BINDURA UNIVERSITY OF SCIENCE EDUCATION

FACULTY OF SCIENCE AND ENGINEERING

COMPUTER SCIENCE DEPARTMENT

IMAGE-BASED SKIN DISEASE CLASSIFICATION USING DEEP LEARNING.

NAME	**FLORENCE T SIYAPEYA**
REG NUMBER	**B191636B**
SUPERVISIOR	**MR MHLANGANISO**

PROJECT TOPIC

A RESEARCH PROJECT SUBMITTED TO THE COMPUTER SCIENCE DEPARTMENT IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE BACHELOR OF SCIENCE HONOURS DEGREE IN COMPUTER SCIENCE

Abstract

This research contributes to enhancing the accuracy and reliability of skin disease classification. The developed model provides valuable insights for dermatologists and researchers, facilitating improved diagnosis and treatment planning. The findings underscore the potential of machine learning in optimizing skin disease classification, leading to more effective healthcare practices in dermatology. The implementation of this project using a mobile application will make it easier for dermatologists to quickly and accurately diagnose patients as it adds to the previous related work done by other researchers.

Acknowledgements

I would like to extend my gratitude and sincere thanks to my supervisor Mr Mhlanganiso for his constant motivation and support during the course of my work . I truly appreciate and value his esteemed guidance and encouragement from the beginning. I also want to thank

Mr. Chaka, and Mr. Matombo for your co-supervision, I really appreciate all the time and efforts you put with the bid of helping me to come up with a quality research. Furthermore, I would like to mention my mother, who made this all possible and also played a supporting role which contributed positively to my studies and welfare.

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List of Acronyms & Abbreviations

ML-Machine Learning

ANN - Artificial Neural Network

MLR -Multiple Linear Regression

SVM - Support Vector Machine

LSTM - Long-Short Term Memory

Chapter 1: Problem Identification

1.1 Introduction

Chronic skin diseases cause a great discomfort and reduces the of quality of life in patients (Lindholm,2016). If not treated, they can lead to severe complications such as limb amputations and death (Sen,2019). In fact, periodic examination and thorough treatment are essential to prevent deterioration. Skin diseases management requires to regularly assess, document, and treat the wound by medical professionals (Othman,2012). Trained nurses annotate the relevant information in assessment reports that are then used to track the healing progression and plan the most appropriate treatment strategy. The assessment is typically performed by visual inspection of the skin features, such as area and depth measurements, and the annotation of growth tissue. Despite the importance of objective and accurate wound documentation, the assessment reports are often inconsistent and sparse (Escandon,2019).

To address these challenges, the field of healthcare is turning towards technology for solutions. The integration of deep learning algorithms with skin diseases classification applications has the potential to revolutionize the way skin diseases are assessed and managed. This chapter will provide an overview of the current challenges in skin diseases management, the motivation for developing a skin disease classification application with deep learning, and the objectives and scope of the research.

1.2 Background Of The Study

Skin care is a critical aspect of healthcare, particularly for patients with chronic conditions, elderly individuals, and those with mobility issues. Accurate and timely assessment of skin healing progress is crucial for effective treatment and management of skin diseases. Traditionally, skin disease classification is performed manually by healthcare professionals, which can be time-consuming and subjective, leading to inaccuracies and inconsistencies in the classification process. Recent advancements in technology have led to the development of image-based skin disease classification and identification methods, which use deep learning algorithms to analyse digital images of skin disease infected area. This approach provides a more objective and quantitative classification and identification of skin diseases healing progress and can facilitate more efficient and effective skin disease management.

Deep learning has shown potential benefits in skin disease classification. For instance, a study conducted in the United Kingdom demonstrated that using deep learning algorithms to analyse skin disease images resulted in more accurate and consistent classification compared to traditional manual methods (Dong, 2018). Similarly, a study carried out in the United States found that utilizing machine learning algorithms to analyse skin disease images improved both the speed and accuracy of classification, leading to enhanced patient outcomes (Bloemen et al., 2019).

Despite these positive results, the use of deep learning for skin disease classification is still in its early stages, and further research is needed to fully understand its potential benefits and limitations. According to a report by Global Market Insights, the global market for skin care was valued at over $20 billion in 2020 and is expected to grow at a compound annual growth rate of 4.5% from 2021 to 2027. This growth is primarily driven by the increasing demand for advanced skin care products and technologies, including image-based scanning and classification systems.

Skin diseases are a significant cause of morbidity and mortality worldwide. Accurate and timely classification of skin diseases is crucial for effective management and improved patient outcomes. However, traditional methods of skin disease classification can be subjective, time-consuming, and prone to errors. To address these challenges, researchers have explored the use of machine learning for image-based skin disease classification. Machine learning algorithms have shown effectiveness in automating the process of skin disease classification, improving accuracy, and reducing the time required for assessment (Escandon, 2019). These algorithms can analyse skin disease images and extract features such as lesions, patterns, and texture, which are important indicators for accurate classification (Othman, 2012).

Image-based skin disease classification using machine learning has the potential to revolutionize the way skin diseases are classified and managed. By providing a more objective and quantitative approach to classification, this technology can improve patient outcomes and facilitate more efficient and effective skin disease treatment. However, further research is needed to fully understand the potential benefits and limitations of this technology. Therefore, in this study, the researcher aims to develop and analyse the effectiveness of skin disease classification using deep learning.

1.3 Statement Of The Problem

Despite the advancements in modern medicine, the classification of skin diseases remains a challenging task for healthcare professionals. The traditional method of skin disease assessment, which involves physically visiting a clinic for evaluation, is time-consuming and prone to human error, resulting in incorrect treatment decisions and prolonged healing times. Additionally, this process can be inconvenient for patients, especially those with mobility issues or living in remote areas, as they have to travel for each assessment. Moreover, the current assessment approach lacks the ability to accurately track the progression of skin diseases over time, making it difficult for healthcare professionals to evaluate the effectiveness of treatments. The proposed solution aims to provide healthcare professionals with a fast and accurate method of classifying skin diseases and tracking their progression over time. This approach eliminates the need for patients to visit a clinic for each assessment, offering greater convenience and accessibility. By leveraging image-based classification using deep learning, this solution can significantly improve the efficiency and effectiveness of skin disease management.

1.4 Research Objectives

- To analyse different deep learning techniques used for skin disease classification.
- To design and implement a deep learning model which scans, segment and classify skin diseases using deep learning algorithms.
- Evaluate the effectiveness applicability of deep learning in the medical field focusing on skin disease classification.

1.5 Research Questions

- What are the different deep learning techniques used for skin disease classification?
- How to design and implement a deep learning model which scans, segment and classify skin diseases using deep learning?
- How effective is deep learning in the medical field focusing on skin disease classification?

1.6 Justification/Significance Of The Study

The goal of this application is to provide healthcare professionals with a fast and accurate method of classifying and identifying skin diseases, as well as tracking their progress over time. The proposed application will also eliminate the need for patients to physically visit a clinic for each assessment, providing greater convenience and accessibility. The application will use deep learning algorithms to analyse skin images and provide meaningful insights into skin disease class. By automating the skin disease classification process, the application will reduce the potential for human error and provide healthcare professionals with more accurate and reliable information to inform their skin disease management decisions. Accurately predicting skin disease is difficult for skin care clinicians due to the complex and dynamic processes involved in skin healing. Skin care teams capture images of patient skin during clinical visits generating big datasets over time. Developing novel artificial intelligence (AI) systems can help clinicians diagnose, assess the effectiveness of therapy, and predict skin diseases.

1.8 Limitations/challenges

- Time needed to carry out the research is limited

1.9 Scope/Delimitation Of The Research

The research is focused on creating a model application that is required to capture or scan the skin, segment and analyse the tissue and determine to a certain confidence level the skin disease using deep learning.

1.10 Definition Of Terms

Machine learning- the use and development of computer systems that are able to learn and adapt without following explicit instructions, by using algorithms and statistical models to analyse and draw inferences from patterns in data.

Skin- Skin is the largest organ of the human body, serving as a protective barrier between the internal organs and the external environment. It is composed of multiple layers of tissue, including the epidermis, dermis, and subcutaneous tissue. The skin plays essential roles in regulating body temperature, protecting against pathogens, providing sensory perception, and synthesizing vitamin D.

Artificial intelligence- the theory and development of computer systems able to perform tasks normally requiring human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages.

Chapter 2: Literature Review

2.1 Introduction

A literature review, according to (Puebo, 2020), is a scientific study prepared from published sources that summarizes current understanding on a given issue. In this chapter, the researcher concentrates on answering the research questions and reveals previous and current systems that are similar to the research project at hand that have been done by other authors. This will be extremely valuable to the author because it will serve as a guide to identifying solutions, strategies, and techniques utilized by prior writers to solve earlier research problems. It is a tool that informs the researcher if the study proposal is possible based on the findings of previous researchers in that field. This chapter, in accordance with the definition of a literature review, provides information on how others have implemented an image based skin disease classification applications and models using machine learning techniques.

2.2 Related Literature

Image-based skin disease classification using using deep learning has gained significant attention in recent years. Several studies have focused on developing deep learning-based models for skin diseases classification and segmentation. For instance, He et al. (2021) developed a deep learning model that could automatically classify skin wound images into acute and chronic wound types. The model used a transfer learning approach with a pre-trained convolutional neural network and achieved an accuracy of 90% in wound classification.

One recent study proposed a deep learning-based approach for skin disease classification that utilizes a convolutional neural network (CNN) to classify skin diseases from images acquired using smartphones. The proposed approach achieved an accuracy of 94.55%, surpassing traditional methods such as thresholding and edge detection. Another study suggested a hybrid approach for skin disease classification, combining fuzzy clustering with level set segmentation. The proposed approach achieved an average dice coefficient of 0.97 on a dataset of 80 skin disease images, indicating its high accuracy in classifying skin diseases. These studies highlight the effectiveness of machine learning-based approaches and hybrid approaches for skin disease classification and their potential for implementation in clinical practice.

The use of deep learning techniques for image-based skin disease classification has gained increasing attention in recent years. One study by Schulze et al. (2018) proposed a deep learning-based method for automated skin disease area measurement using convolutional neural networks (CNNs). The method achieved high accuracy in skin disease segmentation and measurement compared to traditional methods, demonstrating the potential of deep learning in skin disease analysis. Another study by Yao et al. (2020) proposed a deep learning-based method for automatic skin disease classification and achieved high accuracy in differentiating between various types of skin diseases, such as diabetic warts and venous eczema. The method utilized a multi-scale feature fusion network and achieved a classification accuracy of up to 95%.

Deep learning algorithms, such as convolutional neural networks (CNNs), have shown promise in automating the process of skin disease classification and diagnosis. These algorithms can learn complex patterns and features directly from images, enabling them to effectively distinguish between different skin disease types (Schulze et al., 2018; Yao et al., 2020).

For instance, Schulze et al. (2018) proposed a deep learning-based method for automated skin disease classification using a CNN. Their approach achieved high accuracy in differentiating between various skin disease types, surpassing traditional methods (Schulze et al., 2018). Similarly, Yao et al. (2020) developed a deep learning-based method for automatic skin disease classification, which demonstrated excellent performance in accurately classifying different types of skin diseases, including diabetic foot ulcers and venous ulcers (Yao et al., 2020). These studies highlight the potential of deep learning-based approaches in enhancing the accuracy and efficiency of skin disease diagnosis. By automating the process of classification, these methods can assist healthcare professionals in making accurate and timely diagnoses, leading to improved patient outcomes (Schulze et al., 2018; Yao et al., 2020).

Another study by Xu et al. (2020) proposed a multi-task deep learning framework for automated skin disease assessment, simultaneously performing skin disease segmentation, tissue classification, and exudate quantification. The method utilized a U-Net architecture with an attention mechanism and achieved high accuracy in all three tasks. The model achieved an average Dice similarity coefficient (DSC) of 0.86 for skin disease segmentation, an accuracy of

91% for tissue classification, and a mean absolute error (MAE) of 1.56 for exudate quantification.

In addition to skin disease classification and segmentation, deep learning techniques have also been employed for skin disease depth estimation. A study by Ahanj et al. (2021) proposed a deep learning-based method for automated skin disease depth estimation using a U-Net architecture. The model achieved an average error of 0.83 mm in skin disease depth estimation, outperforming traditional methods such as ultrasound imaging and tissue biopsy.

Overall, these studies demonstrate the potential of deep learning in image-based skin disease classification, showing high accuracy in skin disease classification, segmentation, tissue classification, and depth estimation. The use of deep learning in skin disease analysis can improve the efficiency and accuracy of skin disease assessment, allowing for better monitoring of disease progression and treatment planning. However, further research is needed to validate the generalizability and robustness of these methods across different skin disease types and imaging modalities.

2.3.1 Skin

The skin is the largest organ of the human body, serving as a protective barrier between the internal organs and the external environment (Escandon, 2019). Composed of multiple layers of tissue, including the epidermis, dermis, and subcutaneous tissue, the skin plays vital roles in regulating body temperature, protecting against pathogens, providing sensory perception, and synthesizing vitamin D (Escandon, 2019; Othman, 2012). It is responsible for various functions, including sensation, thermoregulation, immune defence, and the synthesis of certain hormones (Escandon, 2019; Othman, 2012). The skin is a vital organ that serves multiple functions in the human body.

2.3.2 Skin Diseases

Skin diseases encompass a broad spectrum of conditions that affect the skin, leading to various symptoms and manifestations (Schulze et al., 2018). These diseases can arise from various causes, including infections, inflammatory responses, autoimmune disorders, genetic predispositions, and environmental factors (Escandon, 2019; Yao et al., 2020). They can range from mild and temporary conditions to chronic and debilitating diseases, significantly impacting an individual's quality of life (Escandon, 2019). Some common skin diseases include:

- Dermatitis: Dermatitis refers to inflammation of the skin and can be caused by irritants, allergens, or genetic factors (Escandon, 2019). It can present as redness, itching, swelling, and the formation of blisters or scales on the skin.
- Psoriasis: Psoriasis is a chronic autoimmune disease characterized by the rapid buildup of skin cells, leading to the formation of thick, silvery scales and itchy, dry patches (Escandon, 2019).
- Eczema: Eczema, also known as atopic dermatitis, is a chronic inflammatory skin condition that causes red, itchy, and dry patches on the skin (Escandon, 2019). It often occurs in individuals with a family history of allergies or asthma.
- Acne: Acne is a common skin condition characterized by the formation of pimples, blackheads, whiteheads, and cysts. It is caused by the blockage of hair follicles by oil, dead skin cells, and bacteria (Escandon, 2019).
- Rosacea: Rosacea is a chronic inflammatory skin condition that primarily affects the face, causing redness, visible blood vessels, and acne-like bumps (Escandon, 2019).
- Skin infections: Various infections can affect the skin, including bacterial, fungal, and viral infections. Examples include impetigo, ringworm, and herpes (Escandon, 2019).
- Warts: Warts are small, rough growths caused by the human papillomavirus (HPV) infection. They can appear on various parts of the body, such as the hands, feet, or genitals. Warts are typically noncancerous but can be contagious and may cause discomfort (Escandon, 2019).
- Vasculitis: Vasculitis refers to the inflammation of blood vessels, which can affect the skin and other organs. This condition occurs when the immune system mistakenly attacks blood vessels, leading to various symptoms, including skin rashes, ulcers, and skin discoloration (Escandon, 2019).

- Scabies: Scabies is a highly contagious skin infestation caused by the microscopic mite Sarcoptes scabies. It results in intense itching and the formation of a rash, often in the folds of the skin, between fingers, or on the wrists. Scabies can spread through close contact with an infected person or by sharing personal items (Escandon, 2019).
- Actinic Keratosis: Actinic keratosis, also known as solar keratosis, is a precancerous skin condition caused by long-term sun exposure. It appears as rough, scaly patches on sun-exposed areas such as the face, scalp, ears, and hands. If left untreated, actinic keratosis may develop into skin cancer (Escandon, 2019).

These are just a few examples of the numerous skin diseases that exist. Accurate diagnosis of skin diseases often requires clinical evaluation, patient history, and sometimes laboratory tests or biopsies (Yao et al., 2020). The use of image-based techniques and deep learning algorithms has shown promise in assisting dermatologists and healthcare professionals in the classification and diagnosis of skin diseases (Schulze et al., 2018; Yao et al., 2020).

2.3.3 Skin Disease Classification

Skin disease classification plays a vital role in accurate diagnosis and effective treatment planning. Traditional methods of skin disease classification rely on visual inspection and subjective interpretation by dermatologists, which can be time-consuming and prone to errors. However, recent advancements in image-based analysis and deep learning techniques have shown great potential in automating and improving the accuracy of skin disease classification. Various studies have explored the use of deep learning algorithms for skin disease classification. For instance, Esteva et al. (2017) developed a deep convolutional neural network (CNN) model that achieved performance comparable to dermatologists in classifying skin cancer. Their model was trained on a large dataset of dermoscopic images and demonstrated the capability to differentiate between different types of skin lesions with high accuracy.

Similarly, Liang et al. (2019) proposed a deep residual network (ResNet) architecture for the classification of common skin diseases. Their model was trained on a diverse dataset of skin images, including conditions such as eczema, psoriasis, and acne. The results showed promising accuracy in classifying various skin diseases, aiding in timely and accurate diagnosis. Furthermore, deep learning models have also been employed for the classification of specific skin diseases. For example, Karimi et al. (2020) developed a deep learning framework for the classification of melanoma, the most aggressive form of skin cancer. Their model utilized transfer learning with a pre-trained CNN and achieved high accuracy in distinguishing between malignant and benign melanoma lesions. Other studies have explored the use of ensemble models and hybrid approaches for skin disease classification. These models combine multiple deep learning architectures or incorporate additional data modalities, such as patient clinical information or histopathological data, to enhance classification performance (Liu et al., 2021; Tschandl et al., 2018). The application of deep learning techniques in skin disease classification has shown promising results, demonstrating the potential to improve diagnostic accuracy and assist healthcare professionals in making informed decisions. However, it is important to continue researching and validating these models on larger and diverse datasets to ensure their generalization and robustness in real-world clinical settings.

2.3.4 Skin Segmentation

Skin segmentation is an essential step in analysing and processing skin images for various applications, including wound assessment, skin disease classification, and image-based diagnostics. Skin segmentation aims to separate the pixels or regions corresponding to the skin from the rest of the image background or other structures. Traditional skin segmentation methods often rely on colour-based approaches, exploiting the characteristic colour distribution of the skin in different colour spaces such as RGB or YCbCr. However, these methods can be sensitive to lighting conditions, skin tone variations, and the presence of artifacts or non-skin regions. With the advent of deep learning, convolutional neural networks (CNNs) have emerged as powerful tools for skin segmentation. These models can automatically learn complex features and spatial relationships from large datasets, enabling accurate and robust segmentation performance.

Several studies have proposed deep learning-based approaches for skin segmentation. For instance, Yuan et al. (2017) developed a fully convolutional network (FCN) model specifically designed for skin lesion segmentation. Their model achieved superior performance by effectively capturing fine-grained details and accurately delineating the boundaries of skin lesions. Another study by Liu et al. (2020) proposed a multi-scale attention U-Net architecture for skin image segmentation. Their model incorporated attention mechanisms to highlight relevant features at different scales, improving the localization and segmentation accuracy of the skin regions. Furthermore, some studies have explored the integration of multiple modalities, such as combining RGB and near-infrared (NIR) images, to enhance skin segmentation accuracy (Biswas et al., 2020).

These multi-modal approaches leverage complementary information from different imaging sources to improve the robustness and reliability of the segmentation results. It is worth noting that the performance of skin segmentation models heavily relies on the availability and quality of annotated training data. The creation of accurate and diverse skin image datasets with precise pixel-level annotations remains a challenge in the field. Skin segmentation plays a crucial role in various skin analysis tasks, facilitating the accurate localization and characterization of skin regions of interest. The advancements in deep learning techniques have opened up new possibilities for achieving more precise and reliable skin segmentation, enabling improved diagnosis, treatment planning, and monitoring of skin diseases.

2.3.5 Skin Tissue Segmentation

Skin tissue segmentation refers to the process of delineating different tissue components within the skin, such as epidermis, dermis, and subcutaneous layers, from medical images. Accurate segmentation of skin tissues is crucial for various clinical applications, including wound assessment, skin disease analysis, and histopathological examination. Traditional approaches for skin tissue segmentation often rely on image processing techniques, such as thresholding, edge detection, and region growing. However, these methods can be limited by their sensitivity to image noise, intensity variations, and complex tissue structures. In recent years, deep learning-based methods have shown promising results in skin tissue segmentation. Convolutional neural networks (CNNs) have emerged as popular models due to their ability to learn hierarchical features and capture spatial dependencies in medical images.

Several studies have proposed deep learning architectures for skin tissue segmentation. For instance, Menegola et al. (2018) developed a U-Net-based model for the automatic segmentation of skin tissues from histopathological images. Their model achieved high accuracy by leveraging the contextual information and local features within the skin tissue regions. Another study by Saikia et al. (2020) proposed a deep residual network (ResNet) combined with a conditional random field (CRF) for skin tissue segmentation in dermoscopy images. The model effectively captured fine-grained details and improved the boundary delineation of different skin tissue components. Additionally, some studies have explored the fusion of multiple imaging modalities, such as combining reflectance confocal microscopy (RCM) and optical coherence tomography (OCT) images, for enhanced skin tissue segmentation (Ricci et al., 2020). These multimodal approaches leverage the complementary information from different imaging modalities to improve the accuracy and reliability of the segmentation results.

It is important to note that skin tissue segmentation challenges remain, including the presence of noise, artifacts, and inter- and intra-patient variability. Furthermore, obtaining accurately annotated datasets for training and validation purposes can be a significant limitation in the field. Accurate segmentation of skin tissues is essential for a comprehensive analysis of skin diseases and wound healing processes. Deep learning-based methods offer promising solutions for precise and automated skin tissue segmentation, facilitating improved diagnosis, treatment planning, and research in dermatology and related fields.

2.4 Deep Learning

Deep learning (DL) is a subset of machine learning that use hierarchical layers of non-linear processing stages to learn unsupervised features and categorize patterns (Deng, 2014). DL is a computer-assisted medical diagnosing approach (Vasilakos et al., 2016). In medical image analysis, DL applications include classification, segmentation, detection, retrieval, and registration of images. In the identification and classification of DR, DL has recently gained popularity. It can successfully learn the features of input data even when many heterogeneous sources are integrated (Chen & Lin, 2014). Only a few of the DL-based approaches include restricted Boltzmann Machines, convolutional neural networks (CNNs), auto encoders, and sparse coding (Guo et al., 2016).In contrast to machine learning, the performance of these methods improves as the amount of training data grows (Deng & Yu, 2014). This is linked to the development of learned characteristics. Furthermore, DL approaches did not necessitate manual feature extraction.

2.5 Convolutional Neural Networks (CNN)

CNN is a deep image processing architecture that consists of two primary layers: the convolutional layer and the pooling layer. CNN is a sort of feed-forward neural network used in artificial intelligence. It's a popular tool for image recognition (Nisha, 2021). The input data is represented by CNN as multidimensional arrays. It works well when there are a lot of labelled data. The convolutional layer calculates the output of the neurons that are connected to the local area network at the input by sharing weights and biases. The pooling layer decreases the data size by subsampling the convolutional layer's output. The learning of a deep CNN's millions of parameters requires a large number of training images as well as the availability of its ground truth, which prevents many better deep CNNs from being used in medical applications.

Convolutional Neural Networks (CNNs) have a long track record in image processing and interpretation, particularly in medical imaging. In the 1970s, network architectures designed to cope with picture data were routinely created with beneficial applications, outperforming other approaches to difficult jobs such as handwritten character recognition (Srivastava, 2014). However, it wasn't until the advent of dropout and rectified linear units, as well as the concomitant rise in computing capacity through graphical processor units (GPUs), that neural networks became practical for more sophisticated image recognition challenges.

Currently, massive CNNs are being used to successfully tackle highly complicated picture recognition problems including a wide range of object classes. Many contemporary state-of-the-art image classification tasks, including the annual ImageNet and COCO challenges, use CNNs

(He et al., 2021). There are two major concerns with automatic grading, particularly CNNs. Furthermore, in neural networks, overfitting is a serious problem. Skewed datasets cause the network to over-fit to the class most prominent in the dataset. Large datasets are often massively skewed(Pratt et al., 2021).

2.5.1 MobileNet CNN Architecture

MobileNet is a convolutional neural network architecture that has been specifically designed for mobile and embedded devices with limited computational resources. The key innovation of MobileNet is the use of depthwise separable convolutions, which significantly reduce the number of parameters and computational complexity without sacrificing accuracy. In a depthwise separable convolution, the input is first convolved with a depthwise convolution filter that applies a separate filter to each input channel. This is followed by a pointwise convolution that applies a 1x1 filter to the output of the depthwise convolution to produce the final output. According to the original paper on MobileNet by Howard et al., this approach can reduce the number of parameters by a factor of 8 to 9 compared to traditional convolutional layers, while still achieving high accuracy on image classification tasks. Additionally, MobileNet includes several other optimizations, such as the use of linear bottlenecks and a global average pooling layer, that further reduce the memory and computation requirements.

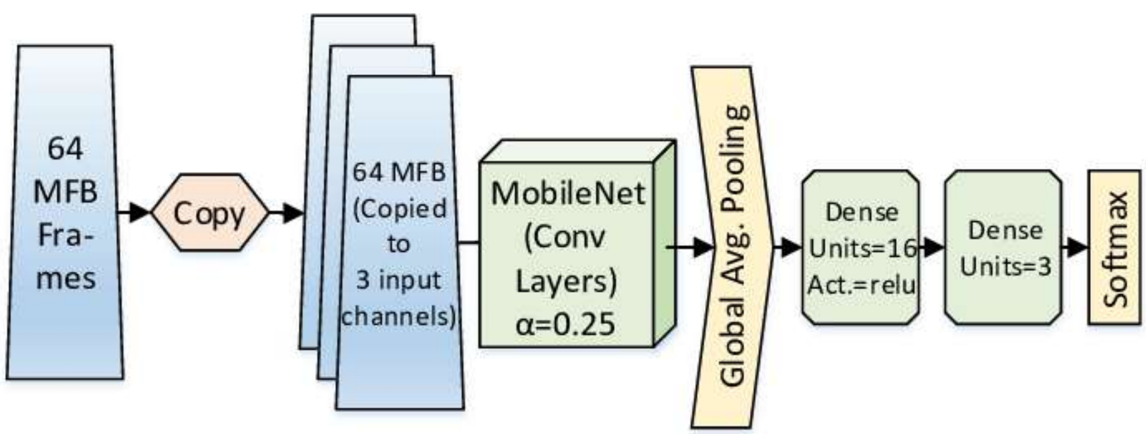

Figure 1: Mobile -Net

MobileNet has been used in a variety of applications, including object detection, face recognition, and even natural language processing. For example, in a study by Chen et al., a modified version of MobileNet was used to perform speech recognition on mobile devices with low memory and processing power. The authors reported that their approach achieved a 10x speedup compared to a traditional deep neural network, while still achieving similar accuracy. Similarly, in a study by Zhang et al., MobileNet was used for text classification tasks in natural language processing, and was found to achieve comparable or better performance than traditional CNN architectures with significantly fewer parameters. These results demonstrate the potential of MobileNet for a wide range of applications.

2.6 Research Gap

Despite the recent advancements in image-based skin disease classification using deep learning, there still exists a research gap in the development of generalized and robust models that can perform skin diseases classification and analysis across different skin conditions and imaging modalities. Most studies have focused on specific skin conditions, such as tinea and scabies, and have used limited datasets, which may not represent the variability and complexity of skin infections encountered in clinical settings. Moreover, there is a need for standardized protocols and benchmarks for evaluating the performance of deep learning models in skin disease classification. Addressing these gaps will enable the development of more accurate and reliable models for skin disease classification, improving the quality of skin care and patient outcomes.

2.7 Chapter Summary

This chapter has provided a comprehensive review of the relevant literature on image-based skin disease classification using deep learning. The author successfully gathered and collected valuable information and data from various sources such as academic papers, textbooks, and the internet. However, it is important to acknowledge that there were certain gaps and limitations identified in the existing literature, which highlights the need for further research and exploration in this field. The information obtained from these diverse sources will serve as a solid foundation for the subsequent chapters of the research study, allowing the author to effectively address the research objectives. By incorporating insights from the reviewed literature, the study aims to contribute to the advancement of skin disease classification using deep learning techniques.

The literature review conducted in this chapter has provided a comprehensive understanding of the current state of image-based skin disease classification using deep learning. It has identified the gaps in the existing knowledge and set the stage for the subsequent chapters, where the proposed solution will be designed, developed, and evaluated. Through the integration of relevant literature and a robust methodology, this research project aims to make valuable contributions to the field of skin disease classification and pave the way for improved diagnosis and treatment of skin conditions.

Chapter 3: Research Methodology

3.1 Introduction

Research is a critical process that involves a systematic investigation or analysis of a specific topic, utilizing either quantitative or qualitative approaches based on the nature of the study. It holds significant value for government institutions and policymakers in making informed decisions (Mackey & Gass, 2015). Methodology, on the other hand, refers to the systematic analysis of methods employed in a particular field of study. In this chapter, the author establishes the approaches utilized to fulfill the research and system objectives. The chapter outlines the necessary procedures, selects appropriate strategies, and builds upon the information gathered in the preceding chapter.

This chapter primarily focuses on the research process, including the methods employed for data collection, research design, and the identification of functional and non-functional requirements. Moreover, it delves into the implementation of the proposed solution, providing insights into the model's structure, dataset acquisition, image pre-processing, model training, and storage. The deployment of the solution is also discussed, outlining the steps taken to put the solution into action, handle the dataset, and ensure its readiness for use. To ensure the robustness and validity of the research, the chapter incorporates appropriate methodologies and data collection techniques, which may include surveys, interviews, experimentation, or analysis of existing datasets. The selection of methods and strategies is driven by the research objectives and the information gathered in the previous chapter. By providing a comprehensive overview of the research methodology, data collection methods, and the implementation of the proposed solution, this chapter serves as a valuable guide for understanding the research process and achieving the desired research outcomes. It offers insights and practical guidance for readers to replicate or adapt the methodology to their specific research needs.

3.2 Research Design

Research design plays a crucial role in providing the structure and framework for a study (Moule & Goodman, 2019). It involves the careful planning and decision-making process to address research questions and overcome potential challenges that may arise (Polit & Hungler, 2013). In the context of image-based skin disease classification using deep learning, the research design focuses on the development of an operational, efficient, durable, and reliable system model. For this project, an experimental research approach was chosen. This approach involves the development, training, and testing of the deep learning model to assess its effectiveness in classifying skin diseases. The experimental research design is particularly suitable for investigating the effects of variable adjustments in a controlled manner. In this case, the researcher actively intervenes by altering variables and examines how the system and objects respond to these changes. Initially, three existing models were utilized as controls, serving as benchmarks for evaluating the improvements achieved by the developed model. This comparative analysis allows for a systematic investigation of the impact of variables and provides a means to evaluate the effectiveness of the proposed solution. By employing an experimental research design, the researcher can gather empirical evidence to support the efficacy and performance of the developed deep learning model in accurately classifying skin diseases. The design enables the systematic exploration and evaluation of the model's capabilities, ensuring that the research objectives are effectively addressed.

3.3 Requirements Analysis

Requirements analysis is essential for the success or failure of a project. The requirements should be practical, documented, tested, actionable, traceable, and measurable. They should also be aligned with identified business needs and detailed enough to support system design. It is crucial to document both functional and non-functional requirements at this stage. To ensure clarity and consistency, the gathered requirements undergo thorough review, revision, and scrutiny. Additionally, any constraints, such as data availability, are taken into consideration to avoid potential design complications. It is recommended to organize and review all research data, as well as examine any user-related constraints that may arise during implementation. This approach leads to a well-defined specification that meets the needs of healthcare professionals.

3.3.1 Functional Requirements

Functional Requirements defines the functions of a system or its modules, with the function often specifying how inputs and outputs interact (Fulton & Vandermolen, 2017). Functional requirements describe the system's services and how it responds to inputs, behavior, and outputs. A function consists of inputs, behavior, and outputs. "Functional requirements are the tasks that a system must be able to perform, regardless of physical limitations," as explained by (Bittner 2016). These tasks include computations, data manipulation and processing, specialized details, and other specific functionalities that define what the system should achieve. In image-based skin disease classification using deep learning, the suggested system must meet the following functional requirements:

- The system should accurately classify and identify different types of skin diseases from input images.
- The system should effectively segment the skin region in the images, distinguishing it from the surrounding tissues.
- The system should provide reliable quantitative metrics and visual representations of the disease classification results.
- The system should be adaptable to various types of skin diseases, accommodating different manifestations and variations.
- The system should offer real-time or near real-time results to facilitate prompt and efficient disease classification.

By addressing these functional requirements, the system will be equipped to perform the essential tasks of accurately classifying and segmenting skin diseases, providing valuable metrics for assessment, and accommodating diverse cases and imaging conditions. These requirements serve as the foundation for developing an effective and reliable system that contributes to the advancement of image-based skin disease classification using deep learning techniques.

3.3.2 Non-Functional Requirements

A non-functional requirement can be expressed as a description of a system's performance characteristics. They indicate how well or to what standard a function should be provided, such as response times, security and access requirements, usability, performance supportability, and project constraints such as implementation on the organization's hardware/software platform, among other things. The most important of all non-functional requirements is for the system to be testable and maintainable. They are also referred to as "quality requirements," and their purpose is to evaluate a system's performance rather than its intended behavior. The proposed system should be able to meet the following requirements:

- The system software is supposed to be easy to install.

- The system is supposed to have a user guide on the installation process.
- The system should be readily available to health specialists and be easy to use.
- Performance: The system should deliver efficient and timely results, ensuring fast classification and segmentation processing times.
- Accuracy: The system should achieve a high level of accuracy in disease classification and image segmentation.
- User Interface: The system should have a user-friendly interface, allowing users to easily interact with the software and input images for classification.
- Scalability: The system should be scalable to handle a growing number of users and increasing volumes of image data.
- Reliability: The system should be reliable and stable, minimizing errors and providing consistent results.

3.3.3 Software Requirements

- Android 8 or higher operating system
- Apache or Tomcat Server
- Python 3.9
- Anaconda Python IDE
- Android Studio IDE

3.3.4 Hardware Requirements

- Android Mobile device phone or tablet
- Camera
- Memory: 4GB RAM to support image processing and deep learning computations.
- Storage: 500MB internal storage for installing the mobile application and storing image data and user information.
- Processor: A processor with enough processing power to handle image analysis and classification tasks efficiently.
- Internet Connectivity: The device should have internet connectivity (Wi-Fi or mobile data) for accessing online resources, updates, and potential cloud-based services.

3.4 System Development

The system development process for the proposed solution, an Android mobile application for image-based skin disease classification, followed several stages to ensure its successful implementation. The process began with clearly formulating the research objectives and designing the system architecture to guide the development efforts. Specialized software tools tailored for deep learning, such as TensorFlow or PyTorch, were chosen to implement the system and train the models. These frameworks provide a robust and flexible environment for building and training deep learning models, which are essential for accurate image analysis and classification.

To achieve the desired functionality, a of deep learning model was employed, i.e. convolutional neural networks (CNNs) depending on the specific tasks involved in skin disease classification. These model was selected based on its proven effectiveness in image analysis and classification tasks, ensuring reliable and accurate results. During the development process, a diverse dataset of skin disease images was collected and pre-processed according to the established methodology. Data augmentation techniques, such as image re-sizing, normalization, and augmentation, were applied to enhance the diversity and quality of the dataset. This helps the models generalize well to unseen data and improve their performance. The training process involved feeding the prepared dataset into the selected deep learning model, adjusting the hyper-parameters, and optimizing the model using techniques like gradient descent and regularization. The model was iteratively refined and fine-tuned to improve their performance and achieve accurate skin disease classification.

Throughout the development process, appropriate software frameworks and libraries were utilized to facilitate efficient model development, training, and evaluation. These frameworks provided essential functionalities such as image processing, model visualization, and performance evaluation metrics, enabling effective development and assessment of the models. By leveraging these specialized software tools, deep learning models, and datasets, a working model was created to fulfill the functional requirements of the system. The integration of deep learning techniques and the developed models resulted in the generation of accurate skin disease classification results. The system development process involved careful consideration of the specific requirements and objectives of the project, as well as the utilization of relevant software tools, deep learning models, and datasets. This approach ensured the successful implementation of the Android mobile application for image-based skin disease classification, enabling efficient and accurate skin disease assessment and diagnosis.

3.5 System Development Tools

In the process of developing the proposed solution, the selection of an appropriate methodology played a crucial role in achieving the desired outcomes. Various methodologies were considered, each offering its own advantages and limitations, with the ultimate goal of developing an accurate and effective system aligned with the project objectives. The author explored different frameworks, including the waterfall model, spiral model, and prototyping model, taking into account the specific requirements of the system. After careful consideration, the prototyping approach was chosen as the preferred methodology for developing the proposed solution. This decision was based on the need for iterative development and frequent testing to refine the system components. The prototyping model allowed for the rapid creation and evaluation of prototypes, enabling the incorporation of feedback and continuous improvement throughout the development process.

By adopting the prototyping approach, the author aimed to ensure that the proposed solution met the defined objectives and delivered accurate results. The iterative development cycle provided opportunities for adjustments and enhancements, guided by insights gained during the prototyping phase. This iterative feedback loop facilitated the creation of a robust and effective system. The choice of the prototyping model as the development methodology for the proposed solution was driven by the requirement for frequent testing and refinement. This approach enabled the team to iterate on the system's design and functionality, ensuring that it was capable of accurately classifying and analyzing skin disease images. The prototyping model allowed for a flexible and adaptive development process, leading to the creation of a functional system that met the specific needs of the project.

3.5.1 Prototyping Model

By selecting the prototyping approach, the author aimed to ensure that the proposed solution met the desired objectives and was able to deliver accurate results. This iterative development cycle allowed for adjustments and enhancements based on insights gained during the prototyping phase, leading to a more robust and effective system. The selection of the prototyping model as the development methodology for the proposed solution was based on the need for frequent testing and refinement. This approach facilitated the creation of a functional system aligned with the defined objectives and ensured the production of accurate results.

The phases of the prototyping model:

- **Identification of Requirements:** The identification of product requirements is thoroughly explained in this section. Users of the system are questioned during this process to learn what they anticipate from it.
- **Design Step: At this stage:** A fundamental system design is created. But it's not a fully realized design. It provides a brief overview of the system to the user. The quick design helps with the development of the prototype.

- **Build the Initial Prototype**: From the original design, a first prototype of the target software is created. It might not be exact or ideal to work off all the product components. The second prototype is created based on the first sample model after it has been modified depending on customer feedback.

- **Prototype Review:** The end user or other project stakeholders are shown the final version of the product once all update iterations have been completed. The feedback is gathered methodically so that it can be used to enhance the system in the future.
- **Prototype Iteration and Enhancement:**
  Following assessment, the product is scheduled for future improvement based on factors including time, people, and budget. The technical viability of actual execution is also looked at. The context includes whole methodologies like rapid application development or extreme programming.

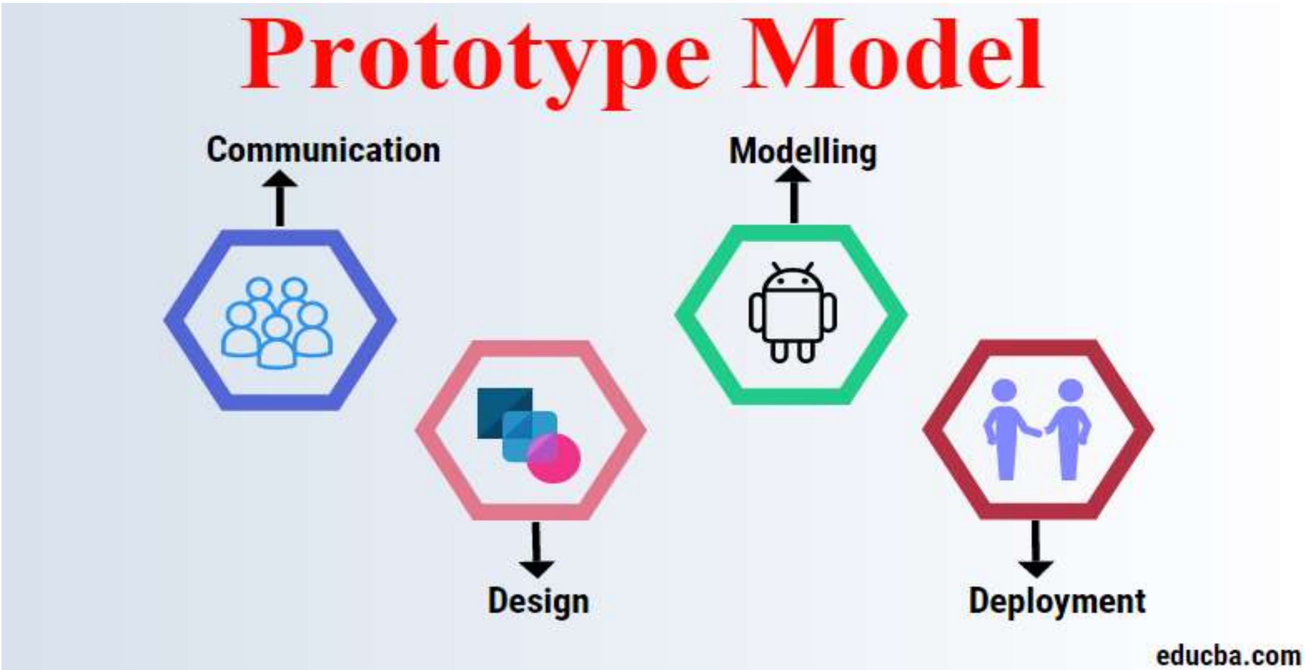

Figure 2: Prototype Method

Apart from the methodology the system was also developed using the following tools:

1. **Python:**

   It is a programming language using to develop systems. Python was used in creating a model which would classify the whether the patient has a skin disease or not to a certain percentage confidence level. Its frameworks of Artificial intelligent made it easier to come up with model to predict.

2. **Keras:**

   Keras is an open-source software library that provides a Python interface for artificial neural networks. Keras acts as an interface for the TensorFlow library. Up until version 2.3, Keras supported multiple backends, including TensorFlow, Microsoft Cognitive Toolkit, Theano, and PlaidML. As of version 2.4, only TensorFlow is supported. Designed to enable fast experimentation with deep neural networks, it focuses on being user-friendly, modular, and extensible.

3. **Anaconda Python IDE:**

   Anaconda is a Python and R programming language distribution for scientific computing (data science, machine learning applications, large-scale data processing, predictive analytics, and so on) that seeks to simplify package management and deployment. Data-science packages are included in the distribution that are compatible with Windows, Linux, and macOS. It is created and maintained by Anaconda, Inc., a company that was established in 2012 by Peter Wang and Travis Oliphant.

3.6 Summary of How the System Works

The system incorporates MobileNet-v2, a deep learning technique, for image processing in the context of the skin disease classification system. The workflow involves several stages to ensure accurate analysis of skin disease images. Initially, the user captures images of the skin condition using the camera feature within the Android mobile application. These images serve as input for the system. The captured images then undergo pre-processing techniques to enhance their quality, encompassing activities such as re-sizing, normalization, and noise reduction. This prepares the images for optimal input into the deep learning model, specifically a convolutional neural network (CNN) tailored for skin disease classification.

The trained MobileNet-v2 model leverages its learned knowledge to classify the input images into various skin disease categories, including warts, eczema, scabies, or actinic. Moreover, the system performs skin tissue segmentation to isolate the affected skin region from the surrounding tissue, enabling precise analysis and assessment of the specific areas impacted by the skin disease. Once the classification and segmentation processes are completed, the system generates quantitative metrics and visual representations of the assessment results. These insights encompass detailed information regarding the type of skin disease present and the severity of the condition. The system aims to provide real-time or near real-time results, ensuring prompt access to assessment outcomes, facilitating immediate medical intervention, or further examination if necessary. The MobileNet-v2 model for image processing empowers the system to deliver accurate and efficient skin disease analysis and assessment capabilities.

3.7 System Design

This step outlines how the system components and data for the system satisfy given requirements after analyzing the requirements specification document. Demonstrating the system's coherence and coordination at the following level.

3.7.1 Data-flow Diagrams

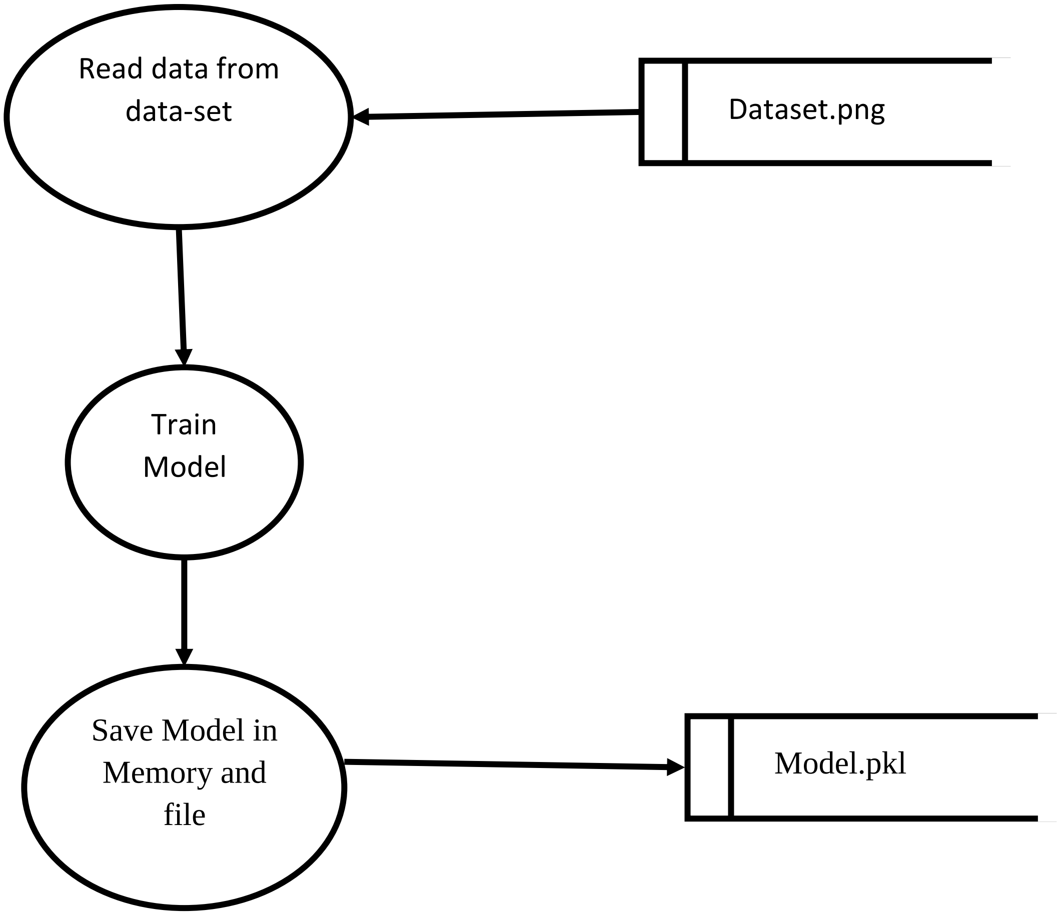

Figure 3: DFD

3.7.2 Proposed System Flow Chart

A flow chart is a diagram that shows the process or work flow of a system that is being created. It demonstrates how the system functions and every choice the system will make throughout the entire procedure. It is sometimes referred to as a diagrammatic depiction of an algorithm, which helps to define the algorithm's sequential steps. The researched system has the flow diagram shown below.

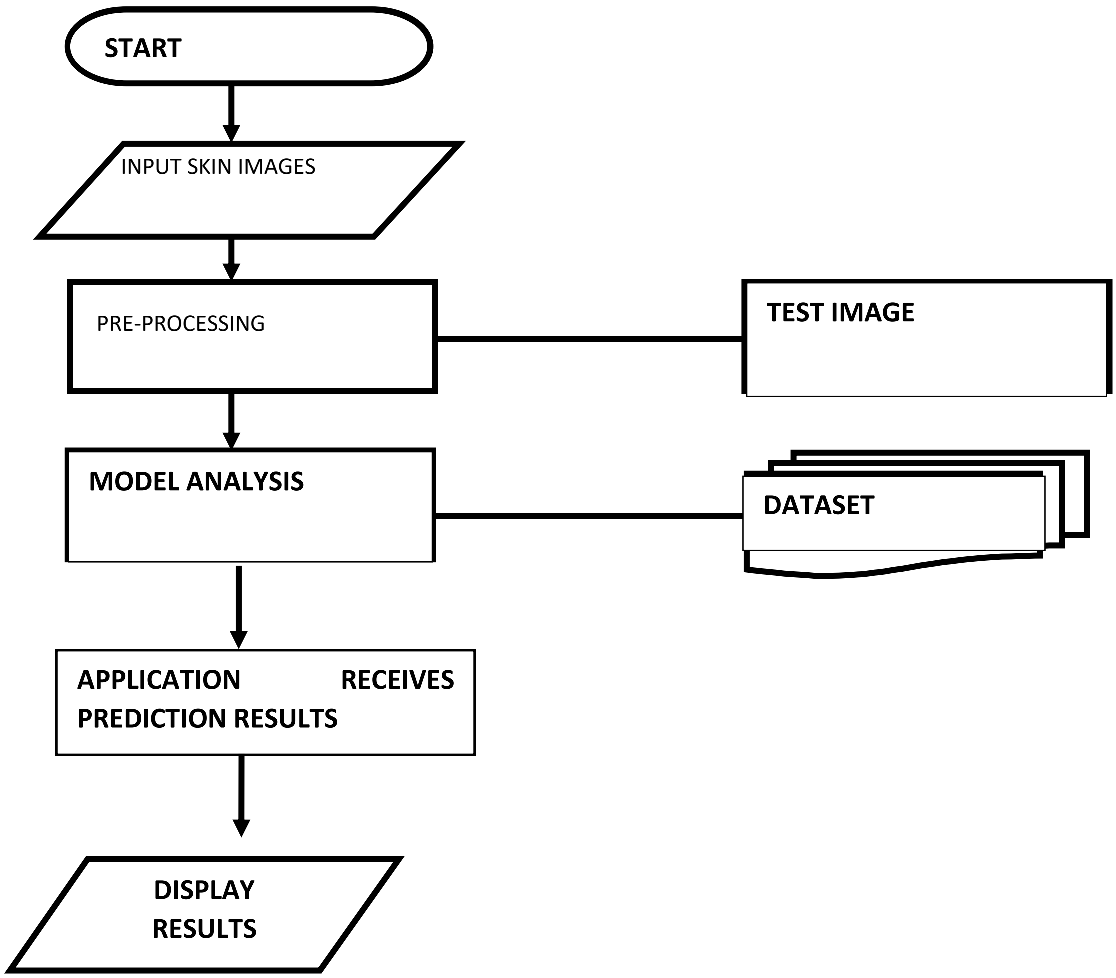

Figure 4: Flow chart of proposed model

3.9 Solution

This section shows the solution model, how it predicts the results using the algorithms of deep learning. To come up with a functional solution that would solve the research problem, the researcher made analysis the algorithm to determine the error rate and accuracy rate so as to get more accurate results in prediction.

3.9.1 Image Processing

3.9.1.1 Resize Image

When defining the architecture of the model, one of the requirements is to define a fixed input form. When performing this task, it is important to keep in mind that there is a balance between speed of computation and loss of information. For clarification, when the size of an image is reduced, information (pixels) is removed. Less information means faster training times; however, it can also mean reduced overall accuracy. An image size of 224 x 224 has been selected.

3.9.1.2 Image Cropping

The wound image region was cropped automatically from each image to remove the background and unwanted region. Figure 14 (a) shows a sample of an original image from the dataset, while Figure 14(b) shows the same image after removing unwanted region.

3.9.1.3 Gaussian Blur

Image smoothing techniques are essential in reducing noise present in images, particularly originating from the camera sensor. Open-CV provides various methods for image smoothing or blurring. One commonly used approach is applying a Gaussian filter, which possesses properties that minimize blurring while reducing sharp edges and overshoot. In this technique, a Gaussian kernel is employed instead of a simple box filter. The ***cv.GaussianBlur()*** function in Open-CV is utilized for this purpose. It requires specifying the kernel's width and height, which should be positive and odd. Additionally, the standard deviation in the X and Y directions, sigma X and sigma Y, respectively, should be provided. If only sigma X is specified, sigma Y is set to the same value. If both are set to zero, they are automatically calculated based on the kernel size. Gaussian blurring is particularly effective in reducing Gaussian noise from images.

In our preprocessing stage, we took several steps to mitigate the effects of lighting conditions. First, we applied masks to the image, followed by re-sizing it to a dimension of 224 × 224. Gaussian blur was then applied to enhance the image quality. Additionally, we cropped out uninformative areas, retaining only the relevant portions. To create a mask, the image was converted to grayscale, and a tolerance value greater than 7 was set. The objective was to eliminate black portions and preserve informative content. After cropping and re-sizing the image to match the required size for our model, Gaussian blur was applied with a standard deviation of 10 in both the X and Y directions. Using a Gaussian kernel, each point in the input array was convoluted and summed to produce the output array. This process improved the quality of the image and prepared it for further analysis and classification.

3.9.1.4 Data Augmentation

Data augmentation is a technique commonly used in machine learning to expand a data-set by applying transformations to existing examples. By synthetically creating new data points, data augmentation helps improve the generalization and regularization of models (Vapnik & Chervonenkis, 1971). It has been widely adopted in various machine learning models and recognized as a critical component (Simard et al., 1992; Ciresan et al., 2010; Krizhevsky et al., 2012; LeCun et al., 2015). One common challenge in machine learning is dealing with unbalanced group sizes within the data-set. During training, the objective is to improve precision with each iteration. However, if certain groups are under-represented, the model may not learn them as effectively as the over-represented groups. To address this issue, data augmentation is employed. By introducing random changes to the original training images, specific parameters are adjusted to create variations. These random changes are applied in each epoch, ensuring that the model trains on slightly different images at each iteration.

3.9.1.5 Dropout Regularization

Dropout is a training method in which some neurons are ignored at random. They are "dropped-out" in a random manner. This means that any weight updates are not applied to the neuron on the backward trip and that their effect to the activation of downstream neurons is temporally erased on the forward pass. Neuron weights within a neural network find their place in the network as it learns. Neuronal weights are customized for particular characteristics, resulting in some specialization. Neighboring neurons start to depend on this specialization, which, if it goes too far, might produce a fragile model that is overly dependent on the training data, can be dangerous. Complex co-adaptations are used to describe how a neuron becomes dependent on circumstances during training. The result is a decrease in the network's sensitivity to the particular neuronal weights. As a result, the network is better able to generalize and is less prone to over fit the training set of data

3.9.2 Implementation

Figure 5: Snapshot of model implementation

3.10 Summary

The chapter mainly focused on the methods and tool that were used to develop the model. Thus, different techniques and methods were used in developing the model up to the end, as mentioned above, the model was developed using python neural network frameworks. Before training, the data was converted to gaussian blur and dropout regularization was done to avoid over-fitting. Furthermore, the model incorporates MobileNet-v2, a deep learning technique and python Jupyter Notebook was used as an IDE. Using the prototyping model was used system development, the author managed to make use of all the process to finish the model and train it in the required time frame.

Chapter 4: Data Presentation, Analysis And Interpretation

4.1 Introduction

In this chapter, the author focuses on evaluating the research model by analysing its efficiency, accuracy, and performance to determine the success of the proposed solution. To assess the performance of the classification model, the author utilizes a confusion matrix. Various matrices are employed to measure the effectiveness and efficiency of the developed solution, including accuracy, recall, specificity, sensitivity, weighted F1 score, prevalence, and error rate. The model is tested using white, black box, and unit testing, and the outcomes are presented in this chapter. Additionally, the author examines the factors considered during result analysis, enabling them to draw conclusions about the success of the research based on the model's performance.

4.2 Testing

Software testing is an essential procedure for confirming that the actual software product adheres to the specified requirements and is error-free. It entails running software/system components through automated or manual methods to evaluate particular attributes of interest. Finding mistakes, discrepancies, or missing requirements in comparison to the defined criteria is the main goal of software testing. The significance of software testing lies in its ability to detect and address any bugs or errors in the software early in the development cycle, prior to the software product's delivery. Thoroughly tested software products offer enhanced reliability, security, and performance, resulting in time savings, cost-effectiveness, and customer satisfaction. To perform the verification and validation process, the author conducted both black box and white box testing on the research project. The test outcomes were then evaluated against the functional and non-functional requirements of the proposed solution to ensure its adherence.

4.1.1 Black Box Testing

Black box testing is a technique where the internal organization, layout, and use of the product are not taken into account. In other words, the tester is unaware of how it operates within. Only the system's exterior behavior is assessed by the Black Box. Both the system's inputs and its outputs, or responses, are put to the test. As a result, once the system has trained, it will be evaluated to see how well it can identify and categorize diabetic retinopathy using the provided data. The following are the findings of the author's black box testing of the model:

Figure 6:Testing the system

Figure 7: Testing the System

4.1.2 White Box Testing

White box testing is a software testing technique where the underlying structure of the software is known to the tester before the software is tested. This kind of testing is typically done by software developers. White box testing requires understanding of programming and implementation. The lower levels of testing, such as unit and integration testing, are applicable to testing. White box testing focuses primarily on testing the computer code of the system being tested, including its branches, conditions, loops, and code structure. White box testing's primary objective is to evaluate the system's functionality. The model was put to the test, as can be seen below.

```
earlyStop = keras.callbacks.EarlyStopping(patience=60)
best_model = keras.callbacks.ModelCheckpoint(filepath='keras_model.h5', save_best_only=True)

with tf.device('/gpu:0'):
    history = incept_model.fit(x_train, y_train, batch_size=32, epochs=1, validation_data=(x_test, y_test), callbacks=[earlyS
```

```
---------------------------------------------------------------------------
InvalidArgumentError                      Traceback (most recent call last)
C:\Users\ENDLES~1\AppData\Local\Temp/ipykernel_17104/2230532889.py in <module>
      3
      4 with tf.device('/gpu:0'):
----> 5     history = incept_model.fit(x_train, y_train, batch_size=32, epochs=1, validation_data=(x_test, y_test), callbacks=
[earlyStop, best_model])
```

Figure 8: Predicting without training and fitting

```
2022-06-20 00:15:48.836334: W tensorflow/stream_executor/cuda/cuda_driver.cc:269] failed call to cuInit: UNKNOWN ERROR (
303)
2022-06-20 00:15:48.972246: I tensorflow/stream_executor/cuda/cuda_diagnostics.cc:169] retrieving CUDA diagnostic inform
ation for host: EndlessHorizonz
2022-06-20 00:15:48.972564: I tensorflow/stream_executor/cuda/cuda_diagnostics.cc:176] hostname: EndlessHorizonz
2022-06-20 00:15:48.975846: I tensorflow/core/platform/cpu_feature_guard.cc:151] This TensorFlow binary is optimized wit
h oneAPI Deep Neural Network Library (oneDNN) to use the following CPU instructions in performance-critical operations:
 AVX
To enable them in other operations, rebuild TensorFlow with the appropriate compiler flags.
2022-06-20 00:15:55.744 No training configuration found in the save file, so the model was *not* compiled. Compile it ma
nually.
2022-06-20 00:16:20.158 No training configuration found in the save file, so the model was *not* compiled. Compile it ma
nually.
2022-06-20 00:22:28.058 No training configuration found in the save file, so the model was *not* compiled. Compile it ma
nually.
```

Figure 9: Predicting without compiling the model

4.2 Evaluation Measures And Results

4.2.1 Confusion Matrix

Once we have obtained and processed the data through cleaning, pre-processing, and wrangling, the initial step is to input it into an exceptional model, which generates output probabilities. However, assessing the effectiveness of the model is crucial to ensure optimal performance. This is where the confusion matrix plays a significant role. A confusion matrix is a table used to evaluate the performance of a classification model, or "classifier," on a test dataset with known true values. Relying solely on classification accuracy can be misleading, especially when there is an imbalance in the number of observations per class or when the dataset consists of more than two classes. By calculating a confusion matrix, we gain a better understanding of which aspects our classification model predicts correctly and the types of errors it tends to make. In the case of skin diseases, the three classes we are dealing with are:

Class 1: Inflammatory Skin Conditions

Psoriasis, Eczema, Dermatitis

Class 2: Infectious Skin Conditions

Warts and Scabies

Class 3: Other Skin Conditions

Vasculitis and Actinic

Please note that this classification is not exhaustive and there can be various ways to categorize skin diseases. The classes provided here are based on general characteristics and commonalities among the mentioned conditions. Predictions with a percentage 50 and above are generalized as positive(patient has the disease) and predictions below fifty are generalized as negative (they do not have the disease).

4.2.1.1 Metrics Of The Confusion Matrix

True Positive (TP)

- It refers to the number of predictions where the classifier correctly predicts the positive class as positive.
- These are cases in which we predicted yes (they have the disease), and they do have the disease.

True Negative (TN)

- It refers to the number of predictions where the classifier correctly predicts the negative class as negative.
- We predicted no, and they don't have the disease.

False Positive (FP)

- It refers to the number of predictions where the classifier incorrectly predicts the negative class as positive.
- We predicted yes, but they don't actually have the disease.

False Negative (FN)

- It refers to the number of predictions where the classifier incorrectly predicts the positive class as negative.
- We predicted no, but they actually do have the disease.

	TP	FP	FN	TN
Class 1: Inflammatory Skin Conditions	9	3	2	46
Class 2: Infectious Skin Conditions	11	4	2	43
Class 3: Other Skin Conditions	10	1	2	47

Table 1:Confusion Matrix values/Metrics

The table 2 above shows the true positive (TP), false positives (FP),false negatives(FN) and true negatives(TN) for each class.

4.2.2 Accuracy

- It gives the overall accuracy of the model, meaning the fraction of the total samples that were correctly classified by the classifier.
- Accuracy formula as adopted from Karl Pearson (1904)
- **Accuracy = (TP+TN)/(TP+TN+FP+FN)**

Table 2: Accuracy for All Classes

Classes	**Accuracy**
Class 1: Inflammatory Skin Conditions	Accuracy = (TP+TN)/(TP+TN+FP+FN) =(9+46)/(9+46+3+2) =55/60

	=**91.66%**
Class 2: Infectious Skin Conditions	Accuracy = (TP+TN)/(TP+TN+FP+FN) =(11+42)/(10+42+4+3) =53/60 =**88.33%**
Class 3: Other Skin Conditions	Accuracy = (TP+TN)/(TP+TN+FP+FN) =(10+47)/(10+47+2+1) =57/60 =**95%**

4.2.2.1 Average Accuracy

Average Accuracy = inflammatory + infectious + other skin conditions / 3

= 91.66+88.33+95

= 275/3

= 91.66%

4.2.3 Misclassification Rate/ Error Rate

- Overall, how often is it wrong?
- It tells you what fraction of predictions were incorrect. It is also known as Classification Error.
- This formula is adopted from Kuha (2005)
- **Error rate = (FP+FN)/(TP+TN+FP+FN) or (1-Accuracy**

Table 3: Misclassification Rate/Error Rate

Classes	**Error-rate**
Class 1: Inflammatory Skin Conditions	Error-rate = 1-Accuracy =1-0.9166 =**0.0834**

Class 2: Infectious Skin Conditions	Error-rate = 1-Accuracy =1-0.8833 =**0.1167%**
Class 3: Other Skin Conditions	Error-rate = 1-Accuracy =1-0.95 =**0.05%**

4.2.3.1 Average Error Rate

Average Error Rate = inflammatory + infectious + other skin conditions / 3

= 0.0834+0.1167+0.05

= 0.2501/3

= 0.0834%

4.2.4 Sensitivity/Recall/True Positive Rate

- When it's actually yes, how often does it predict yes?
- It tells what fraction of all positive samples were correctly predicted as positive by the classifier. It is also known as True Positive Rate (TPR), Sensitivity, and Probability of Detection.
- Adopted from Powers (2011)
- **Recall = TP/(TP+FN)**

Precision

- When it predicts yes, how often is it correct?
- **Precision = TP/(TP+FP) Adopted from Selvik (2007)**

	PRECISION	**RECALL**
Class 1: Inflammatory Skin Conditions	=TP/(TP+FP) =9/(9+3) =9/12 **=75%**	=TP/(TP+FN) =9/(9+2) =9/11 **=81.81%**
Class 2: Infectious Skin Conditions	=TP/(TP+FP) =11/(11+4)	=TP/(TP+FN) =11/(11+2)

	=11/15 =**73.33%**	=11/13 =**84.61%**
Class 3: Other Skin Conditions	=TP/(TP+FP) =10/(10+1) =10/11 =**90.91%**	=TP/(TP+FN) =10/(10+2) =10/12 =**83.33%**

Table 4: Model Precision & Recall

False Positive Rate

- When it's actually no, how often does it predict yes?
- **FP/actual no**

Specificity/True Negative Rate

- When it's actually no, how often does it predict no?
- It tells what fraction of all negative samples are correctly predicted as negative by the classifier. It is also known as True Negative Rate (TNR).
- **Specificity = TN/(TN+FP) or 1-FP rate**
- Equivalent to 1 minus False Positive Rate

Prevalence

- How often does the yes condition actually occur in our sample?
- It shows how often does the yes condition actually occur in our sample
- **Prevalence=Actual YES/(TP+TN+FP+FN)**

4.2.5 F1-Score/F1 Measure

- It combines precision and recall into a single measure.
- **F1-score=2 x (Precision x Recall/ Precision + Recall)**
- **=2TP/(2TP+FP+FN)**

Table 5: Model Specificity & F1 Score

	SPECIFICITY	**F1-SCORE**
Class 1: Inflammatory Skin Conditions	= TN/(TN+FP) =46/(46+3) =46/49 =**93.88%**	=**2 x (Precision x Recall/ Precision + Recall)** **=2 X (75 X 81.81)/ 75+81.81** =2*(12,271.5/156.81) = **78.26%**

Class 2: Infectious Skin Conditions	= TN/(TN+FP) =43/(43+4) =43/47 =**91.49%**	=**2 x (Precision x Recall/ Precision + Recall)** **=2 X (73.33 X 84.61)/73.33+84.61** =2*(12,408.9026/157.94) = **78.57%**
Class 3: Other Skin Conditions	= TN/(TN+FP) =47/(47+1) =47/48 =**97.92%**	=**2 x (Precision x Recall/ Precision + Recall)** **=2 X (90.91X 83.33)/90.90+83.33** =2*(15,149.394/174.23) = **86.95%**

4.3 Summary of Research Findings

After conducting essential black box, white box, and performance testing using the confusion matrix, the author determined that the system performed satisfactorily. The accuracy rates for the three classes of inflammatory, infectious, and other skin conditions were 91.66%, 88.33%, and 95%, respectively, resulting in an average accuracy of 91.66%. The model's error rates were calculated as 0.0834% for the inflammatory class, 0.1167% for the infectious class, and 0.05% for the other skin conditions class. The overall average error rate was determined to be 0.0834%, indicating that, on average, only 0.08% of predictions were incorrect. During black box testing, the system exhibited errors when fed with the wrong file format and when executed without configuring the Streamlit server. In white box testing, the model was run without prior training. Additionally, a test was conducted using a manually compiled Keras model file, and the model displayed the expected output. The model's recall and precision were also assessed, with precision rates of 75%, 73.33%, and 90.91% for the inflammatory, infectious, and other skin conditions classes, respectively. The recall rates were 81.81%, 84.61%, and 83.33% for the inflammatory, infectious, and other skin conditions classes, respectively. This indicates that 80.4% of all positive samples were correctly predicted as positive by the classifier. The F1-measure was utilized to evaluate the model, yielding scores of 78.26% for the inflammatory class, 78.57% for the infectious class, and 86.95% for the other skin conditions class. The specificity rates were 93.88% and 91.49% for the inflammatory and infectious classes, respectively, while the other skin conditions class demonstrated a high specificity of 97.92%. The average specificity was calculated to be 94.43%, indicating that 94.43% of all negative samples were correctly predicted as negative by the model.

4.4 Conclusion

To conclude this chapter, the author used different metrics for performance measurement of the system. Among them being, accuracy, specificity, recall precision, error rate f1-score and true positive rate. The average accuracy rate for all classes reached 91.66% with the other skin conditions class attaining 95%.This is mainly because there were more test samples for the other skin conditions class in the dataset for that class. The overall model performance was affected by the performance of the computer. The researcher used a 3rd generation core i3 computer to train the neural network. This comes as a shortfall since training a CNN requires high-end computer performance.The author believes that the use of a 11th gen computer with GPU will yield more favourable results.

Chapter 5: Conclusion and Recommendations

5.1 Introduction

Concluding this research, this chapter provides a retrospective analysis to determine if the study's objectives were successfully accomplished. It serves as a summary of the findings, conclusions derived from the research, and recommendations for future studies.

5.2 Aims & Objectives Realization

The first objective of this study was to analyse different deep learning techniques used for skin disease classification. The second objective was to design and implement a skin disease classification detection system using the MobileNet-v2 architecture of deep convolutional neural network (CNN). The last and third objective was to evaluate the effectiveness of the applicability of deep learning in the medical field focusing on skin disease classification and diagnosis. Therefore, to this end, the researcher developed a model that uses MobileNet-v2, a CNN to detect and classify the different classes of skin disease conditions which satisfies the second research objective. MobileNet-v2, a deep CNN architecture was introduced to classify the skin diseases into inflammatory, infectious and other skin conditions. The implementation of this project using a mobile application will make it easier for dermatologists to quickly and accurately diagnose patients as it adds to the previous related work done by other researchers like Article: "Automated Skin Cancer Classification in Dermoscopy Images via Deep Learning" (Menegola et al.,2015) andArticle: "Deep Learning for Skin Lesion Classification: A Comparative Study" (Esteva et al., 2019) . This, therefore shows that the objectives mentioned in chapter 1 were achieved.

5.3 Major Conclusions Drawn

Deep learning (DL) approaches can be more effective than standard techniques in diagnosing and early detecting skin diseases, a significant medical health issue that causes great discomfort and is of great concern. The skin diseases classes are determined by the type of the affected skin region features. This study thoroughly discusses skin diseases, including their symptoms and features as well as their causes, it also goes through several ML and DL strategies for detecting abnormal skin disorders and conditions in order to identify the disease and accurately diagnose a patient. In comparison to DL techniques, ML techniques are very non-scalable when dealing with high-dimensional data and need more time in terms of model analysis and training. ML models produce less-than-ideal results as the amount of features and data increases, whereas DL models strive for the best results. Based on the extensive use of DL in recently proposed models, this paper identified and reviewed a sizable number of DL models and their frameworks in order to better understand their working principles, the evolution of and integration with hybrid techniques, and how such models can be shifted on data and resource scarcity to produce efficient models and outcomes, scarcity to produce effective models and outcomes.

Automated screening technologies drastically shorten the time it takes to determine a diagnosis, saving dermatologists time and money while also allowing patients to receive treatment sooner. Automated skin disease classification and detection systems are critical for recognizing skin diseases at an early stage. The algorithm showed promise in learning the features needed to categorize skin images, correctly recognizing the majority of positive cases and patients with no skin disease. The trained CNN allows for a quick and fast diagnosis and response to a patient. The network learns to recognize an image of healthy skin without any trouble. This is likely due to the large number of healthy skin within the dataset. With this proposed approach, dermatologists may accurately and objectively detect and diagnose a skin condition.

5.3 Recommendations & Future Work

In the future, the researcher recommends employing a high-dimensional balanced dataset with supervised learning methods and approaching deep feature extraction, skin identification, skin-based picture classification, and skin disease detection with the best of its kind deep learning (DL) model. He recommends using an ensemble of machine learning (ML) classifiers rather than dense DL classifiers for much better and error detection and multiple prediction to reach the final average prediction, avoiding ambiguity and the error rate. It is also recommended that data be processed using modern approaches for error retrieval and removal in pictures, as well as effective feature extraction and classification. The suggested model also intends to expand the work in the future by introducing feature concatenation using ensembles of DCNNs and accompanying feature descriptors, as well as compact representation techniques.

To boost portability, availability, and flexibility, advanced DL algorithms with higher generalization and error detection will be pursued, taking into account trade-off connections between accuracy, computational complexity, memory limits, and processor power. The current improvements in CNNs allow for far deeper networks to learn the delicate properties that this network failed with. To sum up, the researcher has demonstrated that CNNs can be trained to recognize Diabetic Retinopathy features in fundus images. As networks and datasets improve and real-time classifications become available, CNNs have the potential to be extremely valuable to dermatologists in the future. As a result, this research will be beneficial to ambitious, youthful, and engaged researchers interested in the fields of Dermatology, medical imaging, and DL, making them more approachable to new ideas, innovations, and technology.

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