SKIN DISEASES DETECTION USING DEEP LEARNING TECHNIQUES WITH WEB APPLICATION

BY

FARIHA ZAMAN

ID: 201-15-13619

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

Supervised By

MS. DRISTI SAHA
Lecturer
Department of Computer Science and Engineering
Daffodil International University

DAFFODIL INTERNATIONAL UNIVERSITY

DHAKA, BANGLADESH

July 2024

APPROVAL

This Research titled **"Skin Diseases Detection Using Deep Learning Techniques With Web Application."** submitted by **Fariha Zaman** to the Department of Computer Science and Engineering, Faculty of Science and Information Technology, Daffodil International University, has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of B.Sc. in Computer Science & Engineering and approved as to its style and contents. This Presentation has been held on 14 July 2024.

BOARD OF EXAMINERS

Dr. Sheak Rashed Haider Noori — **Board Chairman**
Professor & Head
Department of CSE
Faculty of Science & Information Technology
Daffodil International University

Most. Hasna Hena — **Internal Examiner**
Assistant Professor
Department of CSE
Faculty of Science & Information Technology
Daffodil International University

Md. Ferdouse Ahmed Foysal — **Internal Examiner**
Lecturer
Department of CSE
Faculty of Science & Information Technology
Daffodil International University

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

DECLARATION

I hereby declare that this research has been done by me under the supervision of **Ms. Dristi Saha, Lecturer, Department of Computer Science and Engineering** Faculty of Science and Information Technology, **Daffodil International University**. I also declare that neither this research nor any part of this research has been submitted elsewhere for the award of any degree.

Supervised by:

Dristi

Ms. Dristi Saha
Lecturer
Department of CSE
Daffodil International University

Submitted by:

fariha

Fariha Zaman
ID: 201-15-13619
Department of CSE
Daffodil International University

ACKNOWLEDGEMENT

At First, I want to sincerely thank Almighty God for His Divine Favor, which has enabled me to successfully complete the final year thesis.

I would like to express my sincere gratitude and heartfelt debt of gratitude to my **Supervisor, Ms. Dristi Saha, Lecturer in the Department of Computer Science and Engineering** at Daffodil International University in Dhaka. Finally, I finished my study on "**Skin Diseases Detection Using Deep Learning Techniques with Web Application.**" Thanks to her profound knowledge, passionate interest, and encouraging guidance, I was successful in the field of deep learning-based research. It would not have been possible to finish this job without their unending patience, scholarly advice, consistent support, energetic oversight, constructive criticism, insightful counsel, and reading numerous subpar versions and editing them at every step.

I would like to express my heartiest gratitude to **Ms. Dristi Saha, Lecturer**, I am very grateful to the professor and Head of the Department of Computer Science and Engineering at Daffodil International University (DIU) for his invaluable guidance and support in helping me complete my thesis. I also extend my sincere gratitude to the other academic members and staff members of the CSE department at DIU.

Finally, I would want to thank everyone once more for their support and inspiration, including friends, family, seniors, and well-wishers. The culmination of a lot of effort, inspiration, and help is this research.

Lastly, I must respectfully thank my parents for their unwavering support and patience.

ABSTRACT

A widely recognized paradigm exists for imaging purposes in the identification of skin disorders. In recent years, many medical professionals, including physicians, use CAD to assist them more accurately detect a range of disorders by looking at clinical pictures. Skin cancer is one of the most deadly diseases in the world. It's challenging to diagnose skin cancer correctly, though. This research offers several image processing techniques to help diagnose different kinds of skin diseases. The purpose for this research is to ascertain whether or not both these eights' skins are diseases, as well as to identify the type of skin illness by utilizing a variety of skin disease classes. In addition to eight additional class types, deep learning-based methods were employed in this experiment: 'BA-cellulitis', 'BA-impetigo', 'FU-athlete-foot', 'FU-nail-fungus', 'FU-ringworm', 'PA-cutaneous-larva-migrans', 'VI-chickenpox', and 'VI-shingles'. Five different models are used: DenseNet169, InceptionV3, VGG16, VGG19, and InceptionResNetV2 to forecast and detect skin photos and categorize illnesses. Lastly, two distinct efficiency metrics are used to evaluate the approach's performance. Five possible results are used in the initial accuracy set, which rates performance under both normal and fractured circumstances: TP, TN, FP, and FN. These models are then applied to investigate the exact nature of each sort of illnesses in mistake settings. With an accuracy percentage of 98.23%, the InceptionResNetV2 technology enables my suggested method to independently identify different kinds of skin disorders. In the end, data classification using the InceptionResNetV2 networks to identify skin illnesses results in the creation of an application in web.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

Introduction

1.1 Overview

The supreme organ in our bodies, the skin, serves as a crucial barrier. The primary roles of the skin are to shield the body from dangerous elements found in the environment and to stop different nutrients from leaving the body. A person's skin health is influenced by a variety of elements during their productive life, including UV rays, smoking, alcohol use, physical activity, infections, and workplace conditions. In addition to impairing skin integrity and function, these variables also harm skin in particular ways, negatively impact human health, and in extreme situations, endanger life. As a result, skin disorders are now among the most prevalent illnesses among people. All age groups and cultural regions are affected by skin disease. Early identification is essential for treating skin diseases in order to cure them, effectively lessen their effects, and increase their survival rate. Use the skin condition melanoma as an illustration. The human outer layer is the biggest organ in the body, made up of nerves, muscles, vessels for blood and lymph, tissues underneath the skin, and the epidermis and dermis. Through the use of fluids, skin can enhance its barrier function by preventing lipid degradation in the epidermis. Invisible germs, fungal growth on the skin, allergic responses, microorganisms changing the texture of the skin, or the production of pigment are all potential causes of skin illnesses [1]. Severe skin diseases can sometimes develop into cancerous cells. Skin illnesses require prompt treatment in order to reduce their growth and proliferation [2]. The primary focus of research nowadays is on methods to use imaging technologies to determine the consequences of various skin conditions.

Many different DL techniques may be used to identify skin-related illnesses. First processing, image acquisition, segmentation feature extraction, and classification are all included in the proposed model. Combining deep learning (DL) and quantitative image analysis, there are several ways accessible for the majority of a process sequence. When comparing drawings, several steps must be taken in order to identify skin conditions. To begin training the computer, you must first obtain damaged JPG, PNG, and Tiff images and scan them. The first results that the system shows are the skin conditions with various skin images. Subsequently, more modifications were made to the original JPG file format's energy density.

As previously said, improved medical advancement and accurate illness categorization depend on the creation of an autonomously technological gadget approach for skin disease detection. Big data, computational imaging, and the widespread usage of the Internet of Things are a few techniques used to classify skin conditions. Furthermore, the advantages of the DL approaches are demonstrated with respect to this objective. The machine can learn on its own and form opinions thanks to deep learning. Unstructured learned learning, and learning by reinforcement are three different neural network architectures that may be identified for deep learning. Numerous cutting-edge deep learning algorithms have been trained to identify skin diseases thanks to this study; these methods will also complete the classification process.

The many skin problems are the subjects of this article. The subsequent picture as a result, in order to achieve a number of goals, several processing techniques are applied to tackle the particular difficulties presented by the real-world skin condition images. The following goals can be accomplished by photo processing:

- Diagnosing conditions using skin photos.
- Using the data obtained from models of DL to determine the severity of skin conditions.
- Developing a web prototype for diagnosing different skin conditions.

1.2 Problem Statements

The primary objective of this project appears to be the combination and evaluation of all these real data sets. The dataset was cleaned up and standardized using a variety of instruments and techniques. I was forced to wait an extended period to view the finished output because of the magnitude of the sets of data and the simple fact that they comprised many layers from different eras. There are many sources of datasets available in this topic. It's difficult for me to swiftly choose the finest answers since It takes a lot of work on my part to each assignment because I didn't complete the study. Classifying the component parts of skin diseases in an online prototypes using deep learning models presented another challenge: maintaining this massive quantity of data and preparing it for classification.

1.3 Objectives

The contemporary period has seen a great advancement in technology. Imagination can help with any problem. Consequently, a great deal of research is being done to support the growth of the medical sector. Right now, the largest flaw in the medical system is skin disease. The human body is able to assume a variety of shapes. The primary Detecting various skin disorders using deep learning strategies was the aim of this endeavor. The main goal is to precisely classify various kinds of skin diseases, which entails making predictions about the skin illness. Using a thorough comprehension and picture analysis is my goal to identify skin diseases in photographs. Consequently, I was able to appoint the following objectives:

- To assist patients and the medical community.
- To use deep learning to forecast the eight categories of skin diseases.
- To compile information in order to predict skin problems.

1.4 Motivation

Because it is such an important component of any healthcare facility, I was driven to designing products for the industry. I think that this industry's system and practices have a significant influence on all types of illnesses, including skin conditions. That's the reason I went into medicine, using DL and AL to treat skin conditions in patients. Finding a subject who would fulfill the study's requirements took some time. I therefore sought assistance from a few of my esteemed teachers. I'm glad I decided to focus my study on the medical industry. That's why I made the decision to write a paper with the subject "Skin Diseases Detection Using Deep Learning Techniques With Web Application." In addition, I observe that medical researchers are delving into novel fields to broaden their understanding of how society uses new findings to advance medical care. I was inspired to do this type of research because of the following. Deep learning is essential because artificial intelligence has connected everything in my environment.

1.5 Research Question

This study is being accomplished with a tremendous deal of enthusiasm and effort. It such an extremely difficult challenge for me. Many obstacles stand impeding the development of a precise, useful, and fair method. Scholars are interested in knowing the answers to the following important questions so that they may look into this topic more thoroughly and analyze these concepts:

- Have I verified this unprocessed dataset?
- Is it obtainable to use a deep learning approach for gathering the data beforehand?
- Could patients benefit from this research and these techniques?

1.6 Thesis Outcome

This section contains a list of the facts that I believe will have the most basic impact. To aid in future study and predict the actual course of an illness, multiple categorization techniques are being used to group the various skin conditions. This study aims to provide a complete, workable strategy or plan that diagnoses skin disorders by employing an algorithm for predictions built on an unprocessed dataset. As a result, the following is a summary of all of the expected outcomes that were previously mentioned:

- I will demonstrate how different skin diseases are based on the study of the bone.
- A more thorough understanding of how to use DL to locate disease cartilage from photos of sick skin.
- One of my goals is to correlate my findings with preceding research by utilizing outmoded photo data.
- Another is to identify whichever CNN model with DL is best at identifying different skin diseases according on the availability of data.

1.7 Report Organization

The methodology the first chapter provided an overview of the study's objectives, sources of motivation, purpose, and expected outcomes. The overall framework of the inquiry is shown below is also explained.

Chapter 2 discusses what has been accomplished in this field to date. Part Two's last section continues to illustrate the intricacy that arises from the subject's constraints. A summary of the main challenges and limitations of the research is given. In addition to covering the subject, this chapter includes sections on related works. It also describes the obstacles that must be overcome in order to complete the task.

Chapter 3 provides an explanation of how this study project was conceptualized. This chapter contains more information on the statistical methods used on the hypothetical portion of the investigation. There are also practical examples of deep training technologies in this chapter. The procedure for acquiring datasets and the method used for data preparation are covered in the upcoming chapter. Confusion matrix analysis is also used in the later portion of this subdivision to assess the strategy and offer the accuracy tag for the classifier. In order to ensure true correctness when using deep learning algorithms, implementation analysis is required. This section covers a variety of topics, including the research question and methodology, necessary models, data collection techniques, workflow, data processing, learning strategy, and operational requirements that must be fulfilled in order to construct this project. There is a thorough explanation provided for each DL methodology and classification used in this study.

The performance evaluation, results discussion, and experimental findings are presented in Chapter 4. To help with the project's execution, a few test images are given in this section. An introduction to the uses of supervised learning methods concludes the present section.

An overview of the study, details on next activities, and a query regarding the findings were all included in Chapters 5 and 6. This chapter provides an authenticated sample to demonstrate whether the report that was delivered complies with all standards. Effects on the Environment and the Entire Group: The last section of this chapter describes the shortcomings of my current projects, which may affect future workers who have similar objectives.

CHAPTER 2

Background

2.1 Overview

The main topics of this part are the research synopsis, pertinent literature, challenges, and study outcomes. Under "related Works," I will examine research papers written by various writers and discuss the connections between their concepts, accuracy, and techniques. I will discuss the articles, their methodologies, and the reliability of additional scholarly sources that are pertinent to my research in the section on related works. a summary of the pertinent literature that contained the descriptions chapter. Then, I describe how I overcome every obstacle I encountered while doing the research and how I increased each stratum's reliability—even in the most difficult parts.

2.2 Related Works

The process of classifying skin disorders utilizing different afflicted ailments has taken a lot of work. The following is a summary of many techniques that have been studied by many researchers in order to identify skin disorders.

Numerous methods now in use machinery to identify and categorize skin conditions. The majority of diagnosis techniques rely on imaging technology; nevertheless, radiological imaging technologies are not necessary for the epidermal detection of some skin disorders. Using algorithms for image processing such as image modification, equalization, improvements, detection of edges, and segmentation, they can identify the problem according to the standard pictures [3, 4, 5]. In order to predict the type of skin disease, the skin images that are taken for disease detection and categorization are processed and fed into a variety of sophisticated artificial intelligence techniques, including deep learning, machine learning, neural networks, back propagation neural networks, convolutional neural networks, and support vector networks.

Using the required image processing techniques, such as morphological actions for skin identification, skin disorders are also categorized [6, 7]. The binary picture produced by threshold-setting is primarily responsible for morphological opening, closure, dilation, and erosion; however, choosing the ideal threshold value requires careful consideration. The morphological operations might not be appropriate for determining the expansion of the damaged area based on the texture of the picture. Skin disease categorization was made possible by the use of Genetic Algorithms (GA) [8,9]. There are issues with the Genetic Algorithm, such as its lengthy convergence time to the the mixture [10]. The model never provides the optimal answer on a global scale, as this would not produce a realistic result [11].

In order to achieve more accurate predictions, Alam et al. [12] computerized the identification of eczema through the use of support vector machines in image processing. This process involved several stages, including segmenting the obtained image, selecting features based on texture-based information, and utilizing SVMs to assess the eczema's progression, as described by I. Immaculate [13]. Understanding the feature-based characteristics is important when dealing with Support Vector Machines (SVMs); the SVM model is not suitable for handling noisy picture data [14]. Should the quantity of parameters for every feature vector surpass the quantity of training data specimens it will perform less well.

A respectable accuracy of 89.90% has been attained for the validation set using the Adjusted Neural Network-based [15] dermatological illness diagnosis model. Still, achieving the required precision requires a large amount of labor in calibrating the network components. A supervising system for learning that refines the weights depending on error rate is the backward propagation Neural Network [16], which operates on the gradient descent concept. But noisy data causes the model to malfunction. One of the main concerns is that the components lose track of their past relationships when they are given new weights, which might have a significant influence on them [17]. Although they have reached a decent accuracy for divergence classification tasks, Fuzz recurrent neural network systems (FRNN) [18] and Takagi-Sugeno-Kang Fuzzy Classifier [19] perform significantly better when managing a changeable dimension entered despite affecting. A The recurrent neural network (RN that data using any arbitrary storage that is available, in contrast to most neural network models that require an additional memory to function. FRNN takes a significant amount of processing time and requires a lot of work to identify patterns from the picture data, whereas RNN is somewhat sluggish because of its high computational requirements [20].

Ma and Luo [21] introduced a novel method for pinpointing fracture locations in X-rays. With the recently developed Break-sensitive Machine Learning Neural Network, segment lines may be accurately recognized and classified. The proposed technique may be able to identify the exact location of a fractured bone in an MRI scan. With its assistance, doctors can recognize a bone fracture. a technique that combines muscle magnetic resonance imaging with retraining to diagnose fractures. After 375 comprehensive testing on the Radioed dataset, the suggested strategy performed better than alternative approaches in terms of general correctness (88.39%), recall (87.50%), and accuracy (89.09%).

The use of machine learning and deep learning were used by Karanam et al. to examine how to classify fractures of bones [22]. Fractures have been assessed, categorized, and recognized utilizing InceptionV3, SVM, randomly generated forest modelling (K-nearest neighbor; The kernel neural network), and Res Next101. Test results were improved by 93.75% with ResNeXt101. The proposed method aids in the diagnosis, classification, and treatment planning of fractures by physicians and other medical professionals. Research indicates that the majority of academics are interested in investigating skeleton splits; yet, a minority number of academics have lately developed an interest in classifying fractures of the bone.

An Accelerated R-CNN to the based technique Zhou provided a method for automated identification and categorization of fractured ribs and associates [23]. Three goals were accomplished with this approach fracture detection and categorization, model robustness, and a functional process. What was investigated tests for accuracy overall detection speed showed that the more potent R-CNN performed better than the YOLO V3 algorithm. This study showed remarkable results, with a 91.1% accuracy and an 86.3% sensitivity.

To sum up, further investigation is being conducted into the classification and identification of skin problems aided by computers. Nevertheless, obtaining a quick, precise, and reasonably priced test is still contingent upon the ophthalmologist's qualifications. It is evident from the scientific literature that past research was erroneous and untrustworthy. Moreover, in contrast to the recommended approach, there isn't a systematic way to ascertain the skin condition fast. I used five different models for skin illness categorization (InceptionV3, VGG16, VGG19, DenseNet169, and InceptionRestNetV2) in order to forecast and identify skin disorders so that the app could run online.

2.3 Comparison between existing works

The study by Bhadula et al. (2019) titled "Deep Learning-Based Skin Disease Detection Using Convolutional Neural Networks (CNN)" employed CNNs to classify skin diseases, achieving an accuracy of 91%. This model was trained on a substantial dataset of dermatological images and demonstrated promising results in distinguishing various skin conditions. Another significant work is by Shanthi et al. (2020), in their research "Automatic Diagnosis of Skin Diseases Using Convolution Neural Network," which also used CNNs for skin disease detection, achieving an accuracy of 89%. Their focus was on optimizing the network architecture to improve classification performance while maintaining computational efficiency. A more recent study published in Sensors (2021), "Classification of Skin Disease Using Deep Learning Neural Networks with MobileNet V2 and LSTM," proposed a combined approach using MobileNet V2 and LSTM models. The MobileNet V2 model was utilized for feature extraction due to its efficiency on lightweight devices, while LSTM was used to maintain stateful information for precise predictions. This method achieved an accuracy of 85% and demonstrated robustness with lower computational requirements (MDPI).

Key Comparisons

Table 2.1: Comparison Table

Study Title	**Model Used**	**Accuracy**	**Key Characteristics**
Deep Learning-Based Skin Disease Detection Using Convolutional Neural Networks (CNN)	CNN	91%	Utilized CNNs to classify skin diseases with a high accuracy using a substantial dataset.

Automatic Diagnosis of Skin Diseases Using Convolution Neural Network	CNN	89%	Employed optimized CNN architecture for improved performance and computational efficiency.
Classification of Skin Disease Using Deep Learning Neural Networks with MobileNet V2 and LSTM	MobileNet V2, LSTM	85%	Combined MobileNet V2 for feature extraction and LSTM for stateful information with lower computational requirements.
Skin Diseases Detection Using InceptionResNetV2 Model	InceptionResNetV2	98.23%	Leveraged Inception modules and residual connections for efficient training and high accuracy classification.

My proposed model demonstrates the highest accuracy at 98.23%, significantly surpassing the 91% accuracy of the CNN model by Bhadula et al. and the 89% accuracy by Shanthi et al. The MobileNet V2 and LSTM approach achieved 85%, which is also lower compared to my model. The InceptionResNetV2 model offers a more complex and deeper architecture compared to the traditional CNNs used in the other studies. This depth allows for better feature extraction and learning of intricate patterns in skin disease images. The combination of Inception modules and residual connections helps mitigate the vanishing gradient problem and improves the overall training efficiency, leading to higher accuracy. I also developed a user-friendly web application prototype that integrates InceptionResNetV2 model for practical use by healthcare professionals and patients. This application aims to provide quick and accurate classifications of skin diseases, facilitating early diagnosis and treatment.

2.4 Challenges

The primary challenges presented by this study consist of additionally interpreting the data that has been provided, but also obtaining it, as organizing the visual data proved to be excessively difficult. Absent often accessing the hospital online medical data, I found it challenging to learn about this problem. To clean and standardize my dataset, a number of techniques and tools were used. The huge datasets required a lot of processing power from my computer system because they had various layer and different epoch. I was forced to wait for result. After a number of tests and physical studies from governmental agencies, Since the prior statistics on this issue did not fully represent my expertise, I was compelled to gather datasets from actual genuine field hospitals. I had to spend a lot of time finding out the best ways to finish the assignment swiftly because I had not attempted research before. As in the previous case, preparation problems with the picture data which were encountered while applying DL models for classification.

2.5 Summary

I took a substantial amount material time to study of many strategies that society provides. Skin illnesses have recently been diagnosed and categorized into five groups using a deep learning-based approach. Using my real dataset, I used a variety of approaches. Using the same source, In addition, I'll be possible to evaluate the dependability on the five techniques I employed and investigate aspects such as the importance of the extra data I provided. The dataset that was merged with the prior dataset is exactly duplicated in the new dataset. By using tags to classify them into groups, it is feasible to make clear what they actually symbolize comparable categories with subcategories. I employed CNN and algorithmic methods for DL for online content extraction, and MATLAB was my primary engine of selection application categorization.

CHAPTER 3

Research Methodology

3.1 Overview

I describe in more detail the methods and approaches I used to categorize the many disease groups I looked at in the section that follows. The three main parts are the data collection, analysis, and proposed model. The pertinent computation, graph, table, and description serve to further elucidate the model. For this investigation, the maximum accuracy was obtained by splitting and forecasting with the DL segmentation architecture and my actual field dataset. The last section of the chapter included a summary of my statistical presumptions. Eight different class types were used in the construction of my visualizations for this exercise. While additional skin illnesses may also be identified by disease pictures, I focused my research on eight primary sickness classes: "BA-cellulitis," "BA-impetigo," "FU-athlete foot," "FU-nail-fungus," "FU-ringworm," "PA-cutaneous-larva-migrans," "VI-chickenpox," and "VI-shingles." All participant images were used to deliver training via eight different class kinds in the current study.

3.2 Requirement Analysis

A studied topic is an area of research that is currently being looked at and analyzed to clarify ideas for developing models, setting and achieving goals, gathering data, managing, teaching, and improving performance. I go over the equipment and techniques I use to take measurements. NumPy was used in the creation of Sk-learn, OpenCV, and other programs in addition to Microsoft software and programming in Python. The Google Co Labs facilities are exclusively utilized for instructional and assessment purposes. Google Colab programmer may write complex machine learning algorithms and Python-based analysis of data.

Libraries:

- **Matplotlib:** One of Matplotlib's visualization capabilities is a set of techniques known as Py-plot graphing. Plotting boundaries and defining lines inside a plot are only two of its numerous applications. Another is shapes.
- **NumPy**: One popular approach for interacting with matrix in Python is to apply the NumPy package. Matrix operations, the Fourier change, and the fundamentals of algebraic geometry are covered. For managing matrices of various sizes, the NumPy package offers

assets and instruments in Python. NumPy allows arrays to be constructed accurately and scientifically. A Python library called NumPy is used conducting numerical computations. It also makes use of the phrase "a wide assortment of varieties Python".

- **Scikit-learn**: This useful and intuitive program for data analysis and forecasting. Software that is open-source is available for anybody to use and modify to their own standards. Matplotlib, SciPy, and NumPy were made use of via growth.
- **Seaborn:** Known for its long tradition of integrating with matplotlib, this popular data visualization tool is user-friendly and provides an simple-to-use tool for creating visuals of data that are engaging and aesthetically pleasing.
- **CV2:** To solve issues with computer vision in particular, a set of Python bindings specified as Python's OpenCV was developed. By examining photos and videos, it also makes it possible to identify people things, as well as notes written by the spot.
- **Job-lib**: Another more efficient method of save time and money by not having to redo the same calculation.
- **H5 Py:** An HDF5 native data wrapper in Python is provided by the h5py element. With NumPy's assistance, handling and storing HDF5 makes handling huge amounts of numerical data easy.
- **OS:** The Python language OS element provides a range of tools that artists may use to interact with the application that powers parts of the computing device they are employed on.
- **TensorFlow:** A Python math framework that is free and helps with the construction of self-learning techniques and deep neural network systems.

3.3 Proposed Methodology

Numerous methods or strategies may be employed to decide how to evaluate the data that was used for this inquiry. In this study, a multi-step technique comprising model construction, extension and improvement, data collection, and production was used.

Step 1: Data Collection: I developed a reliable set of my own by using Kaggle to gather online statistical data and evaluate it. Owing to the challenges associated with discovering and getting data for the many skin illnesses, eight phases' photos of the various diseases, and other factors, a large, full dataset is not readily available.

Step 2: Data preparation: Each sort of data was treated independently after being gathered in its unprocessed state from different medical providers. Numerous data sets may have errors, especially noise. In a technical sense, I take in the information first, then use the chosen data set to proceed to the next step.

Step 3: Data preprocessing: The conclusions were narrowed down and continued to grow as each class was examined. For it to function, I required to add information as well as resize. I restricted the amount of changes I made to the biggest and most appropriate ones because I was concerned about overfitting.

Step 4: Model Selection: Once you've decided, use the available data to train and assess the selected model in order to increase accuracy. DL uses a wide variety of models. Using my technology, multiple versions of the concept were tested to determine the optimal configuration for precise data calculation.

Step 5: Performance Assessment: A discussion of each result is given in this section. After testing and training, my degree of reliability for my subsequent two courses was inadequate because to these strategies. Along with creating a web-based application for detecting different skin conditions, they also created graphics for recall, efficiency, confusion matrix, and f1 measurement.

Step 6: Concluding Thoughts and Future Projects: In the section that follows, there is a schedule and summary of the changes.

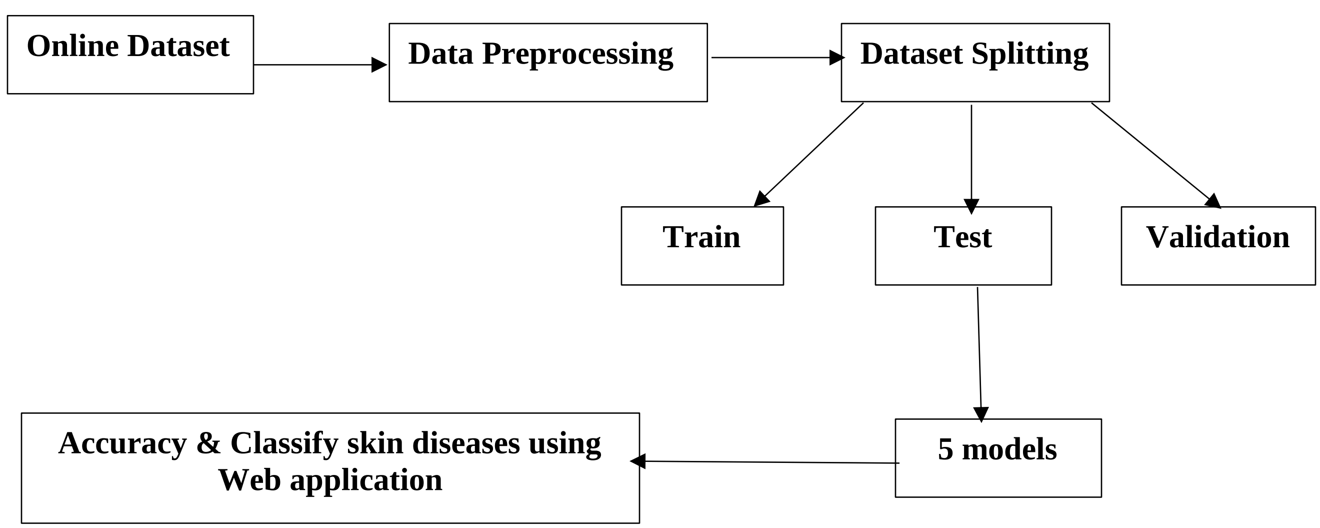

Fig 3.1: The recommended model for the whole research project.

Figure 3.1 shows how skin diseases have been categorized using this fundamental idea. To develop a dataset, online data across all medical categories must first be collected. Subsequently, the picture has undergone resizing, tagging, classification, and data augmentation. The computer could subsequently get this information. Using new, raw datasets, I may utilize this knowledge to train, test, and confirm my proposed deep learning algorithms. The quality of method and the online application allow different illnesses to be identified with the lowest precision of DL interpretations using the skin dataset.

3.4 Data Collection

A total of 1,125 images have been collected by me. Kaggle sources provided the online datasets that were gathered. The eight groups that make up the dataset are named for the kind of skin illness they represent: 'BA-cellulitis', 'BA-impetigo', 'FU-athlete-foot', 'FU-nail-fungus', 'FU-ringworm', 'PA-cutaneous-larva-migrans', 'VI-chickenpox', and 'VI-shingles'. Test and validation include the remaining 50% of the data, with the remaining 20% being classified as train.

Fig 3.2: Sample of data.

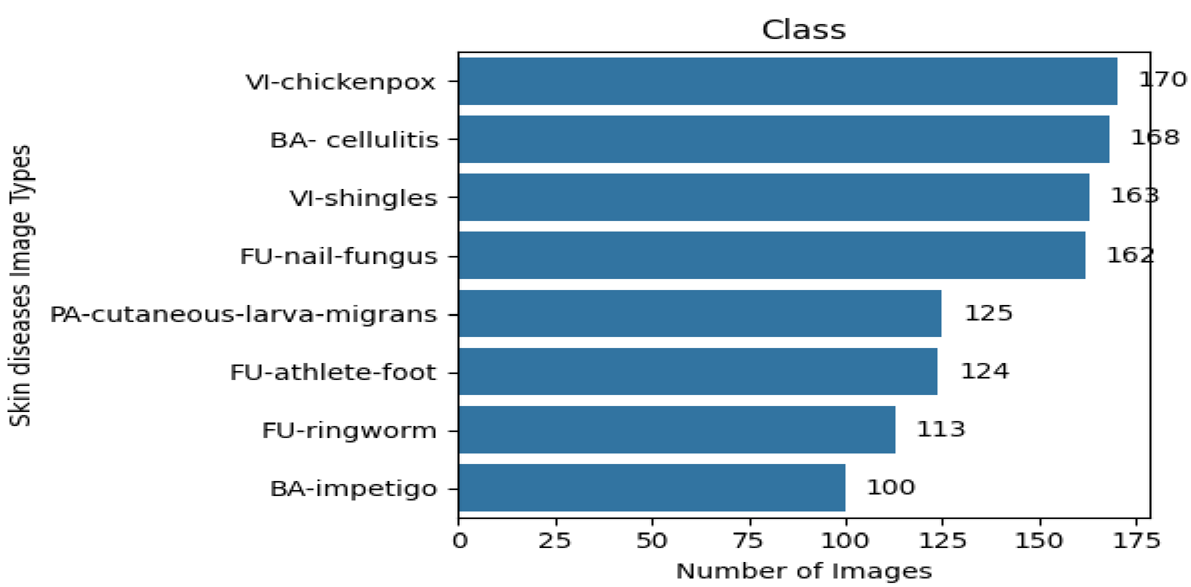

Fig 3.3: Eight classes of data.

Table 3.1: Dataset Table

Class data	Quantity
Images	1,125
VI-Chickenpox	170
BA-Cellulitis	168
VI-Shingles	163
FU-nail-fungus	162
PA-cutaneous-larva-migrans	125
FU-athlete-foot	124
FU-ringworm	113
BA-impetigo	100

3.5 Statistical Analytics

3.5.1 Data manipulation

The vast bulk of information is processed data. It is important to take into account the data collection approach employed for data processing. Refined info comes in quite handy while using the internet. I collected relevant data for the different phases of skin disorders. Following that, data from actual medical domains was mixed with the data to produce a large dataset consisting of eight groups. The effectiveness of a dataset update is often determined by the first data processing that is done. Results generated with greater expertise will be more accurate. A data handling system consists of two phases: gathered data and received supplies data. Stated distinctly, this is the main hardle to this type of study-based project.

- **Gathering and preparing data:** Every image in the collection I utilized was created by combining the different online field data (height and width) that Kaggle had gathered from hospitals. For my model, each image needs to fulfill specific quality requirements, therefore I changed the script to make the image 224 by 224 pixels. In addition, before processing any picture in my model, I prefixed it with "jpg". I separated and altered the photos after data augmentation in order to get them ready for classification. As a result, I used the split equivalent of every dataset to train the framework.

- Pictures that are sized fixed according to codes.
- File formats being changed to JPG.
- Exclude any erroneous pictures.
- Eliminated unnecessary images

```
print("The classes:\n", np.unique(df['label']))
```

```
The classes:
 ['BA- cellulitis' 'BA-impetigo' 'FU-athlete-foot' 'FU-nail-fungus'
 'FU-ringworm' 'PA-cutaneous-larva-migrans' 'VI-chickenpox' 'VI-shingles']
```

Fig 3.4: 8 classes of skin diseases.

3.5.2 Data for Training, Testing and Validation

Researching and developing methods for extracting data from texts and producing results based on that information is known as deep learning, and it is growing in popularity. These algorithms work by taking the input data, generating an equation from it, then using that equation to read the data and make inferences. Usually, these inputs are separated into multiple elements before to using them in the process of creating the model. Three distinct data sets—train, valid, and test—are usually employed in the process of constructing a model. The first training dataset ought to be divided in half, with 20% and 80% going toward learning and fifty percent and 50% going toward testing and validation.

CHAPTER 4

Implementation

4.1 Overview

The data collection must be supplied after completing all subsequent processes in order to guarantee correctness. To make it smooth to execute, I split the work into its most important components. I must adhere to such guidelines to ensure whether my task is completed appropriately.

- Dataset collections.
- Steps done prior to picture processing
- Predicting 8 skin diseases class images.
- The many algorithms that are employed.
- Classifying skins disease images with InceptionResNetV2
- Examine the results and accuracy.

I used tools like Kaggle to compile all of my datasets publicly. I selected a dataset that made sense for the different skin conditions. I could then start working on preparing the data after that. In this instance, I removed any unnecessary information from my data, including noise, erroneous photos, improperly scaled photographs, etc. In addition, I use databases to perform the prolonged intervals for training, testing, and validation.

I started tinkering with the programming before trying the idea out. I assessed each of the five employed algorithms' accuracy. After the procedure was finished, I evaluated its accuracy. I considered the accuracy and selected the one that would work best for my needs. Based on data on skin disorders, this has proven to be fairly accurate in identifying illnesses of the skin. A collection of basic prerequisites has been constructed after a careful analysis of all relevant mathematical and philosophical ideas and techniques. These prerequisites are necessary for each and every attempt at photo classification.

4.2 Train Model

The model training procedure remains the foundation for building the skin disease detection system. Since InceptionResNetV2 architecture introduced state-of-art performance on structuring picture categorization, I exploited the possibility of the framework fully by using all complicated layers of the model. The training dataset consisted of excellent pictures that included different pictures of the diseases affecting the skin. As a way to enhance the possibility of the model to learn and generalize, these photos were preprocessed to near perfection. In an attempt to improve the performance of the model to its best accuracy some optimization algorithms coupled with supervised learning techniques are used in developing phase. Other adjustable variables like the learning rate, batch size, and the number of epochs were set with a lot of focus make the optimization better. Additional measures to prevent overfitting and ensure the model provides good results on unseen data introduce strict validation procedures.

Model of classifying

1. **DenseNet169:** The network's total layer count is indicated by the "169" in DenseNet-169. DenseNet-169, in particular, consists of 169 layers, comprising fully connected, pooling, and convolutional levels. It is a more advanced version of DenseNet-201 and DenseNet-121.DenseNet counts its dense connection structure among its salient characteristics. Traditionally, the input from every single layer of a convolutional neural network (CNN) is generally the output that of the layer before it. All preceding layers' input is received by each layer in Dense Net, as opposed to simply the one before it. Along with promoting feature propagation and helping to solve the vanishing-gradient challenge, this extensive connection aids in feature reuse.

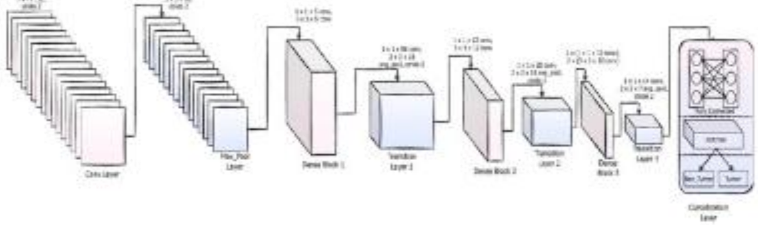

Fig 4.1: The architectural model of DenseNet169.

2. **InceptionV3:** The framework for classifying and recognizing images is CNN InceptionV3. It is one of the concepts that the company's employees created as part of the compilation of Inception DL ideas. The InceptionV3 device has gained a lot of popularity due to its clever use of the "setting up part," a unique component that enhances the system's overall accuracy and efficiency, and its smart design. The architecture of the Inception: Volume Three deep neural network consists of 48 layers. Combinations include levels with optimal pooling, extra classifiers, convolutional layers, and completely linked layers. Networking is able to collect data at multiple levels of abstraction because of the multilayered randomization and periodic mixing of the Creativity modules.

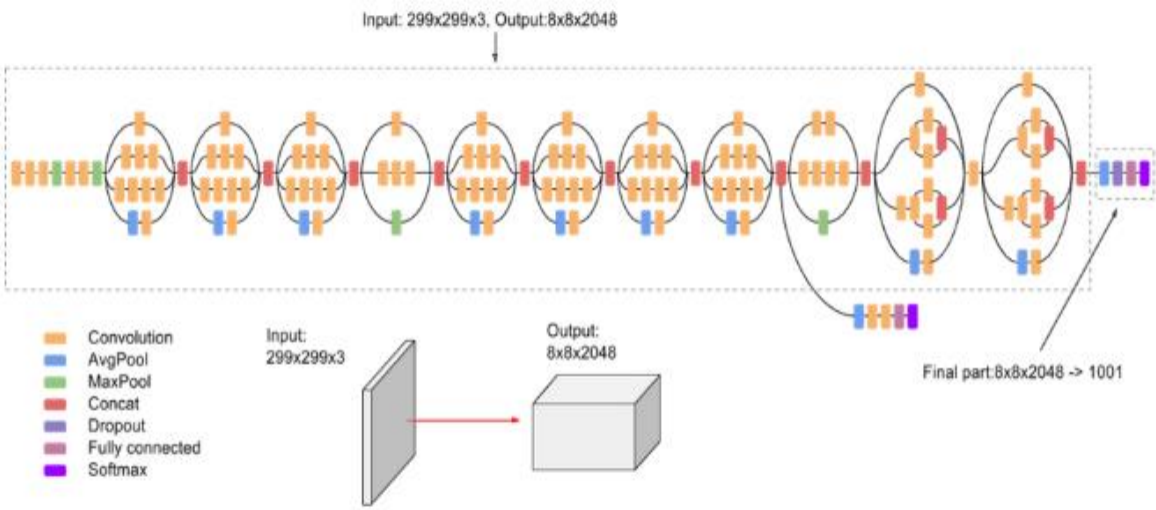

Fig 4.2: The architectural model of Inception V3.

3. **InceptionResNetV2:** Starting off ResNetV2, a neural network architecture, is the result of combining the following additional deep neural network designs: Inception and ResNet. It is an extension of the Inception architecture with residual relationships, a key feature of ResNet. InceptionResNetV2 was presented by Google researchers as a network belonging to the Inception group. It is well known for exhibiting remarkable capabilities in several artificial intelligence applications, including as classifying pictures and identifying objects. When used to the ImageNet massive amounts visual recognition contest (ILSVRC), it demonstrated state-of-the-art performance.

Fig 4.3: The architectural model of InceptionResNetV2.

4. **VGG16:** VGG16 is the abbreviation for this model, referred to as VGG Net in commonThe method is a neural network that makes use of sixteen-layer convolutions (CNNs). Neural networks the fact that have been pretrained ImageNet is a library of over a million pictures. A mouse, pencil, internet keyboard, and other objects are only a few of the 1000 unique item categories that the preconditioned network can identify in images. The network has been trained using a wide variety of visually rich representations of features as a result. The network was able to handle a 224 × 224 picture source size. For further pretrained network alternatives, visit MATLAB's Originally trained Parallel neural network models.

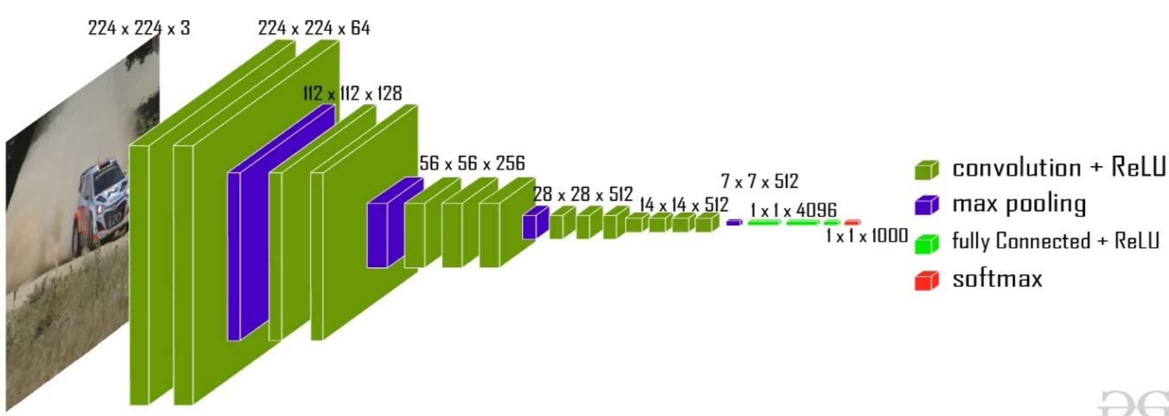

Fig 4.4: The architectural model of VGG16.

The dimensions of the picture that is sent to the network are (224, 224, 3). With the same padding and a 3*3 filter area, the first two layers include sixty-four channels. Following the max pool layer (stride 2, 2), there will be a second layer with convolution layers that have filter sizes (3, 3) and 128 filter measures. The largest pooling layer, which is the same as the one before it and has the greatest frequency (2, 2), comes next in line. After two convolutional layers, a set of 256 filters with filtered widths of three and triple are added. Convolution is used to construct two sets of three independent layers, followed by a max pool layer. Every one of the 512 filters has the same spacing and dimensions (3, 3).

5. **VGG19:** A version on the VGG model, the VGG19 model consists of one SoftMax layer, five maximum pooling layers, three completely interconnected layers, and 19 layers that are convolutional. 224,224, 3 made up the matrix as the system was provided with an RGB image with predefined dimensions of (224 * 224). This one preprocessing step was the removal of each pixel's mean RGB value, which was calculated across the training set. Utilizing kernels with a size of (3 * 3) and a stride of around one pixel, They succeeded in filling the entire picture. The depth of the image was preserved by using spatial padding. To obtain maximum pooling, Speed 2 above two * two-megapixel panes had to be used. The modified uniform component (ReLu) was then used to improve model classification, accelerate computing, and increase non-linearity. The ReLu turned out to be noticeably better than previous models that relied on tanh or exponential functions. Out of the 4096 sized layers created, three were fully connected. The final layer is called the softest max functions, and there is an additional layer with an accompanying channel whose frequency is 1000 appended for a 1000-way classification.

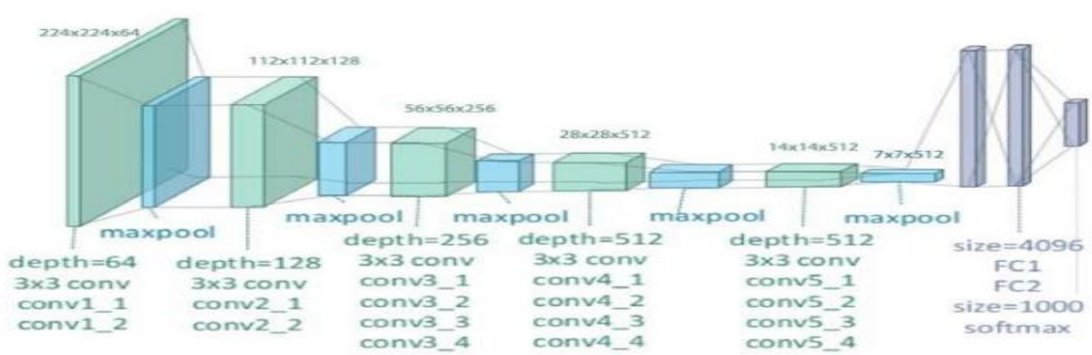

Fig 4.5: The architectural model of VGG19.

4.3 Model Evaluation

In the case of deep learning architectures, five models that specialize in skin diseases identification were reasonably assessed throughout the model assessment phase, with a focus on the assessment of accuracy, precision, recall, and F1-score. identifying that the best model achieved an accuracy of 98.23% after the process of cross-validation at the training and testing of the independent dataset depending on the chosen algorithm, which proves robust ability to classify the range of diseases with high credibility. A comparative analysis of these models for their effectiveness revealed that though, there were differences in matters such as computational complexity, training time, and versatility that are crucial in the implementation of deep learning for clinical use. These outcomes support deep learning methods as highly effective tools increasing diagnostic accuracy and readiness for practical application, which assures significant advances in healthcare diagnostics and patient's outcomes.

4.4 Summary

This thesis paper provides a detailed analysis of the detection of skin disorders with the help of state-of-art deep learning techniques integrated into a web application. The five deep learning models that were tested for this study were as follows and the best model was decided from all of them with a jaw-dropping accuracy of 98.23%. The implementation phase involved pre-processing data, developing the models and tuning the hyperparameters with an aim of improving the already developed models. Studies done on the comprehensive system testing also indicated the ability of the developed system to offer accurate diagnosis consistently regardless of the scenario. The ease of use was also suggested by the simulations, while the system's impact was also illustrated in circumstances in which early and accurate diagnosis plays a decisive role, such as in health care. Overall, this thesis contributes to the existing literature by providing a professional and comprehensive approach to identifying skin diseases employing novel deep learning tools while existing in a realistic and convenient form for users. The designed system is all set to go implemented, thus offering the medical practitioners with a potent tool that can contribute towards raising the chances of accurate diagnosis, and thus, guaranteed better health outcomes.

CHAPTER 5

Experiment Results and Discussion

5.1 Overview

With the use of a disease image categorization system, this section describes the progression of a skin disorder. To cre ate the model, there were several phases involved: getting the photos, evaluating the data, refining the data, changing the volume of data, showcasing models, and offering suggestions in accordance with the accuracy of the subject. The following section presents and discusses the investigation's results.

5.2 Experimental Result

Algorithms have predicted the discovery of many. skin conditions identified from photos of poor skin. As a result, I employed numerous tactics. I considered and assessed a range of options before deciding on the best course of action for the trial. In an effort to improve the caliber of my work, I tried a number of different approaches. used Kaggle's public datasets for eight skin conditions while receiving guidance. The eight photo sets show different stages of skin conditions. I made advantage of the pre-existing Python tools, dictionaries, and content classification strategies. This work classifies skin diseases using Python DL modules and deep learning to choose the appropriate categories based on images of the ailment. developing an online tool to determine whether different skin problems may be recognized from photos.

5.3 Descriptive Analysis

My methods of categorizing affected the results that I got. I have pinpointed the precise locations of skin diseases in images by applying Six distinct deep learning algorithms. I applied deep learning methods (InceptionResNetV2, DenseNet169, InceptionV3, ResNet50V2, VGG16, and VGG19) that have demonstrated potential for precisely recognizing skin disorders over 20 epochs. All the models shared the same dataset, which comprised publicly available data and my own online dataset sourced from Kagle sources. After finishing the dataset method, I assessed the algorithms' soundness using the pre-made libraries in Mat-lab. I also used online prototypes to forecast skin conditions.

Table 5.1: Accuracy Table

Models	**Accuracy Score (AUC)**
InceptionResNetV2	98.23%
DenseNet169	97.35%
ResNet50V2	97%
InceptionV3	81.42%
VGG16	94.69%
VGG19	92.92%

The effectiveness for many models is displayed in the next section. The procedure made use of PyCharm and CoLab, two open-source applications. Overall, there were six models: VGG16, VGG19, InceptionV3, ResNetV2, DenseNet169 and InceptionResNetV2. The top performing models were the InceptionResNetV2 models, which had an accuracy of 98.23%.

	precision	recall	f1-score	support
BA- cellulitis	1.00	0.96	0.98	23
BA-impetigo	1.00	0.92	0.96	13
FU-athlete-foot	1.00	1.00	1.00	10
FU-nail-fungus	1.00	1.00	1.00	21
FU-ringworm	0.91	1.00	0.95	10
PA-cutaneous-larva-migrans	0.91	1.00	0.95	10
VI-chickenpox	1.00	1.00	1.00	10
VI-shingles	1.00	1.00	1.00	16
accuracy			0.98	113
macro avg	0.98	0.98	0.98	113
weighted avg	0.98	0.98	0.98	113

Fig 5.1: Classification Report of InceptionResNetV2's.

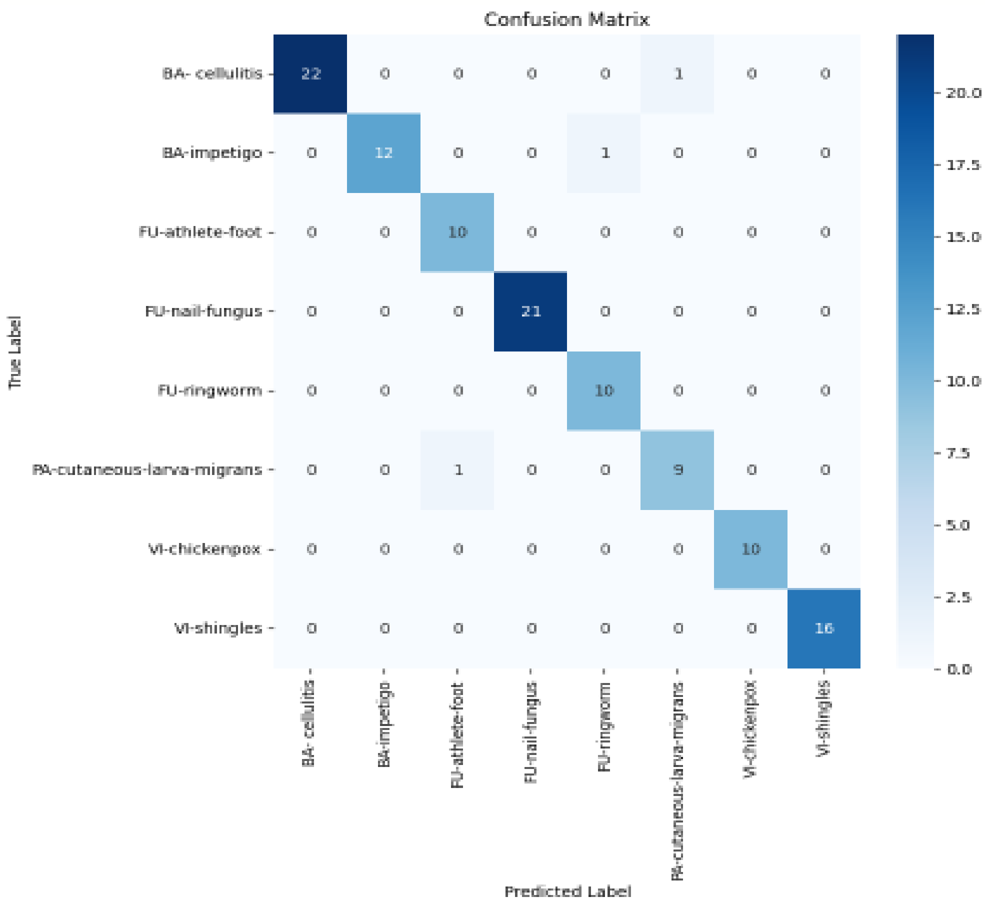

Fig 5.2: Confusion matrix OF InceptionResNetV2's.

For the InceptionResNetV2 models, only the whole classification result is displayed in order to get the best accuracy. The procedures needed to develop a workable web application and classify a specific kind of skin diseases using the CNN approach InceptionResNetV2 model are depicted in Fig. 4.3 below. The eight classes of skin disease photos that were accurately predicted by a web-based program using the figures 4.4, 4.5, and 4.6 show the InceptionResNetV2 dataset. To put it broadly, one among the many least supervised techniques for object detection or forecasting is the use of deep learning.

Fig 5.3: Web prototype for classify skin diseases

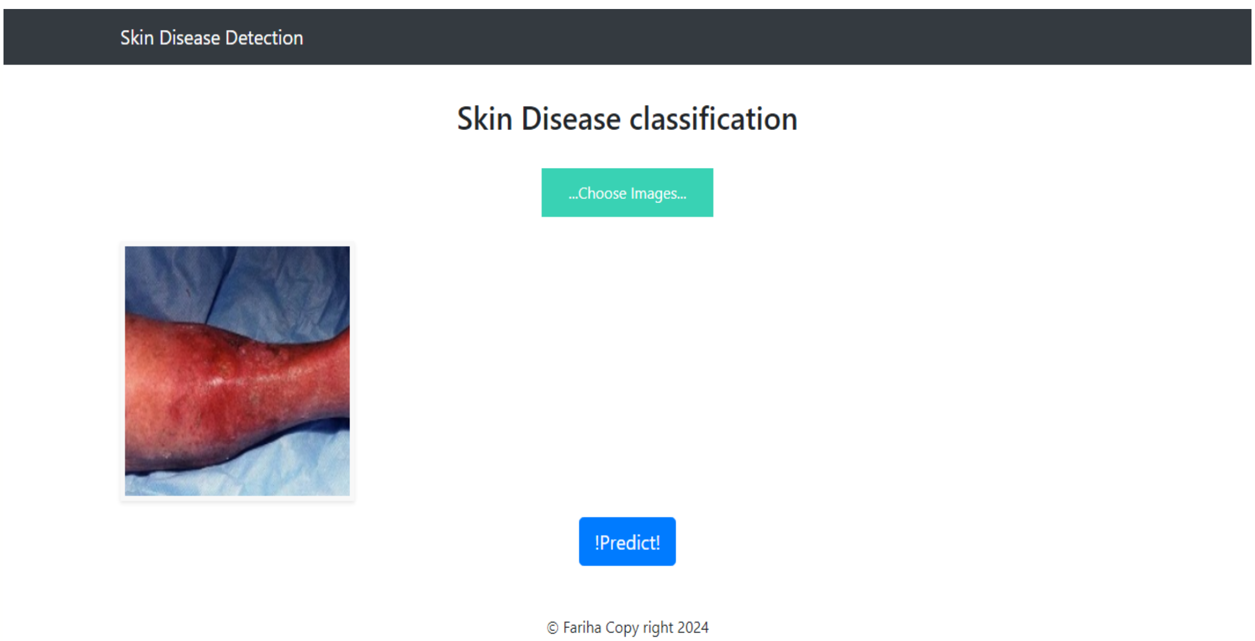

Fig 5.4: Selecting photos of application

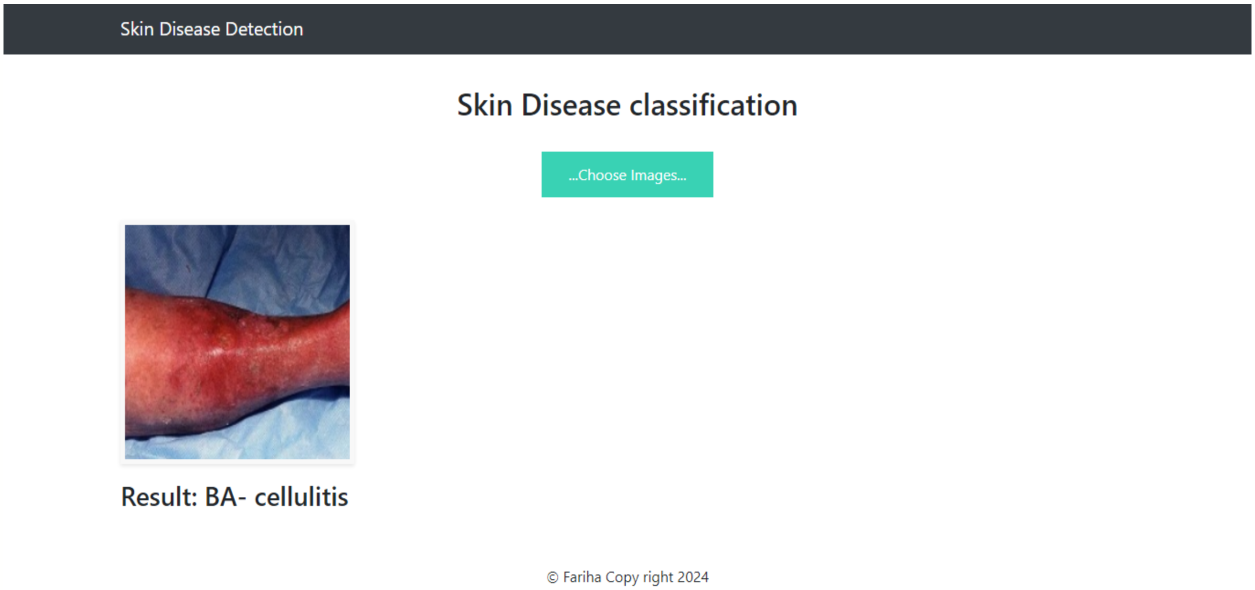

Fig 5.5: Classifying BA- cellulitis of skins diseases

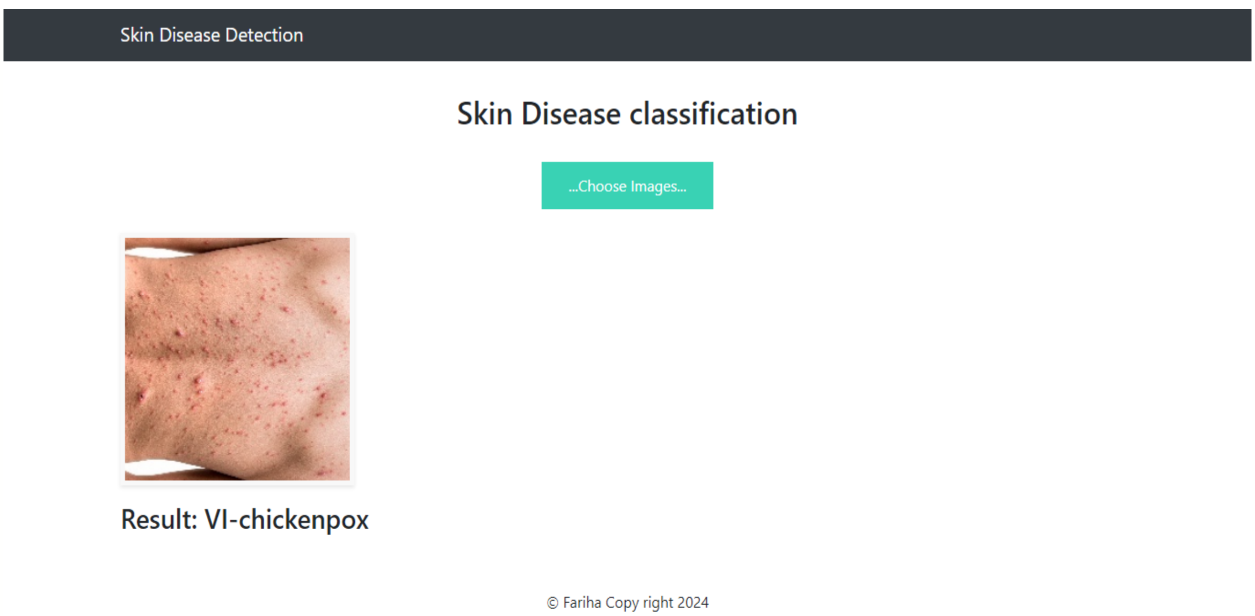

Fig 5.6: Classifying VI- Chickenpox of skins diseases

Figures 4.7 and 4.8 below show the InceptionResNetV2 models' train and validation accuracy as well as loss at an epoch of 20.

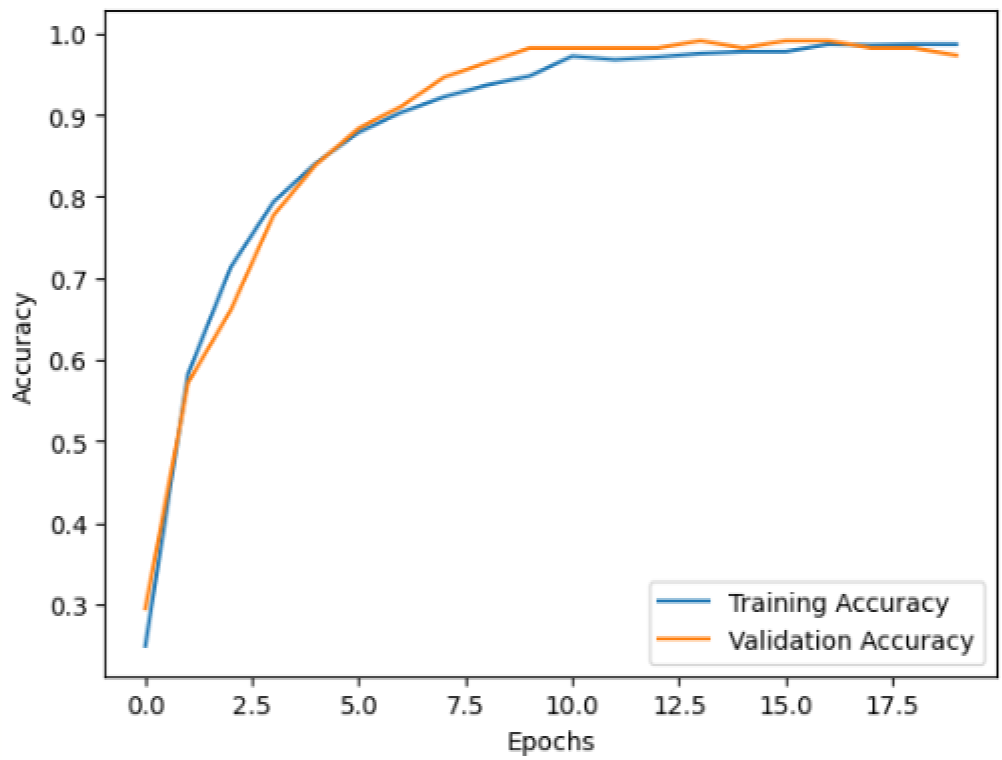

Fig 5.7: Validation and Training Accuracy Curve of InceptionResNetV2.

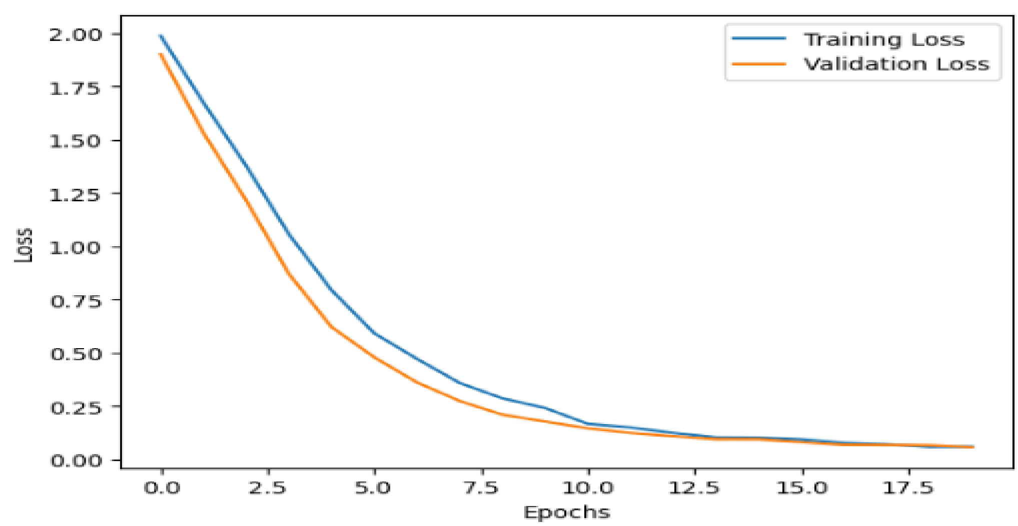

Fig 5.8: Validation and training Loss Curve of InceptionResNetV2.

5.4 Discussion

I'll use DL algorithms and diseases in this study to predict skin ailments. In all fields of study, the categorization procedure should assign a substantial amount of weight to each term. I have always investigated the classification of the skin in an attempt to determine the cause of skin anomalies. The datasets were additionally divided into successive classes using the dl models. One of the most crucial components of any study is the data. The results of the study could be considerably changed by the data that was provided. I thought it was obvious that those who had previously used the two datasets that were made accessible would get different results from this combination of real datasets. Because I used more data, I might be perceived as being slightly more accurate.

I used a range of DL method approaches and accuracy ratings to help me reach my objective. For this project, I employed five distinct algorithms in all. I had several things I needed to get before I could start my present project. Indeed, I did come to a decision and begin working on the algorithm. I then proved that each algorithm was right, as I previously stated. I was able to achieve the highest accuracy of 98.23% in the InceptionResNetV2 tests, which include the following eight categories, by using both of these techniques. It is very interesting since, using the data I provided, it outperforms the other models. the use of online tools and images of the illness in the diagnosis of skin cancer classes.

Precision: Accuracy, or the degree of precision with which the algorithm generates accurate forecasts, is one metric that is commonly used to assess the efficacy of the model. To calculate efficiency, one can multiply the total number of true positives by the total number of correct forecasts.

$$\text{precision} = \frac{TP}{TP+FP}$$

Recall: Regardless of all pertinent instances, retrieval is the proportion of appropriate cases that were eventually located and recovered. When a method has a high recall rate, it is considered to have produced the most relevant results.

$$\text{recall} = \frac{TP}{TP+FN}$$

F1-Score: The validity of a test is established by taking into account its accuracy and recall. Recall and accuracy complement each other well.

$$F1 = \frac{2 \times precision \times recall}{precision + recall}$$

Accuracy: Reliability is described as the correlation between an accepted cost and an expected value.

$$accuracy = \frac{TP+TN}{TP + FN + TN + FP}$$

CHAPTER 6

Impact on Society, Environment and Sustainability

6.1 Impact on Society

Deep learning techniques are applied to improve the identification of images pertaining to skin diseases, and deep learning strategies are used to identify afflicted skin using real data collected from many medical sources. weighing the potential effects on the community. These strategies harm society in a variety of ways, including the following:

- **Boost the Medical Sector**: One of the most notable potential benefits of AI and DL approaches is their capacity to identify skin problems in photographs, which might lead to improved outcomes for the field. Skin disease diagnostics can help doctors, patients, along with various healthcare professionals by enabling them to swiftly resolve issues and advance medical knowledge. Long term, this might lead to improved skin disease therapy and more successful medical operations.
- **Economic Benefits**: Classifying skin disorders with algorithms based on deep learning could benefit society's economy. For example, patients may benefit if the medical field gains more recognition. It would be able to deliver regular status reports without requiring people to visit because of DL-driven technologies. The potential for remote patient monitoring makes this feasible. Prompt intervention can reduce costs for people and health care systems by averting the need for more complicated and expensive therapies. Better financial outcomes and more efficient medical treatment are possible as well. The classification of skin disorders will benefit greatly from the support of individuals with this kind of issue.
- **Social benefits**: In addition to possible financial gains, using DL methods to skin problems may have positive social effects. Systems using deep learning process and evaluate medical images significantly more quickly than human radiologists. This promptness might lead to a quicker diagnosis and treatment strategy since skin illnesses necessitate immediate medical attention. Different radiologists who are human can interpret medical pictures in different ways unlike one another. Standardizing visual analysis with algorithms that use DL may produce reliable and consistent results for a range of medical practitioners.

Healthcare professionals may benefit from training and information that deep learning technology may offer. By providing more information and support to practitioners with less experience, they might raise the standard for medical expertise overall.

Keeping all of this in mind, it's critical to keep in mind that, despite any potential benefits, using in-depth knowledge for medical examinations also raises ethical, legal, and privacy concerns. Safe adoption in the healthcare sector necessitates safeguarding patient confidentiality, data security, and decision-making process transparency for the algorithms.

6.2 Impact on Environment

Data on skin illnesses may be distinguished using deep learning algorithms with little apparent environmental risk. Nevertheless, lacking a chance that by using more resources, creating and implementing these solutions might inadvertently exacerbate environmental degradation. Listed below highlight a small amount of possible damages that these methods might generate to the surroundings:

- **Energy Consumption**: DL for skin disease detection requires a certain amount of energy, which is determined by a number of parameters such as the physical equipment, available processing power, complexity of the dataset, and the particular algorithms utilized. It is related to the type of power used in computations. Energy sources that are not renewable may have an influence on the environment more than energy derived from renewable sources. Even if using deep learning to classify skin illnesses may lead to better health results, energy-related issues nevertheless have to be considered. An increasing amount of effort is being put into developing environmentally friendly techniques and technology in order to decrease the environmental effect of deep learning applications in the medical field.

- **Data archiving**: Deep learning systems should be trained and tested on large amounts of data. To protect this data, it could be required to use materials and electricity, two resources that are harmful to the environment. The potential environmental effects associated with knowledge retention must be considered, along with resource-saving strategies that may be used to lessen these effects.

- **Shipping:** If techniques are available to diverse parts of the world and scattered deeper learning is able to gather more accurate data, then using these approaches could lead to an increase in emissions related to travel. It is critical to take into account how transportation affects the environment and to try my best to reduce emissions.
- **Research Data Illustrations**: Deep learning models' ability to detect skin illnesses is significantly influenced by the caliber and from the first training set of data. If a large percentage of the training data comes from a particular social group or demographic, the model could not work as well when utilized with information from other groups. It needs various training data for an architecture to be effective in a variety of circumstances and patient groups.

In summary, there are a number of ways that the environment influences the usage of deep skin illnesses. Other factors that are also at play include public awareness, regulatory barriers, data distribution structures, data presentation, and environmental concerns. Deep learning technology integration in a range of healthcare settings requires careful consideration of these considerations. It is essential that the necessary actions be performed and that such ideas be implemented in practice given the development and consumption's possible unintended indirect ecological impacts. Several examples of these protections include restricting emissions in contrast to public transportation when appropriate, storing knowledge in a way that saves energy when feasible, and utilizing resource-efficient technologies and computations to decrease pollution and data consumption.

6.3 Ethical Aspects

Deep learning raises various ethical questions that must be addressed before using technology to the diagnosis of skin disorders in order to ensure responsible and equitable deployment. The following are some of the most important ethical components:

- **Patient confidentiality and data security**: In order for deep learning algorithms to be trained, a substantial There needs to be a sufficient amount relevant patient data accessible. It is imperative to maintain the confidentiality and security of this data. Access without authorization and security lapses can be prevented by implementing robust cybersecurity measures and maintaining the confidentiality of medical records.

- **Algorithmic Equality and Bias:** Due to algorithmic bias, diagnostic accuracy may vary throughout various socioeconomic groups. Finding and fixing biases in training data and computational code is necessary to maintain fairness. Audits and routine algorithm monitoring are required to recognize, confront, and advance fair results in the medical field.
- **Clinical Assessment and Credibility**: A thorough clinical validation procedure is required in real-world healthcare settings to ensure the precision and dependability of deep learning simulators. The limits of these approaches ought to be made clear to doctors and nurses, and clear recommendations for when to utilize them should be devised.
- **Responsibility**: It's not obvious who has the last word when it comes to choices made using algorithms for DL. It is imperative to consider who will oversee the moral and efficient implementation of these techniques and ensure that farmers with skin disorders have access to the appropriate support networks.
- **Collaboration and Professional Liberty**: DL must not be viewed as assuming the role of a medical expert, but rather as an assistance. Maintaining the autonomy of physicians and nurses in their decision-making is crucial. AI specialists and medical practitioners may collaborate to ensure that innovation adds to rather than takes away from clinical competence.

Deep learning approaches to illness diagnosis raise ethical concerns that can be effectively addressed with ongoing supervision, regular ethics reviews, and collaboration between regulators from the government, medical professionals, technologists, and ethicists. It usually raises a number of moral questions that require thorough consideration and resolution. Techniques that increase advantages and minimize disadvantages ought to be created and applied in a morally and responsibly manner.

6.4 Sustainability Plan

This is essential for develop a sustainable method it takes the effects onto itself surroundings and the use of resources, as well as the long-term practicality of merging deep learning with the detection of skin illnesses. An example of an environmentally friendly strategy is as follows:

- **Efficiency of Energy:**

  Selection of Hardware: Select hardware that minimizes energy consumption for running deep learning algorithms. To cut down on the energy consumed during diagnostic procedures, try to employ technologies intended for inference tasks. Improving the Infrastructure of the Cloud: Select cloud services with vendors and agreements that prioritize energy conservation. Put scheduling concepts into rehearse to reduce idle time and expand energy use overall.

- **How successful algorithms are**:

  Model Optimization: An Example of Maintain the diagnostic precision of deep learning models while continuously enhancing their performance. Among them are techniques for model compression, quantization techniques, and architectural improvements. "Real-processing" is the pursuit of quick processing capability with the aim of reducing diagnostic time as well as asset requirements while optimizing the use of energy.

  Responsibility: Clear roles and duties must be established for all parties involved in the development and implementation of DL structures in order to guarantee their sustainability. This can mean laying out the specific guidelines for the moral application of the methods as well as the duties of those in charge of ensuring that they are used correctly.

The implementation and ongoing supervision of DL for sustainable development should benefit from the inclusion of these elements, making it possible to design a strategy that balances environmental responsibility with technical advancements in skin disease detection. By including sustainability criteria into the usage of DL simulations for skin disease diagnosis, it may be possible to increase patient happiness, reduce adverse environmental effects, and improve the standard of healthcare.

CHAPTER 7

Conclusion and Future Research

7.1 Summary of the Study

Thanks to this question, I now know a lot more about the subject. An allergic reaction on the skin is quite sensitive. This has a major annual impact on the decline in the medical industry. As such, I was enabled to identify eight distinct kinds of skin illnesses using deep learning and the skin photos in the dataset. As previously demonstrated, I utilize a variety of web resources, like Kaggle skin illnesses photographs, to gather as much information as I can for my study. By utilizing this data for conditioning my computer's algorithms on the patterns of illness identification, I was able to get better at recognizing certain types of skin ailments. Initial fixes were made to a few issues. My intended objective was successfully attained. Different Deep Learning algorithms yield varying results for different users. I discuss this in more depth in the next section.

7.2 Conclusion

My research proves the reliability of my techniques and conclusions. I sincerely hope and believe that additional study in this field will be initiated after I complete my review. The research has given me a ton of ideas on how to improve my work. I made a couple mistakes at work. I discovered that my possibilities for my school route were numerous. As I proceed with the current project, I should be able to fix any flaws or potential issues. In addition, I provide suggestions for how these results might be applied in further studies to produce more comprehensive answers to the queries raised by this inquiry. I'm confident that taking this test will improve my comprehension of the various facets of the medical topic I've chosen for my research. As far as I can tell, this will contribute to the advancement of cutting-edge scientific and technical techniques that enable me to support the medical community and make it easier to use skin images to identify bone skin problems. By using DL to assess the likelihood that eight of these types of skin issues could exist, I hope to offer a novel method of classifying skin illnesses based on many categories of images of healthy people. constructing a skin condition classification web application as well. InceptionResNetV2 performs better than the other five models used in the dataset analysis, with an accuracy rating of 98.23%. To achieve the highest level of precision, a web application is being developed that uses InceptionResNetV2 models to categorize skin diseases.

7.3 Possible impacts

The application of deep learning algorithms may improve the accuracy of skin disease identification from ill images. They might be trained to recognize intricate patterns or tiny skin conditions that would be difficult for actual radiologists to recognize by using large datasets. Deep learning algorithms on skin photos may be able to diagnose skin conditions, which could improve access to healthcare, especially in developing or rural areas where access to trained medical personnel may be scarce. Medical practitioners could allocate their funds more wisely if they could precisely identify which patients are most likely to develop skin problems. Consequently, skilled therapy can be directed toward patients who need it most, and medical personnel can be assigned more effectively.

7.4 Future Works

There are a lot of prospects for future research in this area of medicine, especially within the constraints of my particular studies. I was full of ideas on how to improve my job overall. As previously said, I have also discovered a few flaws, and these inaccuracies offer opportunities to improve this research. By putting my theories into practice and enhancing prediction outcomes with additional opportunities to capture high accuracy, I'll aim to correct this error. I intend to correct any mistakes that arise. I also have a couple more objectives in mind. Given that it uses skin photographs to identify specific skin disorders, this prediction may call for additional skin study. In order to maximize the benefits to users, I intend to include elements that allow users to detect various sorts of skin disorders as the skin is being classified, such as the InceptionResNetV2 imitation for classifying various skin ailments. I think that working in this field will allow me to improve medical technology and increase its important impact on healthcare. I might help the patients' skin diseases be identified early.

Reference

[1] M.A.M .Almeida, I.A.X. Santos, "Classification Models for Skin Tumor Detection Using Texture Analysis in Medical Images". *J. Imaging* 2020, *6*, 51.

[2] V. Ki, C. Rotstein, "Bacterial skin and soft tissue infections in adults: A review of their epidemiology, pathogenesis, diagnosis, treatment and site of care." The Canadian journal of infectious diseases & medical microbiology. *Can. J. Infect. Dis. Med. Microbiol.* 2008, *19*, 173–184.

[3] P. Deepalakshmi, K.T. Prudhvi, C.S. Siri, K. Lavanya, P.N. Srinivasu, "Plant Leaf Disease Detection Using CNN Algorithm." *Int. J. Inf. Syst. Modeling Des.* 2021, *12*, 1–21.

[4] S.P. Naga, T. Rao, A.M. Dicu, C. Mnerie, I. Olariu, "A comparative review of optimisation techniques in segmentation of brain MR images". *J. Intell. Fuzzy Syst.* 2020, *38*, 1–12.

[5] A. Kumar, J. Kim, D. Lyndon, M. Fulham, D. Feng, "An Ensemble of Fine-Tuned Convolutional Neural Networks for Medical Image Classification". *IEEE J. Biomed. Health Inform.* 2017, *21*, 31–40.

[6] G.P.H. Asha, J. Anitha, P.J. Jacinth, "Identification of Melanoma in Dermoscopy Images Using Image Processing Algorithms." In Proceedings of the 2018 International Conference on Control, Power, Communication and Computing Technologies (ICCPCCT), Kannur, India, 23–24 March 2018; pp. 553–557.

[7] L.S. Wei, Q. Gan, T. Ji, "Skin Disease Recognition Method Based on Image Color and Texture Features." *Comput. Math. Methods Med.* 2018, *2018*, 8145713.

[8] S.P. Naga, T. Rao, V. Balas, "Volumetric Estimation of the Damaged Area in the Human Brain from 2D MR Image". *Int. J. Inf. Syst. Modeling Des.* 2020, *11*, 74–92.

[9] S.P. Naga, T. Rao, V. Balas, "A systematic approach for identification of tumor regions in the human brain through HARIS algorithm". In *Deep Learning Techniques for Biomedical and Health Informatics*; Academic Press: Cambridge, MA, USA, 2020; pp. 97–118.

[10] A. Shrestha, A. Mahmood, "Improving Genetic Algorithm with Fine-Tuned Crossover and Scaled Architecture." *J. Math.* 2016, *2016*, 4015845.

[11] E. Saber, S. Ruhul, E. Daryl, "A New Genetic Algorithm for Solving Optimization Problem". *Eng. Appl. Artif. Intell.* 2013, *27*, 57–69.

[12] M. Alam, T.T.K. Munia, K. Tavakolian, F. Vasefi, N. MacKinnon, R. Fazel-Rezai, "Automatic detection and severity measurement of eczema using image processing." In Proceedings of the 2016

38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Orlando, FL, USA, 16–20 August 2016; pp. 1365–1368.

[13] I. Immagulate, M.S. Vijaya, "Categorization of Non-Melanoma Skin Lesion Diseases Using Support Vector Machine and Its Variants." *Int. J. Med. Imaging* 2015, *3*, 34–40.

[14] M. Awad, R. Khanna, "*Support Vector Machines for Classification. Efficient Learning Machines*;" Apress: Berkeley, CA, USA, 2015; pp. 39–66.

[15] Y.C. Lee, S.H. Jung, H.H. Won, M. WonDer, "Skin Lesion Classification with Fine-tuned Neural Networks." In *ISIC 2018 Lesion Analysis Towards Melanoma Detection*; Cornell University: Ithaca, NY, USA, 2018; pp. 1–4.

[16] J. Tarigan, R. Nadia; Diedan, Y. Suryana, "Plate Recognition Using Backpropagation Neural Network and Genetic Algorithm." *Procedia Comput. Sci.* 2017, *116*, 365–372.

[17] N.N. Mohd, R.S. Ransing, M.N.M. Salleh, R. Ghazali, A.H. Norhamreeza, "An Improved Back Propagation Neural Network Algorithm on Classification Problems" *Commun. Comput. Inf. Sci.* 2010, *118*, 177–188.

[18] D. Graves, W. Pedrycz, "Fuzzy prediction architecture using recurrent neural networks." *Neurocomputing* 2009, *72*, 1668–1678.

[19] Y. Zhang, H. Ishibuchi, S. Wang, "Deep Takagi–Sugeno–Kang Fuzzy Classifier with Shared Linguistic Fuzzy Rules". *IEEE Trans. Fuzzy Syst.* 2017, *26*, 1535–1549.

[20] J.G. SivaSai, P.N. Srinivasu, M.N. Sindhuri, K. Rohitha, S. Deepika, "An Automated Segmentation of Brain MR Image through Fuzzy Recurrent Neural Network". In *Bio-Inspired Neurocomputing*; Bhoi, A., Mallick, P., Liu, C.M., Balas, V., Eds.; Studies in Computational Intelligence; Springer: Singapore, 2021; Volume 903.

Appendix

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

Title:

SKIN DISEASES DETECTION USING DEEP LEARNING TECHNIQUES WITH WEB APPLICATION

Student ID: [201-15-13619]

CO Description for FYDP

CO	CO Descriptions	PO
Phase -I		
CO1	For the Final Year Design Project (FYDP), use knowledge that has been obtained recently and, in the past, to identify a problem with the diagnosis of skin disorders.	**PO1**
CO2	Examine many facets of the objectives when creating a solution for this (FYDP).	**PO2**
CO3	Conduct a literature research to investigate several problem domains, identify the concerns, and set this (FYDP) target.	**PO4**
CO4	Throughout the FYDP's development life cycle, carry out cost estimation and economic evaluation and make use of appropriate project management techniques.	**PO11**
Phase -II		
CO5	In this FYDP, ensure that public health and safety regulations are followed while designing and developing technical solutions, system components, or processes that satisfy criteria. Additionally, take cultural, socioeconomic, and environmental concerns into account.	**PO3**

CO6	Select and implement suitable techniques, resources, and modern engineering and IT technologies to handle intricate engineering procedures, including modeling and prediction, while abiding by pertinent restrictions in this FYDP.	**PO5**
CO7	Using logical thinking informed by contextual knowledge, analyze societal, health, safety, legal, and cultural factors as well as related duties in the context of professional engineering practice and the solution to this issue.	**PO6**
CO8	Recognize and assess the long-term viability and influence of professional engineering endeavors in resolving complex engineering problems in social and environmental contexts.	**PO7**
CO9	In this FYDP, put ethical ideals into practice and abide by professional standards and conventions.	**PO8**
CO10	Ability to function well in a variety of teams and interdisciplinary environments as a leader or as a team member in addition to working independently during this FYDP.	**PO9**
CO11	Throughout this FYDP, effectively communicate with the engineering community and the general public about complicated engineering projects. This includes being able to understand, produce, and take clear directions as well as understanding and produce extensive reports and design documentation.	**PO10**
CO12	Recognize the value of self-directed learning and lifelong learning in the context of the rapidly changing technological world, and be prepared and able to participate in lifelong learning activities.	**PO12**

A. Data Collection and Preprocessing

A.1. Data Sources

Dataset 1: Description, source, and any specific attributes.

A.2. Data Preprocessing Steps

Step 1: Data Cleaning - Removing noise and handling missing values.

Step 2: Data Normalization - Scaling pixel values to a range of 0-1.

Step 3: Data Augmentation - Techniques used (e.g., rotation, flipping, zooming).

B. Deep Learning Model Details

B.1. Model Architecture

B.2. Model Training

Training Parameters: Batch size, number of epochs, learning rate.

Hardware Used: GPU/CPU specifications.

C. Results

C.1. Performance Metrics

Accuracy: Definition and how it was calculated.

Precision, Recall, and F1-Score: Detailed explanation and formulas.

Confusion Matrix: Interpretation.

C.2. Comparison with Other Models

Baseline Models: Description and performance comparison.

Advanced Models: Any transfer learning techniques or fine-tuned models.

D. Web Application Development

D.1. Technology Stack

- Frontend
- Backend

D.2. Implementation Details

API Endpoints: Detailed list of API endpoints and their functionalities.

User Interface: Description of the user interface and user experience considerations.

E. Code Listings

E.1. Preprocessing Code

E.2. Model Training Code

F. Additional Figures and Tables

F.1. Sample Images from Dataset

- Figure: Sample images of healthy skin vs. diseased skin.

- Figure: Augmented images demonstrating different preprocessing techniques.

F.2. Detailed Performance Tables

- Table: Detailed accuracy, precision, recall, and F1-score for each class.

G. References

Research Papers: List of cited research papers with complete references.

Web Resources: URLs of datasets, tools, and frameworks used.

H. Glossary

Deep Learning: Brief definition.

Convolutional Neural Network (CNN): Brief definition.

Overfitting: Brief definition.

I. User Guide for Web Application

I.1. Installation Instructions

- Step-by-step guide to install necessary dependencies and set up the environment.

I.2. Usage Instructions

- How to run the web application, upload images, and interpret results.

Classification

ORIGINALITY REPORT

15%	11%	1%	7%
SIMILARITY INDEX	INTERNET SOURCES	PUBLICATIONS	STUDENT PAPERS

PRIMARY SOURCES

1	dspace.daffodilvarsity.edu.bd:8080 Internet Source	8%
2	Submitted to University of Southern Mississippi Student Paper	2%
3	Submitted to King's College Student Paper	1%
4	"Computational Intelligence for Engineering and Management Applications", Springer Science and Business Media LLC, 2023 Publication	<1%
5	"Computational Intelligence in Machine Learning", Springer Science and Business Media LLC, 2022 Publication	<1%
6	Submitted to Southampton Solent University Student Paper	<1%
7	Submitted to University of East London Student Paper	<1%