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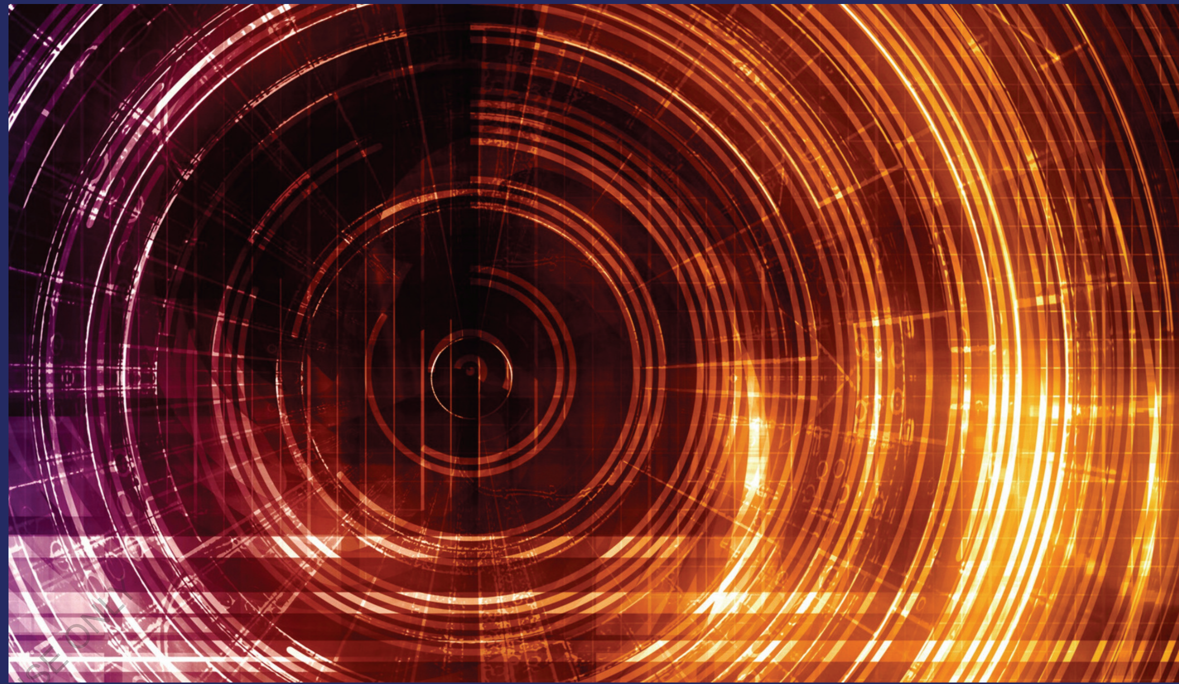

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EVALUATING CUTANEOUS CONDITION AND HEALTH IMPLICATIONS IN RELATION TO HUMAN SOCIETY

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LIST OF ACRONYMS & ABBREVIATIONS

ROI	Region of Interest
ABCD	Asymmetry, border irregularity, color, and dermoscopic structure
AI	Artificial intelligence
ACC	Accuracy
CAD	Computer Aided Diagnoses
AK	Actinic Keratosis
BCC	Basal Cell Carcinoma
SCC	Squamous Cell Carcinoma
ML	Malignant Melanoma
IEC	Intraepithelial Carcinoma
ME	Melacytic Nevus
GLCM	Gray level co-occurrence matrix
HSV	Hue, saturation, and value
IDE	Integrated development environment
ISIC	International skin imaging collaboration dataset
KNN	K-nearest neighbor
MLP	Multi-layer perceptron
MSE	Mean squared error
NB	Naïve Bayes
RGB	Red, green, and blue
RMS	Root mean square
SVM	Support vector machine
SSI	Structural similarity index
HAEM	Haemangioma
PCNN	Pulse Coupled Neural Network
PCN	Pulse Coupled Network
ANN	Artificial Neural Network
SVM	Support Vector Machine
CNN	Convolution Neural Network
RF	Random Forest
CCD	Charge Coupled Device
APCNN	Adaptive Pulse Coupled Neural Network
HD	Hammounde Distance
AT	Adaptive Thresholding
AS	Active Snake
CM	Combine Merit
TP	True Positive
GPU	Graphical Processing Unit
TN	True Negative
FP	False Positive
FN	False Negative
SK	Seborrhoeic Keratosis
DM	Dermatofibroma
BOF	BOF Bag-of-features
KLT	Karkunen-Loeve Transform
GLCM	Gray Level Co-occurrence Matrix
MRF	Markov Random Field

ABSTRACT

Skin Disease is one of the deadliest forms of cancer. Unfortunately, its incidence rates have been increasing all over the world. One of the techniques used by dermatologists to diagnose melanomas is an imaging modality called Dermoscopy. The skin lesion is inspected using a magnification device and a light source. This technique makes it possible for the dermatologist to observe subcutaneous structures that would be invisible otherwise. However, the use of Dermoscopy is not straightforward, requiring years of practice. Moreover, the diagnosis is many times subjective and challenging to reproduce. Therefore, it is necessary to develop automatic methods that will help dermatologists provide more reliable diagnoses.

Since this cancer is visible on the skin, it is potentially detectable at a very early stage when it is curable. Recent developments have converged to make fully automatic early melanoma detection a real possibility. First, the advent of dermoscopy has enabled a dramatic boost in the clinical diagnostic ability to the point that it can detect melanoma in the clinic at the earliest stages. This technology's global adoption has allowed the accumulation of extensive collections of dermoscopy images. The development of advanced technologies in image processing and machine learning has given us the ability to distinguish malignant melanoma from the many benign mimics that require no biopsy. These new technologies should allow earlier detection of melanoma and reduce a large number of unnecessary and costly biopsy procedures. Although some of the new systems reported for these technologies have shown promise in preliminary trials, a widespread implementation must await further technical progress in accuracy and reproducibility.

This thesis provides an overview of our deep learning (DL) based methods used in the diagnosis of melanoma in dermoscopy images. First, we introduce the background. Then, this paper gives a brief overview of the state-of-art article on melanoma interpret. After that, a review is provided on the deep learning models for melanoma image analysis and the main popular techniques to improve the diagnose performance. We also made a summary of our research results. Finally, we discuss the challenges and opportunities for automating melanocytic skin lesions' diagnostic procedures. We end with an overview of a conclusion and directions for the following research plan.

CHAPTER 1

CHAPTER 1

INTRODUCTION

1.1 Introduction

The most important element of the human body is the skin. This shields the body from UV rays, diseases, injuries, temperatures and harmful radiation while also assisting in the synthesis of vitamin D3. Since core temperature regulation depends so heavily on skin health and protection against skin disorders it is necessary to maintain it in good condition. Skin disorders may seem innocent but they can be treacherous if left unattended. Many diseases have early symptoms however majority of them are similar therefore making it hard to diagnose a condition at its initial stage. As for humans whose faces have been disfigured or scarred, this affects not only their physical but also mental state leading to some psychiatric problems among them as well. The skin can be influenced by numerous external and internal factors. Some of these include; artificial damage to the skin, severe chemical causes, adversity illnesses , immunity of a person and genetic aberrations that cause skin disorders . Skin diseases have a huge impact on people's lives including wellness directions towards that together with other things too. Scientists find dermatology challenging to treat because the symptoms are tricky to manage and they change in different conditions. Various diseases can affect the skin, including those that occur frequently among others, which may lead to negative consequences if such approaches are not suitable for such a type of skin disease. Skin infections are common among people who should be treated immediately.

Cancer is considered to be one of the major causes of death worldwide by World Health Organization (WHO), and it is the second most common reason for mortality (death) from skin cancer in Europe. Some 9,500 people are estimated to receive a diagnosis of skin cancer each day in the US. Not only in America, but also in other countries, there are some places where patients with skin cancers would quickly be diagnosed just because of particular interflow factors such as complexion, geographic location, way of life and somewhat gene predisposition . Given that cancer-related deaths can be significantly reduced through early detection and treatment strategies, efforts should thus be directed towards supporting research to develop non-invasive means for early stage cancer detection. Cancer is preventable but requires regular screening if symptoms like abnormal nevi appear . First, it needs to identify the presence of cells' improper growths and estimate an abnormal area among tumor generations on the surface of cutaneous tissues. To diagnose new changes appearing or disappearing on images this process should include routine examinations of skin lesions. During this process, a dermatologist detects a terrible region. The prognosis accuracy completely depends on whether the method of diagnosis used or modality of input images.

These illnesses are categorized according to signs such as swelling, sores, and redness, among others. The typical symptoms of skin conditions include red or itchy skin, rashes, bumps, or patches, and unusual shapes of nails, among others. Moreover, the sores that appear in skin disorders can range from small, localized spots to covering the entire body. As a result, individuals often look up their skin issues online in an attempt to figure out what's wrong. However, the issue with this method is that the information or pictures found online are often mislabeled, leading to confusion. Thus, the goal of this research was to raise awareness about several common skin conditions and provide accurate information about them, as well as to develop advanced machine learning and deep learning tools for diagnosing these conditions.

As a result, the use of automated evaluations for these diseases has grown in significance because it can generate precise outcomes quickly when used in conjunction with human analysis through clinical laboratory procedures. The color of the skin, the outline of the tissue, the distribution of skin size, and the pattern of skin conditions are all visual cues that can be examined to identify the skin condition. The difficulty in categorizing increases when each unique human skin feature is taken into account and the ability of humans to identify these features for classification purposes is not enough. In the field of medicine, artificial intelligence methods are often utilized. Numerous algorithms for diagnosing diseases have been developed to accurately predict diseases. By considering all the disease's aspects, various classification strategies are devised for identifying different types of disease conditions.

On the flip side, deep learning techniques have consistently matched or surpassed human performance in the field of imaging. Consequently, this piece delved into the use of neural networks for categorizing skin conditions based on medical records. The application of deep learning in identifying skin diseases has become a leading area of study in dermatology. The aim of this research is to develop a system for diagnosing skin conditions through deep learning by evaluating the features of skin diseases and the effectiveness of current imaging techniques. However, these deep learning models require extensive training, necessitating a vast collection of labeled images for each category. In this study, several classification techniques are employed, followed by the use of ensemble methods. Additionally, a strategy involving feature selection is applied to these neural network models to enhance prediction accuracy, which can then be utilized to build a sophisticated system. While researchers are constantly developing new prediction methods, the majority focus on specific classification algorithms over ensemble strategies. The ensemble approach combines various data mining techniques to improve prediction accuracy.

A vast majority of research in this area has been conducted, and the following studies have been referenced. The categorization method involves the use of technology to train and learn how to identify various skin conditions in humans by creating a strategy for recognizing, classifying, and organizing skin diseases in people. Actinic Keratosis, Basal Cell Carcinoma, Dermatofibroma, Melanoma, Nevus Pigmentosus, Pigmented Benign Keratosis, Seborrheic Keratosis, Squalors Cell Carcinoma, and Vascular Skin Lesions are signs of skin conditions. The International Skin Imaging Collaboration (ISIC) dataset HAM10000 is a collection of datasets that includes information on the nine types of skin disorders. Skin conditions are among the most severe health issues that people can develop. The long-term exposure to various types of high-frequency wireless devices can lead to skin cancer because of the way the skin's structure is changed by direct exposure to UV radiation. The process of identifying skin conditions is challenging due to the constantly changing and ongoing nature of certain skin areas, and the symptoms of skin conditions can be complex. Diagnosing skin conditions involves looking at various signs, such as the basic structure of lesions, physical characteristics, scaling, color, and patterns. Identifying skin conditions can be complicated by focusing on specific aspects. The lack of clear visibility in images of skin conditions makes it necessary for medical professionals to use advanced tools to accurately diagnose these conditions.

Consequently, the process of assessing skin conditions by hand tends to be subjective, time-intensive, and requires more manual labor. To sum up, the development of a computer-assisted system capable of diagnosing skin conditions automatically should be pursued. Additionally, our study introduces a sophisticated approach involving deep learning for identifying skin diseases, drawing upon multiple neural network models that have shown success in pattern recognition tasks. The most recognized model here is deep learning, which is tailored to learn about the characteristics of images and identify skin issues. For training these networks to handle a wide range of skin data, they are fed a million images. To enhance the accuracy of predicting skin conditions, we integrated these deep learning techniques with the Naive Bayes algorithm, a widely used approach based on probability theory. Through this combined approach, deep learning systems are trained to recognize various skin conditions. Following that, we briefly address the issue at hand and the obstacles encountered during the identification of skin lesions.

1.2 Issue Overview

This study focuses on tackling the issue of identifying irregularities in images of skin lesions. It aims to create effective and strong methods for detecting these irregularities non-invasively. The primary aspects of structured and unstructured data related to skincare, utilizing Ensemble Machine Learning (ML) and Deep Learning (DL) methods, are explored in the context of skincare Data Analysis. These methods are structured around a process of image manipulation, which includes the following steps: pre-processing, segmentation, feature extraction, and classification of skin lesion images.

1.3 Difficulties in analyzing skin lesions

Research has shown that individuals without medical training or specific knowledge in dermatology are capable of categorizing skin lesion images into distinct groups or subgroups. This suggests that certain visual characteristics can act as cues for classification. By applying machine learning techniques, these characteristics can be identified through image processing, leading to the development of an automated system. The following are the main obstacles in the early detection of skin lesions:

• The presence of blood vessels on the skin is noticeable to the human eye. However, the complexity of their patterns and the occurrence of "discontinuities," such as the contrast between skin and hair, make it challenging for computer vision systems in automated applications to detect them.

• The diagnostic guidelines, such as the ABCD rule, do not align with the medical knowledge used by dermatologists for diagnosis.

• A significant challenge for the general public is the design of the visual system and how humans perceive skin lesions. The task becomes particularly difficult when distinguishing between the various shades of each lesion. To address this, human-inspired visual models are utilized. This issue is also present in the analysis of skin lesion colors, which has significant implications for the screening of pigmented skin lesions.

Advanced systems in dermatology, which employ image processing techniques, demand quick and reliable calculations. The specific difficulties in identifying skin lesions can be effectively addressed through non-invasive methods. Dermatologists commonly use dermoscopy, a technique that not only enlarges skin lesions for closer examination but also allows for the observation of both the top and underlying structures that are not visible to the naked eye. Numerous studies have demonstrated that dermoscopy significantly enhances the accuracy of skin lesion diagnoses by dermatologists. These methods are effectively utilized by medical professionals but are not accessible to non-experts or non-medical personnel. To examine these aspects in standard skin lesion images, automated image processing methods are necessary. Beyond economic factors, other obstacles include a lack of awareness, education, and/or cultural barriers that hinder regular screenings. In some cases, these screenings can reveal concerning findings, such as early signs of skin cancer that may progress to cancer. These limitations have spurred research on non-invasive methods for predicting outcomes using image processing in dermatology, which could serve as a supportive tool for less experienced dermatologists. The majority of non-invasive imaging systems reviewed in the literature follow a series of steps: pre-processing, approximating the outline of the lesion, extracting features, and classifying the lesion as either two-class or multi-class. These diagnostic systems have shown improved performance in experimental settings but often focus on features that are not medically significant (designed for imaging rather than for medical use). Alternatively, it is possible to develop a system that concentrates on extracting medically relevant features, which are essential for diagnosing skin conditions. Despite their close relationship to medical diagnosis and their clinical importance, these systems have received less attention in the research literature. Furthermore, the proposed methods aim to investigate dermatological criteria and analyze the clinical data used for diagnosing skin lesions from images. This thesis presents new and enhanced approaches to the system for diagnosing skin conditions.

1.4 Objectives

In the realm of machine learning, ensemble classifications stand out as crucial techniques. Selecting the right classifier for a specific task within this field is a complex challenge in the area of EL. Consequently, the main objective of this thesis is to pinpoint the most suitable classifier for competitive EL among various options. This proposed algorithm is designed to identify the best combinations of methods that lead to more accurate classification results for various skin care issues, utilizing the ISIC2019 Dermatology dataset. Additionally, investigating various method combinations results in more accurate classification outcomes for dermatology datasets and enables the categorization of skin conditions into seven groups. This research aims to create ensemble machine learning and deep learning-based computer-aided systems for identifying abnormalities in skin lesion images through three steps as outlined below: - To accurately locate skin lesions by approximating their boundaries. The methods for boundary detection are categorized into manual, semi-automated, and fully automated approaches to image segmentation. The approach chosen for this thesis employs a self-learning neural network model that mimics the visual cortex's behavior to identify localized objects as lesions. This method automates the process of defining lesion boundaries for all types of skin lesions. The approach is efficient in terms of computation time and accuracy. - To extract relevant features from skin lesion images that provide clinically significant information. This information is essential for dermatologists to understand and interpret skin lesion images. However, implementing a clinical-inspired system is challenging. The approaches discussed in this thesis characterize the clinical features of skin lesions in image space. - To recognize all ten classes of skin lesions, it is necessary to use more detailed feature descriptors. Therefore, there is a need for an effective approach that can enhance the feature extraction process for skin lesion recognition in a dermatology diagnostic system. The robust approach is capable of recognizing multiple-class skin lesion samples.

1.5 Combining Machine Learning and Deep Learning for Analyzing Data

Electronic Health Records (EHR) contain information about a patient's health, gathered from various sources like hospitals, clinics, and laboratory tests, both in a structured and unstructured format. This data can be used to detect diseases early on, potentially preventing serious health issues and lowering death rates. Machine Learning (ML) is crucial in deriving valuable insights from this health data. Identifying skin diseases from existing data is a significant challenge in the medical field. ML is also applied to extract knowledge from healthcare data by using novel techniques to enhance the accuracy of classification. These classification models can enhance patient care by improving the accuracy of decisions made by the model. Recent research has shown that using a single model for classification results in lower accuracy compared to using a combination of models, which is known as Ensemble Learning (EL). The benefit of EL is that it combines the most effective models, outperforming each individual model.

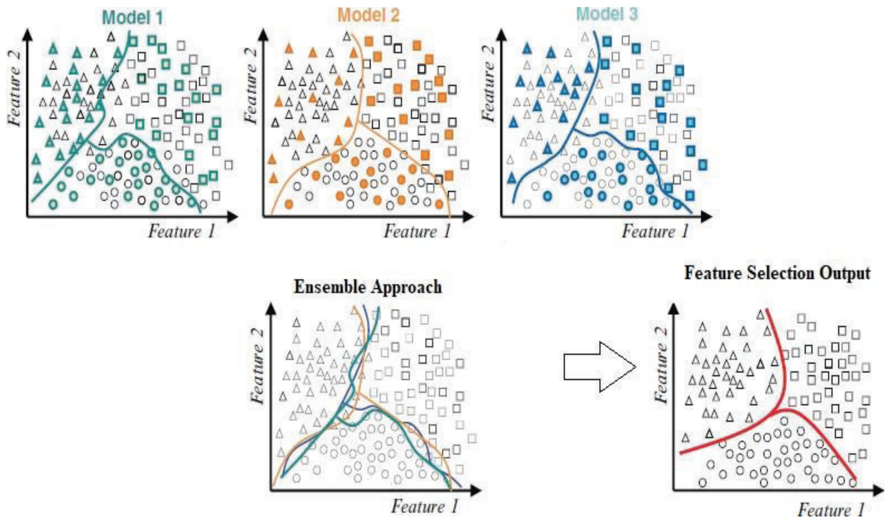


Figure 1.1 Representation of Feature Selection using Ensemble Approach

As the complexity of data increases, the primary step in preprocessing is the selection of features. The use of various feature selection models greatly enhances the capability to choose the right features without negatively affecting the performance of the classification task. It has been demonstrated that using an ensemble of feature selection methods is more effective than using a single method. The process of selecting features using an ensemble is illustrated in Figure 1.1. A similar method is applied to ensemble classification. There are several types of ensemble methods for analyzing both structured and unstructured data: As illustrated in Figure 1.2, the ensemble classification model consists of two types: a cooperative ensemble classifier and a competitive ensemble classifier. Cooperative ensemble classification involves a combination of classifiers where each contributes to the final EL model. Techniques such as averaging, weighted averaging, and generalization classifiers are examples of cooperative ensemble classification methods. Additionally, competitive ensemble classification selects the best classifiers among several. The two primary strategies for competitive learning are: Gating: This strategy is based on the principle of dividing complex problems into smaller, more manageable parts to solve them more easily.

Conditional switching: Specific criteria are met by the model. The result of one

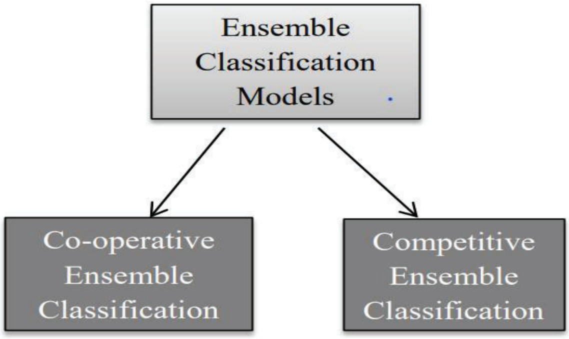


Figure 1.2: Types of Combining Ensemble Classifier Models

Figure1.2: The Combining Ensemble Classifier Models model is introduced as an input to another model. This thesis suggests a competitive-based Extreme Learning Machine (ELM) for various data types. The majority voting methods can be utilized for both feature selection and classification tasks. This approach operates on the principle of determining the number of classifiers in agreement for classification, based on the dataset, by identifying the classifier that receives the highest percentage of votes above 50%. This method involves selecting only those classifiers for the ensemble. Weighted majority voting is another method that assigns importance to classifiers based on their performance. In some cases, certain classifiers outperform others, so to distinguish their performance; weights are assigned to the most effective classifiers. This strategy enhances the classification accuracy. The Bagging ensemble algorithm, known as Bootstrap Aggregation, is designed for datasets with a small size. For larger datasets, they are divided into smaller subsets, which are then used for the voting process. This approach helps to prevent over fitting issues. Boosting is a technique that transforms a weak classifier into a strong one, thereby improving the classification accuracy by reducing errors from weak classifiers. Boosting algorithms, such as Gadabouts and Gradient Boosting, are applied for classification tasks. Deep Learning (DL) is a neural network architecture with multiple hidden layers, which has been proven effective in managing large volumes of data. DL stands as a leading technique in Machine Learning (ML) for healthcare analytics, enabling the analysis of patient data to prevent diseases like diabetes, cancer, and heart attacks. It also serves as a facilitator in improving skincare communication using clinical data. DL is used to analyze patient data and prevent diseases. Additionally, it acts as a mediator

by transforming skincare data into more refined clinical data by identifying complex patterns in the data. Its use is highly regarded in clinical data analysis, offering personalized benefits for each individual. In recent years, DL has been integrated with other techniques for skin disease diagnosis, aiding in the development of efficient treatment plans. Classification of a single model for the same dataset with the same parameter settings is only suitable for datasets with identical characteristics. An alternative solution to this issue is the combination of models with different hyper parameters. This leads to the development of a deep ensemble model, which combines the benefits of deep learning models and ELMs. This approach improves the classification of the ISIC Dataset.

1.6 Structure of Research Work

The structure of the thesis is outlined as follows:

Chapter 1: Overview of the Research on Machine Learning Techniques for Skincare Analysis This chapter provides an overview of the research focusing on machine learning and deep learning techniques for analyzing skincare. It outlines the main problem, the problem statement, the challenges in analyzing skin lesions, the research's primary goal, and the organization of the thesis.

Chapter 2: Detailed Study of Machine Learning and Deep Learning Research on Ensemble Methods This chapter delves into the studies related to machine learning and deep learning, specifically focusing on ensemble methods. It reviews the literature on various techniques, discussing their pros and cons in detail.

Chapter 3: Examination of the Effectiveness of the Proposed Competitive Ensemble and Deep Convolution Neural Networks Classifier (RF-DCNN Deep Classifier) on the ISIC Dataset HAM10000 This chapter evaluates the performance of the proposed Competitive Ensemble and Deep Convolution Neural Networks Classifier (RF-DCNN Deep Classifier) on the ISIC Dataset HAM10000, which includes the international Skin Imaging Collaboration (ISIC) dataset HAM10000. The classification results are validated using various accuracy metrics.

Chapter 4: Approach to Extracting Features from the HAM 10000 Dataset This chapter presents an approach for extracting features from the HAM 10000 Dataset, which includes structured data. It then discusses the pre-processing and analysis of this data using a model, Competitive Ensemble Classification Model for Structured Data, which incorporates machine learning and deep learning techniques for multilevel classification. The performance of this model is assessed based on accuracy metrics.

Chapter 5: Discussion on Deep Learning Models for Structured and Unstructured Data This chapter explores deep learning models for both structured and unstructured data. It introduces Competitive Ensemble models for structured data and Competitive Ensemble models for unstructured data, both of which are used for classifying skincare data. The chapter also emphasizes the benefits of the proposed work in comparison to existing deep learning ensemble methods.

Chapter 6: Conclusion and Future Research Directions This chapter wraps up the findings of the research and summarizes the overall work. It also suggests potential directions for future research.

CHAPTER 2

CHAPTER 2

REVIEW OF LITERATURE

In the preceding chapter, we explored the issue of identifying and categorizing skin lesions from images, a topic that has garnered attention from numerous researchers and dermatologists. This chapter delves into a review of studies focused on predicting various skin diseases in patients by analyzing their personal and clinical data through machine learning algorithms. It summarizes the contributions from the last ten years in this field, aiming to pinpoint the strengths and weaknesses of these approaches in diagnosing skin diseases.

2.1 Summary of Skin Lesion

Skin lesions pose a significant challenge in healthcare, as diagnosing them often consumes a considerable amount of time. Classification, a crucial technique in decision-making for many real-world problems, is central to this research. The primary goal is to accurately classify skin lesions and healthy skin layers, enhancing the precision of these classifications. The use of machine learning and deep learning in diagnosing skin conditions involves extracting patterns from datasets related to skin diseases. In recent years, machine learning has emerged as a reliable and supportive tool in the medical sector.

This study focuses on predicting various skin diseases in patients by analyzing their personal and clinical data using machine learning algorithms. It provides an overview of the research conducted in the last decade, aiming to understand the current state of technology in diagnosing skin diseases. The chapter also covers aspects of skin lesions with a medical perspective, including general information on skin structure, abnormalities related to dermatology, and diagnostic methods employed by medical professionals. This review not only highlights the significant research in this area but also aims to offer insights and perspectives on skin lesion issues, with a focus on their medical implications. The chapter concludes by discussing the limitations of these studies and suggesting possible solutions to address them.

2.1.1 Structure of Skin

The skin is the body's largest organ, serving as a protective layer around it. It shields against heat, UV rays, cuts, and infections. Moreover, it plays a role in regulating body temperature and contains various substances like water, fat, vitamins, and minerals. Figure 2.1 illustrates the two primary categories of human skin. The first is the non-hairy, smooth skin on the palms, soles, and the outer surface, characterized by ridges and sulci that often have unique patterns known as dermatoglyphics. This skin is notable for its thick epidermis, multiple layers, a dense stratum corneum, sensory organs in the dermis, and the absence of hair follicles and sebaceous glands. The second category is hair-bearing skin, which includes hair follicles and sebaceous glands but lacks encapsulated sensory organs. Furthermore, the types of skin can vary significantly across different body areas.

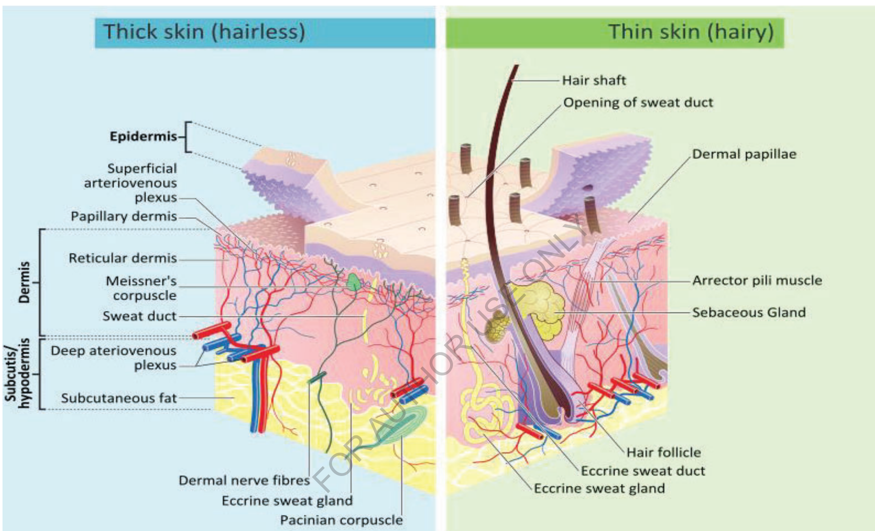


Figure 2.1: Human Skin Category

Layers of the skin: The skin is primarily made up of three main layers, as shown in Figures 2.2 and 2.3.

• The outermost layer, the epidermis, acts as a waterproof barrier and protects against infections.

• Beneath the epidermis is the dermis, which is home to various skin features like hair follicles.

• The sweat and sebaceous glands in the dermis help keep the skin's surface clean and the hypodermis, or subcutaneous layer, helps regulate body temperature and stores energy.

Skin abnormalities: Any unusual growth, bump, sore, or discolored patch on the skin is considered a skin lesion. In the following section, we will explore different types of skin lesions and their classifications.

2.1.2 Skin Lesions

Skin lesions are various types of skin patches that differ from their surrounding areas. There is a wide range of skin lesions that can be organized into a hierarchy. Initially, each lesion is classified based on its origin. Malignant lesions, such as melanoma, develop from melanocytes, the cells that produce melanin, a skin pigment, and other types of skin cells, like basal or squamous cells. The process then involves categorizing lesions as benign or malignant. Lesions are further divided into these two groups.

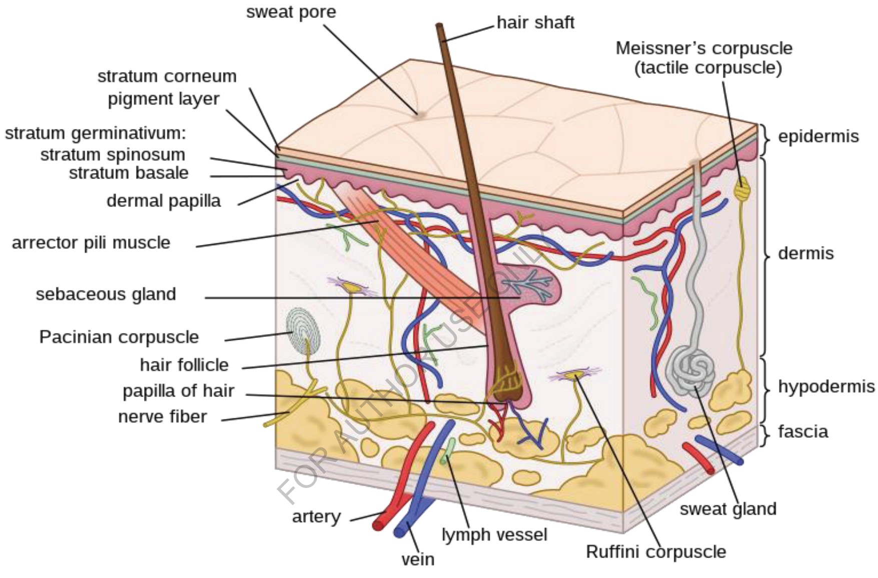


Figure 2.2: Layers of Human Skin

Within each collection of samples, there are various smaller categories. For instance, in a standard dataset, these categories include benign conditions like pyogenic granuloma (PYO), dermotofibroma (DF), and haemangioma (HAEM), and malignant conditions such as melanoma (ML), squamous cell carcinoma (SCC), and basal cell carcinoma (BCC). Additionally, there are pre-malignant categories of lesions that can either be benign or malignant and are challenging to identify, such as intraepithelial carcinoma (IEC), actin keratosis (AK), and seborrhoeic keratosis (SK). Figure 2.3 outlines the different categories of skin lesions present in the standard dataset of Dermofit, excluding moles (nevi). In India, the most prevalent forms of skin cancer are SCC and BCC, as they develop slowly and are considered less dangerous than melanoma. The symptoms of this cancer category closely resemble those of a pre-malignant category (AK), which is believed to be the precursor to SCC and BCC. DF, HAEM, and ME, on the other hand, are vascular lumps or benign skin conditions. Among the three types of cancer, melanoma is the most serious, responsible for the majority of skin cancer-related deaths, yet it remains one of the most common skin cancers.

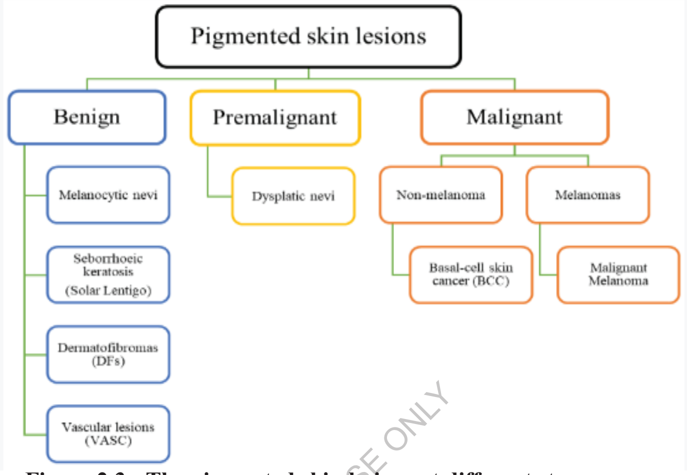


Figure 2.3.: The pigmented skin lesions at different stages

On the contrary, BCCs and SCCs are less severe but challenging to identify compared to melanoma. Both types of skin cancer (BCC and SCC) typically grow slowly but can significantly impact nearby tissues. Although SCCs tend to grow faster, BCCs are more destructive in their behavior. If left untreated in the early stages, they can cause serious harm and potentially affect other parts of the body. It's not possible to categorize these cancers solely based on the appearance of the skin lesion, such as color and shape. There are various factors contributing to this complexity, including the diversity observed among different types of skin lesions. For instance, a single skin lesion sample can include BCCs, SCCs, and malignant lesions. In the upcoming section, we will discuss the standard methods used for diagnosing skin conditions. While non-invasive techniques are not always highly accurate, they are close to the actual conditions.

2.2 Analysis of Skin Lesion Images

This section will review two key areas in the literature related to skin lesion analysis: 1) the diagnosis of skin diseases by dermatologists, and 2) the use of computer-assisted systems for diagnosing skin lesions. While common skin conditions can often be diagnosed through visual observation, more severe conditions require efficient diagnostic methods. Typically, dermatologists recommend treatments based on visual observations, questionnaires, and empirical diagnostic criteria. However, there are some conditions that are not easily recognizable and may require detailed images at high magnification or biopsies, such as cancer. In the medical field, there is a significant focus on diagnosing severe skin conditions non-invasively. This approach is based on the characteristics of skin lesions in medical images, including their shape and color. For example, the structure of a skin lesion can indicate the distribution of textures in the image space, and the color variations among different lesion types can be related to their different wavelengths in medical imaging. This section will summarize the importance of image processing in the screening of skin lesions and the standard medical procedures for diagnosing skin abnormalities.

2.2.1 Methods for Examining Skin Lesions

Various imaging techniques are employed to examine skin lesions, with photography being the simplest method. This approach captures images of the skin's upper layer. Following this, dermoscopy, which uses polarized light cameras, is the next step. It reduces the appearance of surface features and highlights the epidermis – the skin's second layer. This makes it easier to identify the structures of lesions, such as dots, globules, and networks, which are key in diagnosing skin conditions. Dermoscopy is a technique that offers a clearer link between dermatology and specific visual characteristics, leading to the development of epiluminescence microscopy (ELM) as a new approach. This method introduces a new way of investigating by examining morphological markers in pigmented skin lesions. Additionally, the visual examination of lesions through ultrasound is another method used in diagnosis. Ultrasound imaging is typically used to measure the depth of skin lesions, and if there are no differences from normal skin, it's difficult to distinguish between the two areas. When specialists examine lesions and use high-frequency ultrasound (above 30 MHz) to determine the depth of infiltration for accurate surgical cuts and treatment plans. However, there are other techniques like optical coherence tomography (OCT) and confocal laser scanning microscopy (CLSM). Visual inspection by the naked eye has a low sensitivity in detecting early skin abnormalities, which is where non-invasive imaging techniques like dermoscopy come in. These include body photography and confocal microscopy. Research is also underway to enhance the diagnostic accuracy of skin lesion images through the development of microscopy reflectance (RCM), which aims to improve the analysis of microscopic skin structures. The goal is to integrate dermoscopy with computerized photography for better clinical practice. The advancement of imaging techniques in dermatology leads to more precise methods of diagnosis. The next section discusses the standard criteria used in dermatology.

2.2.2 Medical Diagnostic Criteria in Dermatology

Dermatologists employ specific diagnostic criteria to differentiate among various skin lesions. A portion of these criteria focuses on the patterns and colors observed in skin lesion images. The initial approach to diagnosing skin lesions, pattern analysis, was introduced in 1985 by Friedman et al. [1]. This approach identifies a group of patterns, also known as global features, unique to each skin lesion type. A particular pattern is defined by one or more essential skin structures, identified through local features (image descriptors) that may span the entire lesion. Furthermore, there are numerous diagnostic strategies available, including the ABCD rule, Menzies technique, 3-point and 7-point checklist, and non-invasive imaging systems [2,3]. The ABCD rule, a standard diagnostic guideline for skin lesions, was proposed in 1994 by Stolz et al. [4]. This rule is applied to assess lesion properties, including asymmetry, border, color, and diameter.

ABCD Rule: It is primarily based on the four key characteristics of an image used to identify skin lesion abnormalities. These characteristics are:

- Asymmetry Features: This involves evaluating the degree of asymmetry in terms of shape, color, and texture of the lesion.

- Shape Features: These aim to describe the lesion's shape using attributes such as area, perimeter, and circularity index. The characterization of the lesion's border is linked to shape features, often including other attributes like fractal dimension and irregularity index.

- Color Features: This focuses on describing the lesion's color properties. Additional features may include statistical descriptors (mean, standard deviation, skewness, entropy, etc.), color histograms, and chromatic differences. Multiple color spaces (e.g., RGB, HSV, L*a*b*) are typically used in conjunction with these features.

- Texture Features: These are designed to characterize the structures of skin images. Popular features include the co-occurrence gray level matrix (GLCM) and associated statistics, as well as Gabor filters.

2.3 Computer Aided Diagnostic System

Identifying irregularities in standard images of skin lesions is a complex task. Indeed, even with the use of therapeutic calculations, such as the ABCD criteria and the traditional 7-point checklist rules [6]. In every scenario, it's challenging to categorize lesions or distinguish severe skin sores and their types due to factors like noise, hidden structures, biological complexity, and the system's anisotropy, making the automated analysis of dermatological images a difficult endeavor. This situation leads to a lower chance of detecting abnormalities and a higher accuracy in lesion diagnosis. Furthermore, it increases the need for histological tests, as this remains the standard method for diagnosing skin lesions. Additionally, there can be variations in the diagnosis of skin lesions among different dermatologists. This is because the interpretation of specific diagnostic criteria relies on the visual clarity and the expert opinion of the medical professional. The limitations of the past have motivated the development of uniform frameworks for the detection of abnormalities with greater precision.

A computer-aided diagnostic system (CAD) offers various tools that dermatologists can utilize [7]. From one perspective, the system's diagnosis is not dependent on the user at any given moment, ensuring consistent and accurate detection of skin lesions. From another angle, the CAD system can be used by both seasoned and novice dermatologists. This versatility allows for the use of machine learning to enhance diagnosis and bring about significant advancements in dermatology. While there are numerous CAD systems available for the detection of melanoma, the number for non-melanoma skin lesions is relatively limited. One of the most effective methods for diagnosing medical images is to overcome the challenges mentioned above. This involves leveraging any misleading information about the image structures to extract useful information. This information can be derived from the anatomical understanding of the structures' typical appearance (such as shape and gray levels) or from empirical knowledge of their properties. The images can also be categorized based on their texture, color, morphology, and fractal patterns. In a specific study [8], various techniques such as thresholding, morphological analysis, and texture detection were employed to segment a digital image into different regions.

The research community used several standard automated methods in this regard to improve the diagnosis of common pigmented skin lesions and their non-pigmented counterparts with reproducible diagnosis. These methods follow a traditional sequence: image pre-processing, lesion segmentation, feature extraction and classification.

2.3.1 Delimitation of Lesion Area

Delimitation of a lesion area is a first step in an automated study of skin lesion images that is very important for the following reasons: (a) The boundary structure provides crucial information about exact detection of lesions, (b) Extraction of some other significant properties like structures and colors. Because the accuracy of the edges of the lesion depends on its appearance and multifarious colorization, it is a bit complex task due to several reasons:

• A low contrast between region-of-interest and normal skin area.

• Irregularly shaped boundaries are difficult to define

• Different artifacts such as blood vessels, hair; air bubbles etc.,

• Multiple lesions

• Color changes

The performance of this can be done in two stages as I) preprocessing and II) segmentation.

Preprocessing involves conversion of color space, improve image contrast, approximate region of interest and eliminate artifacts [9] making the boundary detection process run faster. Continuing with this, segmentation is done by splitting an image into non-overlapping regions that are uniform with respect to certain features such as brightness level, texture or color.

2.3.1.1 Pre-processing

Pre-processing title-images which are not of high quality and cannot be effectively analyzed is quite important. Such images lack characteristics because of various distortions such as color transformation, effects of illumination, skin hair, nails, blood dots etc [10,11]. The literature has discussed various methods that overcome the weak points in images and deal with them well thereby producing a good diagnostic system for skin lesion detection [12]. There are many colour spaces available for colour transforms which can be

- Commonly employed in the manipulation of images are the Red-Green-Blue (RGB) system, (CIE-L*a*b, CIE-X*Y*Z, CIE-L*u*v), Luma with chrominance (Y'PbPr, YIQ, Y'CbCr, Y'UV), Hue-Saturation-Intensity, Hue-Saturation Value, and Hue-Saturation-Luminance (HSI, HSV, HSL). Typically, digital images of lesions are created in RGB format. These images are then often converted to grayscale for the purpose of performing scalar image processing, which focuses on representing the image's intensity rather than treating it as a standard color image.

Researchers, such as Dobrescu et al. [12], have attempted to improve the accuracy of classifying skin lesions by converting the individual image samples in their study to images with 256 gray levels. However, over time, there has been a growing need for multichannel (vector) processing to leverage the original color information of pigmented skin lesions. This leads to the challenge of computational speed, as there is a demand for vector images.

The initial step in the uniform framework is preprocessing. This typically involves changing colors, fixing images, and eliminating unwanted elements. The way in which images of lesions are taken directly affects the important characteristics that help in distinguishing between different types of lesions. Rahman [13] noted that the recovery and classification of lesions, which can be difficult when taking images from various datasets or devices under different lighting conditions (like brightening), can lead to a non-consistent lighting pattern that disrupts the entire process of diagnosing skin lesions. To overcome these issues, one suggested method is to start with calibrating the device used to capture images [14]. Abbas et al. [15] introduced a method that improves the visibility of skin lesion images by adjusting settings and determining the pixel intensity values of lesions within a specific range of the CIE L*a*b color space. However, a significant challenge in enhancing contrast in areas with a narrow intensity range is the amplification of noise. These challenges can be mitigated by employing Contrast Limited Adaptive Histogram Equalization (CLAHE) [16]. The presence of artifacts, often referred to as noise, poses a significant barrier to the accurate diagnosis of skin lesions by medical imaging. Moreover, the presence of intact skin artifacts includes hair shafts, dermoscopic gels, thin blood vessels, shadows, ruler markings, specular reflections, vignetting, and air bubbles, which can distort the diagnosis and impede the effectiveness of automated diagnosis systems [17,18].

The written material clearly states that the most common artifacts found are hair shafts and ruler markings [19,20]. It has been noted that a significant amount of effort has been put into eliminating hair shafts and ruler markings from images of skin lesions. An impressive study by Abbas et al. [21] was conducted, focusing on comparing the latest algorithms for this purpose. After removing these artifacts, the challenge arises in accurately determining the shape and location of the lesion. Even though the images of skin lesions can be quite large, the lesion itself is often found in a relatively confined area. For various reasons, it can be beneficial to accurately define a bounding box (the smallest rectangular area that contains the lesion). This provides an estimation of the lesion's size and details on related methods are covered in the following section.

2.3.1.2.1 Identifying Skin Lesions

Identifying skin lesions is a challenging task that has been extensively studied in the literature. The diverse shapes, sizes, and colors of lesions, along with different skin types and textures, highlight the importance of creating an accurate method for segmenting these lesions. Estimating the outline of a lesion is essential for correctly extracting its features and thus characterizing the lesions. To prevent misclassification, it is necessary to use an appropriate method for segmentation. Consequently, these methods are classified into manual, semi-automated, and fully automated, and are designed to work with various computer-aided design (CAD) systems used in diagnosing skin lesions.

The shift in public perception regarding the delineation of skin lesions also supports the adoption of automated methods for approximating lesion boundaries through segmentation techniques [22,23]. Dermatologists have been reported to utilize advanced knowledge to determine lesion borders, leading to a consistent average reproducibility of segmentation outcomes. Nonetheless, Silletti et al. [24] contended that the current leading-edge in automated segmentation methods, excluding the Fuzzy C-Means (FCM), were not as effective as those of expert dermatologists. The complexity of the task can be attributed to various factors, including poor contrast, damage to adjacent skin, unclear boundaries, the presence of artifacts, and the irregular nature of skin lesion images. Readers are directed to the preceding section for details on pre-processing methods to improve image contrast and eliminate common artifacts in both global and local image processing techniques for microscopic images. Some studies have suggested that the areas of tumors manually identified by dermatologists have shown inconsistencies, sometimes due to their unique characteristics, which can be validated through automated segmentation methods, thereby enhancing the reliability of the results. Recently, there has been a notable advancement in the segmentation of skin lesions from the surrounding healthy skin areas to better support computer-assisted diagnosis. However, Chang et al. [25] maintained that the complete automatic segmentation of all skin lesion images is not feasible due to the variety of skin lesion types, making the acquisition of skin lesion images even more challenging and crucial. In certain studies, the use of the Karkunen Loeve Transform (KLT), also known as Principal Component Analysis (PCA), has been employed to refine the outlines of lesion images for improved segmentation outcomes. The existing literature suggests [29] that to achieve consistent segmentation of lesions using collective methods, bottom-hat and top-hat transformations have been applied to increase the contrast of lesion images. Research has explored various techniques for detecting the edges of skin lesions, which can assist in separating pigmented skin lesions from their surrounding areas automatically. While the aforementioned segmentation strategies have shown promising results, a common challenge with these methods is that the regions identified by machines are often smaller than those identified by dermatologists (the ground truth). This highlights the need to exclude certain areas near the tumor from further analysis in the diagnostic process. It has also been observed that some algorithms based on color information in non-uniform color spaces have not always led to satisfactory segmentation results. Evaluating the effectiveness of boundary detection methods can be subjective, involving the visual judgment of a medical expert on whether the boundary detection is accurate. Alternatively, objective evaluation may require adjusting parameters or comparing the results with other automated methods. This suggests that a combination of manual input from dermatologists and computer-assisted approaches can help in quantifying the effectiveness of boundary detection methods. In contemporary diagnostic practices, objective measures are increasingly used to assess the quality of segmentation results. When choosing a segmentation method, several factors need to be taken into account.

1) Central Processing Unit (CPU) vs. Graphics Processing Unit (GPU) processing: Over the last twenty years, there have been numerous advancements in methods for separating images into their component parts. However, challenges such as the need for too much computing power have limited their application. To overcome these challenges, there's a demand for more advanced vector processing techniques that can handle data parallelism, a capability that the GPU platform is particularly well-suited for.

2) Semi-automated vs. fully automated: Some image segmentation techniques are completely automated, while others still need some manual input. For instance, active contour methods typically need someone to manually draw the initial contours, whereas region-growing seed methods need specific initial seeds.

3) Structured Supervised Learning: The goal of these learning methods is to reduce the number of parameters needed for training and to segment the pixels of an object from the background. They involve the use of self-learning models to carry out the segmentation task. This discussion focuses on segmentation techniques that accurately identify the true boundaries of skin lesions. Following this, the next section will explore the various characteristics used to classify skin lesions in images.

2.3.2 Feature Extraction

While the extraction of features is crucial, selecting the right feature for a specific application often requires a deep understanding of the subject. Numerous studies have been conducted in this area, identifying a broad spectrum of dermatological features that can accurately characterize skin lesions and classify them correctly. The main aim of feature extraction is to identify the unified signs that pixels use to determine the malignancy of a skin lesion or to classify the type of skin lesion in an image. In an image, accurately isolating features is essential for precise classification.

To carry out a similar task, dermatologists traditionally classified skin lesion images, and it's equally important to identify characteristics that distinguish these lesions within a computer-assisted system. These characteristics can be categorized into two main types: global and local features, which are used for analyzing images. Global features represent the image as a whole, while local features focus on specific areas of the image. However, there's a broad spectrum of dermoscopic images that are characterized by skin lesions, and extracting these features can be a challenging task. These features are linked to skin deformities, and analyzing skin deformities caused by bacterial or viral infections is particularly difficult. The features also include the location on the body, the characteristics of the subject (such as age), the appearance of the image (view angle, lighting), and the impact of these image parameters on categorizing the lesions. These challenges often increase the complexity of the automatic screening and diagnosis of skin lesion images. Various attempts have been made to address these challenges as reported in the literature. One effective strategy is automated feature extraction. This method simplifies the analysis of lesion structures and provides crucial information about the lesions in skin lesion images. This information includes details about the anatomical structures of the lesions (such as shape, size, color, and location) or statistical knowledge about their properties, which are used to classify the skin lesions..

2.3.3 Classification Techniques

The objective of this phase is to reduce the dimensionality of the feature vector by eliminating the irrelevant and/or redundant features, thereby enhancing the accuracy of the classification score. The process of classifying images relies on selected features of the image, which helps in categorizing image pixels into one of several classes based on domain-specific knowledge. This can be achieved by training a model with a dataset and then evaluating the model's performance on a different dataset that is not related to the training set. Typically, the accuracy of classification results is influenced by the choice of descriptors and the robustness of the classifier. The effectiveness of automated classification methods is also dependent on the size of the dataset [36]. As mentioned in the literature on dermatological imaging, there are two primary types of classification techniques: unsupervised and supervised. These techniques aim to achieve effective classification by analyzing the characteristics of each pixel and selecting the most suitable features for matching during the classification of skin lesions. Numerous methods for classifying lesion images have been reported in the literature. These include Artificial Neural Networks (ANN), Support Vector Machines (SVM), K-Nearest Neighbor (KNN), Regression Analysis (RA), and Decision Trees (DT) classifiers. Among these, ANN is an interconnected network of nodes that resembles the structure of the human brain's neurons. Traditionally, neural network models have adaptive weights that are adjusted during the training phase and the capability to analyze the quantitative features of input images. The following subsections provide further insights and a concise overview of the latest advancements in techniques for detecting lesion borders, extracting features, and classifying lesions for skin lesion diagnosis. The main conclusion from this review is that the majority of research has been conducted using a uniform framework for diagnosing skin lesions, with a focus on melanoma. While melanoma is a severe type of skin cancer, there is also a need for methods that can distinguish between other types of skin cancer, such as Squamous Cell Carcinoma (SCC) and Basal Cell Carcinoma (BCC), also known as non-melanoma skin cancers. This highlights a gap in the literature regarding the classification of various lesion types belonging to melanoma or non-melanoma. However, there are notable exceptions, such as Iyatomi's proposed Computer-Aided Diagnosis (CAD) system, which is distinguished by its ability to differentiate between melanocytic and non-melanocytic lesions [41]. Ballerini et al. [42] have developed a robust system capable of classifying both melanoma and non-melanoma skin samples. Over time, numerous research projects have explored the classification of skin diseases through the application of image processing and machine learning methods. Prior to initiating this research, a questionnaire was distributed to collect existing information on the diagnosis of skin diseases through machine learning methods. This information was organized into three main groups: multi-class, binary, and other classification types, to understand the present state of technology in the diagnosis of skin diseases. The section of the chapter details each study, including the collection of data, data pre-processing, extraction of features, and classification.

2.4 Classification of Skin Diseases

Bajaj and colleagues (2018) gathered 813 photos from five distinct skin conditions, including eczema, psoriasis, impetigo, melanoma, and scleroderma, with the goal of identifying them through color analysis. The images underwent pre-processing steps such as median filtering, sharpening, and binary masking, followed by the extraction of Red, Green, and Blue (RGB) color statistics from each image. Subsequently, these color values were analyzed by an Artificial Neural Network (ANN) classifier, achieving a 90% accuracy rate [43]. Wei and his team (2018) explored the classification of herpes, paedures dermatitis, and psoriasis diseases, utilizing 10 standard and 20 test samples. They extracted Gray Level Co-occurrence Matrix (GLCM) texture features through the application of median filtering and marker-controlled watershed algorithm, in addition to clustering. The four GLCM features were evaluated using Support Vector Machine (SVM) classification, with accuracies of 85%, 90%, and 95% being recorded for the respective diseases. A Convolutional Neural Network (CNN) algorithm was applied to classify five different diseases. Images were collected from various online sources and the Dermnet dataset was rotated in all directions to augment the sample set. The softmax model was utilized in the CNN. Features related to border, edge, and color were extracted from each image. This feature-based classification approach resulted in a 70% classification accuracy. Islam and his team (2017) focused on the classification of skin regions affected by eczema, impetigo, and psoriasis using images from the Dermnet skin disease atlas database. The process began with the pre-processing of images and the selection of regions of interest through contrast enhancement, median filtering, and maximum entropy thresholding. GLCM texture features were then extracted and analyzed using an ANN's feedforward method. The system achieved an overall accuracy rate of 80% with a sensitivity of 71.4% and a specificity of 87.5%.

A Convolutional Neural Network (CNN) model, trained using the Non-dominated Sorting Genetic Algorithm – II (NSGA – II) framework, was evaluated with images from the International Skin Imaging Collaboration (ISIC) dataset [47]. This evaluation included images of angioma, basal cell carcinoma, and lentigo simplex. The dataset was prepared by applying the Daubechies DB4 filter to the GLCM (Global Linear Color Model) feature set, followed by Principal Component Analysis (PCA). The resulting GLCM image features included mean, standard deviation (SD), entropy, root mean square (RMS), variance, kurtosis, skewness, contrast, correlation, and homogeneity. These features were then tested across three different types of Neural Networks (NN): those trained with Particle Swarm Optimization, Genetic Algorithm, and NSGA – II. The research findings were summarized with an overall accuracy rate of 87.92% for the ANN-NSGA II model. Liao et al. (2016) explored the performance of a Convolutional Neural Network (CNN) for classifying skin diseases compared to characterizing skin lesions. They gathered 75,665 images from six online databases, including AtlasDerm, Danderm, Derma, Dermanet, and DermQuest. These images were utilized to train two CNN models: one for disease classification and another for lesion classification. The study demonstrated an accuracy of 27.6% for top-1 predictions and 57.9% for top-5 predictions, with an average precision score of 0.42 achieved through fine-tuning. The research also focused on classifying six distinct skin diseases: chronic dermatitis, lichen planus, pityriasis rosea, pityriasis rubra pilaris, plaque psoriasis, and seborrheic dermatitis. This classification was based on Sobel edge detection, color homogeneity, and Hue, Saturation, and Value (HSV) color model features. Images were collected from the Department of Dermatology at M. S. Ramaiah College, Mysore, and the University of California's learning data repository. The process involved converting images to grayscale, segmenting the diseased area using Otsu's thresholding and color-based segmentation techniques, and then analyzing the extracted features with ANN, K-Nearest Neighbor (KNN), and decision tree algorithms. The study concluded with an accuracy rate of 95%. In another study, the Adaboost classification algorithm was applied to classify dermatophytosis, melanoma, and psoriasis diseases. A total of 130 images were sourced from standard databases for this analysis. The classifier utilized luminance, texture, and entropy features, achieving an accuracy rate of 90%. Furthermore, Kumar and Singh (2016) developed a tool for detecting various skin conditions using the K-Nearest Neighbor (KNN) classification algorithm. A dataset of 130 images was collected from various sources for this purpose. The tool employed luminance, texture, and entropy features in its classification process, attaining an accuracy rate of 90%. Lastly, a study by Kumar and Singh (2016) aimed to develop a tool for identifying different skin conditions through the use of the K-Nearest Neighbor (KNN) classification algorithm. A dataset of 130 images was compiled for this research. The tool utilized luminance, texture, and entropy features in its classification algorithm, achieving an accuracy rate of 90%.

This research focused on examining various skin conditions. The images were improved using techniques like histogram equalization, and relevant characteristics were identified through methods such as HSV color histogram analysis and Speeded-Up Robust Features (SURF) blob detection. These characteristics were then analyzed by a K-Nearest Neighbors (KNN) classifier, resulting in satisfactory diagnostic outcomes [51]. In 2015, Sumithra and colleagues collected 141 skin lesions from five different skin diseases, including bullae (26), melanoma

(32), seborrheic keratosis (33), shigles (20), and squamous cell (30) to create a tool for computer-assisted diagnosis [52]. The data was sourced from the internet, and after segmenting the lesions, each was considered as a unique sample, increasing the total to 726. The diseased areas of each lesion were analyzed using various color models such as RGB, HSV, NTSc, Luma component, Blue-difference, and Red-difference (YCbCr), and the mean, standard deviation, variance, and skewness of these features were recorded. The classifiers KNN and SVM were tested with these features following a 70:30 rule, achieving a classification accuracy of 61%. To develop a system for classifying skin diseases, Amartunga and colleagues utilized images of eczema, impetigo, and melanoma, segmented them using thresholding and morphological transformations, and extracted color and shape features. They applied AdaBoost, BayesNet, Multi-Layer Perceptron (MLP), and Naïve Bayes classification techniques to classify these diseases. The system was able to correctly identify 85% of eczema, 95% of impetigo, and 85% of melanoma using the MLP method. Given that skin cancer diagnosis follows specific guidelines, it was straightforward to integrate into a machine learning system. With this in mind, a device for detecting skin cancer was created, incorporating geometry-based features such as area, perimeter, diameter, and circularity and irregularity indexes. Mobile camera images of melanoma, other skin cancers, and normal skin were used. The device achieved high accuracy using the ABCD classification rule.

Rather than setting psoriasis apart from other conditions, a research study identified three distinct forms of psoriasis: plaque, guttate, and erythrodermic psoriasis [55]. A total of approximately 30 photographs were captured using a digital camera with a low flash and a resolution of 1280×960 pixels. Prior to applying Daubechies wavelet transformation, only the affected areas were selected, each with a window size of 64×64 pixels. These feature values were then used to create an error plot with a 95% confidence level. Six different skin diseases were examined, achieving an accuracy rate of 94% [56]. This analysis included acne (107 images), eczema (102 images), psoriasis (105 images), tinea corporis (105 images), scabies (182 images), and vitiligo (101 images), all captured with a Panasonic LumixFZ-35 camera under natural lighting conditions. The skin lesions were then cropped and segmented using morphological processing and thresholding techniques. Following segmentation, GLCM (Global Linguistic Coherence Matrix) features were extracted and inputted into an ANN (Artificial Neural Network) classifier for decision-making. The overall accuracy of the classification process was found to be 94%. A different tool for detecting skin cancer, the Samsung Galaxy S-plus, was utilized to analyze images of three skin cancer types: melanoma, dysplastic nevus, and benign nevi. A total of 3,000 lesions from these three cancer types were used. The analysis included the extraction of color, area, perimeter, and GLCM texture features for classification. These features were tested across 11 different classifiers, with accuracy rates ranging from 80% to 90%. In a separate study by Yusof et al. (2011), the focus was on distinguishing between plaque, guttate, and erythrodermic psoriasis. Images from a digital camera were converted from the RGB color model to the HSV color model and evaluated using a fuzzy logic classifier. The accuracy of classifying within each disease type was found to be 81.82%.

2.5 Binary classification research

Li and Shen (2018) developed a CAD technique for identifying melanoma at its early stages. The research was segmented into three main tasks: identifying the 11th segment of a lesion, extracting features from the lesion's dermoscopic characteristics, and classifying the lesion. A straightforward Convolutional Neural Network (CNN) was utilized to extract these dermoscopic features, while two Fully Convolutional Residual Networks (FCRN) were used together for both segmentation and classification tasks. The dataset used came from the ISIC database's 2017 edition. The system achieved an accuracy of 75.3% for the first task, 84.8% for the second, and 91.2% for the third. Kalaiarasi et al. (2018) gathered images of nevi and ringworms from Google Images with the goal of identifying these diseases based on their shapes. The process involved using the Sobel edge detection method to identify the shapes, followed by enhancing the images with median and smoothing filters, as well as sharpening techniques. The final step was to use an Artificial Neural Network (ANN) classifier, which demonstrated a high level of accuracy. Giotis et al. (2015) employed a cluster-based adaptive metric method to classify images of melanoma from nevus skin cancer. They collected 130 images using either Nikon D3 or D1x cameras, a Nikkor 2.8/105 mm microlens, and a distance of 33 cm. The images were preprocessed to remove hair using the DullRazor software, and then segmented using the HSV color model-based K-means clustering method. The cluster-based adaptive metric method was then applied, achieving an accuracy of 81%. A tool was created to differentiate between plaque psoriasis lesions and normal skin. Images were captured with a Sony Nex-5 camera at a resolution of 350 dpi from 30 patients, resulting in a total of 540 lesions, of which 270 were plaque psoriasis and 270 were normal skin. The tool extracted features from these images, including RGB, HSV, YCbCr, and L*a*b color features, as well as 17 GLCM and GLRM texture features. These features were then tested in 46 different combinations using a Support Vector Machine (SVM) classifier. The classifier was tested with various kernel types, including Radial Basis Function (RBF), linear, and polynomial, in five, 10, and 20-fold cross-validation sets. The tool achieved an accuracy of 99.81% when using a polynomial kernel for classification. Instead of relying on digital camera images, dermoscopy images proved to be highly effective for diagnosing skin diseases, particularly skin cancer. The research by Sheha et al. (2015) involved classifying dermoscopy images of malignant melanoma (n=51) and melanocytic nevi (n=51). All the images were resized and converted to grayscale before extracting GLCM texture features.

The ANN classifier utilized various features to forecast the class labels, achieving an accuracy rate of 72%. In a study by Ramlakhan and Shang in 2011, they aimed to distinguish between benign and malignant melanoma by analyzing images captured with a digital camera. They computed the average and standard deviation of the RGB color values, along with other shape characteristics like significant defects, circularity index, and hull or contour ratio. These attributes were examined through K-Nearest Neighbors (KNN) classifiers, which reported accuracy rates of 80.5% for benign lesions and 60.7% for malignant lesions. [64] Fassihi et al. in 2011 explored the use of wavelet features for classifying melanoma and moles, employing a digital camera to capture images of 71 melanomas and 20 moles. Following the segmentation of the affected areas through morphological processing, the wavelet values were calculated. The system underwent training and evaluation with the ANN classifier, achieving an accuracy rate of 92%.

2.6 Additional categorization or division studies

Munia and colleagues (2017) categorized diseased skin lesions from healthy skin. They captured 45 images of plaque psoriasis using a 16-mega pixel camera and manually cropped them before applying the segmentation process. The CIE's L*a*b color space, along with K-means clustering, was utilized for identifying regions of interest (ROI). The segmentation was refined through erosion and dilation steps. This approach was then validated against manually selected reference areas, achieving an accuracy rate of 93.83% [66]. The segmentation of malignant melanoma lesions involved identifying the affected regions in the body [67]. Images of melanoma and benign nevus were gathered from online databases. The process included morphological closing, transformation of color spaces, and correction of illumination to eliminate noise. Subsequently, the images underwent segmentation using Otsu's thresholding, Canny edge detection, Sorensen Similarity Index (SSI), and hole filling algorithms. This method was successful in achieving a 93.71% accuracy rate for segmenting lesions. Beyond the classification of skin diseases, a study also explored the levels of melanin and hemoglobin in the human hand. Koprowski and colleagues (2014) acquired two-dimensional images (4,000 in total) from five hyperspectral images taken by the Specim PFD-V10E camera. These images spanned three areas of the hand: the fingers (13 in total), the metacarpus, and the wrist. The study isolated these regions using the nearest neighbor method and calculated melanin and hemoglobin values by examining the brightness at specific wavelengths λ.

Lu and colleagues (2013) created a method to divide psoriasis lesions within images. They gathered a total of 722 lesions from 103 images captured with Fuji Pix S2, Nikon D300, and Nikon D3100 cameras in a controlled indoor setting. The method involved extracting L*a*b color and Gabor texture characteristics to distinguish between lesion and normal areas. These characteristics were then evaluated using K-Nearest Neighbors (KNN) and fuzzy C-means clustering to identify the psoriasis region. The results from these classifiers were then compared with those from Support Vector Machines (SVM) and found to perform better [69]. The characteristics of an image also play a role in automatically identifying lesion boundaries. Juang and Wu (2011) managed to automatically isolate plaque psoriasis lesions using edge detection features [70]. They employed five digital cameras and the Sobel edge detection algorithm for this purpose. The K-Nearest Neighbors (KNN) algorithm was used to make decisions, and the tool achieved an accuracy rate of 89%. This review of literature demonstrated that it is feasible to develop a tool for diagnosing skin diseases through the analysis of image-based features. However, several limitations were noted in the reviewed studies, including: 1. Some research groups generated extensive training and testing datasets from the original images by applying image cropping techniques, which could potentially lead to the duplication of lesions and negatively affect the classification process's efficiency. 2. The majority of the studies failed to provide clear explanations for the selection of diseases or features, and only a few included images collected directly from patients at hospitals. 3. The majority of the studies were not independently verified by dermatologists.

CHAPTER 3

CHAPTER 3

PROPOSED METHODOLOGY

This section offers a summary of ensemble learning techniques for classification tasks. It specifically concentrates on structured analysis of skin diseases for disease categorization. The section outlines two proposed stages: the initial stage, which selects the most suitable datasets, and the second stage, which involves a competitive ensemble classification model. This model integrates multiple classification models to compete and determine the most effective classifier for the dataset. These stages aim to enhance the accuracy of classification for structured skin health data. Classification is a key method in decision-making for selecting data. Its primary objective is to develop an Intelligent Skin Disease Prediction System capable of identifying the occurrence of skin diseases to enhance classification accuracy. This section discusses the proposed ensemble learning techniques for classification in the context of predicting skin diseases by classifier, providing a brief overview of the method..

3.1 Understanding Convolution Neural Networks in Melanoma Detection

In this section, we will provide a basic overview of Convolution Neural Networks (CNNs) and discuss how to enhance their performance. Convolution Neural Networks are a specific type of feed-forward neural network designed to automatically extract features from images through a mathematical convolution operation. These extracted features are then passed through additional layers that progressively learn more complex features from the previous ones, mimicking the way the human visual cortex works. As a result, CNNs are capable of creating more intricate concepts from simpler ones, such as identifying a human face by recognizing basic features like the nose and mouth, which are derived from even simpler features like corners and contours. For instance, Figure 3.1 demonstrates a basic CNN model that is trained to determine if a patient has melanoma by mapping the extracted features into more abstract feature spaces. The architecture of a CNN is crucial, encompassing layers, activation functions, and hyper-parameters. The main types of layers in a CNN are Convolution, pooling, and fully connected layers. An activation function is a mathematical transformation that converts the input signals into the output signals necessary for the neural network to operate. Common activation functions include linear activation, Sigmoid functions (which include logistic and hyperbolic tangent), Rectified Linear Units (ReLU), also referred to as piecewise linear functions, Exponential Linear Unit, and Softmax. Hyper-parameters are variables that control the behavior of the network, such as the size of the filter kernel, batch size, padding, learning rate, and choice of optimizers. Optimizers are algorithms that aim to optimize the network's performance, with examples including Adam, Rmsprop, Nesterov, and Sobolev gradient-based optimizers.

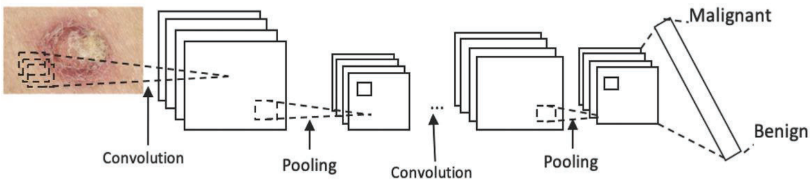
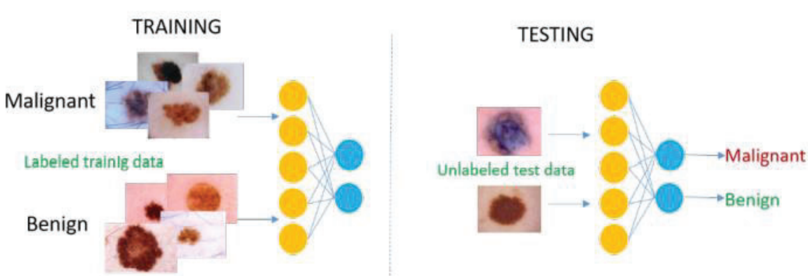


Figure 3.1 Diagnosis of melanoma with a simple CNN model

Convolutional Neural Network Structures

Convolutional neural networks come in a variety of structures. These structures are essential for developing complex machine learning models. In this section, we provide a concise overview of some of the well-known CNN models, such as AlexNet, VGG, Inception, ResNet, DenseNet, Xception, MobileNet, NASNet, and EfficientNet, among more than a hundred CNN models. 3.2 Diagnosis of Skin Cancer Lesions Lesions on the skin can be categorized to aid in the detection of melanoma, a type of skin cancer known for being highly deadly. These skin cancer lesions can be classified into different categories, with the major ones being malignant and benign. They can also be sorted into even more specific classes. Among these, melanoma is the most severe type of cancer lesion. Image classification involves using selected features to classify pixels into classes based on a specific knowledge domain. Most lesion classifications are binary and influenced by feature descriptors and classifier strength, with performance dependent on dataset population.



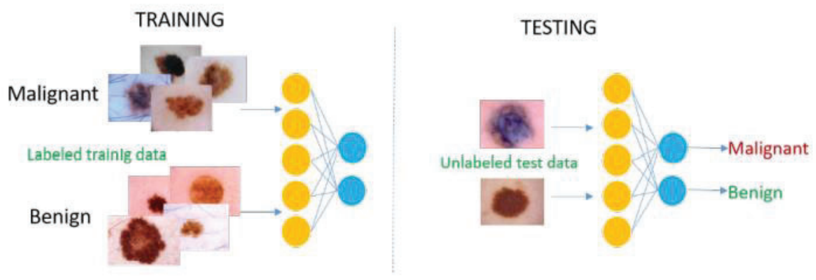


Figure 3.2 A classification model of melanoma.

The paper discusses two main types of medical imaging classification: supervised and unsupervised. Supervised classification uses statistical categorization based on reflectance, matching signatures, and maximum likelihood to assign pixels to the highest probable class. Unsupervised classification divides unknown pixels into categories based on natural groupings using clustering procedures. Both methods have been used in multiple studies for lesion classification.

3.3 Approaches to boost CNN for identifying melanoma

In the last decade, there's been a significant increase in the development and use of modern CNN models to tackle complex real-life problems. To better train these models, scientists also explore advanced techniques. In this section, we'll discuss the four main approaches: multitask models, groups of CNNs working together, methods to increase the size of the training data, and strategies for leveraging knowledge from previously trained models. This part will give a quick overview of the Random Forest Deep Convolutional Neural Networks model, also referred to as the Predictive Ensemble Deep Convolutional Neural Networks Classifier (RF-DCNN). The purpose of this research is to devise a strategy that is effective in categorizing images from dermoscopy into seven categories. This part will explain the process for gathering, accessing, and examining data concerning skin conditions. This method is highly effective in identifying seven distinct skin conditions. The architecture can be broken down into its preprocessing, feature extraction, and classification stages. Figure 3.3 illustrates the proposed design.

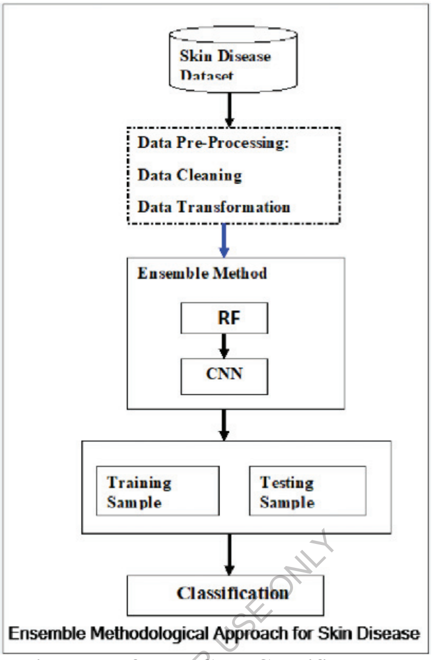


Figure3.3 Architecture of RF-DCNN Classifier based on CNN

3.4 Melanoma image datasets for diagnosis

A number of public and private datasets have been made available in recent years as a result of the disease's ongoing global increase in incidence. This has made it possible to gain a deeper comprehension of the condition and, as a result, to develop methods for automatic diagnosis that are more efficient. The most well-known private collections of dermoscopic images are the Interactive Atlas of Dermoscopy, the Dermofit Image Library, and the dataset that was presented. The dataset used 129,450 clinical images to compare with 21 dermatologists. The ISIC repository has the most publicly available datasets for melanoma research, all of which are dermatologist-labeled images. The 10015 dermatoscopic images that make up the HAM10000 training set were collected from Cliff Rosendahl's skin cancer practice in Queensland, Australia, and the Department of Dermatology at the Medical University of Vienna, Austria, over a period of twenty years. Pictures and meta-information were kept on the Australian site in Succeed data sets and PowerPoint records. The Austrian website began storing photos and metadata in a variety of formats before digital cameras became commonplace. When contrasted with assessment with the independent eye, dermatoscopy is a normally utilized indicative method that upgrades the finding of harmless and dangerous pigmented skin sores. Dermatoscopy images can be used to train artificial neural networks to automatically diagnose pigmented skin lesions. Expectations for automated diagnostic systems that can diagnose various pigmented skin lesions without the need for human expertise have increased in response to recent advancements in machine learning and graphics card capabilities. Additionally, the complexity of these systems' neural networks has broken new records. The dataset is necessary for the neural networks we recommend using for automated diagnosis to be trained. The skin disease dataset HAM10000, which was taken from Kaggle and used as a baseline database, was taken from the original webpages of the ISIC archive. Additionally, the majority of studies do not employ a standard exploratory approach and only use a small number of datasets. Age, orientation, and cell type are remembered for the dataset in metadata designs like a comma-isolated values record (. CSV). More than 10,000 dermatoscopic data points were gathered from individuals all over the world for this collection. Additionally, the dataset includes additional suggestions and recommendations for resolving the issue. The training dataset's real-world facts are used to evaluate the model. In our proposed model, the image's width should be 224 224 pixels. The primary objective of this study is to test our proposed method's diagnostic accuracy for skin cancer based on dermatoscopic data. Figure 2 shows a few images from the HAM 10000 Dataset.

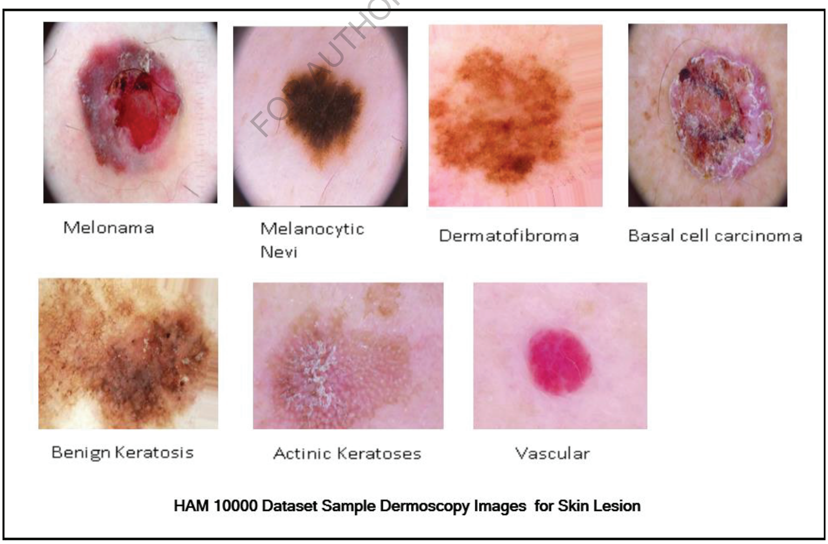


Figure 3.4. HAM 10000 Dataset Sample Images

3.5: Pre-processing Images of Skin Lesion

The model may be able to generalize more successfully if image quality is improved. In a visual, preprocessing can reduce the amount of redundant data while simultaneously increasing the intensity of important data, simplifying data, and increasing reliability. "Image resizing" refers to the process of resizing an image. The issue of various example sizes in the data set is settled by either expanding or diminishing the size of a picture. All images will have the same number of characteristics if their size is reduced. By reducing processing time, reducing the visual also speeds up the system. Preparing the data is the first step in the approach described in this research article. The data acquired from records isn't generally exact and may contain commotion, inaccurate or missing numbers, or conflicting information, in addition to other things. This is a step in the process of getting the data ready. For our study, each input sample image needs to have certain characteristics like color, texture, and form. To dispose of these inconsistencies, we should apply various information cleaning systems. Even after being cleaned, the data are not ready for mining because they are in multiple formats that cannot be used directly. As a result, they must be converted into mining-friendly formats. Normalization is a transformation that accomplishes this, and it also makes use of other techniques like smoothing and aggregation. 3.6 The ensemble method refines models by utilizing skin image data. Algorithms by evaluating the accuracy of the skin disease dataset. Using Convolutional Neural Networks (CNNs) and the Random Forest method, the framework examines two alternative ensemble machine learning techniques.

3.6.1 Random Forest Technique

Random forest technique is therefore appropriate for large data sets and analysis of such datasets. Random Forest classifier was used to enhance accuracy and performance in this study. In the study, we propose using random forest algorithms to improve skin image segmentation, classification and compare them with HAM 10000 data set. This proposed approach might generate high-resolution feature maps that can help keep picture spatial information intact. Also, this model is simple but clever and works even in difficult cases. Man et al.'s work states that Random forest assists in building several decision trees which ultimately export the class of the input variable

In our research, random forest can be used to solve over-fitting problems that often happen with decision tree training set data. They use a bootstrapping aggregating technique for tree learners. The link exists between kernel techniques of the random forests and this is commonly referred to as kernel random forest which makes it easier to understand or interpret them. This algorithm's predictive performance matches some of the best supervised learning algorithms while simultaneously giving constant feature location estimates. Random forests are a kind of meta estimator designed to develop multiple decision tree-based classifiers on various sub-samples of a dataset, while also applying averaging techniques to enhance the accuracy of predictions and prevent over-fitting. The random forest method involves creating numerous decision trees that collaborate as a group, offering a class prediction based on the decision tree with the highest number of votes.

Every distinct structural framework will be surpassed by a vast array of closely unrelated trees functioning as a group. The lack of correlation among various frameworks is the primary concern. The trees within the random forest algorithm shield each other from their specific weaknesses. While single decision trees have been shown to be successful in identifying skin lesions, a group of trees can still achieve success even if a few are flawed, leading to a total accuracy that surpasses that of single decision trees. Given the extensive number of trees involved in the process, the random forest approach is considered a highly precise and strong model. Moreover, it sidesteps the issue of overfitting by averaging all the predictions, which neutralizes the biases. The subsequent are the prerequisites for a random forest algorithm to excel:

a) For models to excel, the spread of attributes needs to hold significance, ensuring that those generated based on these traits outperform those constructed through mere random guessing.

b) Each tree in the random forest technique should have minimal connections or interactions with other trees for the system to accurately predict outcomes. The method outlined here is versatile, capable of addressing both regression and classification issues, and it involves four essential phases:

Phase 1: Select a subset of random samples from a provided array of skin lesion characteristics.

Phase 2: For each selected sample, develop a decision tree and derive a prediction from each tree

Step 3: Cast your ballot for each of the predicted outcomes from the last step

Step 4: As the ultimate decision, select the predicted outcome that garners the highest number of votes. Given the presence of many decision trees, the process of making predictions takes more time and understanding becomes more challenging. Therefore, it is advisable to employ an effective method for selecting or excluding features before classifying.

3.7 Utilizing Deep Neural Networks for Identifying Skin Diseases

Within the domain of computer vision, the convolutional neural network (CNN), characterized by its extensive layers of neuron-like computational units that process data in a step-by-step manner, has seen considerable advancements. To assess the effectiveness of the proposed deep neural network for categorizing skin diseases, the Predictive Ensemble Deep Convolutional Neural Networks Classifier (RF-DCNN Classifier) was created by optimizing the model's parameters. Classifiers are mathematical models that can assign a new observation to one of several categories. In this research, the RF Classifier based DCNN Classifier is utilized for classification. This classifier is particularly well-suited for this purpose.

Because it utilizes a combination of models for pattern recognition, but adding more layers to the model increases the complexity of the training process. The data is processed through integrated modules to extract image representations from the HAM 10,000 database, utilizing a pre-trained framework for analysis. We use three distinct small filter sizes in each module. Each module has 2D capabilities. The hidden layers are multi-layered, capable of handling complex compounds, and are activated by ReLU (Rectified-Linear-Unit) as the activation function. A network is completed with a split module, consisting of three fully integrated layers. In scenarios where the predicted feature values are known but the class label is unknown, the model assigns class labels based on the predicted feature values. This article employs a supervised learning method for classification. Algorithm for RF-DCNN Classifier:

Start To derive multi-dimensional characteristics, transform the visual attributes of skin images from the given dataset (HAM10000) into the deep learning model (RF-DCNN);

Collect the multi-dimensional unique characteristics;
For each skin image in the dataset,
 - Train the deep learning model from the beginning to the end;
 - Extract the skin images with the multi-step features;
 - Supply the deep learning model with the skin image data;
- Classify the skin conditions using the deep learning model; End for each skin image in the dataset.
End

CHAPTER 4

CHAPTER 4

RESULTS AND PERFORMANCE ANALYSIS

EXECUTIVE SUMMARY

This study discussed the use of machine learning and deep learning for predicting Skin Disease cases, both for patients and non-patients. We analyzed the results, which confirmed that the proposed models were more effective than traditional methods. Additionally, the study highlighted several key findings.

4.1 Key Insights from the Research

We used several metrics, such as mean-accuracy, precision, recall, and F1-score, to assess the effectiveness of the Random Forest Deep Convolutional Network (RF-DCNN) Classifier model. Our assessment was made using the HAM10,000 dataset and Python 3.6, with randomly selected images from each class serving as training samples. This research contributed to the creation of a system for predicting skin conditions. The necessity for such a system is clear since regulators and healthcare organizations lack comprehensive plans for developing information systems. This gap may stem from a scarcity of personnel with the necessary technological skills or insufficient staff to manage information systems. On dermatological data, our combination of machine learning and feature selection outperformed standalone machine learning models. This hybrid approach proved to be more reliable and accurate in predicting skin diseases. Table 4.1 outlines the comparison between the proposed ensemble classifier and standalone deep learning models for classification accuracy. Figure 4.1 illustrates the difference in performance between the traditional learning model and our innovative mode

TABLE 4.1. Performance analysis with traditional deep learning-based models

Percentage of performance for various metrics	Classical CNN based Model	RF-DCNN Classifier model
Precision %	88	95.41
Recall %	89	94.93
F-measure %	89	95.17
Accuracy %	88	96.1

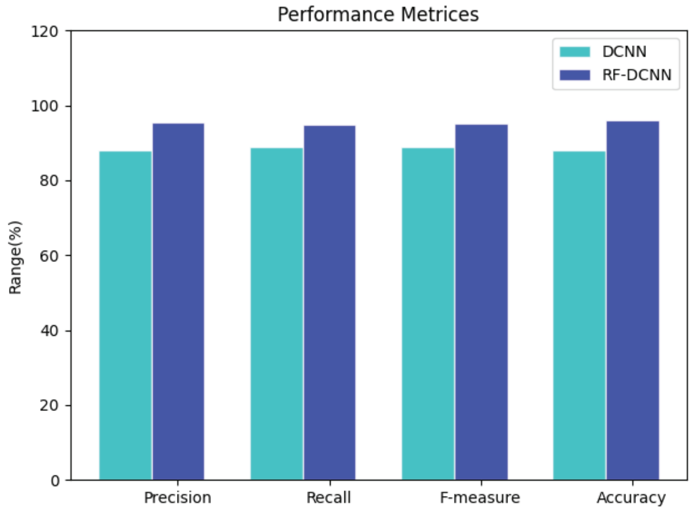


Figure 4.1. Effectiveness of Performance Metrics on RF-DCNN and CNN based Models

The amalgamation approach improved several older Convolutional Neural Network (CNN) models in terms of mean accuracy, precision, f1-score, and recall, as detailed in Table 1. Criteria for assessing the performance of skin lesion segmentation and classification, including accuracy, sensitivity, and specificity, can be utilized for comparison. This research identified a range of advanced techniques for evaluating performance, with the findings presented in Table 2. In these evaluations, terms such as true positive (TP), false positive (FP), true negative (TN), and false negative (FN) are frequently used. The analysis involved maintaining and integrating layers from a previously trained network. The research utilized two distinct classification techniques:

The random forest Classifier and the Deep Convolutional Neural Networks Classifier. By employing these methods, the highest mean accuracy of 96.1 percent was achieved.

Table 4.1 demonstrates this, the model highlighted in the study demonstrated significant similarity in data segmentation with the model presented in Table 1. The combined models achieved a 96.1% accuracy, suggesting that this approach is more effective in identifying seven types of skin disease compared to the deep neural network on its own. The proposed method leverages the strengths of various prediction models and integrates detailed features from numerous well-trained and well-configured Deep Convolutional Neural Networks at different output levels. This study explores various data mining strategies for predicting skin diseases.

To predict skin conditions, two machine learning techniques were applied: random forest classifier and CNN.

4.2 Benefits

Convolutional Neural Networks (CNNs) are being integrated into mobile devices with increasingly favorable outcomes, allowing for a growing variety of applications to leverage the extensive capabilities of today's smartphones and tablets. The widespread use of these devices in daily life simplifies the process for developers to address common issues using these technologies. The potential for real-time detection, such as the Yolo melanoma detector on mobile phones, is on the horizon. When faced with a small amount of data, techniques like k-fold cross-validation can be employed. This method involves training k models simultaneously to compute an average, which is similar to using the same model for various tests on the same data. However, not all training data sets are identical, highlighting the need for an expanded data set. If the average performance of the k models is satisfactory, it indicates that the model exhibits a certain level of generalization capability. In situations with limited data, k-fold cross-validation could prove to be an effective strategy in the future. Our models have identified potential solutions for diagnosing skin conditions using minimal data. dataset by DL and laid the foundation for future mobile applications.

4.3 Drawbacks Nonetheless, our findings are not without their limitations

For instance, the outcomes from our three studies rely on distinct, smaller databases, leading to variations in the actual ground truth and the benchmark for the review model. Establishing a consistent baseline for comparing research is crucial. Moreover, the range of tasks we examine is broad, including classification and detection. Achieving significant advancements in deep learning with such limited data is a considerable challenge. The primary concern is that our accuracy remains significantly lower than the ideal state, which is over 90%. In our skin disease classification study, we only identify two categories: benign and malignant. However, we argue that there should be a category that bridges these two, as this could help in identifying cases of misdiagnosis. Typically, this intermediate category is essential for determining if a patient has been misdiagnosed.

CHAPTER 5

CHAPTER 5

DISCUSSIONS

This part delves into the obstacles and prospects for Deep Learning in the diagnosis of melanoma, with the goal of examining these issues and highlighting both challenges and opportunities within this area. Our analysis is based on the literature reviewed and the related fields of Computer Vision, Pattern Recognition, and Machine Learning. In this section, we offer advice and guidance to address the inherent difficulties in utilizing Deep Learning for melanoma diagnosis.

5.1 Obstacles in Diagnosing Skin Diseases

This thesis addresses the major hurdles in fully leveraging Deep Learning's capabilities for analyzing skin cancer. Rather than detailing the specific problems faced in certain tasks, we concentrate on the fundamental obstacles and elucidate the underlying reasons for these issues.

The Melanoma Imaging group aims to shed light on the specific difficulties faced in the task. We showcase the possibilities of using computer-assisted diagnosis (CAD) systems, which rely on deep learning (DL) models, for identifying skin cancer. However, there are multiple issues that need to be tackled to enhance these systems.

Low contras

Difficulty in identifying melanoma in skin images Identifying melanoma in skin images through automated methods is difficult because of the low contrast of skin spots, the wide range of differences within melanomas, and the significant similarity between melanoma and other skin conditions—there are many distortions in the image. The poor contrast between the normal skin and the areas showing signs of melanoma is often observed. Other reasons for this challenge include differences in skin color, irregularities in the skin, such as the presence of distortions (like hairs, ink, bubbles, ruler lines, date stamps, color calibration charts, etc.), uneven lighting, and inconsistent darkening around the edges (known as vignetting), the position of the skin spot, and the most critical differences in the skin condition, including color, texture, shape, size, and location within the image. Researchers need to take these aspects into account when creating a reliable algorithm for identifying skin spots. Taking the right steps before identifying the spots can reduce the impact of most of these issues.

Black-box

Convolutional Neural Networks (CNNs), on the other hand, are opaque models, meaning there's a lack of clarity on how these models arrive at their final decisions, which could lead to both practical and ethical concerns in the field of biomedicine. The majority of Computer-Aided Diagnosis (CAD) systems that have been studied adhere to a series of steps: removing artifacts, identifying lesions, extracting features, and classifying lesions as benign or malignant. These systems perform well in lab settings but often select features that lack medical relevance or are difficult for doctors to understand. Moreover, the methods for extracting these features are often not clearly outlined, making it difficult for other users to replicate these algorithms.

The main challenge with Deep Learning (DL) is its inability to provide clear explanations for how these algorithms reach their decisions. This can be likened to a black box that takes in inputs and spits out results without detailing the process of how those results were generated. If an algorithm wrongly identifies a malignant lesion, it cannot justify its decision. While the results can be useful when the model fails to explain why it classified a skin lesion as malignant or selected a specific treatment, it poses a risk and issue for the patient. The process of interpreting the model's output by physicians is a significant challeng Need to justify the choice of a diagnosis or treatment method. Deep Learning (DL) systems, like all algorithms, are susceptible to the saying "garbage in, garbage out." This saying suggests that the accuracy of the data provided to the system directly affects the accuracy of the results it produces. Thus, if the labels on these images are not accurate, the results generated by the algorithm will show these mistakes.

Single model

The current research on CNNs often focuses on a single model, which is assessed on a particular dataset. This approach doesn't thoroughly explore ways to address the difficulties associated with diagnosing melanoma, such as the significant imbalance between different classes often found in melanoma datasets. As a result, our knowledge about how well CNNs perform in diagnosing melanoma is rather limited, making it challenging to choose the best model for a given dataset.

Lack of dermatologists

These deep learning models assist in facilitating specialized diagnoses in regions where there's a shortage of dermatologists. Nonetheless, it's challenging to assess the precision of these models when they're employed without any doctor's guidance.

Underrepresented color of skin

The majority of those academics concentrate on data and photographs from North America, Europe, Australia, and the United States. Conversely, there aren't many research in Asia that concentrate on Chinese, Korean, or Japanese patients. Some even observed that research on Asian patient photos outperformed research on Caucasian patient images. Since many cutaneous diseases manifest differently in skin of color, applying algorithms developed on photos of fair skin could be erroneous when applied to skin color. Since DL models are still in their infancy, there is a chance to advance these research by making sure patients of all racial and cultural backgrounds can utilize this technology.

Uncertainty and the dataset

CNNs have demonstrated efficacy, however their diagnostic capabilities for melanoma remain restricted mostly because to the volume of data required for the construction of precise models. However, gathering medical data is difficult, especially when it comes to skin cancer. Consequently, the scarcity of training data is one of the primary issues with using deep learning for this purpose. As previously said, the ISIC archive is crucial to solving this problem. The sample size that is now available, nevertheless, is still too small and uneven among the courses. Numerous methods, including weighted loss, data augmentation, transfer learning, and up/down sampling, have been proposed to address these issues. However, there is still room for advancement in the future and methods to advance with little data.

To enhance the accuracy of clinical recognition models, lesion sites associated with skin diseases can be the focus of attention mechanisms or target detection techniques. This will facilitate the extraction of features from the lesion sites. It is also crucial to recognize that one of the task's limitations is the dearth of clinical data that is currently available. The degree of information that is available in each image varies significantly between dermoscopic, clinical, and histological images. Therefore, it is not possible to reuse a model that was trained solely on dermoscopic pictures in order to predict clinical symptoms. Previous clinical data-related works either merged tiny datasets or had access to private ones. Thus, a coordinated effort is required to develop a clinical and histological

Prejudice

Understanding the current bias that skews the models' performance is another difficulty in the identification of skin cancer. The research conducted indicates that the models are guided by misleading correlations. Additionally, a few skin kinds are present in some databases, like the one that was used, which adds to the bias. To implement a model to identify skin cancer in a more varied population, all these factors have to be taken into account.

Uniformity of images

To guarantee the reproducibility of results, the medical research community should embrace image standardization. To enable appropriate benchmarking of study findings, efforts should also be made to establish a comprehensive picture collection comprising a range of skin lesion samples, categorized according to the types of lesions, and made available to researchers. To cut down on complexity and laborious calculation, we suggest concentrating more efforts on optimizing feature selection. Many of the classification models that have been suggested in the literature still have certain drawbacks, such as imbalances between the classes of lesion images, difficulties identifying distinguishing visual characteristics, and the impact of multiplicities of certain lesion image classes. We think that the quantity of features needed may be less stressed.

Metadata

In order to diagnose a patient, patient information is crucial. From now on, we can include patient history in the classification step, including things like age, hair loss, and skin itching. It is imperative to incorporate the patient's demographic information (metadata) with the photos. It has been demonstrated that the DL systems may be able to handle the lack of a large number of images by using metadata.

The problems mentioned above are most data problems that we all face when doing skin disease image processing. However, we also have three algorithm directions to continue to advance and explore in the future. Despite the advantages that some techniques offer for better training

5.2 Prospective avenues

The majority of the data issues that we all encounter when processing images of skin diseases are those that were previously described. In the future, nevertheless, we still have three algorithmic avenues to pursue and investigate. While ensemble, multitask, and GAN learning approaches have advantages over other methods for improving CNN model training, it should be noted that their application has serious drawbacks. For instance, GAN-based models necessitate a sophisticated training procedure that finds a balance between the discriminative and generative models. As gradients may cause random oscillations, GANs commonly fail to converge. A GAN-based model must be set up through an expensive tuning procedure, which restricts its appropriate use in some real-world scenarios. Lastly, the primary obstacle to multitasking learning using this paradigm is the scarcity of publicly available datasets. It includes inconsistent data for every sample (e.g., clinic data and dermoscopic pictures with their corresponding metadata), which hinders the creation of precise multitask models for diagnosing melanoma. As we can see, the ultimate diagnosis can be made by the expert by recognizing recognized patterns in the image. Even if it is a difficult undertaking, the ultimate objective of a CAD system used for skin cancer detection should be achieved. CNN still has many limitations and has not been proven effective in prospective clinical trials for the screening of melanoma or non-melanoma skin malignancies.Beyond the straightforward job of distinguishing benign from malignant lesions, DL has applications in teledermatology, dermatopathology, differential diagnosis, mobile apps, and personalized medicine. While deep convolutional neural networks have achieved great success in pixel-by-pixel image segmentation, their computational inefficiency hinders real-time and practical applications.

To achieve state-of-the-art outcomes in skin lesion segmentation while proposing an efficient network architecture.

CHAPTER 6

CHAPTER 6

CONCLUSION AND FUTURE ENHANCEMENT

6.1 Conclusion

This thesis provides an overview of the work done so far on melanoma classification. As we've seen, DL offers a wide range of possible uses in the diagnosis and treatment processes of dermatologists. Dermatologists can use DL to enhance their practice in both diagnosis and tailored medicine. The development of deep learning algorithms with human-like intelligence in dermatology has been aided by recent developments in computation speed, data storage cost, and access to big datasets (e.g., electronic medical records, image databases, and omics).
There are many promising opportunities for DL in the dermatologist's practice. The most emphasis has been paid to the classification of photos using CNNs because of its potential to improve dermatologists' workflow and make skin cancer screenings more accessible. This research contributed to the creation of a method for predicting skin conditions. Finally, data mining plays a critical role in the healthcare industry. This work develops integrated predictive heterogeneous ensemble models with several basic and weight-bearing criteria that are effective for multiclass dermatitis. To illustrate the efficacy of our method, the findings obtained in this investigation were contrasted with additional data from the literature. In order to compare the effectiveness of the suggested treatment of skin classification, we employed a large number of technical studies that used the same data but different classification techniques. We then created an ensemble method using multiple models to compare the effectiveness of the suggested treatment of skin classification. Next, in order to get the highest accuracy of 96.1 percent, we combine these two data mining techniques using a multi-model ensemble approach. We obtain the highest accuracy reported in the literature on the skin disease dataset. The machine learning-based multi-model collection approach reduces generation errors and gathers more data by using the first-stage prediction as a feature instead of a separate training. Additionally, machine learning is used to automatically understand the intricate relationships between classifiers, enabling the collection strategy to make

Algorithms and datasets for further validation and testing should be made publicly available to facilitate transparent research in deep learning. Prior to entering the market, strict Moreover, at 96.1 percent, the Random Forest Deep Convolutional Neural Networks (RF-DCNN) Classifier exhibits the highest accuracy among all these methods. Future developments and additions will be numerous.

A skin lesion on the skin layer should be discovered first, followed by the process of developing a skin illness in a developed smart phone system, and lastly, the detection of all skin diseases in the region as well as the degree of each disease. Prospective clinical trials with peer review ought to be carried out. In general, more dermatologists must be involved in the development and testing of DL if useful and therapeutically applicable technology is to be produced.

Smartphones, PDAs, and tablets are examples of mobile electronics that have become indispensable to modern life. Future trends will include the treatment of skin diseases and AI diagnosis on intelligent robots. Nonetheless, high-performance graphics processors are used to detect the majority of skin conditions. To make the algorithm easy to use on mobile phones and wearable intelligent devices, the computational complexity should be kept to a minimum while the system's recognition capacity is improved. The detection and treatment of skin diseases by AI will greatly benefit from this study with Reinforcement learning.

We also consider using dermoscopy and clinical imaging both in our work. When our accuracies

Significant restrictions. Future research will focus on developing a new classifier and improving it to use less complicated learning techniques. When deep learning algorithms reach a certain point, we'll also think about releasing the finished model for real mobile use. With further training sets, the tool can be developed for a greater variety of skin conditions.

The goal for the future is cost-effectiveness and accurate classification. By mining vast amounts of health data, it can be accomplished through healthcare data prediction. It is possible to adjust the threshold values that are set to each classifier. It enhances the performance of classification. Additional training parameters for EL can also be taken into account in the DL models. Selecting the most pertinent parameter for classification is helpful.

The proposed effort will aid medical personnel, including doctors, in accurately diagnosing illnesses and delivering high-quality health care.

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