For the model InceptionV3, 5.22 initially the train loss shows approximately 1.4. When the epoch decreases to 5–15 times, the train loss decreases to 0.12 and less and continues to decrease with the increase in epoch.After 40 epochs the training loss decreases and comes to approximately at 0.03. If we look at the validation loss at the initial stage, it shows approximately 2.4, which increases and decreases when the epoch increases.With the increase in epoch, the validation loss curve has a considerable number of ups and downs.After 40 epochs the training loss decreases and comes to approximately at 1.3.

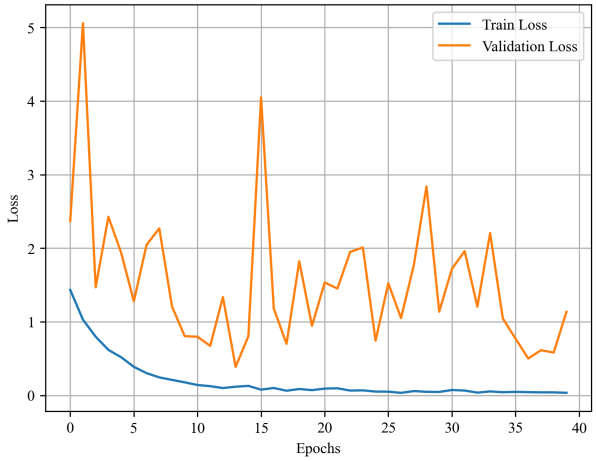

Figure 5.22: InceptionV3 Model Loss curve

Confusion Matrix

The Confusion Matrix for InceptionV3 shown in figure 5.23Acne Out of 200 instances that truly belong to Acne, the model correctly predicted 100 instances as Acne. However, it misclassified 32 instances as Dermatofibroma, 1 instance as Eczema, 48 instances as Melanoma, 17 instances as Psoriasis, and 2 instances as Solar Lentigo. There were no instances misclassified as Scabies. Dermatofibroma Among the 255 instances belonging to Dermatofibroma, the model accurately identified 193 as Dermatofibroma. It made mistakes by classifying 1 instance as Acne, 1 instance as Eczema, 47 instances as Melanoma, and 13 instances as Psoriasis. There were no instances misclassified as Scabies or Solar Lentigo. Eczema For the 221 instances of Eczema, the model correctly classified 209 as Eczema. It misclassified 1 instance as Acne, 2 instances as Melanoma, and 4 instances as Psoriasis. There were no instances misclassified as Dermatofibroma or Solar Lentigo. Melanoma Among the 223 instances of Melanoma, the model accurately predicted 216 as Melanoma. It misclassified 5 instances as Dermatofibroma and 2 instances as Eczema. There were no instances misclassified as Acne, Psoriasis, Scabies, or Solar Lentigo. Psoriasis Out of 222 instances belonging to Psoriasis, the model correctly identified 216 as Psoriasis. However, it misclassified 3 instances as Dermatofibroma, 1 instance as Eczema, and 1 instance as Melanoma. There were no instances misclassified as Acne, Scabies, or Solar Lentigo. Scabies For the 195 instances of Scabies, the model correctly predicted 120 as Scabies. It misclassified 4 instances as Eczema, 4 instances as Melanoma, 65 instances as Psoriasis, and 2 instances as Solar Lentigo. There were no instances misclassified as Acne or Dermatofibroma. Solar Lentigo Among the 217 instances of Solar Lentigo, the model accurately predicted 165 as Solar Lentigo. It misclassified 6 instances as Acne, 9 instances as Dermatofibroma, 2 instances as Eczema, 15 instances as Melanoma, and 19 instances as Psoriasis. There was one instance correctly classified as Scabies.

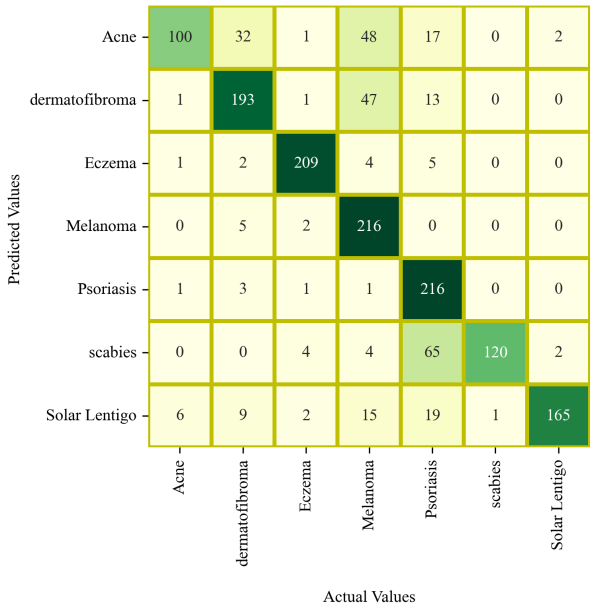

Figure 5.23: InceptionV3 Confusion Matrix

Receiver Operating Characteristic Curve

The ROC curves form the figure 5.24 for various skin conditions, including Acne, Dermatofibroma, Eczema, Melanoma, Psoriasis, Scabies, and Solar Lentigo, show good but varying discriminatory performance, with AUC values ranging from 0.79 to 0.95. While some conditions, such as Eczema, exhibit a higher AUC of 0.95, indicating strong discrimination, others like Psoriasis have a slightly lower AUC of 0.79. Overall, the model demonstrates reasonable accuracy in distinguishing these specific skin conditions from non-condition cases. However, it's important to note that there is room for improvement in the model's performance, particularly for Psoriasis, Dermatofibroma, and Acne, where the AUC values are comparatively lower. Further refinement of the model may enhance its reliability as a diagnostic tool for dermatological conditions.

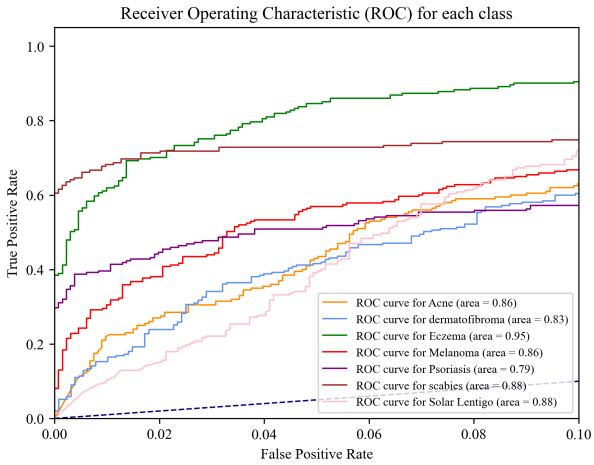

Figure 5.24: InceptionV3 ROC curve

5.1.7 Resnet50

Model Accuracy

For the model Resnet50, We can see in the figure 5.25 initially the train accuracy shows approximately 0.55. The train accuracy almost reaches its optimal which is around 0.98 when it is approximately 12 epoch. After 40 epochs the training accuracy increases and comes to approximately at 0.99.If we look at the validation accuracy at the initial stage, it shows 0.27 approximately, which fluctuates later on when the epoch increases.It reaches a highest value 0.92 approximately when the epoch is 38. After 40 epochs the validation accuracy comes to approximately at 0.92.

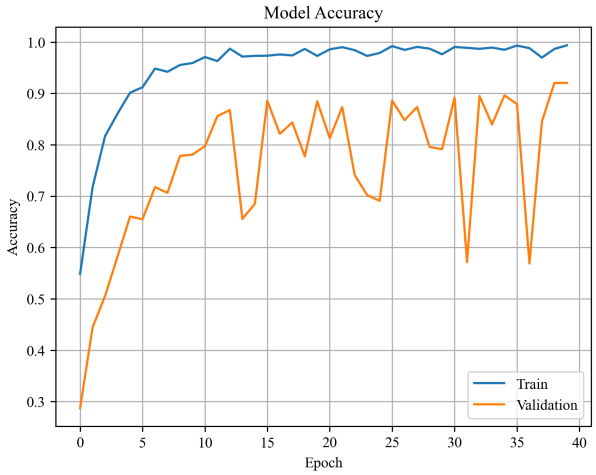

Figure 5.25: ResNet50 Model Accuracy curve

Model Loss

For the model Resnet50, We can see in the figure 5.26 initially the train loss shows approximately 1. When the epoch decreases to 5–10 times, the train loss decreases to 0.1 and less and continues to decrease with the increase in epoch.After 40 epochs the training loss decreases and comes to approximately at 0.01. If we look at the validation loss at the initial stage, it shows approximately 11, which increases and decreases when the epoch increases.With the increase in epoch, the validation loss curve has a considerable number of ups and downs.After 40 epochs the training loss decreases and comes to approximately at 0.8.

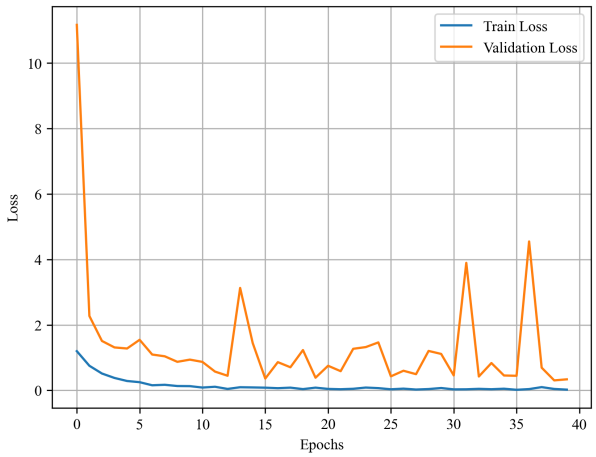

Figure 5.26: ResNet50 Model Loss curve

Confusion Matrix

The Confusion Matrix for ResNet50 shown in figure 5.27 Acne Out of 200 instances that truly belong to Acne, the model correctly predicted 186 instances as Acne. However, it misclassified 10 instances as Dermatofibroma, 3 instances as Melanoma, 1 instance as Psoriasis. There were no instances misclassified as Eczema, Scabies, or Solar Lentigo. Dermatofibroma Among the 255 instances belonging to Dermatofibroma, the model accurately identified 198 as Dermatofibroma. It made mistakes by classifying 25 instances as Acne, 3 instances as Eczema, 16 instances as Melanoma, 10 instances as Psoriasis, and 3 instances as Solar Lentigo. There were no instances misclassified as Scabies. Eczema For the 221 instances of Eczema, the model correctly classified 209 as Eczema. It misclassified 1 instance as Acne, 7 instances as Psoriasis, 3 instances as Scabies, and 1 instance as Solar Lentigo. There were no instances misclassified as Dermatofibroma or Melanoma. Melanoma Among the 223 instances of Melanoma, the model accurately predicted 204 as Melanoma. It misclassified 2 instances as Acne, 11 instances as Dermatofibroma, 1 instance as Eczema, and 3 instances as Solar Lentigo. There were no instances misclassified as Psoriasis or Scabies. Psoriasis Out of 222 instances belonging to Psoriasis, the model correctly identified 215 as Psoriasis. However, it misclassified 6 instances as Scabies. There were no instances misclassified as Acne, Dermatofibroma, Eczema, Melanoma, or Solar Lentigo. Scabies For the 195 instances of Scabies, the model correctly predicted 188 as Scabies. It misclassified 7 instances as Psoriasis. There were no instances misclassified as Acne, Dermatofibroma, Eczema, Melanoma, or Solar Lentigo. Solar Lentigo Among the 217 instances of Solar Lentigo, the model accurately predicted 211 as Solar Lentigo. It misclassified 2 instances as Acne, 1 instance as Eczema, and 1 instance as Psoriasis. There were no instances misclassified as Dermatofibroma, Melanoma, or Scabies.

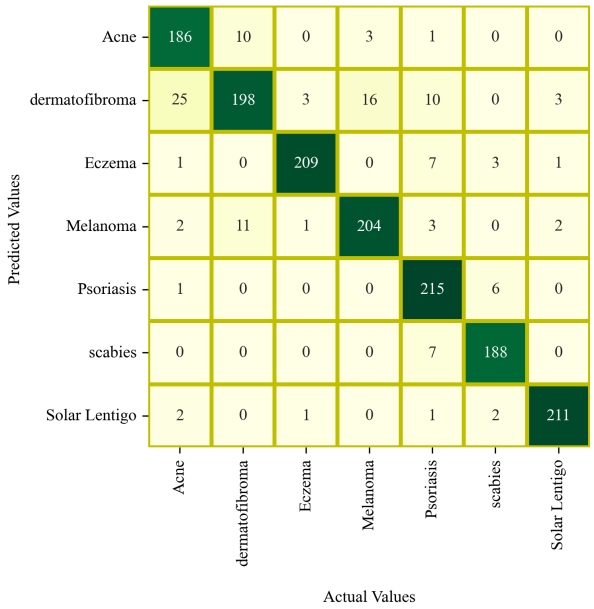

Figure 5.27: ResNet50 Confusion Matrix

Receiver Operating Characteristic Curve

The ROC curves form the figure 5.28 for various skin conditions, including Acne, Dermatofibroma, Eczema, Melanoma, Psoriasis, Scabies, and Solar Lentigo, all exhibit excellent discriminatory performance, with AUC values ranging from 0.99 to 1.00. These curves collectively highlight the model's outstanding accuracy in distinguishing these specific skin conditions from non-condition cases. Melanoma, Psoriasis, Scabies, and Solar Lentigo achieve a perfect AUC of 1.00, signifying flawless discrimination, while the other conditions are close behind with AUCs of 0.99. These results underscore the model's exceptional reliability and effectiveness as a diagnostic tool for dermatological conditions, making it an invaluable asset in clinical practice.

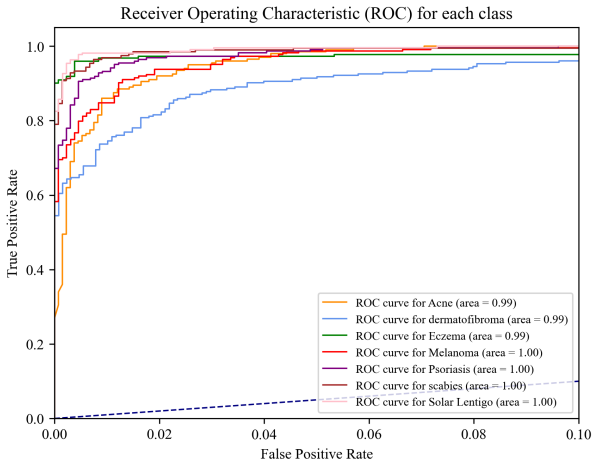

Figure 5.28: ResNet50 ROC curve

5.1.8 Ensemble Model- X1

Model Accuracy

For the model Ensemble Model- X1, We can see in the figure 5.29 initially the train accuracy shows approximately 0.97. The train accuracy almost reaches its optimal which is around 1.00 when it is approximately 5 epoch. After 40 epochs the training accuracy increases and comes to approximately at 0.99.If we look at the validation accuracy at the initial stage, it shows 0.70 approximately, which fluctuates later on when the epoch increases.It reaches a highest value 0.96 approximately when the epoch is 38. After 40 epochs the validation accuracy comes to approximately 0.94.

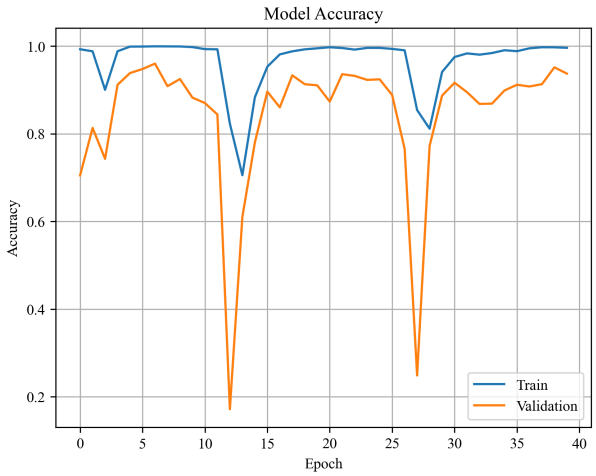

Figure 5.29: Ensemble Model Accuracy curve

Model Loss

For the model Ensemble Model- X1, We can see in the figure 5.30 initially the train loss shows approximately 0.1.After 40 epochs the training loss decreases and comes to approximately at 0.01. If we look at the validation loss at the initial stage, it shows approximately 1, which increases and decreases when the epoch increases.With the increase in epoch, the validation loss curve has a considerable number of ups and downs.After 40 epochs the training loss decreases and comes to approximately at 0.5.

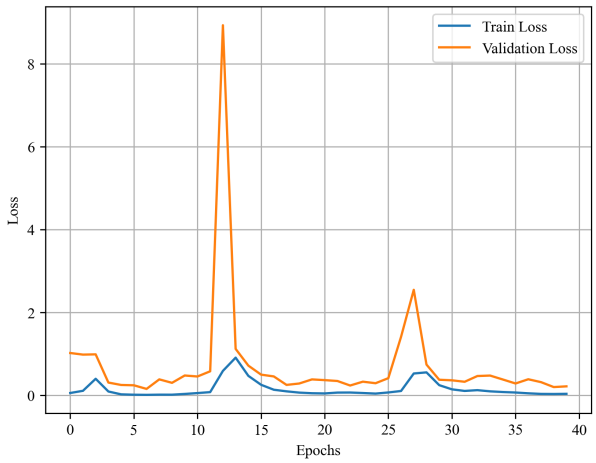

Figure 5.30: Ensemble Model Loss curve

Confusion Matrix

The Confusion Matrix for Ensemble Model- X1 shown in figure 5.31 Acne:Out of 200 instances that truly belong to Acne, the model correctly predicted 181 instances as Acne. There were no instances misclassified as any other class. Dermatofibroma: Among the 255 instances belonging to Dermatofibroma, the model accurately identified 231 as Dermatofibroma. It made mistakes by classifying 5 instances as Acne, 16 instances as Melanoma, 3 instances as Psoriasis. There were no instances misclassified as Eczema, Scabies, or Solar Lentigo.Eczema: For the 221 instances of Eczema, the model correctly classified 215 as Eczema. It misclassified 2 instances as Acne, 1 instance as Melanoma, and 2 instances as Psoriasis. There were no instances misclassified as Dermatofibroma, Scabies, or Solar Lentigo.Melanoma: Among the 223 instances of Melanoma, the model accurately predicted 221 as Melanoma. There were no instances misclassified as any other class. Psoriasis: Out of 222 instances belonging to Psoriasis, the model correctly identified 217 as Psoriasis. It misclassified 3 instances as Acne, 1 instance as Scabies, and 1 instance as Solar Lentigo. There were no instances misclassified as Dermatofibroma, Eczema, or Melanoma. Scabies: For the 195 instances of Scabies, the model correctly predicted 165 as Scabies. It misclassified 1 instance as Acne, 1 instance as Dermatofibroma, 1 instance as Melanoma, 25 instances as Psoriasis, and 2 instances as Solar Lentigo. There were no instances misclassified as Eczema. Solar Lentigo: Among the 217 instances of Solar Lentigo, the model accurately predicted 207 as Solar Lentigo. It misclassified 3 instances as Acne and 7 instances as Dermatofibroma. There were no instances misclassified as Eczema, Melanoma, Psoriasis, or Scabies.

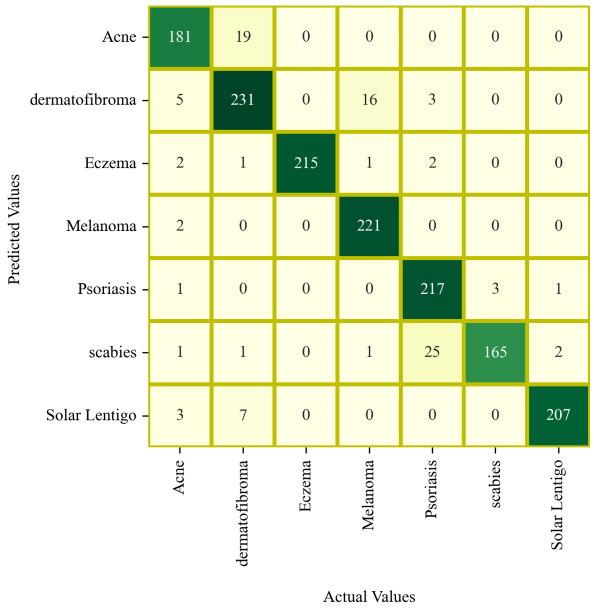

Figure 5.31: Ensemble Confusion Matrix

Receiver Operating Characteristic Curve

The ROC curves form the figure 5.32 for various skin conditions, including Acne, Dermatofibroma, Eczema, Melanoma, Psoriasis, Scabies, and Solar Lentigo, all exhibit excellent discriminatory performance, with AUC values ranging from 0.99 to 1.00. These curves collectively highlight the model's outstanding accuracy in distinguishing these specific skin conditions from non-condition cases. Acne, Eczema, Melanoma, Psoriasis, Scabies, and Solar Lentigo achieve a perfect AUC of 1.00, signifying flawless discrimination, while the other conditions are close behind with AUCs of 0.99. These results underscore the model's exceptional reliability and effectiveness as a diagnostic tool for dermatological conditions, making it an invaluable asset in clinical practice.

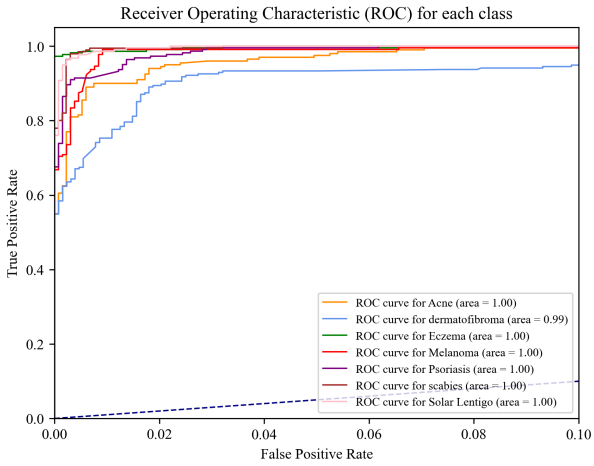

Figure 5.32: Ensemble ROC curve

5.2 Discussion

The analysis tried to make predictions using the models covered below as shown in the table 5.1. The study found that the chosen algorithms are reasonably good at detecting skin diseases in digitized skin scans. Therefore, NasNetMobile, on the other hand, has the best metrics. That confirms the findings of the study here. From our study, we can find that NasNetMobile obtained an F1-score of 0.99, better than the present report's results.This research complements their findings by evaluating the model against others like it to guarantee satisfactory outcomes.
From our study, we get better accuracy, precession call, and f-1 score in MobileNet and Resnet50 Model. Because the data was insufficient to use train, validation, and splitting operations.
In NasNetMobile, we found a mean accuracy of 99%, and a precession of 0.99. F-1 score of 0.99 and mean recall of 0.99. In the MobileNet model, the mean precession is 0.96, the mean recall is also 0.96, the mean f-1 score is 0.96 and the accuracy is 96% . The scores are close to NasNetMobile. But in NasNetMobile, we get more accuracy and better precession calls.
More specifically, when comparing skin diseases, our technique can distinguish between affected skin and normal skin. As a consequence of this, it is extremely important to differentiate it from other conditions that display themselves as sores on the skin. This study only looked at four different labels, however previous research has looked at a far larger number.
Several skin diseases are being investigated. Apart from acne, solar lentigo, psoriasis etc, the 'many models' technique has also been used to detect other diseases. One of the benefits of using a variety of models is that the researcher is given the opportunity to evaluate each one and determine which one has produced the best results. Images of dermatofibroma, eczema, acne etc may be hard to come across right now due to their scarcity. A number of the photographs on Google may not be of the disease, although they are labeled as their designated names by certain websites. Before incorporating skin scans in model prediction and training, researchers must pay a microbiologist to evaluate them.

Table 5.1: Preliminary Computational results of the ML algorithms used during this studies

Model	Precision	Recall	$F_1 Score$	Accuracy	AUC
NasNetMobile	0.99	0.99	0.99	0.99	1.00
MobileNet	0.96	0.96	0.96	0.96	0.987
Resnet50	0.92	0.92	0.92	0.92	0.995
Densenet201	0.90	0.87	0.88	0.87	0.987
Xception	0.89	0.86	0.87	0.87	0.993
InceptionV3	0.84	0.80	0.79	0.80	0.864
EfficientNetB0	0.68	0.61	0.59	0.61	0.864

Chapter 6

Conclusion and Future Works

6.1 Conclusion

The identification and classification of skin conditions like as acne, melanoma, solar lentigo, dermatofibroma, psoriasis, and scabies have garnered significant attention in the academic real of deep learning. Various models, including Xception, Inception, DenseNet201, NASNetMobile, DenseNet201, ResNet, and EfficientNet, are now being explored and studied in this context. The utilization of deep learning models has demonstrated promising outcomes in the identification and categorization of dermatological illnesses. Several significant findings have emerged from recent study, which are outlined below:There is nothing in an individual's text that could be used for academic revision. Detecting skin problems can be challenging due to the visual proximity effect and the intrinsic intricacy of human skin. Deep learning methodologies can be employed to develop frameworks capable of discerning a wide range of dermatological disorders. The identification of skin diseases can now be facilitated by the utilization of a smartphone's camera and advanced image processing techniques. A novel approach in the field of cutaneous illness involves the development of an adaptive federated machine learning model. This model demonstrates the capability to accurately detect various ailments pertaining to the skin, while also exhibiting the potential for continuous improvement in accuracy over time.Previous research has demonstrated that the utilization of deep learning techniques has the potential to automatically detect cutaneous lesions, given an adequate number of training instances. Deep transfer learning shows promise for the classification of melanoma, a particularly deadly form of skin cancer. Using deep learning algorithms has shown a lot of potential for diagnosing and classifying skin conditions. However, the quality and quantity of the training data greatly affect the accuracy of these models. More research is needed to increase the precision and consistency of deep learning models for skin disease diagnosis.

6.2 Future Works

There existing prospective future improvements and additions that might be applied. The computational efficiency of our suggested model is enhanced as it has been designed for utilization on low-power devices. Furthermore, the integration of skin disease detection technology with a tailored mobile application can provide a platform for acquiring comprehensive knowledge regarding various manifestations,

underlying factors, therapeutic approaches, and other pertinent aspects related to the identified illness. Potential enhancements to the model should be implemented in order to enable comprehensive identification of all skin conditions across global regions. There are several potential enhancements that may be achieved through the modification of the model. To commence, it is recommended to procure novel dermatological imaging datasets and integrate them into the training data repository in order to enhance its diversity and amount.The efficacy of the model in detecting less prevalent diseases can be improved by providing it with training to identify uncommon or distinctive instances within the categories of skin disorders. Furthermore, extensive hyperparameter tuning and optimization were necessary for both the individual CNN models and the ensemble model. This was followed by an examination of various optimization strategies and learning rate schedules in order to improve convergence and overall performance.In addition, we explore several transfer learning techniques, such as layer freezing and layer unfreezing, in order to identify the most optimal approach for the goal of detecting skin diseases.Ultimately, the ensemble model undergoes fine-tuning. To maximize the performance of CNN models, it is advisable to initially refine the fusion strategy employed by the ensemble model. Subsequently, conducting experiments to assess the impact of adding or eliminating models would facilitate the identification of the most effective configuration.

Bibliography

[1] N. Codella, Q.-B. Nguyen, S. Pankanti, *et al.*, "Deep learning ensembles for melanoma recognition in dermoscopy images," 2016. eprint: 1610.04662.

[2] T. J. Brinker, A. Hekler, J. S. Utikal, *et al.*, "Skin cancer classification using convolutional neural networks: Systematic review," en, *J. Med. Internet Res.*, vol. 20, no. 10, e11936, 2018.

[3] T. J. Brinker, A. Hekler, J. S. Utikal, *et al.*, "Skin cancer classification using convolutional neural networks: Systematic review," en, *J. Med. Internet Res.*, vol. 20, no. 10, e11936, 2018.

[4] R. Yamashita, M. Nishio, R. K. G. Do, and K. Togashi, "Convolutional neural networks: An overview and application in radiology," en, *Insights Imaging*, vol. 9, no. 4, pp. 611–629, 2018.

[5] N. Codella, V. Rotemberg, P. Tschandl, *et al.*, "Skin lesion analysis toward melanoma detection 2018: A challenge hosted by the international skin imaging collaboration (ISIC)," 2019. eprint: 1902.03368.

[6] M. S. Junayed, A. A. Jeny, S. T. Atik, *et al.*, "AcneNet - a deep CNN based classification approach for acne classes," in *2019 12th International Conference on Information & Communication Technology and System (ICTS)*, IEEE, 2019, pp. 203–208.

[7] A. Ameri, "A deep learning approach to skin cancer detection in dermoscopy images," *J. Biomed. Phys. Eng.*, vol. 10, no. 6, 2020.

[8] M. N. Bajwa, K. Muta, M. I. Malik, *et al.*, "Computer-Aided diagnosis of skin diseases using deep neural networks," en, *Appl. Sci. (Basel)*, vol. 10, no. 7, p. 2488, 2020.

[9] R. Binti Roslan, I. N. Mohd Razly, N. Sabri, and Z. Ibrahim, "Evaluation of psoriasis skin disease classification using convolutional neural network," en, *IAES Int. J. Artif. Intell. (IJ-AI)*, vol. 9, no. 2, p. 349, 2020.

[10] Y. N. Fu'adah, N. K. C. Pratiwi, M. A. Pramudito, and N. Ibrahim, "Convolutional neural network (CNN) for automatic skin cancer classification system," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 982, no. 1, p. 012 005, 2020.

[11] P. Guimarães, A. Batista, M. Zieger, M. Kaatz, and K. Koenig, "Artificial intelligence in multiphoton tomography: Atopic dermatitis diagnosis," en, *Sci. Rep.*, vol. 10, no. 1, pp. 1–9, 2020.

[12] M. S. Junayed, A. N. M. Sakib, N. Anjum, M. B. Islam, and A. A. Jeny, "EczemaNet: A deep CNN-based eczema diseases classification," en, in *2020 IEEE 4th International Conference on Image Processing, Applications and Systems (IPAS)*, IEEE, 2020, pp. 174–179.

[13] M. S. Junayed, A. N. M. Sakib, N. Anjum, M. B. Islam, and A. A. Jeny, "EczemaNet: A deep CNN-based eczema diseases classification," in *2020 IEEE 4th International Conference on Image Processing, Applications and Systems (IPAS)*, IEEE, 2020, pp. 174–179.

[14] M. A. Al-masni, D.-H. Kim, and T.-S. Kim, "Multiple skin lesions diagnostics via integrated deep convolutional networks for segmentation and classification," en, *Comput. Methods Programs Biomed.*, vol. 190, no. 105351, p. 105 351, 2020.

[15] A. Naeem, M. S. Farooq, A. Khelifi, and A. Abid, "Malignant melanoma classification using deep learning: Datasets, performance measurements, challenges and opportunities," *IEEE Access*, vol. 8, pp. 110 575–110 597, 2020.

[16] H. Wu, H. Yin, H. Chen, *et al.*, "A deep learning, image based approach for automated diagnosis for inflammatory skin diseases," en, *Ann. Transl. Med.*, vol. 8, no. 9, pp. 581–581, 2020.

[17] S. Zhao, B. Xie, Y. Li, *et al.*, "Smart identification of psoriasis by images using convolutional neural networks: A case study in china," en, *J. Eur. Acad. Dermatol. Venereol.*, vol. 34, no. 3, pp. 518–524, 2020.

[18] S. Zorgui, S. Chaabene, B. Bouaziz, H. Batatia, and L. Chaari, "A convolutional neural network for lentigo diagnosis," in *Lecture Notes in Computer Science*, Cham: Springer International Publishing, 2020, pp. 89–99.

[19] S. Zorgui, S. Chaabene, B. Bouaziz, H. Batatia, and L. Chaari, "A convolutional neural network for lentigo diagnosis," en, in *Lecture Notes in Computer Science*, vol. 12157, Cham: Springer International Publishing, 2020, pp. 89–99.

[20] L. Alzubaidi, J. Zhang, A. J. Humaidi, *et al.*, "Review of deep learning: Concepts, CNN architectures, challenges, applications, future directions," en, *J. Big Data*, vol. 8, no. 1, 2021.

[21] M. Cullell-Dalmau, S. Noé, M. Otero-Viñas, I. Meić, and C. Manzo, "Convolutional neural network for skin lesion classification: Understanding the fundamentals through hands-on learning," *Front. Med. (Lausanne)*, vol. 8, 2021.

[22] M. Dildar, S. Akram, M. Irfan, *et al.*, "Skin cancer detection: A review using deep learning techniques," en, *Int. J. Environ. Res. Public Health*, vol. 18, no. 10, p. 5479, 2021.

[23] H. A. Haenssle, J. K. Winkler, C. Fink, *et al.*, "Skin lesions of face and scalp – classification by a market-approved convolutional neural network in comparison with 64 dermatologists," en, *Eur. J. Cancer*, vol. 144, pp. 192–199, 2021.

[24] M. A. Kassem, K. M. Hosny, R. Damaševičius, and M. M. Eltoukhy, "Machine learning and deep learning methods for skin lesion classification and diagnosis: A systematic review," en, *Diagnostics (Basel)*, vol. 11, no. 8, p. 1390, 2021.

[25] N. Pancholi, S. Goel, R. Nijhawan, and S. Gupta, "Classification and detection of acne on the skin using deep learning algorithms," in *2021 19th OITS International Conference on Information Technology (OCIT)*, IEEE, 2021, pp. 110–114.

[26] Z. Rahman, M. S. Hossain, M. R. Islam, M. M. Hasan, and R. A. Hridhee, "An approach for multiclass skin lesion classification based on ensemble learning," en, *Inform. Med. Unlocked*, vol. 25, no. 100659, p. 100 659, 2021.

[27] R. B. Roslan, I. N. M. Razly, N. Sabri, and Z. Ibrahim, "Evaluation of psoriasis skin disease classification using convolutional neural network," en, *IAES Int. J. Artif. Intell. (IJ-AI)*, vol. 9, no. 2, p. 349, 2021.

[28] W. M. Salamaa and M. H. Aly, "Deep learning design for benign and malignant classification of skin lesions: A new approach," en, *Multimed. Tools Appl.*, vol. 80, no. 17, pp. 26 795–26 811, 2021.

[29] Sanskar_, *Skin disease image*, Jan. 2021.

[30] P. N. Srinivasu, J. G. SivaSai, M. F. Ijaz, A. K. Bhoi, W. Kim, and J. J. Kang, "Classification of skin disease using deep learning neural networks with MobileNet V2 and LSTM," en, *Sensors (Basel)*, vol. 21, no. 8, p. 2852, 2021.

[31] Y. Yang, J. Wang, F. Xie, *et al.*, "A convolutional neural network trained with dermoscopic images of psoriasis performed on par with 230 dermatologists," en, *Comput. Biol. Med.*, vol. 139, no. 104924, p. 104 924, 2021.

[32] Y. Yang, L. Guo, Q. Wu, *et al.*, "Construction and evaluation of a deep learning model for assessing acne vulgaris using clinical images," en, *Dermatol. Ther. (Heidelb.)*, vol. 11, no. 4, pp. 1239–1248, 2021.

[33] B. Zhang, X. Zhou, Y. Luo, *et al.*, "Opportunities and challenges: Classification of skin disease based on deep learning," en, *Chin. J. Mech. Eng.*, vol. 34, no. 1, 2021.

[34] C.-Y. Zhu, Y.-K. Wang, H.-P. Chen, *et al.*, "A deep learning based framework for diagnosing multiple skin diseases in a clinical environment," *Front. Med. (Lausanne)*, vol. 8, 2021.

[35] A. Aboulmira, H. Hrimech, and M. Lachgar, "Comparative study of multiple CNN models for classification of 23 skin diseases," en, *Int. J. Onl. Eng.*, vol. 18, no. 11, pp. 127–142, 2022.

[36] S. F. Aijaz, S. J. Khan, F. Azim, C. S. Shakeel, and U. Hassan, "Deep learning application for effective classification of different types of psoriasis," en, *J. Healthc. Eng.*, vol. 2022, pp. 1–12, 2022.

[37] K. Aljohani and T. Turki, "Automatic classification of melanoma skin cancer with deep convolutional neural networks," en, *AI (Basel)*, vol. 3, no. 2, pp. 512–525, 2022.

[38] G. Alwakid, W. Gouda, M. Humayun, and N. U. Sama, "Melanoma detection using deep learning-based classifications," en, *Healthcare (Basel)*, vol. 10, no. 12, p. 2481, 2022.

[39] G. Alwakid, W. Gouda, M. Humayun, and N. U. Sama, "Melanoma detection using deep learning-based classifications," en, *Healthcare (Basel)*, vol. 10, no. 12, p. 2481, 2022.

[40] J. P. Jeyakumar, A. Jude, A. G. Priya Henry, and J. Hemanth, "Comparative analysis of melanoma classification using deep learning techniques on dermoscopy images," en, *Electronics (Basel)*, vol. 11, no. 18, p. 2918, 2022.

[41] R. Kaur, H. GholamHosseini, R. Sinha, and M. Lindén, "Melanoma classification using a novel deep convolutional neural network with dermoscopic images," en, *Sensors (Basel)*, vol. 22, no. 3, p. 1134, 2022.

[42] I. Kousis, I. Perikos, I. Hatzilygeroudis, and M. Virvou, "Deep learning methods for accurate skin cancer recognition and mobile application," en, *Electronics (Basel)*, vol. 11, no. 9, p. 1294, 2022.

[43] P. R. Kshirsagar, H. Manoharan, S. Shitharth, A. M. Alshareef, N. Albishry, and P. K. Balachandran, "Deep learning approaches for prognosis of automated skin disease," en, *Life (Basel)*, vol. 12, no. 3, 2022.

[44] Z. Li, K. C. Koban, T. L. Schenck, R. E. Giunta, Q. Li, and Y. Sun, "Artificial intelligence in dermatology image analysis: Current developments and future trends," en, *J. Clin. Med.*, vol. 11, no. 22, p. 6826, 2022.

[45] K. A. Muhaba, K. Dese, T. M. Aga, F. T. Zewdu, and G. L. Simegn, "Automatic skin disease diagnosis using deep learning from clinical image and patient information," en, *Skin Health Dis.*, vol. 2, no. 1, 2022.

[46] G. Poornima and D. S. Sakkari, "Diagnosis of skin diseases based on deep learning and machine learning approach," en, *Int. J. Health Sci. (IJHS)*, pp. 4224–4240, 2022.

[47] B. Shetty, R. Fernandes, A. P. Rodrigues, R. Chengoden, S. Bhattacharya, and K. Lakshmanna, "Skin lesion classification of dermoscopic images using machine learning and convolutional neural network," en, *Sci. Rep.*, vol. 12, no. 1, 2022.

[48] M. H. Shuvon, R. Sadia, S. H. Shormi, U. T. Arafin, and M. R. M. Chowdhury, "Skin disease detection and classification using deep learning," en, Ph.D. dissertation, Brac University, 2022.

[49] H. Wen, W. Yu, Y. Wu, *et al.*, "Acne detection and severity evaluation with interpretable convolutional neural network models," en, *Technol. Health Care*, vol. 30, no. Suppl 1, pp. 143–153, 2022.

[50] L. AlSuwaidan, "Deep learning based classification of dermatological disorders," en, *Biomed. Eng. Comput. Biol.*, vol. 14, 2023.

[51] G. Arora, A. K. Dubey, Z. A. Jaffery, and A. Rocha, "A comparative study of fourteen deep learning networks for multi skin lesion classification (MSLC) on unbalanced data," en, *Neural Comput. Appl.*, vol. 35, no. 11, pp. 7989–8015, 2023.

[52] M. A. Arshed, S. Mumtaz, M. Ibrahim, S. Ahmed, M. Tahir, and M. Shafi, "Multi-class skin cancer classification using vision transformer networks and convolutional neural network-based pre-trained models," en, *Information (Basel)*, vol. 14, no. 7, p. 415, 2023.

[53] H. M. Balaha and A. E.-S. Hassan, "Skin cancer diagnosis based on deep transfer learning and sparrow search algorithm," en, *Neural Comput. Appl.*, vol. 35, no. 1, pp. 815–853, 2023.

[54] H. K. Jeong, C. Park, R. Henao, and M. Kheterpal, "Deep learning in dermatology: A systematic review of current approaches, outcomes, and limitations," en, *JID Innov.*, vol. 3, no. 1, p. 100 150, 2023.

[55] M. Moncho-Santonja, S. Aparisi-Navarro, B. Defez, and G. Peris-Fajarnés, "Segmentation of acne vulgaris images techniques: A comparative and technical study," en, *Appl. Sci. (Basel)*, vol. 13, no. 10, p. 6157, 2023.

[56] G. M. Rao, D. Ramesh, P. Gantela, and K. Srinivas, "A hybrid deep learning strategy for image based automated prognosis of skin disease," en, *Soft Comput.*, 2023.

[57] D. A. Reddy, S. Roy, S. Kumar, and R. Tripathi, "A scheme for effective skin disease detection using optimized region growing segmentation and autoencoder based classification," en, *Procedia Comput. Sci.*, vol. 218, pp. 274–282, 2023.

[58] J. Sun, K. Yao, G. Huang, *et al.*, "Machine learning methods in skin disease recognition: A systematic review," en, *Processes (Basel)*, vol. 11, no. 4, p. 1003, 2023.

[59] H. Tabrizchi, S. Parvizpour, and J. Razmara, "An improved VGG model for skin cancer detection," en, *Neural Process. Lett.*, vol. 55, no. 4, pp. 3715–3732, 2023.

[60] V. Venugopal, N. I. Raj, M. K. Nath, and N. Stephen, "A deep neural network using modified EfficientNet for skin cancer detection in dermoscopic images," en, *Decision Analytics Journal*, vol. 8, no. 100278, p. 100 278, 2023.

[61] H. Zendah and K. Dimililer, "Using of conventional neural network to diagnose scabies by dermoscopy," in *Lecture Notes in Networks and Systems*, Cham: Springer Nature Switzerland, 2023, pp. 274–281.