SKIN DISEASE CLASSIFICATION USING FINE-TUNED TRANSFER LEARNING TECHNIQUES

BY

BIJOY DHAR
ID: 202-15-3830
AND

MONIR HUSAIN SHUVO
ID: 202-15-3853

FINAL YEAR DESIGN PROJECT REPORT

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

Supervised By

Mr. Md Assaduzzaman
Lecturer (Sr. Scale)
Department of CSE
Daffodil International University

Co-Supervised By

Dr. Arif Mahmud
Associate Professor & Program Director MIS
Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

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APPROVAL

This Project titled "SKIN DISEASE CLASSIFICATION USING FINE-TUNED TRANSFER LEARNING TECHNIQUES", submitted by **Bijoy Dhar** and **Monir Husain Shuvo** to the Department of Computer Science and Engineering, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on 15-07-2024.

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Dr. Sheak Rashed Haider Noori — **Board Chairman**
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Daffodil International University

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Assistant Professor
Department of CSE
Faculty of Science and Information Technology
Daffodil International University

Mr. Mohammad Jahangir Alam — **Internal Examiner 2**
Sr. Lecturer
Department of CSE
Faculty of Science and Information Technology
Daffodil International University

Dr. Md. Arshad Ali — **External Examiner**
Professor
Department of Computer Science and Engineering
Hajee Mohammad Danesh Science and Technology University

DECLARATION

We hereby declare that this project has been done by us under the supervision of **Mr. Md. Assaduzzaman, Lecturer (Senior Scale), Department of Computer Science and Engineering, Daffodil International University**. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

Supervised by: 14.7.24

Mr. Md. Assaduzzaman
Lecturer (Senior Scale)
Department of CSE
Daffodil International University

Co-Supervised by:

Dr. Arif Mahmud
Associate Professor & Program Director MIS
Department of CSE
Daffodil International University

Submitted by:

Bijoy Dhar

(Bijoy Dhar)
ID: 202-15-3830
Department of CSE
Daffodil International University

Monir Husain Shuvo

(Monir Husain Shuvo)
ID: 202-15-3853
Department of CSE
Daffodil International University

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ABSTRACT

Millions of individuals worldwide suffer from skin illnesses, which pose considerable health and economic difficulties. Accurate and prompt diagnosis is crucial for successful treatment and management. Traditional treatments relying on dermatologists' visual assessments can be time-consuming and prone to mistakes. This study studies the use of transfer learning with fine-tuned convolutional neural networks (CNNs) to increase the classification accuracy of skin disorders. Five pre-trained models—VGG16, InceptionV3, MobileNetV3, EfficientNetB2, and EfficientNetB5—were chosen for their demonstrated performance in image recognition tests. The study's objective is to build a credible skin disease categorization system utilizing these models. Experimental results indicated that the EfficientNetB2 model attained the best accuracy at 89.37%, followed closely by EfficientNetB5 with roughly 87%. The findings emphasize the potential of transfer learning to transform dermatological diagnostics by delivering a reliable and efficient method to early diagnosis and treatment, therefore improving patient outcomes and maximizing healthcare resources. Future research should focus on increasing the dataset and researching more AI approaches to better the diagnostic capabilities of these models. This technique will further develop their efficacy and dependability in clinical applications, opening the path for improved patient care and resource management.

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CHAPTER 1
Introduction

1.1 Overview

The disease of the skin has become the most common disease worldwide since the 1970s. People with other types of skin disease and melanoma skin cancer diagnoses have increased during the past few decades, respectively. Melanoma is distinguished by the fact that only one in three cases of melanoma are classified as such by the World Health Organization (WHO) [1]. Melanin exists in human skin, and melanocytes are the cells in the skin layer that create melanin, based on to research on the science of melanoma Each person's body produces diverse amounts and types of melanin from their melanocytes. Skin not only provides color to our skin but also shields it from the sun's UV radiation. Excessive exposure to ultraviolet (UV) radiation from the sun, having a lot of unique or numerous moles, having different skin types, and having a family history of melanoma are all risk factors for skin cancer [2]. Therefore, immediately skin disease detection may result in a treatment that improves survival rates [3]. As the largest organ in the body, the skin serves a crucial role for insulating the body from pollutants in the environment and for retaining vital nutrients. Roughly 60% of British people suffer from skin problems, reported to the 2018 British Skin Foundation Study [4]. The health of the skin is critical for preserving general wellbeing since it serves as a barrier of defense for sensitive interior organs. The synthesis of vitamin D, which is crucial for many bodily functions, emphasizes just how crucial it is to have a skin area free of infections. Global aspects that affect our skin's health directly or indirectly include weather patterns, surroundings, humidity levels, and food habits. Given the potential consequences of many illnesses, particularly fungal infections, diagnosing skin disorders is crucial [5]. Numerous skin illnesses are caused by the complex makeup of the skin, which includes blood vessels, pigmentation, and cells in its three primary layers (epidermis, dermis, and hypodermis. So, in order to successfully address the complexity and diversity of skin problems, this summary highlights the complex nature of skin health and emphasizes the need for advanced diagnostic approaches such as deep learning.

1.2 Background and Present State

Dermatological conditions constitute a substantial proportion of worldwide healthcare issues, impacting millions of people and exhibiting a diverse array of clinical presentations. Prompt and precise diagnosis is essential for successful therapy, but it remains difficult due to the intricate and diverse nature of dermatological disorders. Conventional diagnostic techniques mainly depend on the proficiency of dermatologists, which might be subjective and lacking in consistency. The emergence of deep learning, namely convolutional neural networks (CNNs), has fundamentally transformed the field of image analysis. It provides a highly promising approach to automating and improving the precision of skin disease classification. Transfer learning, the process of adjusting pre-trained models on specific datasets, has proven to be a highly effective technique. Researchers can get impressive results with minimal medical imaging data by using pre-trained models that have been built on huge datasets such as ImageNet. Recent progress has shown that these strategies have the ability to equal or even exceed human skill in specific diagnostic tasks. Nevertheless, despite these progressions, there are still ongoing research areas that present hurdles, including the requirement for extensive annotated datasets, the capacity to comprehend models, and the ability to apply them to varied populations and imaging settings.

1.3 Problem Statement

The primary roles of the skin are to shield the body from poisonous substances in the environment and to keep numerous types of nutrients inside the body. According to the 2018 British Skin Foundation Survey, approximately sixty percent of British suffer from diseases of the skin [4]. Fungus can affect the skin and result in various fungal infections [5]. Melanoma is thought to be relatively uncommon than other types of skin cancer, despite being the most-deadly generous. As previously mentioned, it may progress very rapidly to additional areas of the body. Melanoma grows through the aggressive growth of melanocytes, which are produced from neuronal crest neoplasm Melanoma is responsible for 55500 cancer deaths annually, or 0.7% of all cancer deaths. [6]. Various seasons and climate are two more geographical factors that affect. Skin disease prevalence ranged from 6.3% to 11.2% in an additional care center located in Garhwali Hills, North India, in 2014. [7]. Eczema, another name for a form of atopic dermatitis, is a long-term skin problem marked by allergic reactions on the limbs of the elbows, and face in addition to dry, itchy skin.

1.4 Objectives

The objective of this work is to develop and evaluate an advanced transfer learning-based skin disease classification system. The main goals are to: use and contrast different pre-trained deep learning models for skin lesion analysis optimize fine-tuning strategies to improve classification efficiency and accuracy handle challenges with the dataset by using efficient data augmentation and balancing techniques guarantee the robustness of the model across a variety of skin types and imaging conditions; enhance the interpretability of the model using cutting-edge visualization techniques; and compare the developed approach against conventional machine learning techniques. By demonstrating the effectiveness of transfer learning in increasing diagnostic accuracy, decreasing computational demands, and possibly helping medical professionals in the early and accurate detection of skin diseases, the study ambitions to advance the field of dermatological image analysis.

1.5 Scope and Limitations

This study's focus is on applying optimized transfer learning methods to the categorization of different skin conditions. This study aims to improve the efficiency and accuracy of automated skin disease diagnosis by utilizing pre-trained models such as EfficientNetB2, EfficientNetB5, MobileNetV3, InceptionV3, and VGG16. The goal is to improve these models using a large dataset that is obtained from Kaggle and contains various kinds of images of skin diseases. By improving the models' ability to identify and categorize various skin conditions, this approach requires to advance dermatology and medical imaging.

There are a few limitations on this research, though. First off, even though the dataset is large, it might not include every variety of skin conditions that arise in clinical settings, which could restrict how broadly the findings can be applied. Furthermore, there may be variations in the dataset's image quality and resolution, which might impact the way the models perform. The dependence on transfer learning is another drawback; although it provides computational efficiency, it might not always be able to capture the distinctive characteristics of particular skin conditions as well as models developed from the ground up using specialized datasets. Additionally, the primary focus of the evaluation metrics is classification accuracy, which may not accurately reflect the diagnostic tool's clinical relevance even though its significance. These limitations might be overcome in the future by using more varied and superior quality datasets, investigating different performance metrics, and creating models especially for the classification of skin diseases.

1.6 Report Organization

The framework of this thesis is to facilitate a thorough comprehension of the conducted study. Chapter 1 establishes the foundation by providing clear explanations of the problem statement, motivation, objectives, scope, and expected outcomes. Chapter 2 provides an extensive literature review to establish the background and basis for the study. Chapter 3 provides a detailed explanation of the procedures used to collect and analyze data. It specifically emphasizes the research approach and the interpretation of the results. Chapter 4 provides a comprehensive account of the experimental outcomes, including the configuration, methodologies, and outcomes derived from examinations conducted utilizing the constructed models. The text examines performance indicators and conducts comparative analysis of several models to emphasize their strengths and weaknesses. Chapter 5 explores the societal and environmental consequences of the study, delving into ethical considerations, societal ramifications, and sustainability. Additionally, it pertains to the impact on advancements in medical diagnosis and healthcare. Chapter 6 presents a concise overview, definitive findings, and suggestions for future research, highlighting important insights and proposing avenues for further exploration. Chapter 7 finishes by providing a comprehensive discussion that emphasizes the significance of ongoing research and proposes ways in which future studies can enhance the classification of skin diseases and its therapeutic implications.

1.7 Summary

The introduction highlights the critical role of the skin in safeguarding the body and maintaining overall health, with approximately 60% of the British population experiencing skin problems. The diverse factors influencing skin health, including climate, genetics, and lifestyle, underscore the complexity of skin disorders. Notably, untreated conditions can lead to severe consequences, necessitating advanced diagnostic approaches. The problem statement elucidates the prevalence of skin diseases, particularly fungal infections and melanoma, emphasizing the need for timely and accurate diagnosis. The motivation stems from the significant social and health impact of skin conditions, driving the objective of enhancing diagnostic accuracy through deep learning. The project aims to create models for precise skin disease classification, alleviate the workload on dermatologists, and expedite care. The study's scope encompasses various skin disorders, utilizing datasets like Dermnet and HAM10000 to train deep learning models, primarily focusing on Convolutional Neural Networks and in transfer learning various models has already been trained with ImageNet, a huge collection of over Fourteen million, One hundred & ninety-seven thousand. And the anticipated outcome includes efficient disease detection, algorithm selection, practical implementation, model evaluation, and performance analysis using confusion matrices. The report organization ensures a systematic exploration of the research, spanning literature review, methodology, findings, discussions, conclusions, and recommendations, thereby providing a comprehensive understanding of the study's intricacies.

CHAPTER 2
LITERATURE REVIEW

2.1 Overview

The literature review looks on the way skin disease classification has advanced recently with improved transfer learning techniques. It also covers significant studies that apply different deep learning architectures to image analysis in dermatology, involving convolutional neural networks (CNNs). The review investigates whether the classification of skin lesions has been refined using pre-trained models on large data sets such as ImageNet, leading to notable improvements in accuracy and fewer in training period. It also talks about the difficulties this field faces, such as the lack of labelled dermatological datasets, the disparity in class sizes, and the requirement for models that are easy to understand. The review emphasizes the value of using ensemble methods and data augmentation techniques to improve model performance. Furthermore, it looks at how transfer learning techniques compare to more conventional deep learning techniques for classifying skin diseases, highlighting the superiority of well-tuned deep learning models. Identifying research gaps and prospective areas for further research is where a literature review proceeds. Faster and more accurate diagnosis is one of the advantages, particularly in underprivileged areas. Primary fields of ongoing research are model enhancement, accuracy, and ethical deployment. Everything being considered, deep learning provides an immense potential for transforming the diagnosis and treatment of skin diseases.

2.2 Related Works

Allugunti, et al [1], Developed "A machine learning model for skin disease classification using convolutional neural network." Their approach was evaluated on the https://dermnetnz.org/. Website dataset. Using four different types of classifier algorithms such as DT, RF, GBT and CNN. The accuracy achieved from these it was 67 ,71.35, 73.44 and 88.83 % respectively. The best accuracy achieved from CNN and it was 88.83 %.

Javaid et al. [2], Developed the model which was "Skin cancer classification using image processing and machine learning. Their approach was tested on the dataset of ISIC-ISBI 2016. For classifying data, random forest, SVM (Medium Gaussian), quadratic, and discriminant classifiers. The accuracy achieved from these 93.89, 88.17, 90.84 % respectively. The maximum accuracy attained using random forest was 93.89%.

Ali et al. [3] proposed a deep learning approach for the classification of benign and malignant skin lesions using deep convolutional neural networks (DCNNs). First, they preprocessed the images to remove noise and artifacts, normalize the inputs, and extract helpful features. Then, they used data augmentation to increase the number of images, which improved the accuracy of the classification rate. The proposed DCNN model outperformed several transfer learning models, such as AlexNet, ResNet, VGG-16, DenseNet and MobileNet, on the HAM10000 dataset, achieving an accuracy of 93.16% for training and 91.93% for testing.

Kemal Polat et al. [4], developed Detection of Skin Diseases from dermoscopy Image Using the combination of Convolutional Neural Network and One-versus-All. They made use of the Philipp Tschandl-prepared HAM10000 dataset. The dataset contains seven classes. They employed Two distinct approaches have been put out to automatically categorize skin diseases: i) the Alone Convolutional Neural Network model, and ii) the Combination of Convolutional Neural Network and One-versus-All. The accuracy achieved from these it was 77, 92.90 %. 92.90% was the highest accuracy obtained using a Convolutional Neural Network in a one-versus-all comparison.

Tanzina Afroz Rimi et al. [5], created Convolutional Neural Network-Based Skin Diseases Detection. Their research lies at the intersection of image processing and machine learning. On the other hand, CNN prepared the image that it used to schedule the classes. The preparation information consists of the five classes of skin that were previously discussed. They obtained a 73% accuracy rate by putting their framework to the test on 500 pictures of various illnesses taken from the Dermnet dataset.

Daghrir et al. [6] developed the model which was Melanoma skin cancer detection using deep learning and classical machine learning techniques. A public dataset from the ISIC (International Skin Imaging Collaboration) archive was used in their research. Using three different types of classifier algorithms—KNN, SVM, and CNN—the dataset contained over 23,000 images of melanoma. The accuracy obtained from these algorithms was 57.3, 71.8, and 85.4%, respectively. CNN recorded the highest accuracy rate, which was 85.5%.

T. Shanthi et al. [7], has primarily processed on the automated detection and classification of skin diseases, particularly Acne, Keratosis, Eczema herpeticum and Urticaria, using Convolutional Neural Networks (CNN). The key methods employed in this research encompass the use of CNN architecture, Rectified Linear Unit (ReLU) layers for thresholding, Pooling layers (either Average or Maximum Pooling), and the Stochastic Gradient Method for training. The CNN model achieved the highest accuracy for each skin disease classification as follows: Acne with a 85.7% accuracy, Keratosis with a 92.3%, Eczema herpeticum with a 93.3% and Urticaria with a 92.8% accuracy. The effectiveness of the CNN-based approach in accurately identifying and classifying different skin diseases. The proposed CNN Classifier results in an accuracy of 98.6% to 99.04%.

Karunanayake et al. [8] developed a mobile application for detecting and classifying acne severity from photos taken by a cellphone. Several methods were used in the research. For segmentation, three different methods were utilized, with two-level k-means clustering performing the best. For classification, two machine learning methods were employed, namely Fuzzy C-means (FCM) and Support Vector Machine (SVM). The FCM method outperformed the SVM in terms of accuracy. In terms of the classification of acne type, three different Convolutional Neural Network (CNN) models were implemented, using a total of 15 different CNN architectures. The research used several methods for classifying acne subtypes, density, and skin sensitivity. The methods used include a Convolutional Neural Network (CNN), a content-based algorithm, and the SEResNet152 model. The highest accuracy results achieved for each method are as follows: Acne subtype classification using symptoms: 84% accuracy, Acne density classification: 85.11% accuracy, Skin sensitivity classification: 95.76% accuracy, further highlighting the robustness of the system.

Chaitra T C et al. [9] introduces a unique system for the diagnosis of several skin diseases. The application of algorithms like Self Organizing Map (SOM) and Radial Basis Function (RBF) for disease recognition, the development of a system that combines image processing and machine learning algorithms for skin disease prediction, and a focus on the advantages of combining shape, substance, and color features in disease classification—achieving an overall accuracy of 93.15%
are among the key contribution. The methodology includes picture enhancing pre-processing techniques, k-means clustering segmentation and form, texture and color-focused feature extraction techniques. The combined SOM and RBF algorithms beat other classifiers in achieving the classification. The results demonstrate how effectively the suggested method can identify a range of skin conditions and how blending multiple feature extraction techniques significantly improves classification accuracy, making it a useful tool for dermatological diagnosis.

ALEnezi et al. [10] discussed on the detection of skin diseases through the application of image processing and machine learning techniques. The authors adopted a well-defined methodology encompassing image preprocessing, feature extraction, and classification for analyzing skin disease images. In regards to the highest accuracy attained, the paper reports the successful detection of three distinct skin diseases with a remarkable accuracy of 100%. However, it does not explicitly specify the particular method or technique responsible for achieving this level of accuracy.

Pugazhenthi et al. [11] focused on developing a Skin Disease Detection System using image processing and classification techniques. It aims to detect and classify specific skin diseases, such as Melanoma, Eczema, and Leprosy. The methods involve a series of steps, including image pre-processing, segmentation, feature extraction, and classification The methodology includes pre-processing, segmentation, feature extraction, and classification using Support Vector Machine (SVM) and K-Nearest Neighbors (KNN). While the highest accuracy isn't explicitly mentioned, using a combination of SVM and KNN achieves an 86.67 % accuracy when classifying images based on texture features. Future work includes expanding the system to classify more facial skin disease types and engaging with cosmetic entrepreneurs and dermatologists for product recommendations.

Meenakshi M.M. et al. [12] introduces an automated technique for detecting melanoma. It emphasizes how important it is to detect skin cancers early, especially melanoma, which is the most-deadly kind. The approach comprises a three-phase model: gathering information from the ISIC dataset, preprocessing images to extract characteristics, and building the model with CNN, SVM, and neural networks. The system's 85% accuracy rate revealed the value of artificial intelligence and image processing for melanoma identification. The findings of the research emphasize the value of early and efficient skin cancer detection and highlights how it may enhance diagnosis and therapy. This research constitutes a major breakthrough in dermatological and medical imaging.

Rathod et al. [13] proposed an automated image-based system for diagnosing skin diseases using Convolutional Neural Networks (CNNs). Using computational techniques based on different image features, the system processes, analyzes, and ranks image data. Skin images are enhanced and filtered to eliminate unwanted noise. CNNs and the softmax classifier algorithm are used to generate a diagnostic report. Because it produces results more quickly and accurately than traditional methods, this system is an effective and dependable tool for the detection of dermatological diseases. For students studying dermatology, it can also be an invaluable live teaching tool. Although it was roughly 70% at first, the training accuracy can be raised by expanding the training dataset.

Patnaik et al. [14] proposes a deep learning-based system for diagnosing skin conditions. The system integrates and modifies three pre-existing image recognition models—InceptionV3, InceptionResnetV2, and Mobile Net—to identify skin diseases. 10% of the data is used for validation/testing, while the remaining 90% is used for training. Using the majority vote among the three models, the algorithm makes a prediction on the skin condition. According to the paper, the system can recognize 20 skin conditions with 88% accuracy, which is an improvement over earlier techniques. Additionally, the paper argues that the approach can be employed in real-world settings for improving the diagnosis and treatment of skin diseases.

Archana Ajith et al. [15], introduced a mobile-based skin disease detection method that relies on image processing techniques for accessibility, especially in remote areas, without invasive procedures. Patients submit skin images for analysis. The system, implemented in MATLAB on Windows 10, achieves up to 80% efficiency in disease detection. The research employs three transforms: Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT), and Singular Value Decomposition (SVD). The parallel combination of all three transforms offers the most efficient detection, enabling faster diagnosis by excluding SVD. Here, DCT transforms images into frequency domains, with optimal accuracy using 16 coefficients. And DWT decomposes images into approximation and detail coefficients, with level 1 achieving the highest accuracy. And SVD excels at detecting acne. The study's results display varying accuracy levels for each transform, with the parallel combination yielding the highest accuracy.

2.3 Comparison Between Existing Works

Research which is now available highlights multiple approaches and their results in the classification of skin diseases, highlighting the effectiveness of transfer learning and convolutional neural networks (CNNs).

Additionally, comparative evaluations between various algorithms demonstrate CNNs' superiority in a number of investigations. As compared to other classifiers like decision trees (67%), random forests (71.35%), and gradient boosting (73.44%), Allugunti et al. [1] achieved an accuracy of 88.83% with CNN. Similarly, T. Shanthi et al. [7] used CNNs to classify specific skin diseases with high accuracy varying from 85.7% to 93.3%. Earlier research has shown that CNNs are capable of reaching excellent classification accuracy for skin diseases. For example, using the HAM10000 dataset, Ali et al. [3] used deep CNNs to reach an accuracy of 93.16%. In a similar vein, Daghrir et al. [6] reported an 85.4% detection accuracy ratio for melanoma using CNNs. The efficient use of CNN-based models in skin diagnoses is made clear by these results.

In summary, the proposed study seeks to further improve the precision and effectiveness of skin disease classification by utilizing these insights through the application of enhanced transfer learning techniques. This work seeks to significantly improve dermatological methods using sophisticated deep learning techniques by building on standard approaches and resolving limitations found in previous research.

Table 2.3.1. Comparative analysis Table

SL No	Author Name	Used Algorithm	Best Accuracy with Algorithm
1.	Allugunti, et al. [1]	DT, RF,GBT and CNN	CNN =88.83 %
2.	Javaid et al. [2]	Random forest, SVM (Medium Gaussian), quadratic, and discriminant classifiers.	Random forest =93.89 %
3.	Ali et al. [3]	AlexNet, ResNet, VGG-16, DenseNet, and MobileNet,	______
4.	Kemal Polat et al.[4]	Convolutional Neural Network model, and the Combination of Convolutional Neural Network and One-versus-All.	Convolutional Neural Network and One-versus-All=92.90%
5.	Tanzina Afroz Rimi et al. [5]	CNN	CNN =73 %
6.	Daghrir et al. [6]	KNN, SVM, and CNN	CNN=85.5%
7.	T. Shanthi et al. [7]	CNN	CNN=98.6% to 99.04%.
8.	Karunanayake et al. [8]	K-Means Clustering , Fuzzy C-Means (FCM) , Convolutional Neural Network (CNN), SEResNet152	______
9.	Chaitra T C et el. [9]	Self Organizing Map (SOM) and Radial Basis Function (RBF)	Self Organizing Map (SOM) and Radial Basis Function (RBF) = 93.15%
10.	ALEnezi, et al. [10]	Multiclass Support Vector Machine (SVM), Pretrained convolutional neural network (AlexNet)	Pretrained convolutional neural network (AlexNet) + multiclass SVM =100%
11.	Pugazhenthi et al. [11]	Support Vector Machine (SVM) and K-Nearest Neighbors (KNN)	SVM + KNN = 86.67%

12.	Meenakshi M. M.et al. [12]	CNN, SVM	______
13.	Rathod et al.[13]	CNN	CNN=70%
14.	Patnaik et al. [14]	InceptionV3, InceptionResnetV2, and Mobile Net	InceptionV2 : Rank-1= 68.15% and Rank-5 = 85.62%
15.	Archana Ajith et al. [15]	Discrete Cosine Transform (DCT), Discrete Wavelet Transform (DWT), and Singular Value Decomposition (SVD)	DCT + DWT + SVD = 80%

2.4 Open Issues

Although the classification of skin diseases using fine-tuned transfer learning techniques has made promising progress, there are still a number of remaining problems that require more research. A major obstacle that may limit the robustness and generalizability of trained models is the limited number and lack of diversity of annotated medical image datasets. Furthermore, variations in lighting and image quality between datasets can impact model performance, requiring the creation of more complex preprocessing and data augmentation methods. Because deep learning models are "black-box" algorithms, it can be challenging for clinicians to trust and fully understand the decision-making process. In order for AI methods to produce model predictions, interpretability is essential. Overfitting is a risk, particularly when fine-tuning models on tiny datasets, which calls for thorough validation procedure Last but not least, there are practical issues with implementing these models in actual healthcare environments. These issues include the requirement for real-time processing capabilities, integration with current medical systems, and protection of patient privacy and security. Solving these remaining issues is essential to effectively converting scientific discoveries into useful, dependable, and that is widely utilized medical tools.

2.5 Summary

Convolutional neural networks, also known as CNNs, have achieved conventional machine learning techniques to become the latest technology for classifying skin diseases. On open-source databases like HAM10000, Dermnet, and ISIC, numerous studies have tested CNN architectures like VGG, ResNet, Inception, and MobileNet. They have achieved high accuracy between 70-95% for multi-class classification through five to seven skin diseases. For CNN to perform better, data preprocessing methods like augmentation, normalization, and noise mitigation have been significant.

To achieve more effective outcomes with less training data, pretrained CNNs are fine-tuned through transfer learning. Accuracy has been further increased by emulating CNNs using conventional techniques for machine learning, such as SVM in a one-vs-all scheme. Recent work has broadened to cover more classes and identified severity of disease, with a focus on common skin diseases such as melanoma, eczema, and acne. Additional research is required to integrate deep learning into clinical practice, despite some studies developing real-time diagnosis systems and mobile apps with clinical relevance.

CHAPTER 3
Research Methodology

3.1 Overview

With the goal to classify numerous skin illnesses comprehensively, the project intends to use advanced Transfer Learning models of CNN, such as EfficientNet (B2 and B5), VGG-16, Inception (InceptionV3), and MobileNet (MobileNetV3). The primary objective of this project is to use automated image analysis to improve the efficiency and accuracy of skin disease detection. The study is significant because it addresses the increasing need for accurate and timely diagnosis of skin conditions, including Eczema, Warts Molluscum and other Viral Infections, Melanoma, Basal Cell Carcinoma (BCC), Melanocytic Nevi (NV), Benign Keratosis-like Lesions (BKL), Psoriasis pictures Lichen Planus and related diseases, Seborrheic Keratoses and other Benign Tumors, Tinea Ringworm Candidiasis and other fungal infections. The project is to contribute to the creation of precise, trustworthy and easily available tools for dermatological diagnostics through the use of cutting-edge CNN architectures. The planned contributions include improvements in the automation of the recognition of skin diseases, which may result in better patient outcomes, reduced incorrect diagnoses, and easier access to dermatological challenge details using transfer learning.

3.2 Proposed Methodology

The dataset was then preprocessed including adjusting image dimensions and using augmentation methods (Fig. 3.3.1). The study used a Kaggle dataset of photos of skin conditions that had been preprocessed utilizing augmentation techniques to increase the diversity and resilience of the photographs. Techniques based on transfer learning, such as VGG16, Inception-V3, MobileNetv3, EfficientNetB2, and EfficientNetB5, were employed because of their ability to identify a range of difficulties. The F1-score, accuracy, sensitivity, and precision were used to assess performance. To comprehend model behavior, confusion matrices, accuracy, and validation graphs were utilized. The most effective model was incorporated into an Android-powered system, assisting medical professionals and offering a dependable tool for precise classification of cervical feature scan sample photographs.

The following figure 3.2.1 shows basic structure of the proposed work.

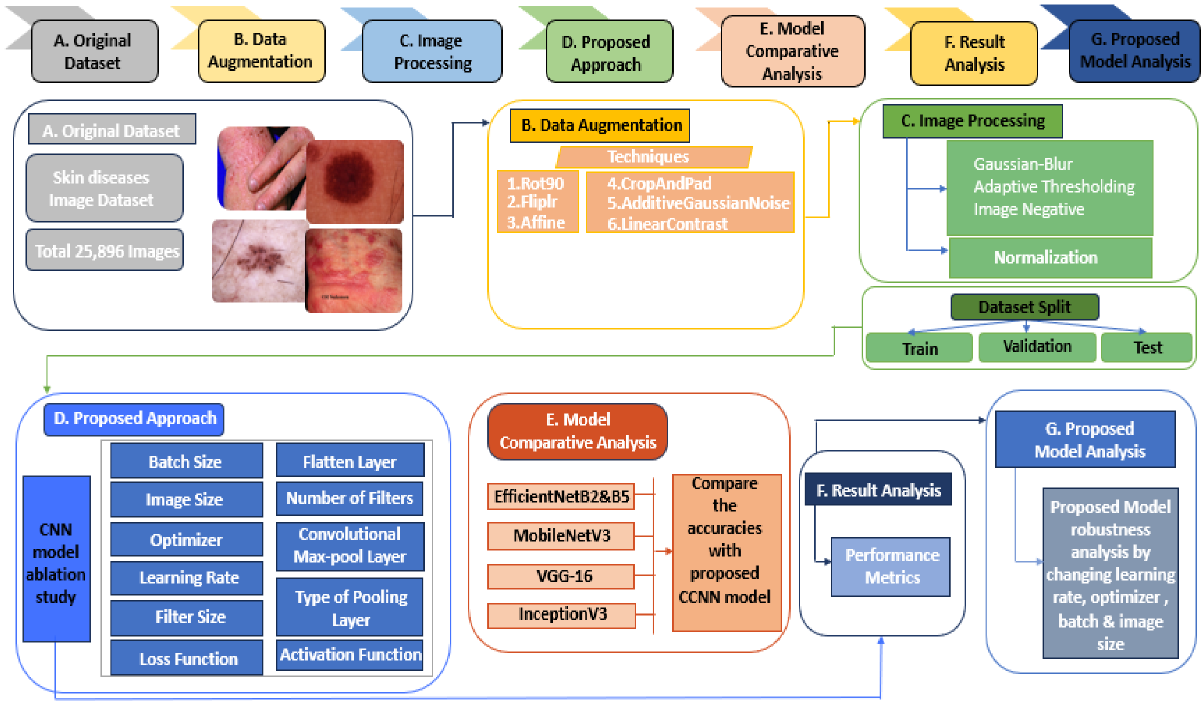


Figure 3.2.1: Process of Experiments.

(The models are described below in 4.2)

3.2.1. Dataset Description

The open-source website Kaggle provided the dataset [16]. There are 25,896 photos in the dataset overall and the average dimensions for each image spans 654 by 557 pixels. The dataset includes 9 classes: Eczema, Warts Molluscum, Basal Cell Carcinoma, Psoriasis pictures Lichen Planus, Melanocytic Nevi (NV), Tinea Ringworm Candidiasis and other Fungus, Atopic Dermatitis, Benign Keratosis-like Lesions (BKL), Seborrheic Keratoses & other Benign Tumor And Melanoma. To create the usable dataset, discard Train, Test and Val folders each class has a subdirectory in the dataset The data formats of the images are JPG. The detailed description of the dataset is displayed in Table 3.2.1.1:

Table 3.2.1.1: Dataset Description

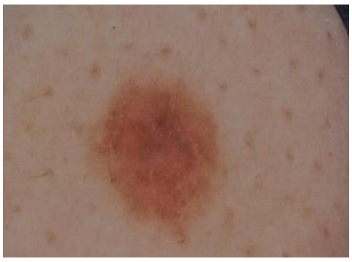
Sr. No.	**Class No.**	**Name**	**Description**
01		Total Number of Images	25,896
02		Dimension	224 x 224
03		Data Formats	JPG
04	0	Eczema	1677

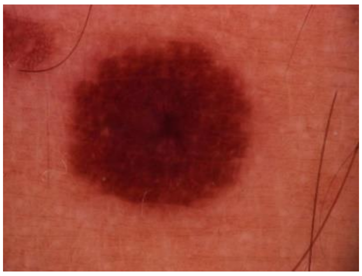
05	1	Warts Molluscum	2103
06	2	Melanoma	3140
07	3	Basal Cell Carcinoma	3323
08	4	Melanocytic Nevi (NV)	7970
09	5	Benign Keratosis-like Lesions (BKL)	2079
10	6	Psoriasis pictures Lichen Planus	2055
11	7	Seborrheic Keratoses and other Benign Tumor	1847
12	8	Tinea Ringworm Candidiasis and other Fungal	1702

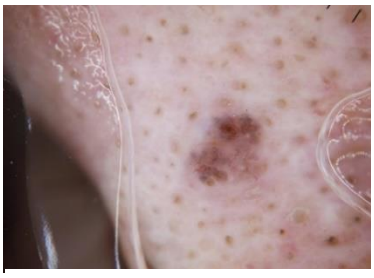
Sample view of Dataset


A. Eczema


B. Warts Molluscum


C. Atopic Dermatitis


D. Basal Cell Carcinoma Infection


E. Melanocytic Nevi Infection


F. Bening Keratosis


G. Psoriasis Lichen Planus


H. Seborrheic Keratoses


I. Tinea Ringworm Candidiasis and Fungal Infection

Figure 3.2.1.1: Data Class Samples.

All diseased skin imaging was carried out as part of the patient's routine clinical care. Before being removed from the study of diseased skin photos, each diseased skin was checked for quality control. Two qualified doctors graded the images before to their use in training the model. A third professional assessed the evaluation set to correct for any grade mistakes.

Here's the dataset link. _ Skin diseases image dataset | Kaggle

TABLE 3.2.1.2: Images Used in the Train, Test and Validation Sets.

	Train	**Test**	**Validation**
Raw Dataset	20714	2596	2586

3.2.2 Process of Experiments

The first stage of the proposed system is the collection of data from skin-disease images. Deep neural networks require more data for training and greater performance; hence data augmentation technologies are occasionally used to address the issue of insufficient data. Here's a breakdown of how the experiment was supposed to go:

Image Acquisition:

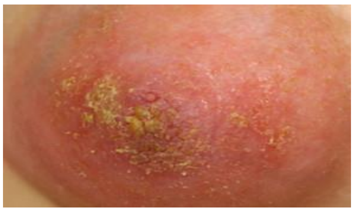
The skin disease Image Dataset provided data for model evaluation. This level incorporated targeted website visuals. To ensure white backgrounds, dataset photos were rigorously examined. Colored graphics appear on white backgrounds.

Image Augmentation:

Image enhancement is used at this stage. Data augmentation is a strategy for increasing the size and quality of training datasets. It entails creating new photos by modifying existing ones using techniques such as rotation, zooming, or color correction, while keeping their original labeling. This increased dataset improves the model's ability to generalize, making it more resilient to new, unknown inputs.

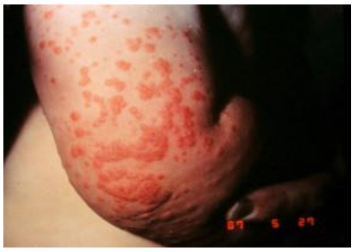
Data augmentation enabled us to meet our training data objectives. Nonetheless, brightness, contrast, saturation, scaling, cropping, flipping, and revolution were used to enhance color and position. Data augmentation comprised random spins ranging from -18 to 18 degrees, unintentional 90-degree rotations, bending, vertical and horizontal reversals, luminous intensity conversion, and distortions. Randomly, some original pictures were upgraded four times only in the class which have less than 2,500 original images in them in order to gain 1000 augmented images from these classes. A subset of changes enhances a diverse image.

Original **Augmented**



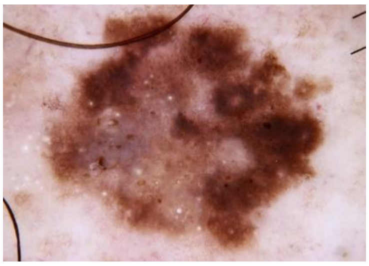
Eczema

Eczema

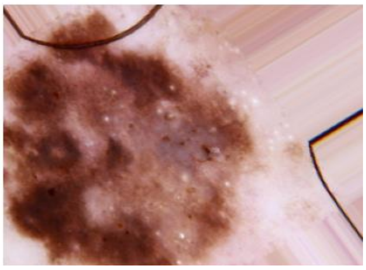


Warts Molluscum

Warts Molluscum

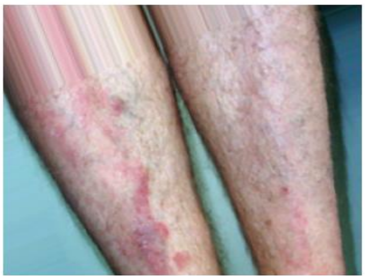


Bening Keratosis

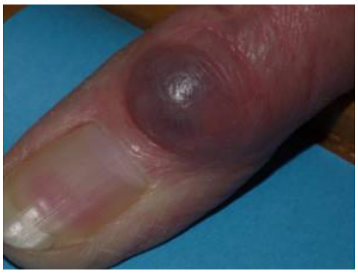


Bening Keratosis

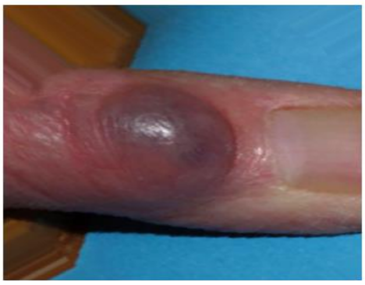
Psoriasis Lichen Planus



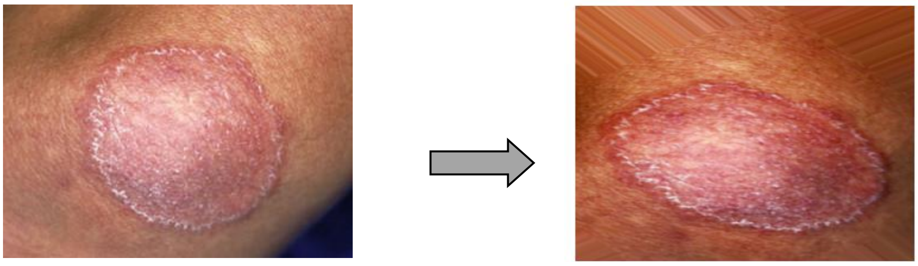
Psoriasis Lichen Planus



Seborrheic Keratoses



Seborrheic Keratoses



Tinea Ringworm Candidiasis & Fungal Infection

Tinea Ringworm Candidiasis & Fungal Infection

Figure 3.2.2.1: Original vs Augmented Image

Original vs Augmented Comparison:

TABLE 3.2.1.3: Images in Original and Augmented Dataset.

Sr. No.	**Original Dataset**	**Original Dataset's Description**	**After Augmentation**
01	Total Number of Images	25,896	31896
02	Dimension	224 x 224	224 x 224
03	Data Formats	JPG	JPG
04	Eczema	1677	2677
05	Warts Molluscum	2103	3103
06	Melanoma	3140	3140
07	Basal Cell Carcinoma	3323	3323
08	Melanocytic Nevi (NV)	7970	7970
09	Benign	2079	3079
10	Lichen Planus	2055	3055
11	Seborrheic Keratoses	1847	2847
12	Tinea Ringworm Candidiasis & Fungal	1702	2702

Convolutional Neural Network

The Convolutional Neural Network (CNN) is a popular neural network technology used for image processing and training. The matrix layout of the Convolution layer is specifically designed to filter images. Multiple layers, each addressing a different computation, are involved in the Convolution Neural Network data training process. These layers include input, convolutional, fully connected, pooling, dropout, and linked dataset categorization.

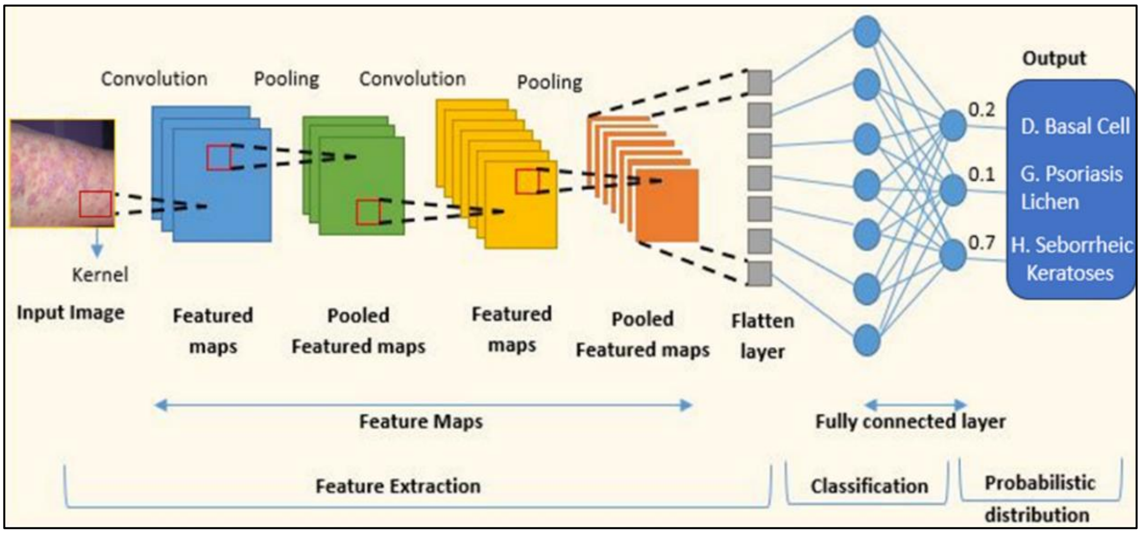


Figure 3.2.2.2: working Flow with Convolutional Neural Network

3.3 Hardware/ Software Requirement

Software Requirements:

- Programming Languages: Specialization of Python for demonstrating, data manipulation, and analysis.
- Frameworks: TensorFlow 2.0+ and Keras for building deep neural networks. PyTorch for implementing CNN architectures.
- IDE: Tools for developing and debugging code, increasing productivity through a variety of plugins and extensions, such PyCharm or Jupyter Notebook.
- Cloud Platform: Google based Platform like Google Colab, providing flexibility and scalability for model deployment and training.
- Version Control: Git and GitHub are tools for version control in software development, teamwork and project administration.

Hardware Requirements:

- Graphics Processing Unit (GPU): Although it's not technically required, a dedicated GPU may significantly speed up model training. CPU-based training is a choice; however, it may take more time.
- Central Processing Unit (CPU): For model training and inference, any current CPU with at least four cores can be used.
- Random Access Memory (RAM): Training small- to medium-sized models as well as handling datasets of a reasonable size require not more than 16GB of RAM.
- Storage: To store datasets, model files, and outputs, a normal SSD or HDD of at least 500GB or more of capacity is sufficient.
- Display: For a visual review of medical images, any common screen with a resolution of 1080p will be a better choice.

3.4 Project Management and Finance

This table includes a breakdown of the project expenditures. Hardware refers to necessary physical elements such as Computers, RAMs, SSDs etc. Meeting transportation and lodging are included in visiting stakeholders. The purchase or licensing of the software and tools needed to execute the project is covered under the third component, Software and Tools. The fourth component, Data Collection and Processing, deals with the expenses associated with obtaining and evaluating data for the project. The fifth component, Documentation and Report Writing, covers the expenses related to documenting and presenting the progress and results of the project. The sixth component, miscellaneous, covers additional expenses such as tools, licenses etc. Lastly, contingency acts as a safety net against unanticipated expenses. Every section needs resources to proceed smoothly and is essential to the project's success. The precise expenses will change based on how complicated the project is.

Table 3.4.1: Estimated Cost for Financial Analysis

SN	**Components**	**Estimated Cost (BDT)**
01.	Hardware/Infrastructure	10,000-12,000
02.	Visiting Stakeholders	3,000-4,000
03.	Software and Tools	15,000-20,000
04.	Data Collection and Processing	5,000-7,000
05.	Documentation and Report Writing	1,000-2,000

06.	Miscellaneous (e.g., licenses, tools)	5,000-7,000
07.	Contingency (10% of total)	4000-6000
	Total Estimated Cost	44,000-58,000

3.5 Summary

The article presents a study that aims to improve the precision and effectiveness of diagnosing skin diseases by employing advanced Transfer Learning models of Convolutional Neural Networks (CNN) such as EfficientNet (B2 and B5), VGG-16, InceptionV3, and MobileNetV3. The text highlights the significance of promptly and accurately diagnosing different skin disorders such as eczema, melanoma, and fungal infections. The methodology encompasses the acquisition of a dataset from Kaggle, the application of augmentation techniques to preprocess images, and the utilization of transfer learning to refine pre-trained models. The performance of the models is assessed using measures such as F1-score, accuracy, sensitivity, and precision. The models that perform well are then incorporated into an Android system for practical application in clinical environments. The project specifies the necessary hardware and software requirements, which involve employing TensorFlow, Keras and PyTorch for model building, as well as Google Colab for scalability. Financial analysis calculates the expenses associated with hardware, software, data processing, and other charges, ensuring a thorough approach to project management and implementation.

CHAPTER 4
IMPLEMENTATION

4.1 Overview

In Chapter 4, we explore the practical application and assessment of several convolutional neural network (CNN) structures employing transfer learning methods for the purpose of picture classification, specifically in the context of identifying skin diseases. The chapter commences by presenting the five distinct CNN models employed in this study: VGG16, InceptionV3, MobileNetV3, EfficientNetB2, and EfficientNetB5. Each of these models is thoroughly examined, providing a comprehensive analysis of their architectural design, unique characteristics, and the rationale behind their selection for picture categorization tasks.

The paper offers an elaborate account of the training methodologies employed for CNN models, encompassing the stages of dataset preparation, intricate aspects of the training process, and the optimization of hyperparameters. The discussion revolves around the use of techniques like as early stopping and optimizers, which aim to mitigate overfitting and enhance the efficiency of training. The models are assessed using metrics such as F1 Score, Precision, Recall, and Support, which offer valuable insights into their capacity to classify pictures and identify skin conditions.

Subsequently, the outcomes of the experimental training and evaluation are showcased, whereby the performance of the various models is compared using the predetermined metrics. The text also addresses the computing efficiency of each model throughout the training phase, emphasizing the practical aspects of utilizing these models in real-world scenarios. Subsequently, a thorough analysis is conducted to evaluate the merits and drawbacks of each CNN design. This part offers a comprehensive comprehension of the experimental results, examining the consequences for real-world implementations and proposing prospective avenues for future investigation.

The chapter ends with a concise overview of the main discoveries, considering their importance in the wider scope of picture classification and medical diagnostics. This text emphasizes the significance of this research in the field and examines its possible influence on future studies and applications.

4.2 Train Model

This section presents a detailed description of training five different designs of transfer learning models of convolutional neural networks (CNNs):

VGG16: A variation of the VGG architecture with 16 layers (three fully linked layers and thirteen convolutional layers) is called VGG16. This design is especially effective in situations where things have distinct shapes. VGG16 makes a substantial contribution by employing small (3×3) convolution filters to evaluate networks of increasing depth, which aids in the efficient acquisition of spatial data. These tiny filters are used by the architecture to record orientations in both the left and right directions. First, the input is linearly transformed by adding 1x1 convolution filters. Next, non-linearity is introduced by using an activation function called a Rectified Linear Unit (ReLU). The retention of spatial resolution following convolution is guaranteed by the fixed convolution stride of one pixel. On top of that, VGG16 reduces the spatial dimensions of the feature maps by using max pooling layers with a stride of 2 pixels, which offers translation invariance and lessens computational cost.

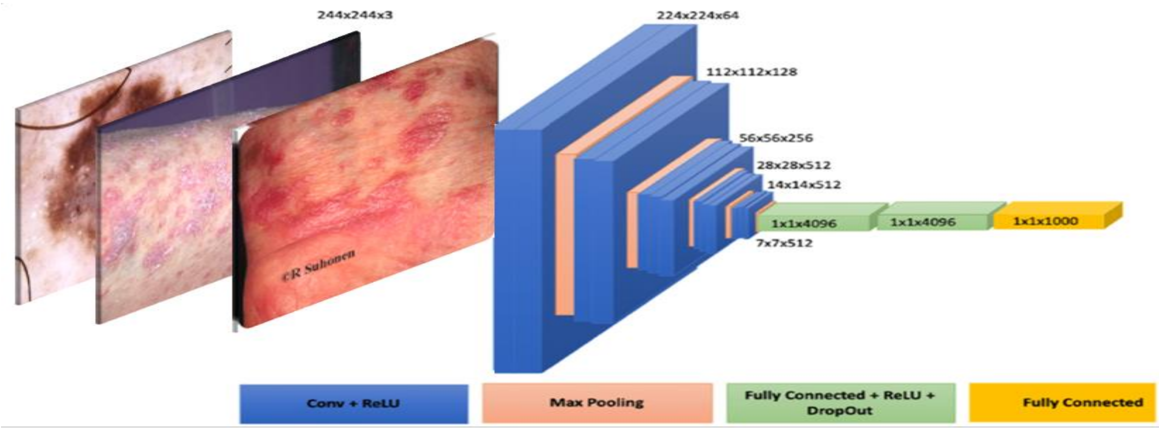


Figure 4.2.1: Schematic representation of VGG16 (R. Cattell et al. [27])

InceptionV3: InceptionV3, released by Google in 2015, has demonstrated its superiority in ImageNet and MS-COCO contests. In transfer learning, InceptionV3 is frequently used to fine-tune a pre-trained model on a new dataset. This entails taking advantage of the rich feature representations learnt from large-scale datasets like as ImageNet and customizing them to specific tasks, therefore considerably decreasing the time and computer resources required to train deep neural networks from scratch. The main innovation in InceptionV3 is factorized convolutions and grid size reductions, which improve computational efficiency and representational power. It also uses auxiliary classifiers to solve vanishing gradients in deep networks. InceptionV3's architecture consists of 48 layers, including multiple convolutions, pooling layers, and fully linked layers. It contains about 23,000,000 parameters and incorporates modules such as 1x1, 3x3, and 5x5 convolutions with varying filter counts, which are coupled in an effective manner to capture diverse spatial information. InceptionV3's novel design improves visual understanding and localization tasks, demonstrating great performance in both areas. Mapping ImageNet classes to Wolfram Language Entities poses a unique challenge. The InceptionV3 architecture effectively tackles these issues, making it a useful tool for a variety of picture identification and localization tasks.

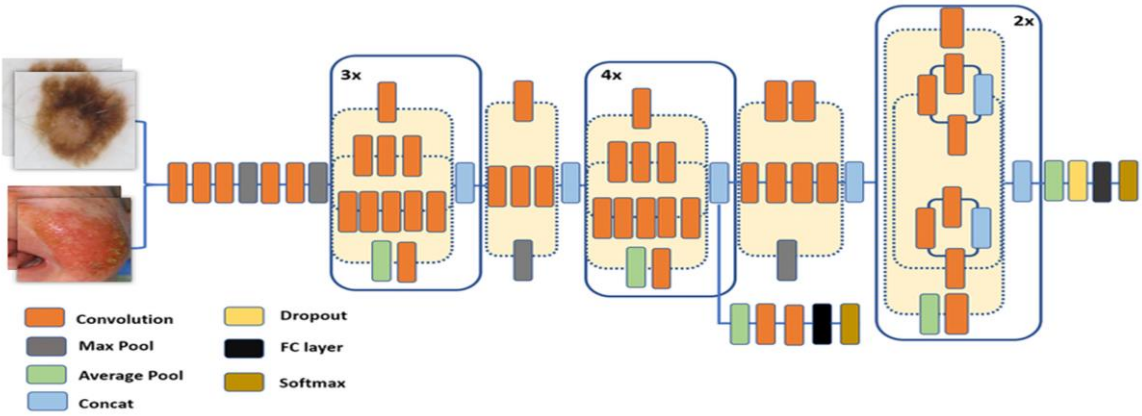


Figure 4.2.2: Schematic representation of InceptionV3 (S. El-bana et al. [25])

MobileNetV3: MobileNetV3 is an advanced convolutional neural network (CNN) architecture that strikes a balance between computational efficiency and excellent performance, carefully tailored for mobile devices. The inverted residual structure, which deliberately positions residual connections between bottleneck layers to improve information flow and gradient propagation, is fundamental to its design. Lightweight depth-wise (Dwise) convolutions are used in the intermediate expansion layers of this design to filter features and introduce non-linearity efficiently and at a minimal computational cost. The architecture strikes a balance between complexity and performance, beginning with 32 filters and ending with 19 residual bottleneck layers. The network architecture is shown graphically in Figure 4, which also shows the connectivity and layering strategy that allow MobileNetV3 to achieve great accuracy with low computational resources, which makes it perfect for mobile applications.

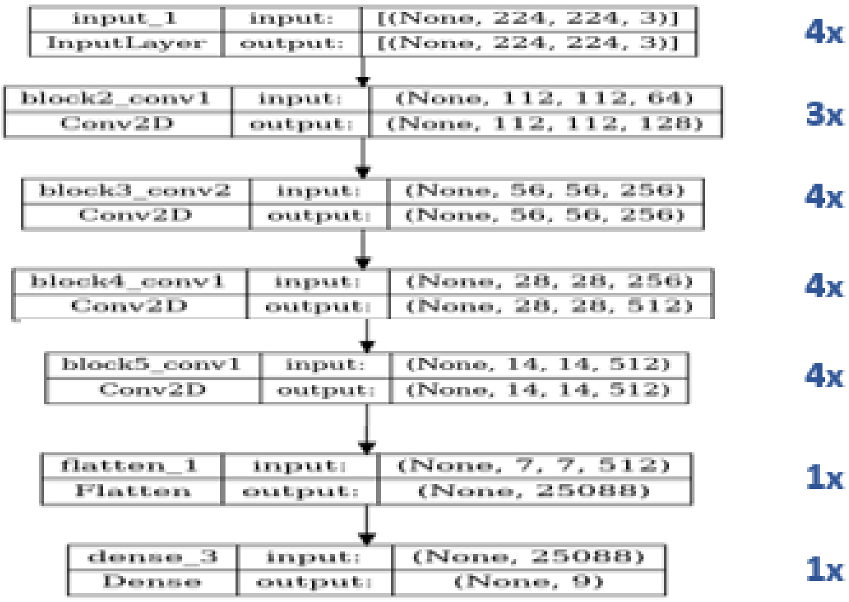


Figure 4.2.3: Schematic representation of MobileNetV3

EffcicientNetB2: EfficientNetB2 is a deep neural network that optimizes performance and efficiency by consistently adjusting the network's depth, width, and resolution. EfficientNetB2 improves on the baseline EfficientNetB0 in these dimensions, resulting in improved accuracy with fewer parameters. The architecture uses depth-wise separable convolutions, which divide traditional convolutions into depth-wise and pointwise convolutions, resulting in a significant reduction in parameter count and computational complexity. EfficientNetB2 employs squeeze-and-excitation blocks for channel-specific feature recalibration, which increases representational capacity. EFB2 includes an initial convolutional layer with 32 filters. It employs the Swish activation function for smoother gradients and enhanced training dynamics, resulting in superior performance on image recognition tasks with less computational overhead.

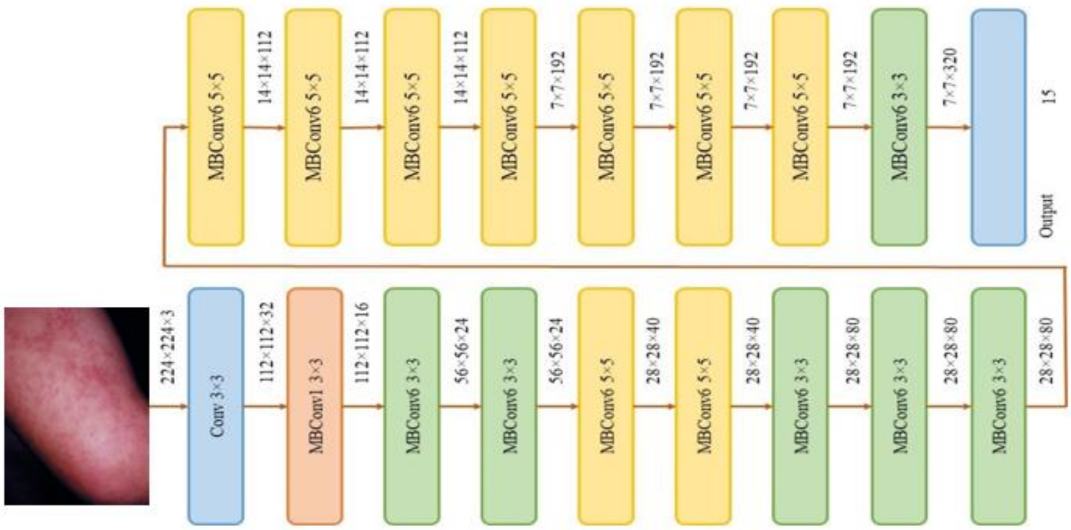


Figure 4.2.4: Schematic representation of EfficientNetB2

EffcicientNetB5: EfficientNetB5 is a deep neural network that has been tuned for performance and efficiency via compound scaling. It enhances the depth, width, and resolution dimensions, resulting in greater accuracy while retaining parameter efficiency. It contains a first convolutional layer with 48 filters. EfficientNetB5, a potent method for image recognition, is renowned for its precision and computational capability. Like EfficientNetB2, its larger design produces better results in high-precision applications. Its seven-block architecture, with several layers and processes in each, makes it perfect for high-precision applications.

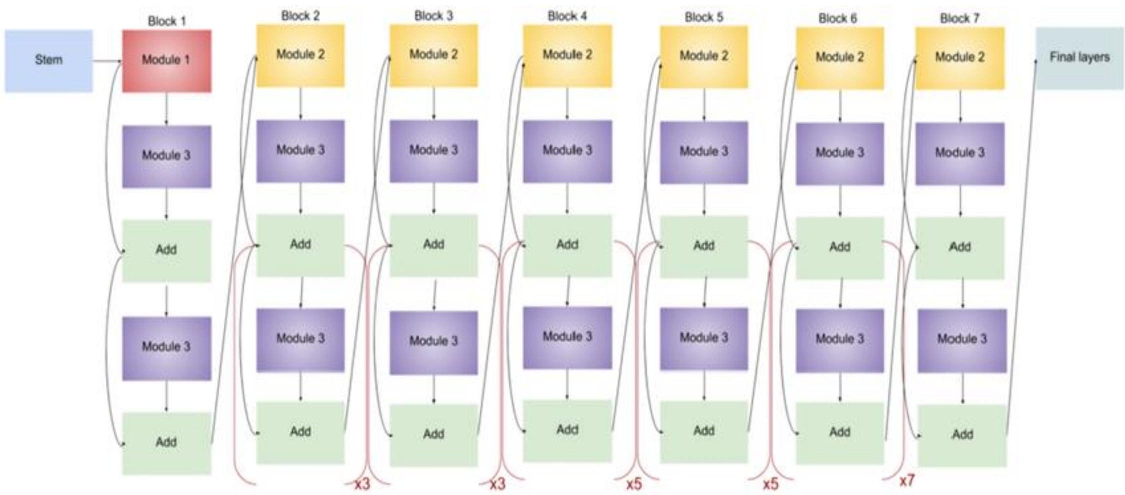


Figure 4.2.5: Schematic representation of EfficientNetB5 (T. Awan et al. 2023)

Training:

This stage generates a CNN learner model. The dataset was used to train and evaluate a model for classification accuracy with VGG16, Inception-V3, MobileNetv3, EfficientNetB2, and EfficientNetB5. All representations were trained over 25 epochs using early stopping call-backs. Patience refers to the number of epochs without progress before training ceases. Learning rate = 0.001, Beta1 = 0.9, and Beta2 = 0.999. An Adamax optimizer takes momentum from previous gradients and adjusts the learning rates based on the scaled gradient magnitude. Four representations received a similar optimizer (Adamax), although only one model (VGG-16) employed the Adam optimizer. MobileNet takes 86 seconds every epoch, while InceptionV3 takes 334 seconds, VGG16 takes 72 seconds, efficientNetB2 takes 209 seconds, and efficientNetB5 takes just 442 seconds.

In this study, the standard deviation was used as a model performance parameter because the dataset contained no substantial imbalances. Categorical cross-entropy was chosen as a loss target for all CNN designs because this study requires multi-class sorting. Here were the hyperparameters: There were multiple epochs in various models, where EfficientNet b2 & b5 and InceptionV3 use epoch 25, mobilenetV3 uses 15, and VGG-16 uses epoch 100, EfficientNet b2 & b5, InceptionV3, mobilenetV3 all use 32 batches except for VGG-16, which uses 128 batches, only VGG-16 uses a dropout rate of 0.5 while others use 0.45 dropout rate, and VGG-16 & InceptionV3 have a learning rate of 0.0001 EfficientNetB2, B5, and MobileNetV3 have a lr of 0.001. Prior to resizing, all photographs were reduced to the architecture's default picture size.

4.3 System Testing

Evaluation Metrics in Classification: F1 Score, Precision, Recall, and Support

Understanding and accurately assessing the performance of classification models in machine learning, particularly Convolutional Neural Networks (CNNs) for tasks like skin disease classification, necessitates the use of robust evaluation metrics. Here, we delve into the definitions and significance of four key metrics: F1 Score, Precision, Recall, and Support, drawing on references from relevant studies.

Evaluation metrics commonly used in classification tasks include the F1 score, precision, recall, and support. To comprehensively evaluate the performance of classification models in machine learning, namely Convolutional Neural Networks (CNNs) used for tasks such as skin disease detection, it is essential to employ reliable assessment measures. In this analysis, we will explore the definitions and importance of four crucial metrics: F1 Score, Precision, Recall, and Support. We will refer to pertinent studies to provide accurate information.

Precision:

Precision is a crucial statistic that quantifies the correctness of the positive predictions provided by a model. Precision is the quotient obtained by dividing the number of true positive predictions by the total number of positive predictions, which includes both true positives and false positives. Accuracy is essential in situations where the consequences of incorrect positive results are significant. In the context of skin disease categorization, it is crucial to prevent the misclassification of healthy samples as sick in order to avoid unwarranted alarm or treatment. In their work on CNN algorithms for skin disease classification, Wu et al. [19] emphasized the importance of precision in reducing false positives and enhancing the accuracy of diagnosis.

Precision (P): Measures the accuracy of the positive predictions.

$$P = \frac{TP}{TP+FP} \quad \text{---} \quad (1)$$

Recall:

Recall, also referred to as Sensitivity or True Positive Rate, quantifies the model's capacity to correctly detect all pertinent occurrences. Precision is defined as the quotient between the number of correct positive predictions and the total number of real positive cases, which includes both true positives and false negatives. Ensuring accurate identification of ill patients is crucial in medical diagnostics, necessitating a high level of recall Rezaoana et al. [20]. In the same vein, Maduranga et al. [21] emphasized the significance of recall in their mobile-based system for diagnosing skin diseases. This was done to guarantee the proper detection of all positive instances.

Recall (R): Measures the ability to capture all positive samples.

$$R = \frac{TP}{TP+FN} \quad \text{---} \quad (2)$$

The F1 score:

The F1 Score is a mathematical measure that combines Precision and Recall using the harmonic mean, resulting in a single metric that effectively balances both considerations. It is especially advantageous in situations where there is an imbalanced distribution of classes, providing a more comprehensive evaluation of a model's accuracy compared to precision or recall alone. Wu et al. [19] emphasized the use of F1 Score to evaluate CNN algorithms for classifying facial skin diseases. They noted that the F1 Score effectively balances the trade-offs between precision and recall. In addition, Anand et al. [22] employed the F1 Score to assess the effectiveness of their transfer learning model in classifying skin diseases across multiple categories. This choice of evaluation metric highlights its ability to provide a fair and comprehensive measure of the model's performance.

F1-Score (F1): Harmonic mean of precision and recall, providing a single metric that balances both concerns.

$$F1 = 2 \times \frac{P \times R}{P + R} \quad \text{--} \quad (3)$$

Support:

Support is a measure that indicates the actual number of times each class appears in the dataset. The statistic is crucial as it gives context to the assessment of precision, recall, and F1 Score by displaying the distribution of classes. Anand et al. [2022] employed assistance to assign weights to the average metrics in their study on classifying skin diseases in several categories. This approach ensured a fair evaluation of classes with varying frequencies. In addition, Taner et al. [24] examined the effectiveness of deep learning CNN models in categorizing different types of hazelnuts. They utilized assistance to gain a better understanding of the distribution of these categories and how they influenced the evaluation of the models.
Support=Number of true instances of each class in the dataset.

Besides, these four, there are two major deals available here. They are called accuracy and confusion matrix.

Accuracy:

Accuracy of classification models is one metric. Accuracy is the percentage predicted by the model. Accuracy is the proportion of correctly categorized images to total samples.
Accuracy (A) : Measures the overall correctness of the model's predictions.

$$A = \frac{TP + TN}{TP + TN + FP + FN} \quad \text{--} \quad (4)$$

Measures the ability of the model to distinguish between classes. These metrics comprehensively assess the model's predictive capabilities, highlighting its robust performance and diagnostic accuracy.

$$\text{AUC} = \int_0^1 TPR(FPR)d(FPR) \quad \text{--------------------------------} \quad (5)$$

where:

TPR $= \frac{TP}{TP+FN}$ (True Positive Rate or Recall) and $FPR = \frac{FP}{FP+TN}$ (False Positive Rate)

Confusion Matrix:

The confusion matrix (CM) is a table format used to measure the effectiveness of an algorithm. CM is used to demonstrate important predictive metrics such as recall, specificity, precision, and accuracy.

Furthermore, confusion matrices are useful for determining precision, recall, F1 score, and ROC curve, which collectively offer a thorough assessment of model performance. This is particularly important in medical diagnostics, where the severity of different errors can vary (B. Ahmad et al. [18])

The table displays the true positives, false positives, true negatives, and false negatives, which are crucial for understanding the algorithm's performance and evaluating the accuracy and reliability of the model.

The study conducted by Sadik et al. [23] emphasized the application of transfer learning in assessing convolutional neural network topologies, hence aiding in achieving a balance between sensitivity and specificity.

The authors Zhu et al. [36] employed confusion matrices to evaluate their deep learning framework for the diagnosis of skin diseases. This allowed them to determine the model's sensitivity and pinpoint areas that needed development. The authors Ahammed et al. [37] utilized confusion matrices to evaluate the performance of their machine learning method in detecting skin diseases, identifying both its advantages and limitations.

The confusion matrix is an essential tool for assessing the performance of classification algorithms. It offers valuable insights beyond accuracy by uncovering issues such as high false positives or negatives that may not be evident when considering overall accuracy.

ROC Curve:

The Receiver Operating Characteristic (ROC) curve is an essential tool used to assess the effectiveness of diagnostic tests and machine learning models. The Receiver Operating Characteristic (ROC) curve illustrates the relationship between the sensitivity (true positive rate) and the specificity (1 - false positive rate) at different threshold values. The Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC) is a numerical figure that provides a concise summary of the overall performance of a test. An AUC of 1.0 signifies perfect accuracy, while an AUC of 0.5 suggests performance that is no better than random chance (Janssens and Martens et al. [35]).

ROC curve is widely used in different fields, including medical diagnostics, to assess the accuracy of tests like enzyme-linked immunosorbent assays (ELISA) for autoimmune illnesses (Tampoia et al. [28]). The Receiver Operating Characteristic (ROC) curve is crucial for assessing and contrasting the efficacy of various diagnostic instruments and algorithms. For example, it has been employed to assess the diagnostic efficacy of deep learning models in the field of dermatology (Wu et al. [32]) and to compare different machine learning classifiers in the identification of skin diseases (Gupta et al. [34]).

ROC curves are highly useful in machine learning when dealing with imbalanced classes, since they offer significant insights into the trade-offs between sensitivity and specificity at various thresholds. Accuracy is of utmost importance in medical applications, as the consequences of both false negatives and false positives can have substantial financial implications (Srinivasu et al. [33]). In addition, the ROC curve helps in choosing the best model by determining the threshold that maximizes the diagnostic accuracy (Arifin et al. [29]). ROC curve is valuable because it may visually and quantitatively assess model performance without being affected by the distribution of classes. Due to its versatility, this instrument is highly effective for evaluating performance in a wide range of scenarios, including clinical diagnostics and applications in artificial intelligence and machine learning (Muhaba et al. [31]).

4.4 Summary

The use of transfer learning to convolutional neural network (CNN) architectures for image classification is examined in this part with an emphasis on skin conditions. There are five CNN models available: InceptionV3, MobileNetV3, EfficientNetB2, EfficientNetB5, and VGG16. Every model is examined in terms of its architectural layouts, features, and functions. There are training protocols available that cover hyperparameter optimization and dataset preparation. Reducing overfitting and increasing training efficiency are achieved through the use of optimizers and early pausing. To evaluate the models' effectiveness in classifying images and identifying skin conditions, evaluation metrics such as F1 Score, Precision, Recall, and Support are employed. The paper assesses the applicability of CNN models, pointing out their advantages and disadvantages as well as possible directions for further investigation. The paper covers important findings that have important ramifications for future study in the areas of picture classification and medical condition identification.

CHAPTER 5
RESULT AND ANALYSIS

5.1 Overview

The paper "Skin Disease Classification using Fine-tuned Transfer Learning Techniques" investigates sophisticated approaches to diagnose skin disorders by employing convolutional neural networks (CNNs), with a particular focus on the utilization of transfer learning. The study utilizes powerful computing resources, advanced programming frameworks such as TensorFlow or PyTorch, and a carefully curated collection of varied medical photos. The essence of the study revolves around optimizing pre-trained deep CNN architectures to improve their capacity for reliably detecting different skin states.

The document provides a comprehensive analysis that compares five distinct CNN models: EfficientNetB2, EfficientNetB5, InceptionV3, MobileNetV3, and VGG16. The performance of each model is evaluated using important measures such as accuracy, precision, recall, and F1 score. The results reveal significant disparities in the efficacy of these models, with EfficientNetB2 exhibiting the highest level of accuracy, particularly excelling in the context of the study's meticulous dataset and preprocessing criteria. In addition, the study examines the qualitative aspects of model performance by assessing how each model addresses various obstacles faced in the classification of skin disease photos. This complete method evaluates not only the quantitative efficacy of the models but also investigates their operational attributes in different settings, offering insights into possible enhancements and the consequences of changes in architecture and training strategies.

This study also provides a comprehensive examination of the suitability of CNNs in the domain of dermatological diagnostics. It showcases both the achievements and areas that could be improved in the classification of skin diseases through the use of modern machine learning methods.

5.2 Experimental/ Simulation Result

This section provides an elaborate comparison of five distinct designs of convolutional neural networks (CNNs): EfficientNetB2, EfficientNetB5, InceptionV3, MobileNetV3, and VGG16. The study investigates the categorization efficacy of different models for skin disorders, with a specific emphasis on their respective advantages and limitations. It additionally evaluates their general attributes, encompassing accuracy, precision, recall, and F1 score. The study surpasses quantitative assessments to offer an intricate comprehension of the models' conduct in diverse circumstances. The study also examines the elements that influence different results, such as the suitability of CNN networks for medical imaging, the intricacy of the design, and the parameter setup. The objective is to conduct a thorough analysis of both the quantitative and qualitative components of model performance. The study emphasizes the possibility of advancing the categorization of skin disorders through the use of models. However, it is essential to pinpoint regions that are not doing well in order to make future improvements in the design, training, and augmentation of datasets. The study concludes by examining the qualitative factors that impact the results of VGG16, InceptionV3, MobileNetV3, EfficientNetB2, and EfficientNetB5.

The categorization effectiveness of these networks is also evaluated statistically. This study enhances our comprehension of the CNN networks' suitability in the critical field of skin-disease classification by conducting a thorough evaluation of the models' skills and identifying areas for enhancement. In addition, the study explores possible improvements and modifications that could boost the performance and dependability of models in clinical settings, thereby significantly developing the area of medical imaging.

TABLE 5.2.1: Accuracy for Classification of Individual CNN Networks in skin disease classification (TransferLearning CNN Networks)

Architecture	**Training Accuracy**	**Test Accuracy**
VGG16	98.03%	79.02%
Inception-V3	97.07%	80.31%
MobileNetv3	99.05%	86.48%
EfficientNetB2	99.79%	89.37%
EfficientNetB5	99.26%	87.10%

The Table 5.2.1 provides a comprehensive analysis of five different Convolutional Neural Network (CNN) architectures: VGG16, InceptionV3, MobileNetV3, EfficientNetB2, and EfficientNetB5. The test set accuracy is a crucial metric that shows how well the models can detect samples. The results demonstrate notable performance for each of these structures, indicating their applicability within the study's parameters. The EfficientNetB2 model performs exceptionally well; its 89.37% accuracy rate is an impressive accomplishment that shows how well the algorithm was able to recognize skin-disease samples in the dataset. Furthermore, EfficientNetB5 showed promise in terms of performance with a good accuracy, indicating room for improvement. Diverse results contribute to the quantitative assessment of CNN designs and offer valuable insights into the relative effectiveness of various models in the difficult task of diagnosing skin diseases.

TABLE 5.2.2: Precision, Recall, F1-Score, and Support (n) result of Transfer Learning CNN networks(based on the number of images, n= numbers)

VGG16				
	Precision	**Recall**	**F1-Score**	**Support**
0	0.57	0.56	0.57	169
1	0.62	0.65	0.64	211
2	0.93	0.92	0.93	314
3	0.89	0.92	0.9	333
4	0.91	0.94	0.92	797
5	0.8	0.67	0.73	209
6	0.54	0.55	0.55	206
7	0.66	0.6	0.63	186
8	0.56	0.57	0.56	171
Accuracy			0.79	2596
Macro avg	0.72	0.71	0.71	2596
Weighted avg	0.79	0.79	0.78	2596
Inception-V3				
	Precision	**Recall**	**F1-Score**	**Support**
0	0.48	0.56	0.52	169
1	0.63	0.71	0.67	211
2	0.97	0.9	0.94	314
3	0.68	0.98	0.81	333
4	0.88	0.95	0.91	797
5	0.93	0.21	0.34	209
6	0.46	0.5	0.48	206
7	0.66	0.55	0.6	186
8	0.6	0.36	0.45	171
Accuracy			0.81	2596
Macro Avg	0.8	0.71	0.63	2596
Weighted Avg	0.81	0.74	0.72	2596
MobileNetv3				
	Precision	**Recall**	**F1-Score**	**Support**
0	0.7	0.61	0.65	169
1	0.73	0.82	0.77	211
2	0.98	0.98	0.98	314
3	0.93	0.98	0.95	333
4	0.95	0.98	0.97	797
5	0.95	0.76	0.84	209
6	0.64	0.71	0.67	206

7	0.73	0.78	0.76	186
8	0.79	0.58	0.67	171
Accuracy			0.86	2596
Macro Avg	0.82	0.8	0.81	2596
Weighted Avg	0.87	0.86	0.86	2596
EfficientNetB2				
	Precision	**Recall**	**F1-Score**	**Support**
0	0.68	0.83	0.75	169
1	0.78	0.78	0.78	211
2	0.98	0.98	0.98	314
3	0.88	0.96	0.92	333
4	0.97	0.96	0.96	797
5	0.88	0.83	0.85	209
6	0.73	0.73	0.73	206
7	0.86	0.81	0.83	186
8	0.83	0.68	0.75	171
Accuracy			0.89	2596
Macro Avg	0.85	0.85	0.85	2596
Weighted Avg	0.88	0.89	0.88	2596
EfficientNetB5				
	Precision	**Recall**	**F1-Score**	**Support**
0	0.61	0.78	0.69	169
1	0.74	0.74	0.74	211
2	0.99	0.99	0.99	314
3	0.88	0.98	0.93	333
4	0.98	0.96	0.97	797
5	0.86	0.79	0.83	209
6	0.68	0.67	0.68	206
7	0.83	0.77	0.8	186
8	0.79	0.64	0.71	171
Accuracy			0.87	2596
Macro Avg	0.82	0.82	0.82	2596
Weighted Avg	0.87	0.87	0.87	2596

In Table 5.2.2, an thorough review of the results obtained for skin-disease classification utilizing transfer learning Convolutional Neural Network (CNN) architectures is provided. The results include precision, recall, F1-score, and specificity. Notably, transfer learning performs well to improve the accuracy of skin-disease categorization, as evidenced by the parameters of support, recall, and precision showing constant increases across many models. However, the 88% classification accuracy for the EfficientNetB2 and EfficientNetB5 models points to a minor observation in the dataset that needs to be noticed. This specific accuracy result calls for further investigation as it may imply limitations in the discriminatory potential of these models for the detection of skin disorders in the context of the dataset under study, even though precision, recall, and F1-score all demonstrated an overall favorable trend. This insight, which emerged from a close examination of all 5 tables, highlights the need of both praising successes and critically evaluating model-specific performance. This will assist in gleaning nuanced insights and guiding subsequent advancements toward the objective of higher diagnostic accuracy.

Training and Validation Accuracy and loss of Transfer Learning CNN Networks:

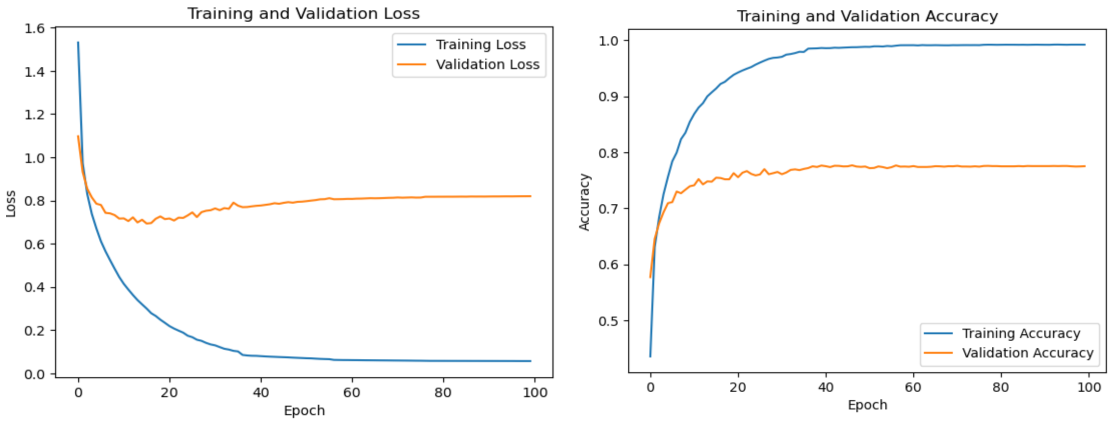


Figure 5.2.1: Training and validation accuracy and loss over the epochs (VGG16 Transfer Learning CNN Network).

Figure 5.2.2: Training and validation accuracy and loss over the epochs (InceptionV3 CNN Network).

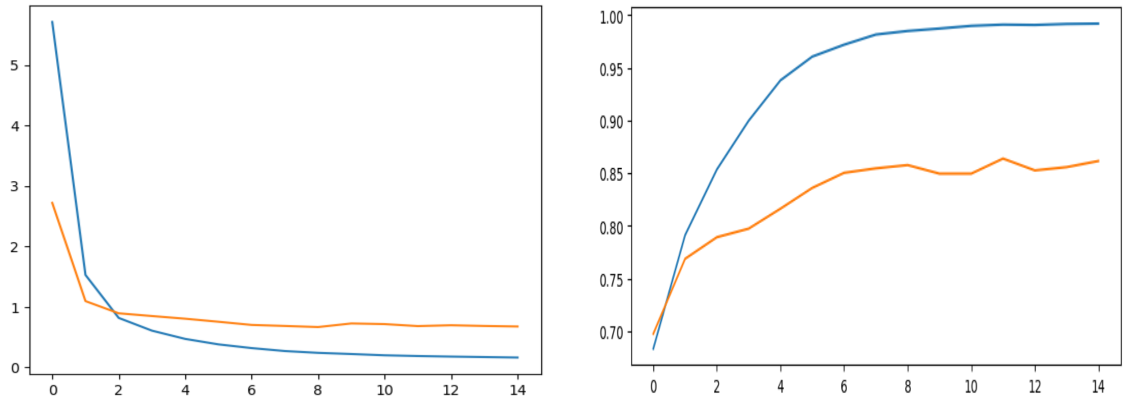


Figure 5.2.3: Training and validation accuracy and loss over the epochs (MobileNetv3 Transfer Learning CNN Network).

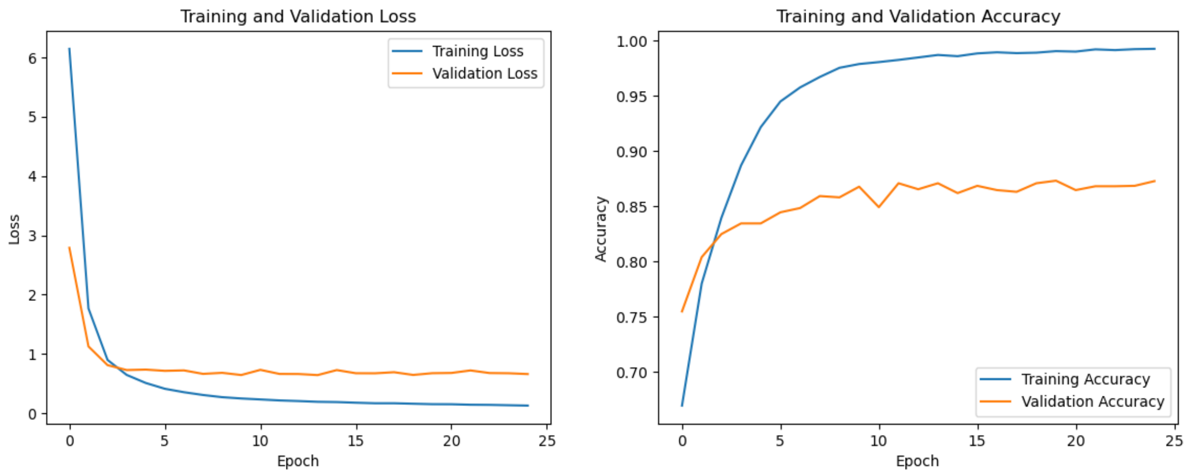


Figure 5.2.4: Training and validation accuracy and loss over the epochs (EfficientNetB2 Transfer Learning CNN Network).

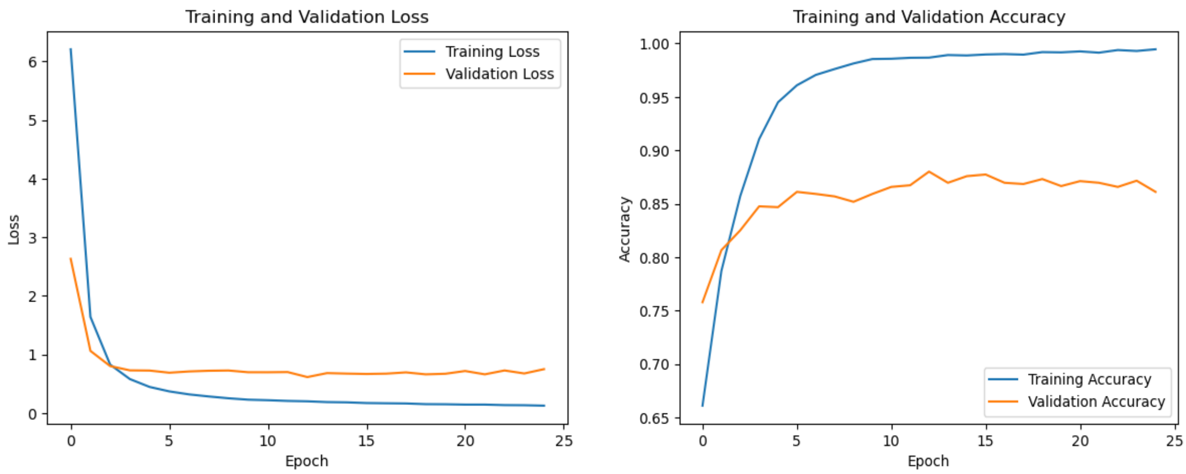


Figure 5.2.5: Training and validation accuracy and loss over the epochs (EfficientNetB5 Transfer Learning CNN Network).

The graphical representation of Transfer Learning (TL) training and validation losses over multiple epochs is a crucial tool for researching the iterative improving process of CNN architectures. Loss functions are crucial in guiding CNN model development over several epochs. They calculate the discrepancy between actual and predicted values. The trajectory of these losses provides valuable insights into the model's learning dynamics and emphasizes the necessity of optimizing network parameters. Determining the model's capacity for generalization requires analyzing its performance on both training and validation datasets. The model's efficacy after a specific optimization cycle is represented by each point on the loss curve, which offers a comprehensive understanding of the model's evolving competency. The quantity of example mistakes associated with each training or validation set improves understanding of model performance by emphasizing the impact of optimization cycles on error minimization. These loss values are essentially dynamic indicators of the model's performance that demonstrate how it improves over the course of additional training epochs.

Confusion Matrix

Figure 5.2.6: Confusion matrix of VGG16

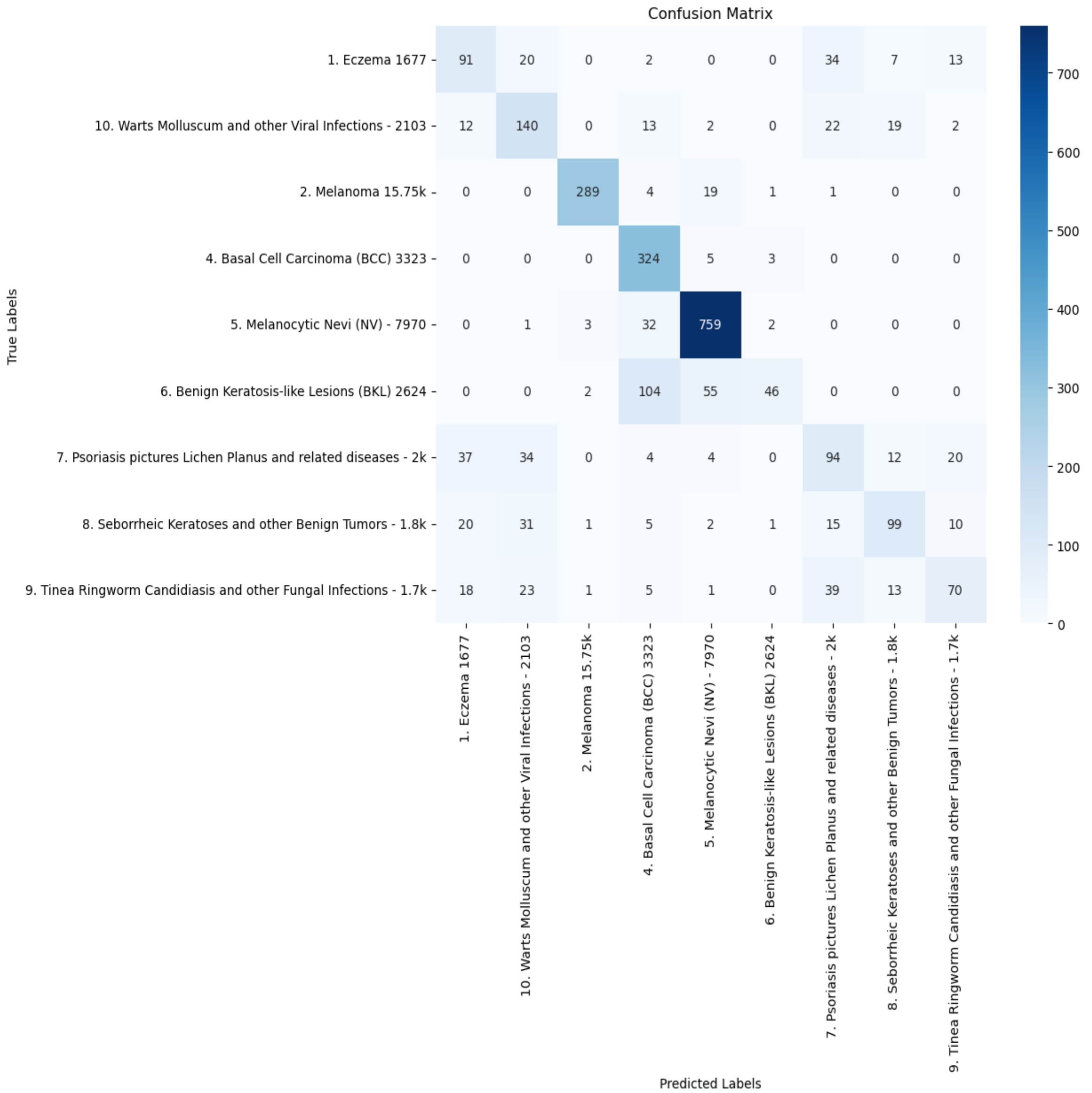


Figure 5.2.7: Confusion matrix of InceptionV3

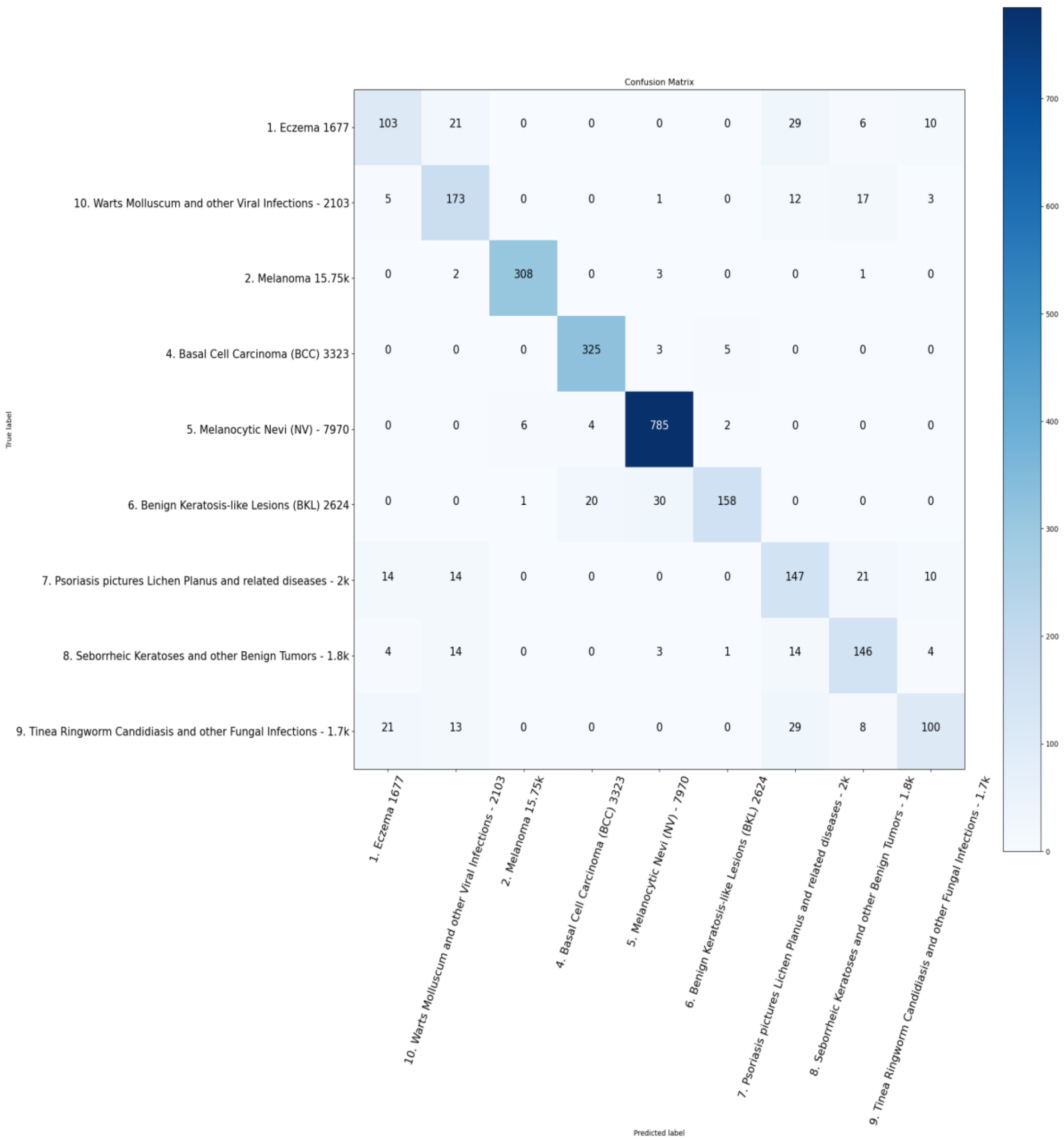


Figure 5.2.8: Confusion matrix of MobileNetv3

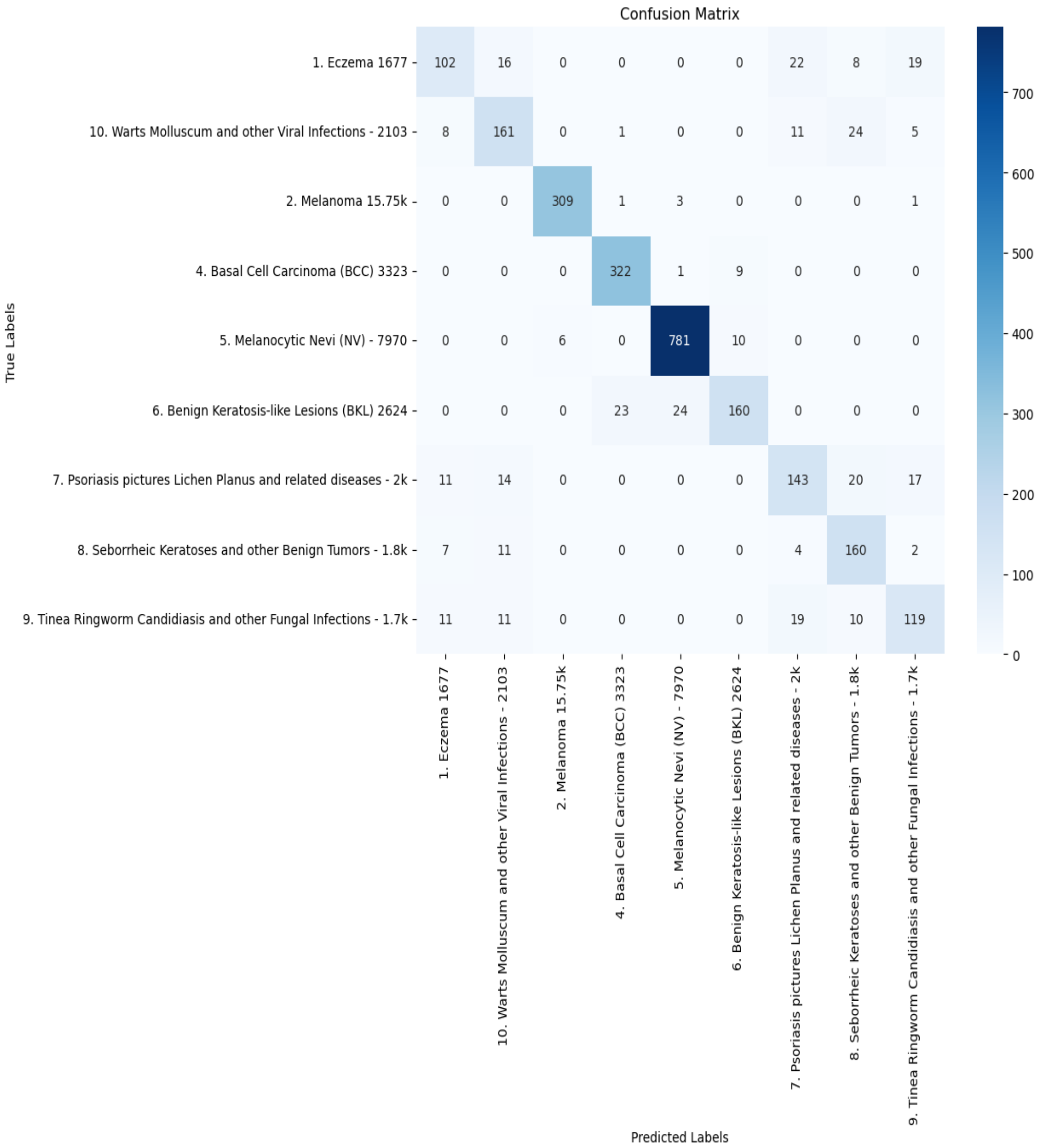


Figure 5.2.9: Confusion matrix of EfficientNetB2

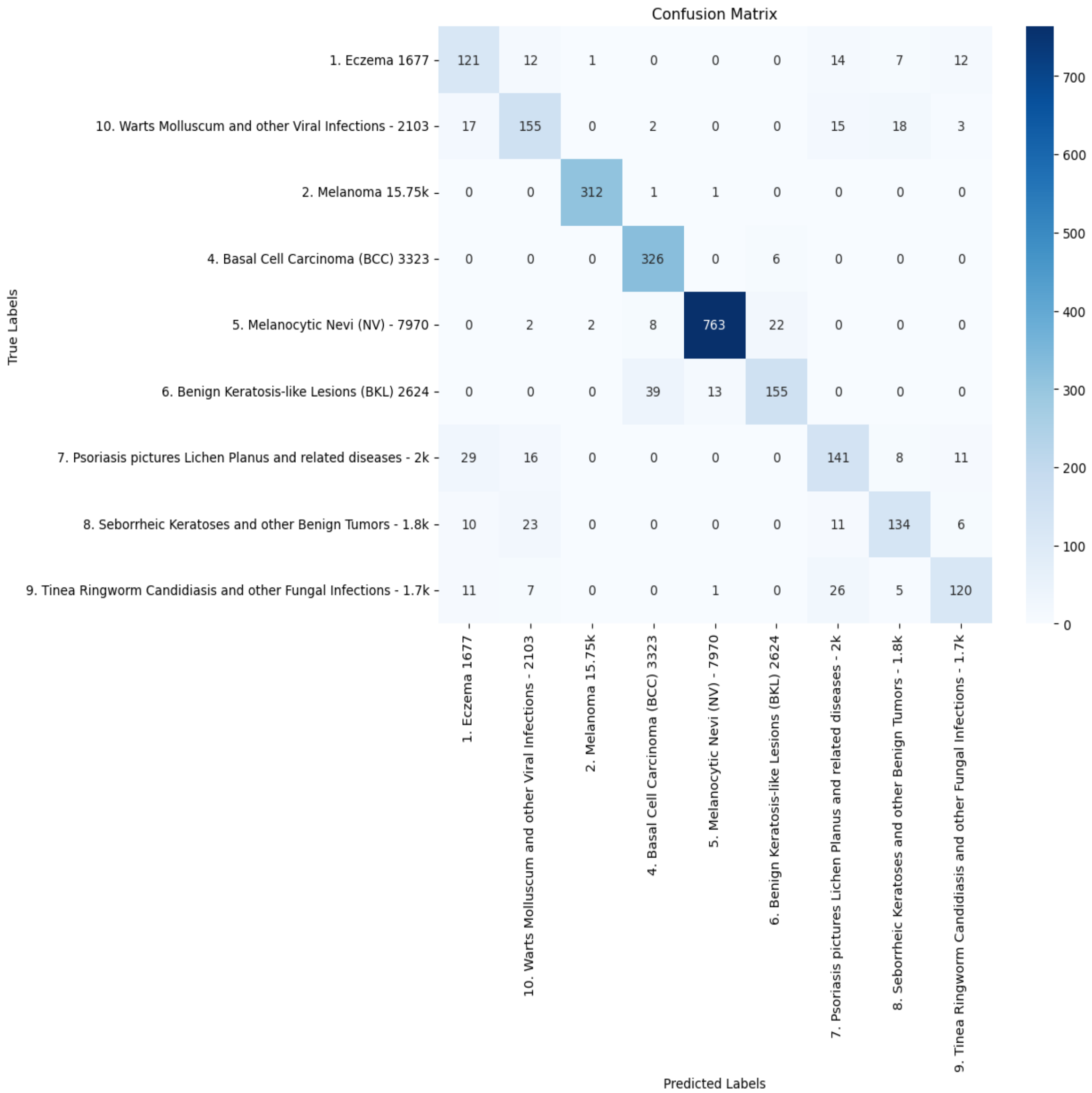


Figure 5.2.10: Confusion matrix of EfficientNetB5

The model appears to be operating well overall, as seen by its high proportion of true positives and true negatives. Still, a small percentage of false positives and false negatives occur. False negative results may postpone or prevent patients from receiving the essential care, while false positive results may result in patients receiving needless therapy when they don't genuinely have skin disease classification. It's crucial to remember that this is only a little sample of data, and that the model's performance can change based on the dataset used for training. Furthermore, the confusion matrix only provides a portion of the picture. Additional measures that can reveal more about the success of the model include precision, recall, and F1 score. All things considered; the confusion matrix offers a useful means of visualizing a classification model's performance. We can enhance the model's performance by comprehending the many kinds of mistakes it is making.

ROC Curve:

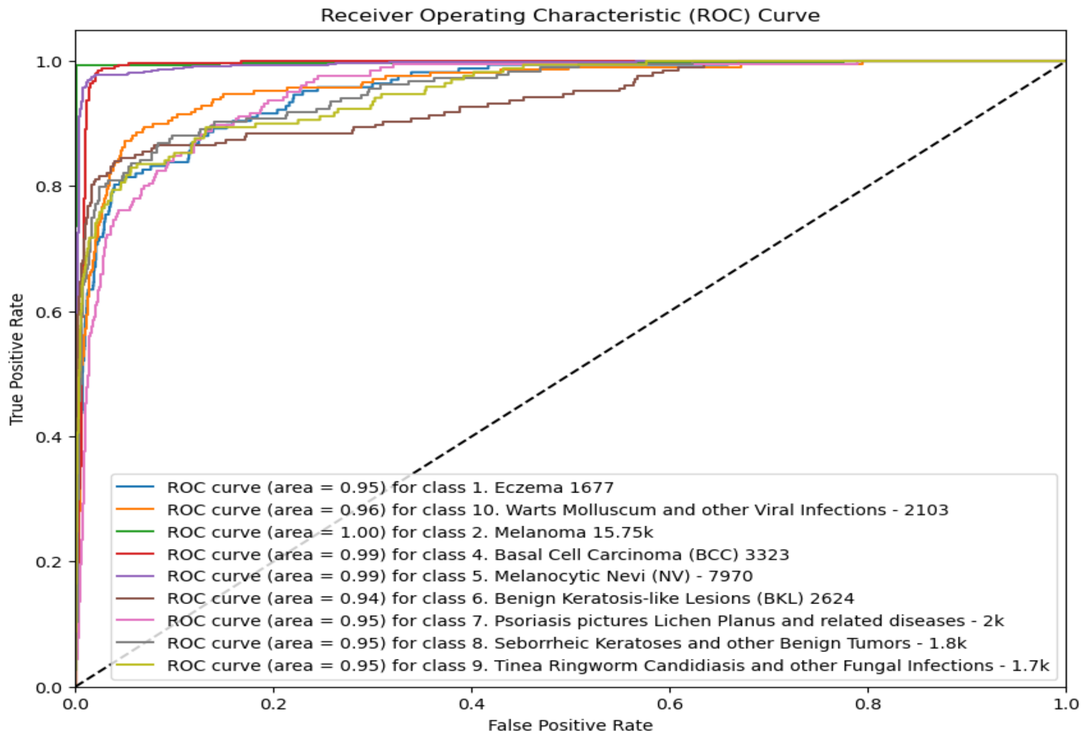


Figure 5.2.11: ROC curve of EfficientNetB5

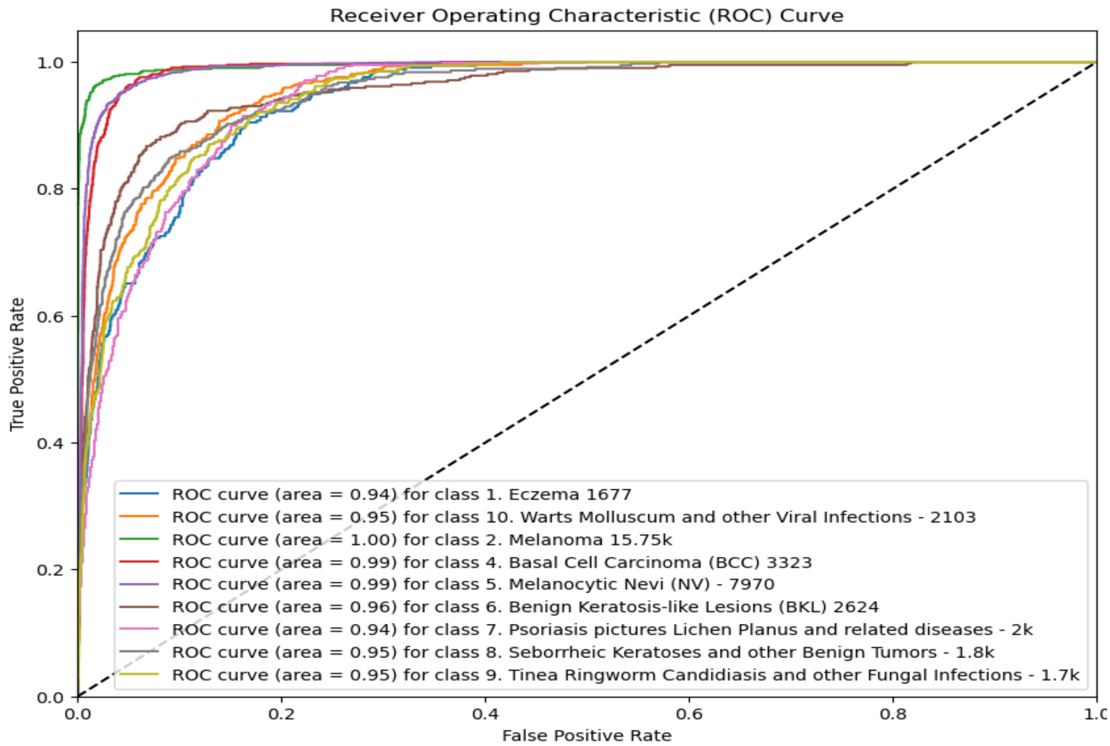


Figure 5.2.12: ROC curve of MobileNetV3

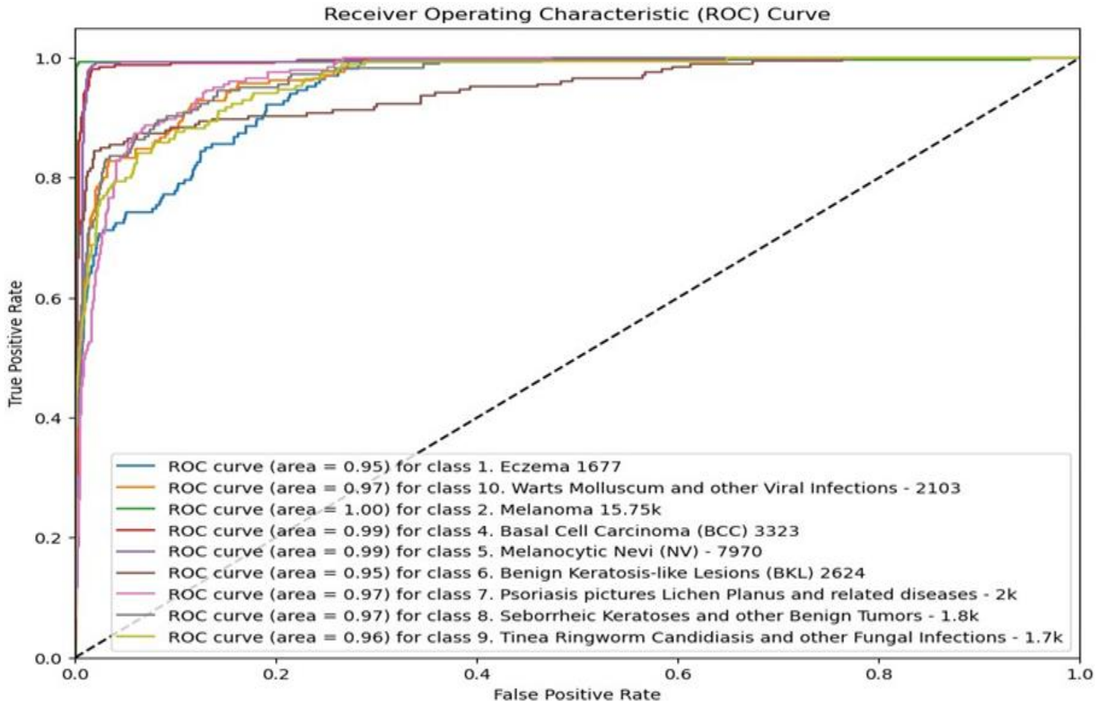


Figure 5.2.13: ROC curve of EfficientNetB2

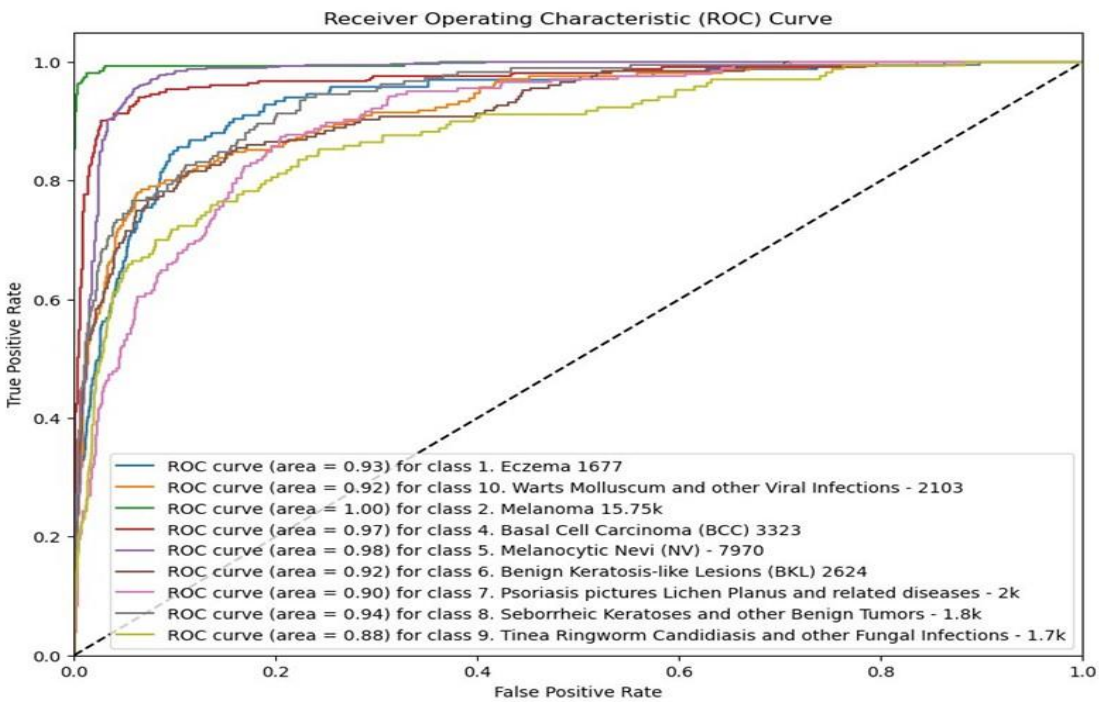


Figure 5.2.14: ROC curve of VGG-16

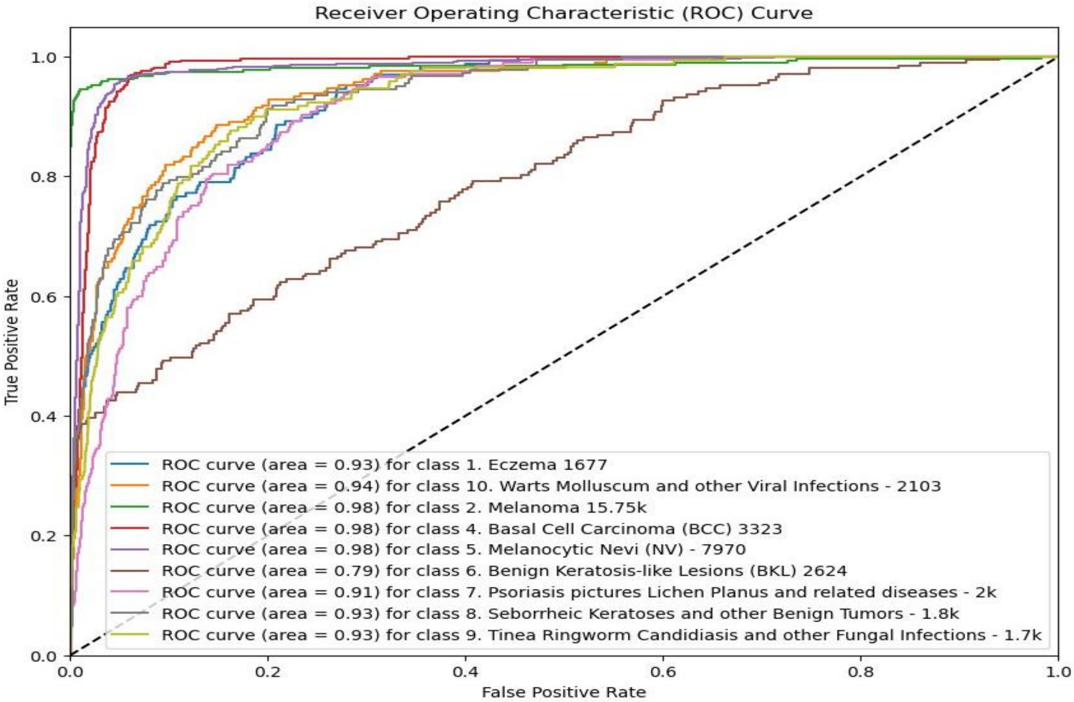


Figure 5.2.15: ROC curve of InceptionV3

5.3 Performance/ Comparative Analysis

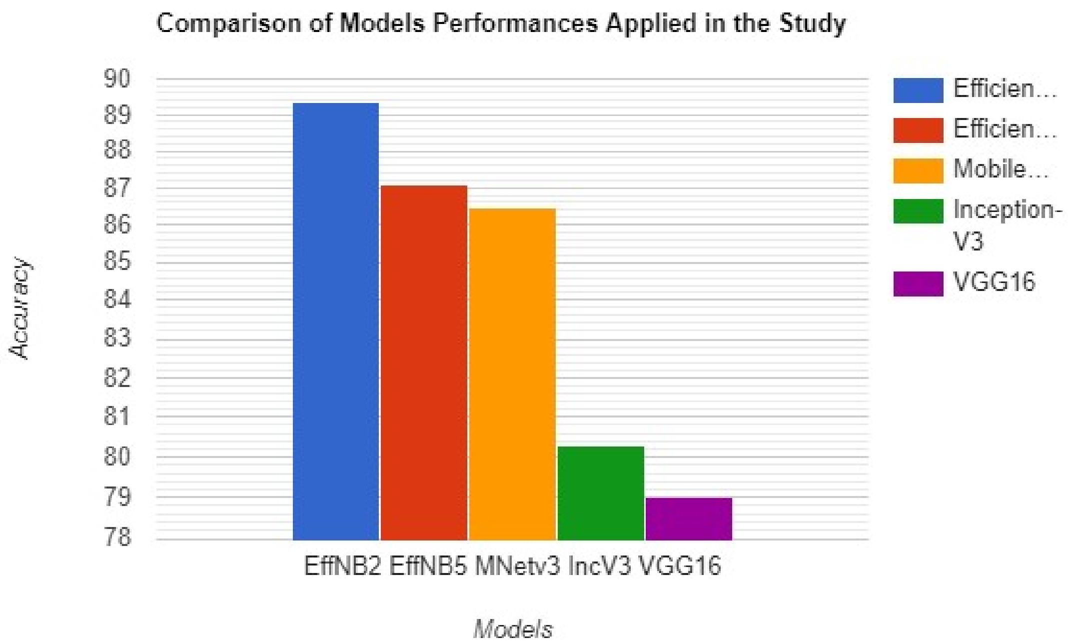


Figure 5.3.1: Accuracy comparison among individual transfer learning models.

In this extensive study, "Eczema, Warts Molluscum, Basal Cell Carcinoma, Psoriasis pictures Lichen Planus, Melanocytic Nevi (NV), Tinea Ringworm Candidiasis and other Fungus, Atopic Dermatitis, Benign Keratosis-like Lesions (BKL), Seborrheic Keratoses & other Benign Tumor And Melanoma" are among the nine different types of skin diseases that are examined in this thorough study. Utilizing a sizable dataset of (25,896+6,000) or 31,896 images, the study also makes use of a sophisticated augmentation technique. The usefulness of transfer learning strategies in some models is investigated in this study. Specifically, the study examines the calculation of detection and segmentation, acknowledging these as separate steps in the diagnostic pipeline. In order to determine, to which group the skin illness can be classified into, the graph presents a comparison of the performance of five well-known CNN transfer learning models: EfficientNetB2, EfficientNetB5, MobileNetV3, InceptionV3, and VGG16.

Notably, EfficientNetB2 has the best accuracy, surpassing 89% merely. This indicates how well it can categorize fresh photos and make generalizations from the training set. With a little lower accuracy of 87%, EfficientNetB5 trails behind EfficientNetB2, demonstrating its robustness but marginally poorer performance.

With an accuracy of greater than 86%, MobileNetV3, another lightweight model, has a decent performance. This shows that although it uses less computing resources and yet it is more efficient since its accuracy is really close to high as that of the EfficientNet models.

With an accuracy of about just a tiny bit above of 80%, InceptionV3, which is renowned for its intricate architecture and deeper layers, demonstrates its ability to handle minute details in the photos. Despite this, it is not as good as the EfficientNet models, presumably because it is more prone to overfitting on the enhanced dataset.

The CNN architecture with the lowest accuracy, VGG16, is one of the older and simpler models; its accuracy is just a little bit greater than 79%. This suggests that while though it is straightforward and simple to use, it could not be as efficient as the more sophisticated models for this particular purpose.

A thorough review reveals that the study acknowledges the constraints of a specific class size, emphasizing the possible influence on prediction abilities, primarily in relation to transfer learning. Results from earlier studies support the recommendation to expand the dataset size for tiny classes, especially when updates are made to the input image. In addition to highlighting the higher performance of more modern architectures like EfficientNetB2 and EfficientNetB5, the study emphasizes the significance of model selection in medical imaging applications. Different augmentation procedures and variations in background noise have been found as issues that can negatively impact performance. Essentially, this work offers a detailed investigation of CNN-based models for the categorization of skin diseases, providing insightful knowledge about the nuances of detection, segmentation, and the complex interactions among various model designs.

5.4 Summary

Convolutional neural networks (CNNs) are investigated in the project "Skin Disease Classification using Fine-tuned Transfer Learning Techniques" in order to improve the diagnostic accuracy of skin diseases. Deep learning frameworks like TensorFlow or PyTorch are used in the research using Python-based programming and high-performance computer resources. The ability to recognize different skin states is enhanced by pre-trained CNN architectures such as EfficientNetB2, EfficientNetB5, InceptionV3, MobileNetV3, and VGG16. Preprocessing a variety of medical picture datasets is part of the methodology to guarantee normalization and standardization. Every model's performance is assessed, taking into account its F1 scores, recall, accuracy, and precision.

Important results indicate that models such as EfficientNetB2 and EfficientNetB5 have good accuracy rates. The study highlights how crucial it is to continually assess and modify models in order to enhance their capacity for diagnosis. By offering a comparative examination of CNN-based models, the study makes a substantial contribution to medical imaging and may pave the way for more precise and trustworthy skin disease diagnosis.

CHAPTER 6

Impact on Society, Environment and Sustainability

6.1 Impact on Life

A timely and precise diagnosis is essential for the effective treatment of skin diseases, which are an increasing health risk. Conventional approaches have the potential to be undefined, time-consuming, and specialized. Deep learning-based, fine-tuned transfer learning techniques provide a novel approach to the classification of skin diseases, with significant consequences for people's lives. In certain situations, these methods may even be more accurate than human judgment when it comes to identifying different skin conditions. In the end, this improves patient outcomes by leading to earlier and more accurate diagnoses. Additionally, transfer learning enables the creation of automated diagnostic tools that can be accessed via mobile applications or telemedicine platforms. Particularly for patients with limited mobility or in remote areas, this can greatly improve access to dermatological care.

The effect also extends to medical expenses. In cases where skin diseases are advanced, a quicker and more precise diagnosis may result in earlier interventions and a possible decrease in the cost of specialized consultations and treatments. Additionally, by highlighting areas of concern and pre-screening cases, these tools can help dermatologists work more efficiently. This enables them to focus their knowledge on complex diagnosis and treatment design. It's critical to recognize the limitations, which include the demand for sizable, higher quality datasets for training, possible biases in the data, and the ongoing significance of human opinion in interpreting insights and providing final diagnoses. However, by facilitating a quicker, more precise, and easily accessible diagnosis of skin diseases, optimized transfer learning approaches for skin disease classification have tremendous potential to enhance the lives of patients and medical professionals.

6.2 Impact on Society and Environment

Skin illnesses must be precisely and quickly diagnosed to enable for an immediate and effective treatment, which can greatly enhance patients' quality of life and reduce healthcare costs due to incorrect or awaited diagnosis of disease. The suggested skin disease classification system, which makes use of enhanced transfer learning algorithms, has the potential to fundamentally change the dermatology industry by offering a dependable, easily accessible, and cost-effective approach for diagnosing a variety of skin problems. Through the utilization of deep learning and transfer learning, this system might overcome the limitations of conventional approaches that significantly depend on dermatologist knowledge, which may be limited in specific areas or societies. This approach's automated approach ensures impartial and consistent analysis, decreasing the possibility of bias or errors caused by humans in diagnosis. Additionally, the system's outstanding performance in classifying skin disorders may make it easier to identify and treat them early on, thereby delaying the progression of conditions and reducing its impact on health care systems. The overall well-being of patients can be enhanced by early diagnosis and treatment, which can help minimize the psychological discomfort and social exclusion that are often associated with visible skin conditions. By integrating this approach into telemedicine systems, patients in limited resources or distant places with limited access to dermatologists could receive expert-level diagnoses remotely. This might greatly increase access to healthcare and reduce the need for expensive and time-consuming trips to specialized hospitals. In addition, the suggested approach might be a useful instructional tool for medical students and other healthcare workers, providing them with a trustworthy resource for classifying skin diseases and improving their diagnosis skill. Across ultimately, this might result in better patient outcomes and more effective use of resources in the healthcare system. Being considered, the effective application of this approach for classifying skin diseases could have a beneficial effect on society by increasing healthcare accessibility, lowering healthcare expenses, and improving the lives of those with skin disorders.

The implementation of fine-tuned transfer learning skin disease classification systems’ development and deployment may also be advantageous for the environment. This is explained by the fact that the patients will no longer require physical consultations and transportation. Virtual diagnosis systems can work at a distance, which means that the human’s carbon footprint related to traveling to the diagnostician may be reduced. Moreover, using advanced computational approaches such as transfer-learning can enhance the training process and eliminate the need for excessive computational rescues, which can be energy-driven and have a notable environmental outcome. Designed algorithms and models can ensure a sustainable approach to these systems’ development and implementation. Finally, prognosis and identification of skin diseases may help regarded variant to be controlled and cured on time instead of a more extensive treatment.

However, it is important to consider the environmental effects of the infrastructure and data centers needed to host and operate these systems, as well as the embodied carbon emissions from the production and disposal of the computing devices used in the development and deployment processes. In conclusion, it is anticipated that the research will have little direct environmental impact. Even though the study's findings are put through procedure, the healthcare industry may have a lower carbon footprint due to fewer travel and improved computational procedures, which is consistent with sustainability and environmental awareness.

6.3 Ethical Aspects

The approach and application of the study on "Skin Disease Classification using Fine-tuned Transfer Learning Techniques" are guided on an extensive ethical framework. Ensuring patient privacy and confidentiality is of the highest priority when using medical data, especially dermatological images. During the research process, sensitive patient information is handled with the greatest concern and responsibility via adherence to ethical standards and regulatory regulations. The significance of ethical implementation is highlighted by the way this research affects healthcare and society. The objective is to prioritize patient privacy and security while using predictive modeling developments for skin condition classification to increase diagnosis accuracy and, eventually, patient treatment. Transparency and methodological documentation are integral components of ethical thinking. Thorough and unambiguous documentation facilitates examination, replication, and conscientious sharing of information. This transparency ensures that the study findings can be successfully implemented for the good of society and develops confidence between the scientific community.

In conclusion, ethical concerns were at the core of the study’s dedication to the well-being of society and the ethical use of cutting-edge transfer learning methods in dermatology. This study is intended to contribute to the advancement of medical science in a safe and ethical manner.

6.4 Sustainability Plan

The purpose of the study "Skin Disease Classification using Fine-tuned Transfer Learning Techniques" offers a sustainability plan that aims to reduce its negative effects on the environment and enhance its positive impact on society. Through the course of the study, the studies together will focus on optimizing computing efficiency. In order to lower the overall energy consumption related to the model training and deployment operations, this will include investigating energy-efficient techniques and utilizing cloud computing technologies. Additionally, efforts will be focused on implementing environmentally friendly data management and storage procedures. In order reduce its carbon footprint and encourage sustainable data habits, the research will use eco-friendly storage technologies and effective data processing approaches. In addition, ongoing awareness about and application of environmentally friendly computing principles will be given the highest priority. This includes keeping informed of developments in deep learning and transfer learning that relevant to eco-friendly technology and approaches. In order to ensure continued advancement and connection with environmental sustainability goals, the research process includes ongoing review and adaption of sustainable techniques. The current study intends to demonstrate ethical and environmentally conscious scientific innovation in the field of dermatological image analysis through integrating environmentally aware strategies back to the research procedure.

6.5 Summary

Accurate and timely diagnosis is essential for skin diseases in order to provide timely and efficient treatment, which improves patients' quality of life and lowers medical expenses related to misdiagnosed or delayed conditions. With its potential to transform dermatology by offering a dependable, easily accessible, and reasonably priced diagnostic approach, my research focuses on a system for classifying skin diseases that utilizes enhanced transfer learning techniques. This system makes use of deep learning and transfer learning to get around the drawbacks of traditional approaches that mainly rely on dermatologist expertise—which may not be available everywhere. Human bias and error are less likely according to the automated approach, which guarantees objective and consistent analysis.

The system's remarkable ability to categorize skin disorders makes it easier to identify and treat them early on, which slows the progression of conditions and lessens the burden on healthcare systems. Patients' general well-being is enhanced by early diagnosis and treatment, which also lessens the psychological issues and social stigma frequently connected to visible skin conditions. By incorporating this technology into telemedicine, patients in underserved or remote areas can obtain expert diagnoses, improving access to healthcare and reducing the need for expensive and time-consuming trips to specialty clinics. Furthermore, this technique is a great teaching tool for medical students and other healthcare workers, improving their diagnostic abilities and ultimately improving patient outcomes and healthcare resource utilization. By lowering costs, improving the quality of life for those with skin disorders, and expanding access to healthcare, the effective application of refined transfer learning techniques for the classification of skin diseases holds great potential benefits for society.

CHAPTER 7

Conclusion and Future Work

7.1 Conclusions

Effective patient diagnosis and treatment depend on the early and highly accurate detection and classification of skin diseases. An extensive performance evaluation of transfer learning techniques to enhance skin disease classification is presented in this study. In order to improve the accuracy and predictability of skin disease classification, our research highlights the usefulness of utilizing advanced convolutional neural networks (CNNs), particularly EfficientNetB2, EfficientNetB5, InceptionV3, MobileNetV3, and VGG16. Additionally, there has been a limited focus on the purpose of fine-tuning transfer learning for skin disease classification, despite noteworthy advances in medical image analysis, according to the research that is currently available. Therefore, our comparative analysis is highly significant and provides valuable insights into the field of dermatological diagnostics.

Throughout our research, we carefully evaluated the effectiveness of the selected CNN models. As compared to conventional techniques, the results show that fine-tuning these networks greatly increases classification accuracy. The models that performed the best were EfficientNetB2 and EfficientNetB5, which showed excellent accuracy and robustness. It's fundamental to recognize, however, that while these tuned models typically effective, inaccurate classifications occurred on rare. This emphasizes the necessity for additional research into alternative tactics, like sophisticated image preprocessing methods and the inclusion of other data augmentation techniques.

Furthermore, we recommend using image segmentation before classification to improve the CNN models' ability to extract pertinent features from skin image data. The potential for increased diagnostic accuracy exceeds the computational cost of the fine-tuning process, even though its high computational demand. Future research could investigate optimization techniques like snapshot ensemble and other approaches to lessen this burden. To sum up, this study is a major advancement in the improvement of methods for diagnosing skin diseases. It offers useful insight that has the potential to greatly impact clinical practice and stimulate more research in the dynamic field of dermatological image analysis.

7.2 Further Suggested Works

Our proposed study focused on fine-tuning transfer learning techniques for skin disease classification. Future studies regarding this topic could, however, go within a variety of directions. Investigating advanced transfer learning strategies like few-shot learning, meta-learning, or self-supervised learning could be one way to improve the accuracy and performance of the model. Extending the dataset to include a wider range of age groups, ethnicities, and skin conditions is another thing to consider regarding This might improve the model's robustness and ability for use in real-world scenarios. Moreover, adding multimodal data—such as patient histories, clinical notes, or other pertinent medical data—may enhance the classification model's their comprehension and accuracy. Deploying the skin disease classification model in clinical settings, either as the technique platform or as a supporting tool for dermatologists, will be a crucial phase following further validation and improvement. This would make it easier to identify skin conditions early and determine it correctly.

Future research might focus on creating models for the classification of skin diseases that are easy to understand and comprehensible, particularly as the field of AI ethics and reliability acquires success. This would enhance transparency—which is important in medical applications—and allow a better understanding of the model's decision-making process. Lastly, given the increasing popularity of smartphones and other mobile devices, future studies may investigate the creation of mobile applications that make use of the skin disease classification model, which might make it possible for those with limited resources to receive healthcare services and receive remote diagnosis.

7.3 Limitations

Although our research on skin disease classification using optimized transfer learning techniques produced encouraging results, there are a few important limitations that need to be recognized. The generalizability of our findings may be impacted by class imbalances and incomplete coverage of skin diseases in the Kaggle dataset. Although no single model consistently outperforms the others, there is an accessible range in algorithm performance, with EfficientNetB2 attaining the highest accuracy at 89.37%. It takes a lot of computational power to implement these complex algorithms, which might not be available in all clinical settings. Additionally, training takes time. Furthermore, the interpretability of deep learning models is limited by their "black box" nature, and certain models' high accuracy raises concerns about possible overfitting. The study's findings need to be externally validated using various datasets and clinical settings in order to demonstrate their robustness and generalizability. Ethical and privacy concerns regarding the use of patient data must also be addressed.

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Appendix A

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

Title:
SKIN DISEASE CLASSIFICATION USING FINE-TUNED TRANSFER LEARNING TECHNIQUES

Student ID: [202-15-3830 , 202-15-3853]

CO Description for FYDP

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

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

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

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

SN	EP Definition	Attainment	CO	Justification (with Knowledge Profile)	References
1.	**EP1: Depth of Knowledge required**	Yes	CO1, CO2, CO3, CO5, CO6, CO7 and CO8	This project demonstrates **fundamental engineering (K3)** principles by employing deep neural networks, data augmentation techniques, and diverse CNN architectures for image processing and classification tasks. The project demonstrates **specialist knowledge (K4)** by conducting transfer learning with advanced CNN architectures like EfficientB2, EfficientB5, MobileNetV3, VGG16, and InceptionV3, enhancing skin disease classification accuracy, crucial for computer-aided diagnosis.	**Page no:** [13-19] **Section:** [3.2] **Page no:** [22-27] **Section:** [4.2]
				The project applies **engineering practice & design (K5)** by the figure of process of experiments. The project addresses **engineering practice & technology (K6)** by employing CNN model.	**Page no:** [14] **Section:** [3.2] **Page no:** [19]

					Section: [3.2]
				This project ensures to **K8 (Research Literature)** by synthesizing insights from recent studies to advance skin disease classification using fine-tuned transfer learning techniques, showcasing a comprehensive understanding of current methodologies.	**Page no:** [5-11] **Section:** [2.2, 2.3]
2.	**EP2: Range of Conflicting Requirements**	Yes	CO2, and CO7	This project addresses **EP-2** by recognizing the hurdles in skin disease classification, including limitations of traditional methods and the complexities of integrating fine-tuned transfer learning techniques. Through comparative analysis, it confronts challenges in understanding diverse dermatological presentations, offering insights for refining diagnostic methodologies in skin disease classification using fine-tuned transfer learning techniques.	**Page no:** [11-12] **Section:** [2.4, 2.5]
3.	**EP3: Depth of analysis required**	Yes	CO2, and CO6	This project addresses **EP 3** by meticulously comparing experimental outcomes by applying different types of pretrained models of CNN, such as EfficientB2, EfficientB5, MobileNetV3, VGG16, and InceptionV3, and multiple potential approaches in the context of skin disease classification using fine-tuned transfer learning techniques.	**Page no:** [32-45] **Section:** [5.2]

4.	**EP4: Familiarity of Issues**	Yes	CO8	This project's interdisciplinary approach extends beyond computer science and engineering, impacting medical diagnostics in skin diseases through skin disease classification using fine-tuned transfer learning techniques. This research contributes to advancements in public health and healthcare practices which indicates **EP-4.**	**Page no:** [5-9, 11] **Section:** [2.2, 2.4]
5.	**EP5: Extends of application codes**	No	CO5	N/A	N/A
6.	**EP6: Extends of stakeholders involved and conflicting requirements**	No	CO8	N/A	N/A
7.	**EP7: Interdependence**	Yes	CO5	This project's comprehensive approach addresses high-level problems in skin disease classification using fine-tuned transfer learning techniques. It integrates various components across data collection, statistical analysis, and proposed methodology, ensuring a holistic solution to complex challenges in medical diagnostics. This approach to skin disease classification ensures **EP-7**.	**Page no:** [13-21] **Section:** [3.2, 3.3, 3.4]

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

SN	EA Definition	Attainment	CO	Justification	References
1.	**EA1: Range of resources**	Yes	CO11	Our project utilizes diverse resources such as high-performance computing infrastructure, GPUs, deep learning frameworks, annotated datasets, and ethical considerations to ensure systematic research and contribute to advancements in skin disease classification using fine-tuned transfer learning techniques and deep CNNs.	**Page no:** [20-21] **Section:** [3.4]
2.	**EA2: Level of interaction**	No		N/A	N/A
3.	**EA3: Innovation**	No		N/A	N/A
4.	**EA4: Consequences for society and the environment**	Yes		This project contributes to society by improving healthcare through advanced skin disease classification using fine-tuned transfer learning techniques, while also promoting environmental sustainability by employing efficient computational resources and adhering to ethical guidelines for patient data privacy.	**Page no:** [48, 50-51] **Section:** [6.1, 6.3, 6.4]

5.	**EA-5: Familiarity**	Yes		This project expands upon existing research by examining a novel approach in skin disease classification using fine-tuned transfer learning techniques, demonstrated through preliminary terminologies and a comprehensive comparative analysis, offering new insights into the field.	**Page no:** [5, 9-11] **Section:** [2.1, 2.3]

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

SN	COs	Attainment	Justification	References
1	CO4	Yes	This project addresses **CO4** by integrating effective project management and financial oversight, ensuring meticulous planning, resource allocation, and budget estimation for optimal resource utilization throughout the research lifecycle.	**Page no:** [20-21] **Section:** [3.4]
2	CO9	Yes	The project demonstrates adherence to ethical principles by prioritizing patient privacy, obtaining informed consent, and transparently documenting the research process, ensuring responsible knowledge dissemination and societal well-being through the ethical application of advanced healthcare technologies which comply with **CO9**.	**Page no:** [50] **Section:** [6.3]
3	CO10	No	N/A	N/A
4	CO12	Yes	The project's dedication to continuous learning **(CO12)** and adaptation within the dynamic technological landscape is reflected in its comprehensive data collection, rigorous statistical analysis, meticulous methodology development, and thorough experimental results and analysis, showcasing a commitment to staying updated and refining techniques to address modern challenges.	**Page no:** [13-21, 32-45] **Section:** [3.2, 3.3, 3.4, 3.5, 5.2]

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