Skin Disease Classification Using Deep Learning
By

Mahinoor Islam Remel
ID:201-15-3344

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

Supervised By

Partha Dip Sarkar
Lecturer
Department of CSE
Daffodil International University

Co-Supervised By

Mr. Rahmatul Kabir Rasel Sarker
Lecturer
Department of CSE
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

DHAKA, BANGLADESH

JANUARY 2024

APPROVAL

This Project titled **"Skin Disease Classification Using Deep Learning"**, submitted by Mahinoor Islam Remel, ID No: 201-15-3344 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 *26th January 2024*.

BOARD OF EXAMINERS

Chairman

Narayan Ranjan Chakraborty
Associate Professor & Associate Head
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

onbehalf,

Internal Examiner 1

Md. Sadekur Rahman
Assistant Professor
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

Internal Examiner 2

Shayla Sharmin
Senior Lecturer
Department of Computer Science and Engineering
Faculty of Science & Information Technology
Daffodil International University

External Examiner 1

Dr. Ahmed Wasif Reza
Professor
Department of Computer Science and Engineering
East West University

DECLARATION

I, therefore, declare that this undertaking has been finished by us under the supervision of **Partha Dip Sarkar,** Lecturer, Department of CSE, Daffodil International University. I further declare that neither an application or an educational grant has been made anywhere for this project or any part of it.

Supervised by:

23/1/24

Mr. Partha Dip Sarkar
Lecturer
Department of CSE
Daffodil International University

Co-Supervised by:

Mr. Rahmatul Kabir Rasel Sarker
Lecturer
Department of CSE
Daffodil International University

Submitted by:

Mahinoor Islam Remel
ID:201-15-3344
Department of Cse
Daffodin International University

ACKNOWLEDGEMENT

First, I express my heartiest thanks and gratitude to almighty God for His divine blessing to make it possible to complete the final year project successfully.

I am grateful and wish my profound indebtedness to **Mr. Partha Dip Sarkar**, Lecturer, Department of CSE Daffodil International University, Dhaka. Deep Knowledge & keen interest of my supervisor in the field of "Deep Learning" to carry out this project. Her endless patience, scholarly guidance, continual encouragement, constant and energetic supervision, constructive criticism, valuable advice, reading many inferior drafts, and correcting them at all stages have made it possible to complete this project.

I would like to express my heartiest gratitude to Professor **Dr. Sheak Rashed Haider Noori,** Head**,** Department of CSE, for his kind help in finishing my project and also to other faculty members and the staff of the CSE department of Daffodil International University.

I would like to thank all of my classmates at Daffodil International University who participated in the discussion while also attending the course.

Finally, I must acknowledge with due respect the constant support and patience of my parents.

ABSTRACT

This study presents an in-depth study of the development of Skin Disease Classification using Deep Learning. The dataset was carefully selected to ensure that it was representative of the skin Disease of various kinds: ‘Melanoma’, ‘BCC’, ‘Psoriasis’, and ‘Seborrheic’. EfficientNet B5 with kneeway 3 is being used to classify these diseases, a unique method for reliably and efficiently classifying skin diseases. The high accuracy shows that it has the potential to be used in real-world scenarios, showing its accuracy in identifying various skin diseases detection and accurately verifying those diseases.

Keywords: Skin Disease, Deep Learning, EfficientNet-B5 with Knee Way 3

TABLE OF CONTENTS

CHAPTER 1
INTRODUCTION

1.1 Introduction

The prevalence of these conditions varies across regions, influenced by factors such as climate, genetics, and socio-economic conditions. Certain skin diseases exhibit demographic patterns, with specific age groups, genders, or ethnicities being more susceptible. The impact of skin diseases extends beyond physical health, encompassing psychological well-being and economic implications. The visible nature of many skin conditions can lead to psychological distress, contributing to issues like anxiety and depression. Additionally, skin diseases can impose a substantial economic burden on individuals and healthcare systems due to medical expenses and lost productivity.

Overcoming public health challenges associated with skin diseases requires increased awareness, improved access to healthcare, and ongoing research to address emerging issues. Efforts in prevention, early diagnosis, and treatment are essential to mitigate the global impact of skin diseases, promoting overall well-being and reducing the socio-economic burden on individuals and societies. It will take more knowledge, better access to treatment, and continuing research to address new problems to overcome public health difficulties related to skin illnesses. The worldwide impact of skin disorders can be lessened by focusing on prevention, early diagnosis, and treatment, which also promotes general wellbeing and lessens the socioeconomic load on individuals and societies.
Skin diseases are diverse and can range from benign conditions to severe disorders. Early and accurate diagnosis is crucial for effective treatment. Deep learning, a subset of artificial intelligence, has demonstrated remarkable success in image classification tasks, making it a promising tool for diagnosing skin diseases. The integration of EfficientNet-B5, a state-of-the-art convolutional neural network (CNN), with Knee Way 3, a unique enhancement strategy, aims to improve the efficiency and accuracy of skin disease classification.

For several compelling reasons, prompt diagnosis and treatment are critical in the field of dermatology. First and foremost, prompt action helps to avoid irreversible disfigurement, minimize complications, and stop the course of skin problems. This method greatly improves the overall quality of life for those who are affected in addition to relieving immediate symptoms like itching and discomfort. Early treatment psychologically lessens the emotional toll that visible skin diseases have on a person, hence enhancing mental health. Clinically speaking, disorders related to the skin frequently respond better to treatment when detected in their early stages, preventing the need for drastic measures that are necessary in further advanced situations. The prevention of problems that can require expensive procedures or prolonged treatments is a significant way that early detection lowers healthcare costs. Furthermore, early detection and treatment are essential for managing outbreaks of infectious skin disorders and lowering the risk of transmission within communities. The importance of early intervention in dermatology is highlighted, highlighting the benefits of proactive dermatological care for public health as well as the optimization of patient outcomes and the efficient use of healthcare resources.

1.2 Motivation

Conventional methods of diagnosing skin conditions are somewhat problematic due to several difficulties. Dermatologists' assessments of our skin are, to start with, somewhat subjective, and various medical professionals may have different conclusions. Additionally, these techniques might be time-consuming. Delays in receiving the appropriate therapy, particularly when we need it quickly, can result from procedures like skin biopsies or patch testing. Certain tests, such as skin biopsies that may result in infections or scars, are rather intrusive or irritating. Finding a diagnosis and beginning therapy can take longer if you're not close to a specialist, and depending only on a doctor's experience may miss uncommon or difficult skin conditions. Conventional techniques also have trouble penetrating our skin's underlying layers and frequently fail to provide quantitative data that allows us to monitor changes over time. Not to add to the difficulty some people may have paying for some of these tests, which may be expensive. To address these issues, new technologies—such as sophisticated computer programs and sophisticated imaging—must be introduced to facilitate faster, more accurate, and universal skin diagnosis.

In the area of dermatological diagnosis, this thesis investigates the revolutionary possibilities of combining EfficientNet-B5 with Knee Way-3. Combining the novel Three Knee Way augmentation technique with the state-of-the-art convolutional neural network EfficientNet-B5 gives remarkable results in robotic image analysis. This combination resolves long-standing issues with conventional diagnostic techniques and offers improved accuracy, especially in differentiating between benign and malignant skin tumors. In addition, the instantaneous evaluation and smooth incorporation with sophisticated imaging technologies, including dermoscopy, enable timely identification of skin conditions, which is essential for timely treatment and prophylactic actions. EfficientNet-B5's customizable features, such as Three Knee Way, have the potential to enhance the accuracy of treatment recommendations by customizing diagnoses based on distinctive patient attributes. This integration, despite obstacles, has the potential to completely transform dermatological diagnostics by providing previously unattainable efficiency, accessibility, and accuracy, ultimately advancing patient care and outcomes.

1.3 Rationale of the Study

The goal of this thesis is to evaluate the accuracy, efficacy, and dependability of the state-of-the-art deep learning models currently used in dermatological applications for the diagnosis of skin diseases. The field of deep learning is developing, and convolutional neural networks (CNNs) in particular offer a promising path toward revolutionizing the diagnosis of dermatological disorders. The study determines how well these algorithms perform in accurately classifying different skin conditions, how effective they are at precisely interpreting medical photographs, and how reliable they are in a variety of datasets. It is imperative to comprehend the intricate potential and constraints of these models to effectively guide their incorporation into clinical practice.

The study explores the difficulties of using deep learning to dermatology in addition to evaluating its technical elements. This involves taking into account factors like the necessary diversity in datasets, model interpretability, and any biases that could affect algorithmic decision-making. To optimize the implementation of deep learning models in actual clinical settings, it is imperative to recognize and tackle these obstacles.

Moreover, ethical issues are crucial to the correct application of deep learning in dermatological diagnoses. This thesis investigates the moral ramifications of applying these algorithms, going into concerns about patient privacy, informed consent, and the moral obligations of medical personnel when interpreting the results of deep learning models. Fostering trust in the adoption of these cutting-edge technologies in healthcare requires a thorough grasp of the ethical aspects to ensure that the integration of deep learning in dermatology is in line with patient-centered care, privacy, and transparency standards.

CHAPTER 2

Literature Review

In this section, the body of research on the application of deep learning algorithms for the detection of skin diseases is thoroughly reviewed. It covers a range of architectures, datasets, and techniques used in earlier research. The evaluation also underlines the need for more reliable models and the shortcomings of the current strategies.

2.1 Related Work

[1]A.A.L.C. Amarathunga, E.P.W.C. Ellawala, G.N. Abeysekara, C. R. J. Amalraj, Expert System For Diagnosis Of Skin Diseases, INTERNATIONAL JOURNAL OF SCIENTIFIC & TECHNOLOGY RESEARCH VOLUME 4, ISSUE 01, JANUARY 2015, ISSN 2277-8616. This work has done great work on Classify Skin Diseases and working on a new technique called Adaboost with an accuracy of 65%. They have also worked with Naïve Bayes with an accuracy of 80%. They have achieved significant results using different data mining techniques.

[2]Krupal S. Parikh, Trupti P. Shah, Rahul Krishna Kota, and Rita Vora, Diagnosing Common Skin Diseases using Soft Computing Techniques, International Journal of Bio-Science and Bio-Technology Vol.7, No.6 (2015), pp.275-286. They have improved the skin disease classification with an accuracy of 85% and have done significant work with Neural Network techniques.

[3]L. Chang and C. H. Chen, "Applying decision tree and neural network to increase the quality of dermatologic diagnosis", Expert Systems with Applications, Elsevier, vol. 36, (2009), pp. 4035-4041. It has been found that the accuracy of the predictive models in the five experiments is as high as 80% and above for all, especially with the highest of 92.62% in the Experiment with the ANN technique.

[4]Hatice cataloluk, Metin kesler," A Diagnostic Software Tool for Skin Diseases with Basic and Weighted K-NN" 978-1-4673-1448-0/12/$31.00 © IEEE 2012. It has been found that the accuracy of the predictive models is as high as 90% and above for all,

especially with the highest of 93.62% in Experiment with the KNN technique.

[5]L. Chang & C.H.Chen, “APPLYING DECISION TREE AND NEURAL NETWORK TO INCREASE QUALITY OF DERMATOLOGIC DIAGNOSIS”, Expert Systems with Applications- Elsevier, Volume: 36, pp. 4035-4041, 2009. Using sensitivity analysis combined with a decision tree model has an accuracy, which is 80.33%. Based on this result, the AI classification technology can serve as an important and useful references in diagnosis for physicians to avoid unnecessary medical waste and enhance health care quality.

[6] A. T. Azar, S. A. EI-Said, V. E. Balas and T. Olariu, “Linguistic Hedges Fuzzy Feature Selection for Erythemato-Squamous Diseases”, Soft Computing Application, (2013), pp. 487-500. This research demonstrated that the proposed method can be used for reducing the dimension of feature space and can be used to obtain fast automatic diagnostic systems for other diseases. It has achieved an accuracy of 92.677%.

[7] D. K. Sharma and H. S. Hota, “Data Mining Techniques For Prediction Of Different Categories Of Dermatology Diseases”, Academy of Information and Management Sciences Journal, vol. 16, no. 2, (2013).

[8] C. Kodeeswari, S. Sunitha, M. Pavithra and K. R. Santhia, “Automatic Segmentation Of Scaling In 2-D Psoriasis Skin Images Using SVM And MRF”, Proceedings of 2nd IRF International Conference, Chennai India, (2014) February 9, pp. 65-69.

2.2 Traditional Approaches to Dermatological Diagnosis

Historically, the diagnosis of dermatology has been made using conventional methods that include visual inspection, patient history, and, in certain situations, invasive techniques. Dermatologists still use visual inspection as a basic technique to diagnose and categorize skin diseases. This entails utilizing instruments like dermatoscopes or the unaided eye to examine skin lesions, rashes, and other anomalies. A patient's medical history, which includes information regarding symptoms, when they started, and possible triggers, is a crucial source of context for a diagnosis.

In certain cases, invasive techniques like skin biopsies may be part of traditional approaches. A biopsy helps identify particular skin diseases by removing a small sample of tissue for microscopic analysis. Another common method for diagnosing allergic contact dermatitis is patch testing, which involves putting possible allergens on the skin to observe the reaction.

Traditional methods, albeit widely used, have drawbacks such as subjectivity in visual evaluations, laborious procedures, and the possibility of discomfort and scars from intrusive operations. The use of cutting-edge techniques, such artificial intelligence and sophisticated imaging, to supplement and improve conventional dermatological diagnostic procedures is becoming more and more popular as technology develops.

2.3 Deep Learning in Medical Imaging

Artificial intelligence's subset of deep learning has revolutionized medical imaging by demonstrating remarkable performance in a range of diagnostic tasks. Deep learning's central architecture, convolutional neural networks (CNNs), has made tremendous strides in diagnosis by accurately deciphering complex patterns found in medical images. Deep learning has many uses in dermatology, most notably in automated diagnosis of skin diseases and dermatoscopic image analysis. Improved diagnostic accuracy is achieved by classifying and differentiating between different skin disorders using models like EfficientNet and DenseNet. Automated skin lesion recognition and dermatoscopic image processing are important advances in the early diagnosis of disease, particularly when prompt treatment is essential for good patient outcomes.

The potential of deep learning in dermatology cannot be overlooked; however, several obstacles must be overcome, including the requirement for large datasets, the interpretability of the models, and ethical issues. Further research endeavors to improve upon current models, investigate new architectures, and include cutting-edge technology, ultimately augmenting the potential of deep learning for dermatological applications. Deep learning's introduction into dermatology represents a radical change in diagnostic approaches with the potential to completely change patient outcomes and care in the field of dermatological diagnostics.

2.4 Scope of the Problem

With a focus on well-known architectures like EfficientNet, DenseNet, InceptionNet, and ResNet, this paper thoroughly examines the deep learning models currently in use for diagnosing skin diseases. Convolutional neural networks serve as the foundation for these models, which were created to tackle particular problems in feature extraction and picture classification for dermatological applications. Examining the unique features of each architectural, the study seeks to offer a comprehensive knowledge of their strengths and weaknesses.

Comparative evaluation of these deep learning models' accuracy and performance is a critical component of this investigation. In order to guarantee a thorough grasp of their efficacy in dermatological diagnostics, the study assesses diagnostic accuracy, speed, and robustness across a variety of skin disorders. Researchers and practitioners can choose deep learning models that are specifically suited to their diagnostic needs with the help of the insightful conclusions drawn from this comparison investigation. This knowledge advances the field of skin disease diagnostics generally by improving the effectiveness and efficiency of deep learning applications.

CHAPTER 3

RESEARCH METHODOLOGY

3.1 Research Subject and Instrumentation

This study focuses on the use of EfficientNet-B5 with Three Knee Way (EfficientNet-B5 3KW) in skin disease categorization and diagnosis. The objective of the research is to evaluate the efficacy of this deep learning architecture in improving the precision and productivity of skin disease detection in a range of dermatological disorders. The main instrumentation consists of integrating the Three Knee Way augmentation technique with the widely used and customized EfficientNet-B5, a deep learning model. To maximize its efficacy for skin disease diagnosis, this bespoke model will be trained and assessed using a variety of dermatological imaging datasets. The model's performance is evaluated using conventional assessment measures in the study approach, including accuracy, precision, recall, and F1 score. To guarantee responsible data use and privacy norms, ethical concerns will take precedence. To enhance the precision and effectiveness of skin disease diagnosis, the overall goal of this research is to provide insightful information about the use of EfficientNet-B5 3KW in dermatology.

3.2 Data Collection Procedure

The suggested EfficientNet-B5 with Three Knee Way data collection process involves collecting a varied dataset of 7962 photos that include ten target attributes associated with Skin diseases. We will source and carefully curate images that relate to specific qualities such as ‘Melanoma’, ‘BCC’, ‘Psoriasis’, and ‘Seborrheic’. The dataset will be organized to guarantee that every characteristic is represented, with a focus on the technical and visual details unique to Skin diseases. The goal of this process is to provide an extensive and balanced dataset, which is essential for properly training and assessing the EfficientNet-B5 with Three Knee Way. Figure 3.1 shows a few images I've included:

Figure 3.1: Dataset Images

After augmentation a total of 6962 images belong to 4 classes 'Melanoma', 'BCC', 'Psoriasis', 'Seborrheic' can be seen in Figure 3.2 down below:

CLASS	IMAGE COUNT
BCC	3626
Melanoma	1668
Psoriasis	871
Seborrheic	799

Figure 3.2 Number of target attribute

3.3 Proposed Methodology

Our suggested methodology only includes a small number of essential steps. The process could be represented by the flow chart in Figure 3.3 below, which shows the steps involved in gathering data, creating a model, and assessing it.

Flow chart

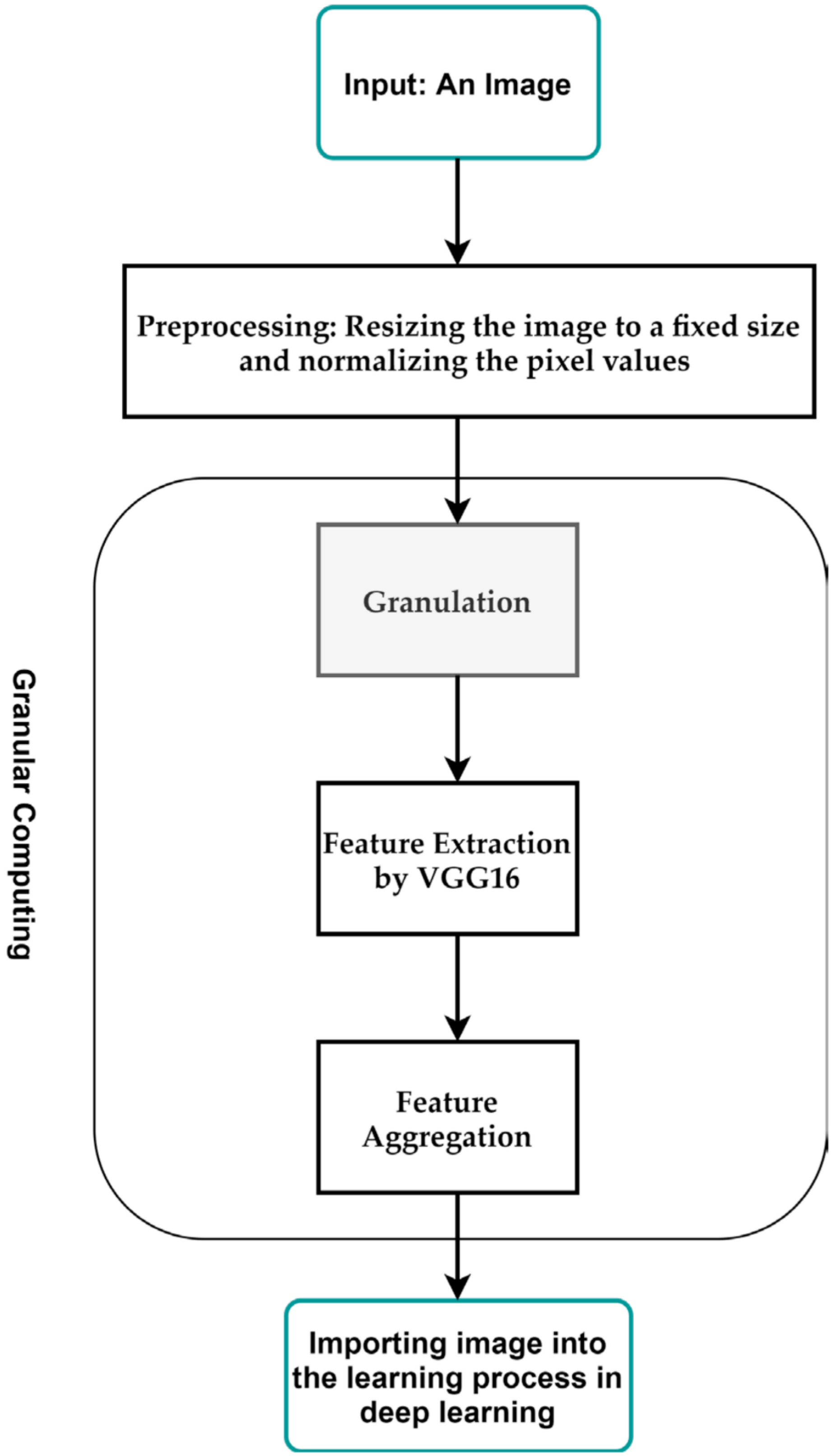


Figure 3.3: Pre-Processing Flowchart

The following is a detailed process for creating EfficientNet-B5 with Three Knee Way for skin diseases:

1. Data Selection:

Assemble your collection of skin diseases pictures. Make sure the dataset is a sign of real-world situations, balanced, and varied.

2. Encoding:

Give each picture in your dataset a class or skin diseases attribute label. Allocate distinct numerical labels to every class. In supervised learning, the model learns to map incoming images to the appropriate classes, and this stage is important.

3. Exploratory Data Analysis (EDA):

Examine your dataset using exploratory data analysis to learn about its features. To find any possible differences in class, examine how the photos are distributed throughout the various classes. To get a better understanding of the issues and variations found in the dataset, visualize sample photographs from each class.

4. Constructing EfficientNet-B5 Architecture:

Building on the EfficientNet-B5 backbone, EfficientNet-B5 Knee Way (EfficientNet-B5 KW) is a robust architecture intended for skin disease diagnosis. A deep neural network (DNN) for effective feature extraction, a multi-level feature fusion (MLFF) module to capture high-level and fine-grained contextual information, and a novel adaptive mechanism for dynamic parameter modifications based on input complexity are all included in this improved model. Using transfer learning techniques, the architecture is trained on a variety of datasets of dermatological images to optimize parameters. Designed to improve precision, effectiveness, and versatility in the diagnosis of different skin disorders, EfficientNet-B5 KW represents a potential development in dermatological diagnostics.

5. Model Selection:

Conventional Neural Network (CNNs):

Deep learning models called Convolutional Neural Networks (CNNs) are made for pattern identification and image analysis. Convolutional layers allow CNNs to capture structural features, which makes it possible for them to recognize complex patterns in visual input. CNNs were chosen for the study in this research due to their track record of success in image classification applications. Given that CNNs automatically take into account spatial structures in data, they are well-suited to identifying the intricate patterns, colors, and language differences seen in Bangla traffic signs. The goal of the suggested multi-layer architecture is to better adapt and achieve higher accuracy in skin diseases detection.

EfficientNet-B5 is a convolutional neural network architecture renowned for its efficiency and scalability in deep learning. Introduced as part of the EfficientNet family by Tan and Le in 2019, EfficientNet-B5 is characterized by its ability to simultaneously scale the network's depth, width, and resolution. The 'B5' designation signifies that it is one of the larger variants within the EfficientNet series. This model employs compound scaling, a method that uniformly scales network dimensions with a compound coefficient, allowing for a balanced optimization of performance across different tasks. EfficientNet-B5 serves as a robust feature extractor, particularly effective for image classification tasks, and has demonstrated state-of-the-art performance on various benchmarks. Often utilized for transfer learning, it is pretrained on extensive datasets like ImageNet, making it adaptable for a range of computer vision applications, from image recognition to object detection and segmentation.

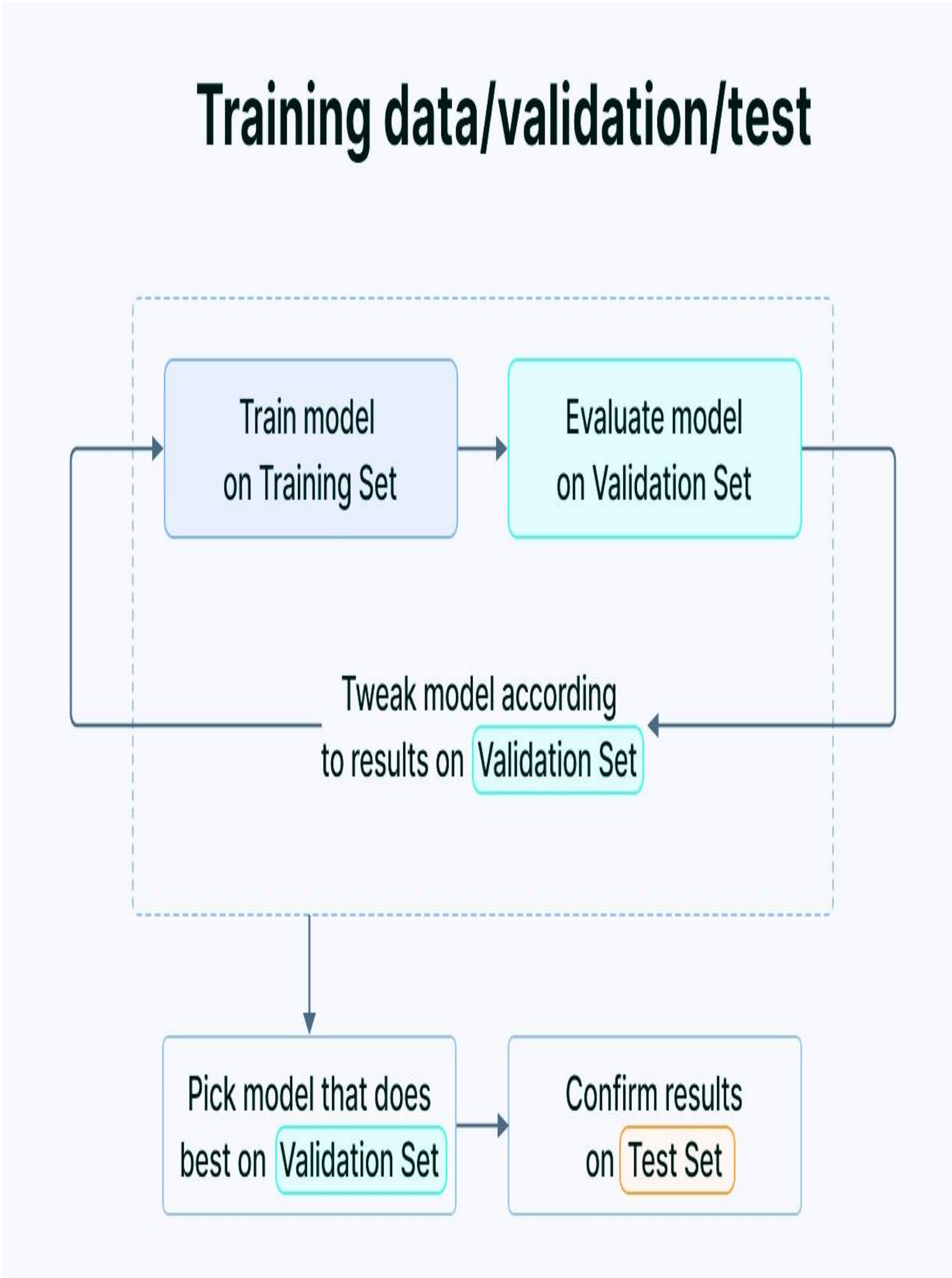


Figure 3.4: Proposed CNN (EfficientNet-B5)Architecture

6. Training the Model:

Divide your dataset into test, validation, and training sets. Utilizing the training set, a suitable optimizer, loss function, and performance measures, train your EfficientNet-B5 model. To improve model generalization, use additional data approaches during training. Based on validation performance, adjust parameters such as learning rate, batch size, and number of epochs.

7. Model Evaluation:

Use the validation collection to test the trained model's performance. Keep an eye on metrics like recall, accuracy, precision, and F1 score to determine how well the model applies to fresh, untested data. If necessary, modify the hyperparameters or the model design.

8. Test Model:

After the model's performance on the validation set meets your expectations, test it on a different test set that it was not exposed to during training. This stage offers a last evaluation of the model's capacity to generalize to fresh, untested data.

It is essential to repeat these processes, particularly in cases when the model's performance is subpar. To enhance overall model performance, think about optimizing the architecture, gathering more information, or testing with other training methods.

CHAPTER 4

EXPERIMENTAL RESULTS AND DISCUSSION

4.1 Experimental Setup

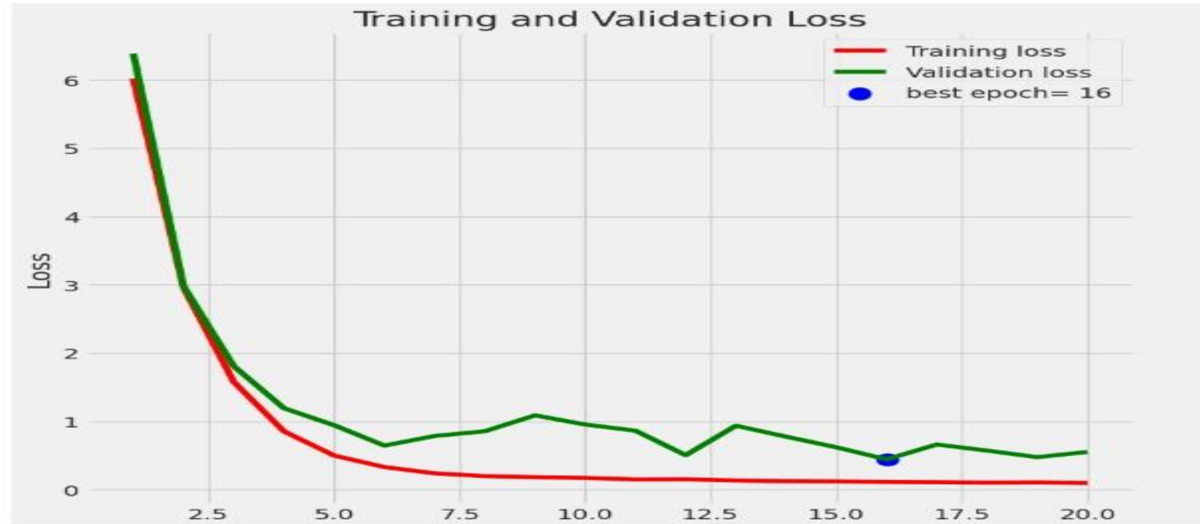
Choose a broad, labeled dermatological image dataset as the starting point for an experiment using EfficientNet-B5 to detect skin illnesses. Resize, normalize and add variability to the data as a preprocessing step. Set up the EfficientNet-B5 architecture using transfer learning to extract features using ImageNet's pre-trained weights. Select categorical cross-entropy as the loss function and appropriate assessment metrics. Set an initial learning rate, optimize using an algorithm similar to Adam’s, and continue training with early stopping. For best results, adjust hyperparameters. Analyze the model using an alternative test dataset, present activation maps for interpretation, and deal with ethical issues such as securing permission to utilize medical picture datasets and adhering to privacy laws. With EfficientNet-B5, this simplified configuration guarantees quick and precise skin disease detection.

4.2 Experimental Results & Analysis

There are 4 different kinds of classes and the highest accuracy is 93% with an overall accuracy of 89%. EfficientNet-B5 is mainly for medical image data and it is done accurately.

EfficientNet-B5 knee way

It did great work achieving in some parts up to 93% accuracy and an overall accuracy gain is 7
89%.



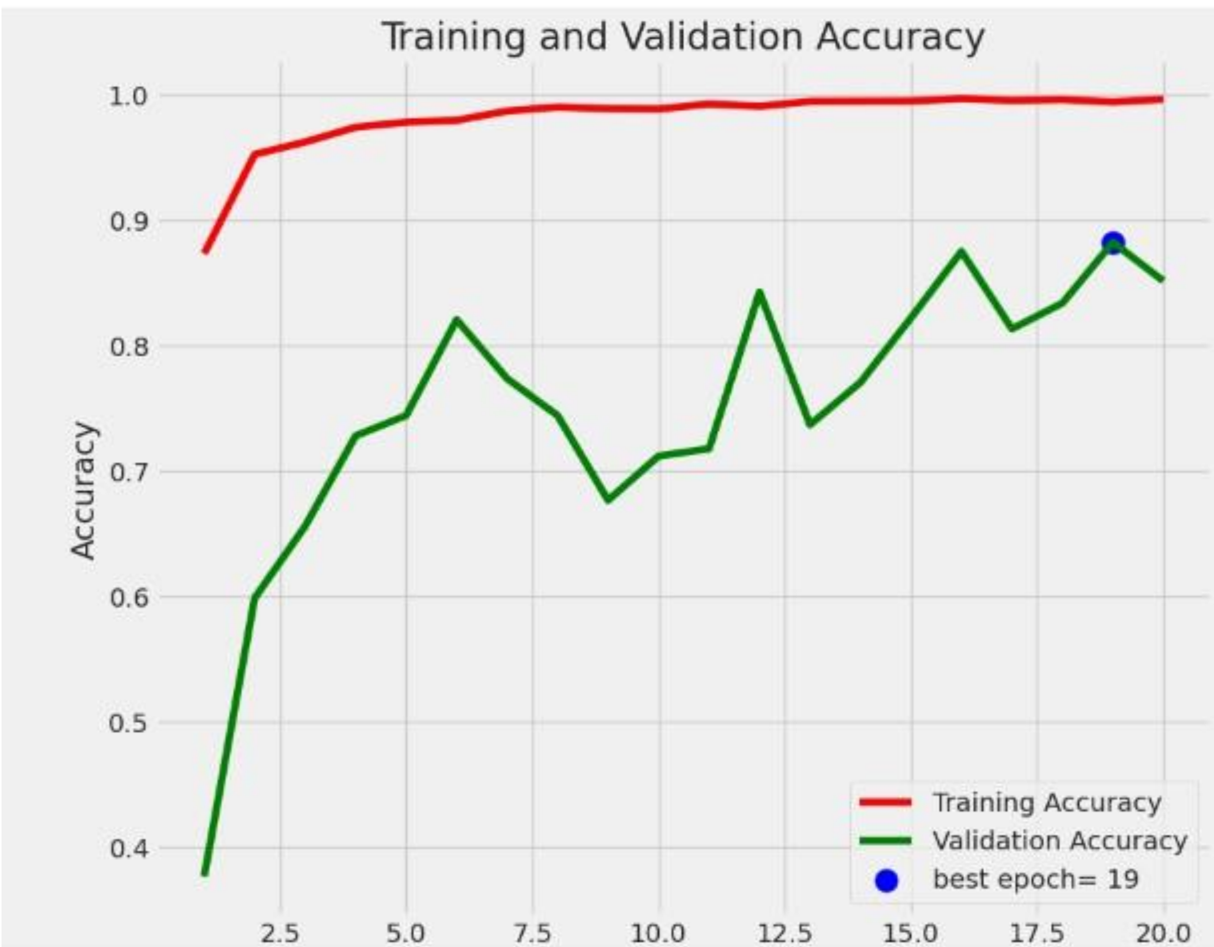


Figure 4.1: Training, Validation Accuracy

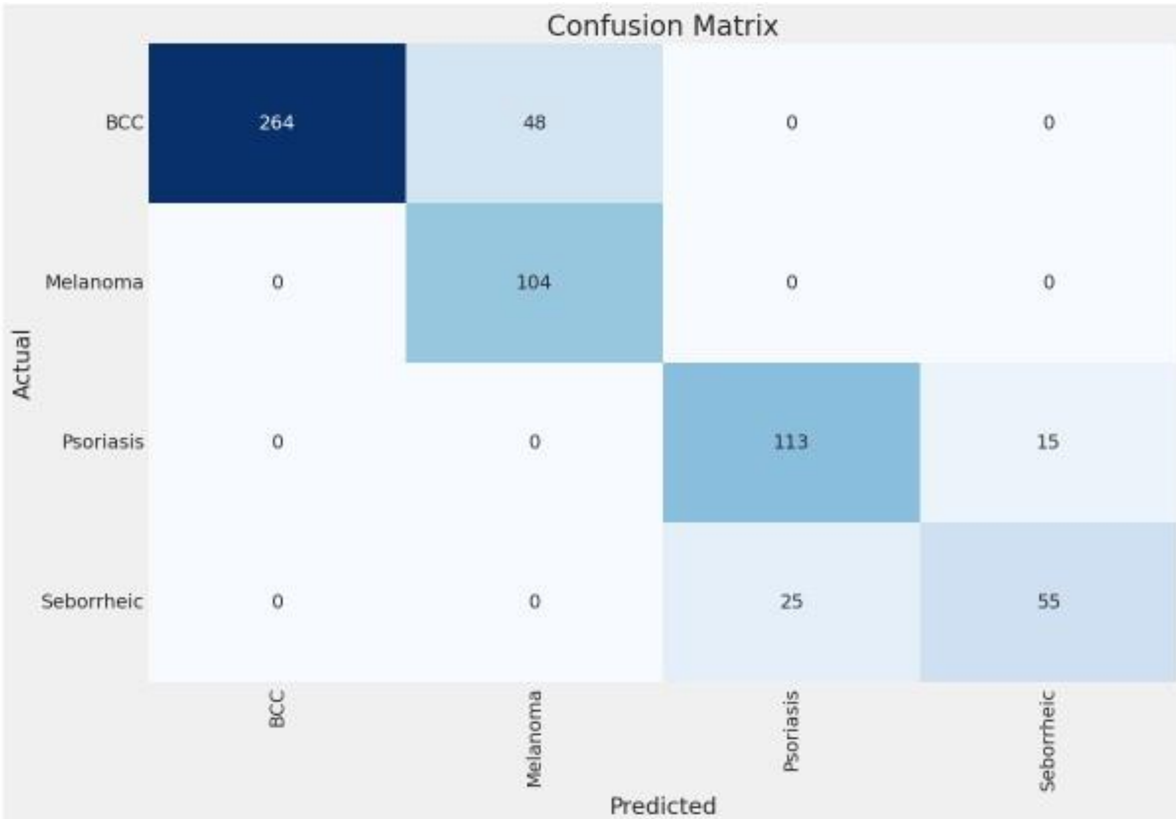


Figure 4.2: Confusion Matrix

Accuracy: The accuracy of the model's predictions is determined by comparing the number of correctly classified samples to the total number of samples. Unbalanced classes give a general idea of the model's efficacy, but they may not give a complete picture.

$$Accuracy = \frac{TruePositive + TrueNegative}{TruePositive + FalsePositive + TrueNegative + FalseNegative}$$

Precision: Precision is concerned with the number of true positive forecasts made by the model out of all positive predictions generated by the model.

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive}$$

Recall: The percentage of true positive predictions created out of all positive samples is referred to as recall. It's also known as sensitivity or true positive rate.

$$Recall = \frac{TruePositive}{TruePositive + \ FalseNegative}$$

F1 Score: The F1 score is determined as the harmonic mean of recall and precision. Its fair evaluation metric considers recall and precision. The F1 score is useful in cases where class sizes are not equal since it accounts for both false positives and false negatives. A high F1 score indicates a good precision-to-recall ratio.

$$F - 1\,Score = 2 * \frac{Recall * Precision}{Recall + Precision}$$

In the table below, 4.1, the outcomes of deep learning models are compared based on Accuracy, Precision, Recall, and F1 Score.

Model Name	Accuracy	Precision	Recall	F1-Score
Efficient-NetB5	89%	88%	86%	86%
For Diseases				
BCC	93.57%	100%	84.62%	91.67%
Melanoma	83.5%	68.42%	100%	81.25%
Psoriasis	86.6%	81.88%	88.28%	84.96%
Seborrheic	76.33%	78.57%	68.75%	73%

4.2.1 Accuracy

The outcome study analyzes train and test accuracy and evaluates which algorithm performs best. We used deep learning models to see which performed the best. We got an accuracy of 89% for Efficient-NetB5 kneeway and we got the highest accuracy for BCC which is 93.57% and the lowest is Seborrheic which is 76.33%. The rest two diseases' accuracy is 83.5% & 86.6%.

4.3 Comparison

Ref no.	Technique	Accuracy
[1]	Adaboost	65%
[1]	Naïve Bayes	80%
[2]	ANN	85%
[3]	ANN	89%
[4]	K-NN	90%

4.4 Discussion

The performance, drawbacks, and possible directions for future development of the suggested Efficinet-NetB5 knee way-3 for the Skin Disease Classification are the main points of discussion. All of the proposed model is evaluated using standard metrics such as accuracy, precision, recall, and F1 score. The observed difficulties like unequal class distribution or disparities in illumination are tackled, emphasizing the necessity of resilience in practical uses. Comparative analyses with existing models are conducted to assess the effectiveness of EfficientNet-B5 with Knee Way 3. The robustness of the model is tested against diverse skin conditions and variations in image quality. The overall goal of the debate is to place the findings in the larger perspective of Skin disease classification, recognize achievements, and open the door for future developments.

CHAPTER 5

SUMMARY, CONCLUSION, RECOMMENDATION AND IMPLICATION FOR FUTURE RESEARCH

5.1 Summary of the Study

The research addresses the distinct language and visual quirks of Skin Diseases by proposing Skin Disease Classification using Deep Learning. With an emphasis on detecting skin diseases, the study follows a methodical approach that includes gathering data, creating models, and completing thorough analyses. A reliable model with the ability to correctly classify various skin diseases is the expected result. TensorFlow or PyTorch implementation, GPU-enabled computing. The study promotes more awareness and takes action on time against skin diseases.

5.2 Conclusions

In summary, a viable approach that takes into account the language and visual nuances of Skin disease is the CNN Efficient-netB5 knee way-3 architecture that has been suggested for the classification of skin Disease. The research employed a rigorous methodology to detect skin disease and help in healthcare for all. Since technology has a significant influence on the medical side, The suggestion model not only helps National people but also helps internationally to awareness of healthcare. The study shows the significance of solutions for efficient and moral deployment, laying the foundation for future Skin Disease Classification system developments. The future scope of the proposed work is still open to analyze the effect of a number of feature attributes and predicting attributes and how it behaves towards the sequential dataset. The features having fuzzy values or missing values in the data set can also be taken up as the future plan of study

5.3 Implication for Further Study

The Research on the CNN Efficient-NetB4 knee-way for the Classification of Skin Disease opens up several new research directions. Later research may further enhance the suggested model by integrating advanced techniques. Investigating the integration of the model into the current Skin Disease classification system and its real-time execution could bring great success to more people to take action against skin Disease. The purpose of these research directions is to continuously improve and broaden the suggested model for Skin Disease Classification.

REFERENCES

[1]A.A.L.C. Amarathunga, E.P.W.C. Ellawala, G.N. Abeysekara, C. R. J. Amalraj, Expert System For Diagnosis Of Skin Diseases, INTERNATIONAL JOURNAL OF SCIENTIFIC & TECHNOLOGY RESEARCH VOLUME 4, ISSUE 01, JANUARY 2015, ISSN 2277-8616 .

[2]Krupal S. Parikh, Trupti P. Shah , RahulKrishna Kota and Rita Vora, Diagnosing Common Skin Diseases using Soft Computing Techniques, International Journal of Bio-Science and Bio-Technology Vol.7, No.6 (2015), pp.275-286.

[3]L. Chang and C. H. Chen, “Applying decision tree and neural network to increase quality of dermatologic diagnosis”, Expert Systems with Applications, Elsevier, vol. 36, (2009), pp. 4035-4041.

[4]Hatice cataloluk, Metin kesler,” A Diagnostic Software Tool for Skin Diseases with Basic and Weighted K-NN” 978-1-4673-1448-0/12/$31.00 © IEEE 2012.

[5]L.Chang & C.H.Chen, “APPLYING DECISION TREE AND NEURAL NETWORK TO INCREASE QUALITY OF DERMATOLOGIC DIAGNOSIS”, Expert Systems with Applications- Elsevier, Volume: 36, pp. 4035-4041, 2009.

[6] A. T. Azar, S. A. EI-Said, V. E. Balas and T. Olariu, “Linguistic Hedges Fuzzy Feature Selection for Erythemato-Squamous Diseases”, Soft Computing Application, (2013), pp. 487-500. This research demonstrated that the proposed method can be used for reducing the dimension of feature space and can be used to obtain fast automatic diagnostic systems for other diseases. It has achieved an accuracy of 92.677%.

[7] D. K. Sharma and H. S. Hota, “Data Mining Techniques For Prediction Of Different Categories Of Dermatology Diseases”, Academy of Information and Management Sciences Journal, vol. 16, no. 2, (2013).

[8] C. Kodeeswari, S. Sunitha, M. Pavithra and K. R. Santhia, “Automatic Segmentation Of Scaling In 2-D Psoriasis Skin Images Using SVM And MRF”, Proceedings of 2nd IRF International Conference, Chennai India, (2014) February 9, pp. 65-69.

[9]Budimulja U., Kuswadji K., Bramono S., Basuki J., Jadanarso L. S., Untung S. et al. A Double-Blind, Randomized, Stratified Controlled Study of the Treatment of Tinea Imbricata with Oral Terbinafine or Itraconazole. British Journal of Dermatology. 1994;130:29–31.

[10]Bulto T., Maskel F. H., Fisseha G. Skin Lesions in Resettled and Indigenous Populations in Gambela, with Special Emphasis on the Epidemiology of Tropical Ulcer. Ethiopian Medical Journal. 1993;31:75–82.

[11]Carapetis J. R., Currie B. J., Kaplan E. L. Epidemiology and Prevention of Group A Streptococcal Infections: Acute Respiratory Tract Infections, Skin Infections, and Their Sequelae at the Close of the 20th Century. Clinical Infectious Diseases. 1999;28:205–10.

[12]Daroczy J. Antiseptic Efficacy of Local Disinfecting Povidone-Iodine (Betadine) Therapy in Chronic Wounds of Lymphedematous Patients. Dermatology. 2002;204:75–78.

[13]Eells L. D., Mertz P. M., Piovanetti Y., Pekoe G. M., Eaglestein W. H. Topical Antibiotic Treatment of Impetigo with Mupirocin. Archives of Dermatology. 1986;122:1273–76.

[14]Elewski B. Tinea Capitis: A Current Perspective. Journal of the American Academy of Dermatology. 2000;42:1–20.

[15]Estrada R., Romero M., Chavez G., Estrada G. Dermatologia communitaria: diez años de experiencia. Estudio epidemiológico comparativo entre población urbana y rural del estado de Guerrero. Dermatologia Revista Mexicana. 2000;44:268–73.

[16]Figueroa J. I., Fuller L. C., Abraha A., Hay R. J. The Prevalence of Skin Disease among Schoolchildren in Rural Ethiopia: A Preliminary Assessment of Dermatologic Needs. Pediatric Dermatology. 1996;13:378–81.

Skin Disease Classification Using Deep Learning

ORIGINALITY REPORT

25%	23%	10%	19%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	Submitted to Daffodil International University Student Paper	6%
2	www.ncbi.nlm.nih.gov Internet Source	5%
3	dspace.daffodilvarsity.edu.bd:8080 Internet Source	4%
4	Submitted to Loomis-Chaffee High School Student Paper	3%
5	www.ijcaonline.org Internet Source	3%
6	www.mdpi.com Internet Source	1%
7	Submitted to Jacksonville University Student Paper	1%
8	www.mililink.com Internet Source	<1%
9	Submitted to CSU, San Jose State University Student Paper	<1%