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Human Skin Fungal Diseases Classification Using Deep Learning Technique

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Declaration

This thesis work is my original work and has not been presented for any other university.

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Approval Sheet

This is to certify that this thesis prepared by Tsedenya Debebe titled: 'Human Skin Fungal Diseases Classification Using Deep Learning Technique' has been read and approved as meeting the requirements of Jimma University Institute of Technology Faculty of Computing and Informatics in partial fulfillment for the degree of Master of Science in Information Technology conforms with the regulations of the University and meets the accepted standards concerning originality and quality.

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Acronyms

AI----Artificial Intelligence

ANN---Artificial Neural Network

CNN…..Convolutional Neural Network

GLCM…..Gray Level Co-Occurrence Matrix

JUMC---Jimma University Medical Center

IP…Image Processing

SVN…. Support Vector Machine

KNN-----K-Nearest Neighbors

ML-----Machine Learning

TN -------True Negative

TP---------True Positive

FN--------False Negative

FP---------False Positive

WHO----World Health Organization

DIP------- Digital image processing

MLP-----------Multi-Layer Perceptron

ReLU----------- Rectifier Linear Unit

ELU-------------Exponential Linear Unit

ILSVRC---------- ImageNet Large Scale Visual Recognition Challenge

ResNet -------------Residual Network

Abstract

The skin is our body's outermost layer. It has a lot of different functions. Since it is the outer covering of the whole body part that acts as a barrier, protecting our body from harmful things in the outside world such as sun rays, germs, and toxic substances. Skin plays a great role in body temperature regulation. Several risks affect the skin from those the common cause of skin disorder are bacteria, viruses, fungus. It takes a long time to identify a disease based on manual feature extractions or symptoms, and it requires a lot of expertise to do so correctly. There have been previous studies on the diagnosis, detection, and classification of skin diseases. However, in the previous work tinea pedies, and tinea corpories are not identified especially for black skin color.

In this thesis, we develop a model that uses CNN to classify skin fungal diseases such as tinea pedies, tinea capitis, tinea corpories, and tinea unguium. The images are then classified as tinea pedies, tinea capitis, tinea corpories, or tinea unguium by Softmax. We have collected 407 skin fungal lesion images from patients at Dr. Gerbi medium clinic of Jimma, and JUMC using the smartphone camera (Techno pop 2 power, Techno Spark4, SamsungA20). After collecting datasets, Image Preprocessing, Image augmentation techniques are applied to increase the performance of the human skin disease classification model. In this study, we have done image preprocessing (image size normalization, RGB to Grayscale conversion). We have normalized the images to three image sizes which are 120 x120, 150X150, and 224x224. From the total augmented 1069 images, 80% (727) for training, 10% (164) validation, and the remaining 10% (178) for testing. We have registered the overall performance accuracy of 83% using our CNN-based HSFDCModel after the model is evaluated. The accuracy achieved 79%, 69% for MobileNetV2 and ResNet50 respectively. This implies the developed model is better than the MobileNetV2 and ResNet50 pre-trained CNN Models for our dataset.

Keywords: Skin Disease, Deep Learning, Image processing, MobileNetV2, ResNet50, CNN.

CHAPTER ONE

INTRODUCTION

1.1 Background:

Human skin is the body's soft outermost layer. It contributes significantly because it is the largest organ distributed throughout the body, accounting for 16% of total body mass [1]. The human skin plays a big role in the physical appearance of a person. It offers protection against fungal infection, bacteria, allergy, and viruses and controls the temperature of the body situations that change the texture of the skin or damage the skin can produce symptoms like swelling, burning, redness, and itching [2]. When exposed to sunlight, the skin helps in the manufacture of vitamin D, It stores water and fat, acts as a barrier between the body and its environment, the skin surrounds all other parts of the body. The skin thickness varies all over the body, between men, women, and young or old.

Skin is composed of three primary layers: the epidermis, the dermis, and the hypodermis. The epidermis is the skin's outermost layer. It is constantly replaced as dead skin cells are shed every day, as it is the top, visible layer of skin. This layer contains melanocytes, which produce melanin, the pigment that gives skin its color. It also contains Keratin, a protein made by cells, and the epidermis gives skin its toughness, strength, and protects skin from drying out. It provides a waterproof barrier. The second layer is called Dermis. It is the skin's middle layer, found below the epidermis. It is the skin's thickest layer and contains nerves and blood vessels. Sweat glands, oil glands, and hair follicles are also found here. The dermis gives skin flexibility and strength. The roles of the dermis include sensing pain and touch, Producing sweat and oils, Growing hair, Bringing blood to the skin, and fighting infection. It is the deeper subcutaneous tissue, which is composed of fat and connective tissue. It aids in the insulation of the body against heat and cold. It also serves as a fat storage area for energy. This fat provides padding to cushion internal organs as well as muscle and bones and protects the body from injuries [3].

Skin diseases are one of the most common diseases found among humans that harm them, whether it is a small bump, which might lead to bothersome or a vicious structure and then to mortality [4]. There are more than 3000 known skin diseases worldwide [5].

Skin diseases are a huge burden on the world, and there is an alarming need to get them into control at early stages. Skin diseases are becoming the most common health issue among all the countries worldwide [6]. Skin diseases are the most common cause of all human illnesses which affects almost 900 million people in the world at any time [7]. Skin diseases are reported to be the most common disease in humans among all age groups and a significant root of infection in sub-Saharan Africa [8]. An estimated 21–87 % of children in Africa are affected by skin diseases [9]. Skin can be affected by fungal infections, viruses, bacteria, etc. According to the most recent WHO data published in 2018, the number of skin disease deaths in Ethiopia reached 2,459, accounting for 0.40 percent of total deaths [10]. It affects education, relationships, self-esteem, career choices, social, sexual, and leisure activities. Beyond these, skin diseases may cause a sense of depression, frustration, isolation, and even suicidal ideation [11]. Pathogenic fungi infections that only affect the human hair, nails, epidermis, and mucosa are referred to as superficial fungal infections. Dermatophytes are the most common cause of superficial fungal infections worldwide, and they are especially common in developing countries. Tropical and subtropical countries, such as Sub-Saharan Africa, are particularly vulnerable. The most common fungal infections are tinea corpories, Tinea capitis, Tinea Pedis, Tinea cruises, Pityriasis vesicular, etc. [12].

These infections are among the world's most frequent diseases, resulting in significant chronic morbidity. Tinea pedies is a fungal-caused skin infection that mostly affects the legs and feet. It's a fungal infection that commonly begins between the toes. It's especially common among persons who have sweaty feet from being constrained in tight-fitting shoes. A red rash between the toes, usually between the fourth and fifth toe, is the most prevalent symptom of athletes' foot. Tinea Corpories is a type of fungal infection that mostly affects the overall body like a hand, leg. It affects mostly children and young adults. Tinea Capitis is a fungus that affects the skin surrounding the scalp. Tinea unguium is a fungal nail infection caused by a fungus. Onychomycosis is another name for it. The Global Prevalence of onychomycosis is 5.5 % and contributes 50% of all nail diseases [13]. Tinea is a geographically widespread group of fungal infections caused by dermatophytes. Type predominance is influenced by the organism, its hosts, and geographical conditions. Contact with sick individuals and animals, soil, or inanimate items can all lead to infection. Tinea infections can be difficult to diagnose and treat accurately because of the similarity between different types of fungal morphology. Now, in our research work, we develop a model to classify the most common fungal skin diseases using a convolutional neural network.

1.2 Motivations

Nowadays, many image classification models have been developed by various scholars over the last three decades. This indicates that this area is so important that it has received the attention of ongoing research and remains a hot research topic. Although a lot of research work has been done on the identification and classification of skin diseases, there is still a gap that needs to be filled. The majority of this area of research is focused on images with white skin. But in reality, many parameters affect the detection [14]. In the previous work, all common skin diseases are not recognized. This motivates us to contribute a little effort in the classification of a skin lesion by developing a model which considers the most common skin fungal disease that is not identifiable in the previous work.

1.3 Statement of the Problem

Any disorder that affects the human skin is referred to as a skin disease. Since skin is the outer covering of our body mostly, it is affected by bacteria, fungus, and viruses. All of the organs in the human body are completely protected by the skin. As a result, it's critical to pay attention to the skin's overall health. Because any change in its normal, functioning can cause to affect the other parts of the body. Skin diseases are the world's fourth leading cause of skin burden. [15]. Eczema, melanoma, Vitiligo, mycosis, Papillomas, impetigo, scabies, herpes, dermatitis, wart, psoriasis, acne, tinea corpories, tinea pedies, tinea capitis, and other skin illnesses are common [16]. Those are very harmful to the skin and can spread throughout if not detected accurately as early as possible. Skin diseases are a leading cause of non-fatal disability worldwide, particularly in resource-limited areas. [17]. Skin diseases have a psychological effect on humans. It affects people psychologically due to the visible effects of skin diseases on the human body. Based on current epidemiology, human fungal infections can be divided into primary, secondary, and invasive. Fever, pain, and dyspnea are some of the clinical symptoms of skin fungal diseases. Because they are not specific, combined with the complexity of the fungal spore microscopic image itself and the similarity between different types of fungal morphology so that fungal infections Accurate and timely diagnosis and treatment have great difficulties [18]. Early detection and diagnosis of the disease is critical to provide appropriate treatment and prevent further spread. In our country, Ethiopia, blood tests may be used by dermatologists to make a symptom-based diagnosis and further analysis. Common methods for diagnosing skin diseases include history and symptom analysis, skin scraping, visual inspection, dermoscopy, and skin biopsy. However, those diagnosis methods are tedious, time-consuming, requires an extensive understanding of the domain, and are vulnerable to subjective diagnosis. The majority of them require the dermatologist's experience and excellent visual perception. The optic visualization of experts is that the main old-style approach adopted for the popularity and identification of human disease of the skin.

Detection, diagnosis, and classification were done previously by different researchers.in the previous works, researchers used different methodologies and therefore the performance rates of their models are different. However, human skin disorder like tinea pedies and tinea corpories are the foremost common disease that wasn't considered within the previous human skin disease classification model. In this thesis, we develop a model for detecting and classifying tinea corpories, tinea pedies, tinea capitis, and tinea unguium. The problem is addressed in this study by answering the following research questions:

I. Which algorithm achieves better performance and computational time?
II. Which image size is better to improve performance and computational time?
III. Which activation function is better to improve performance and computational time?
IV. Which image color is suitable to detect and classify skin fungal diseases?

1.4 Objectives of the study

1.4.1 General objective

The main objective of the research is to investigate and classify human skin fungal disease using the deep learning approach.

1.4.2 Specific Objectives

I. To review works on skin disease detection and classification.
II. To compare three different image size
III. To compare two different activation function
IV. To train, test, and evaluate the performance of the designed model using different evaluation metrics.

1.5 Scope and Limitations of the study

Our proposed work focused on the detection and classification of common skin fungal diseases like tinea corpories, tinea pedies, tinea capitis, and Tinea Unguium. The limitation of our work is other skin fungal diseases are not included, Disease types, which experts cannot identify, and are not possible to capture by camera did not include in this study.

1.6 Significance of the study

Skin disease is common in developing countries like Ethiopia. Dermatologists in Ethiopia diagnose skin illnesses based on symptoms they spent a lot of time and labor during diagnosis and sometimes health implications happened. The health sector is the study's primary beneficiary. Experts (Dermatologists) and patients are the two main stakeholders.

- For Dermatologists: to find out skin infection problems as much as possible quickly and accurately.
- For the patient: health implications and psychological impact will be minimized and recovered within a short period by the right diagnosis.
- For researcher: to receive both an academic award and scientific community recognition
- For country: since our country has a limited number of Dermatologists, so our proposed model will address this problem.

1.7 Research Organization

This thesis is divided into five chapters.

Chapter 1 The motivation, statement of the problem, objectives of the study, the scope and limitations, and significance of the study, as well as the study's organization, are all included in the introduction.

Chapter 2 discussed the background of the general anatomy of the human skin, an overview of common fungal infections, and the steps of the image processing technique, and also the conceptual and review of related works to this study.

Chapter 3 presents the methods and algorithms used for developing skin fungal diseases classification model including the system`s architecture were discussed.

Chapter 4 This chapter discussed the experimental results. It also goes through the data sets that were used in the current study, as well as the parameters that were employed in the implementation. In addition, the chapter discusses the performance evaluation methodologies used in this thesis.

Chapter 5 is about the conclusion, contribution, and future works of the study

CHAPTER TWO

LITERATURE REVIEW AND RELATED WORKS

2.1 Introduction

One of the most rapidly evolving diagnostic techniques is image processing. Currently, digital image processing techniques are being used in a variety of fields of interest, including medical visualization, law enforcement, and agricultural product quality inspection [19]. First, we will provide an overview of human skin structure and fungal skin disease in this chapter. The basic steps of image processing, referred to as digital image processing (DIP), will be discussed. Finally, works of literature related to the concepts that serve as the basis for this thesis are reviewed.

2.2 Human Skin Structure

Skin is an impressive vital organ. It is a fleshy surface with hair, nerves, glands, and nails. It is composed of hair follicles, which fix the hair strands on the skin. It protects us from external factors, regulates body temperature by releasing water in the form of sweat, and allows feelings of touch, heat, and cold. It also protects the bones, muscles, and other vital organs of our body. Skin is composed of three primary layers: the epidermis, the dermis, and the hypodermis [19]. The general skin structure is explained in Fig 2.1.

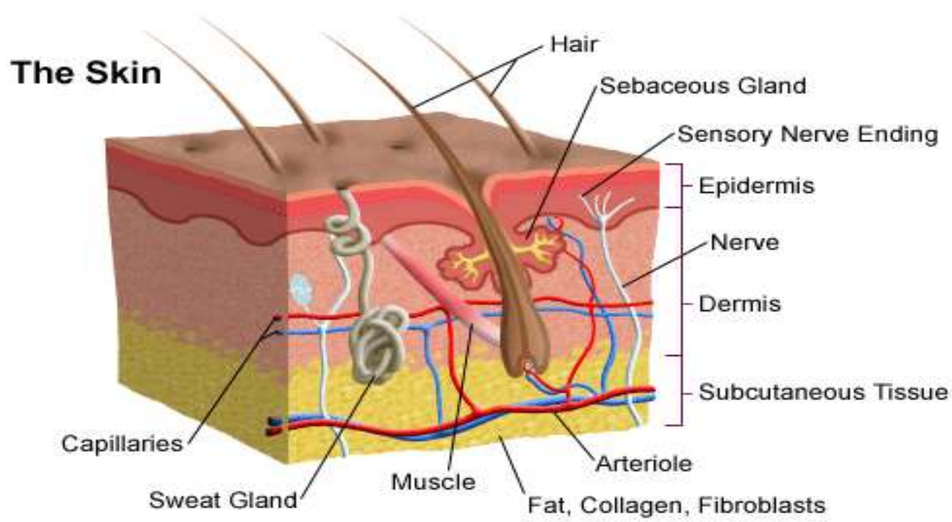


Figure 2. 1 The general human skin structure

2.2.1 Epidermis

It is slim and durable and can act as a protective barrier between your body and the world around you. The main function of the epidermis is to protect your body, avoid potentially harmful things, and exclude what your body needs for normal function. Staying away from bacteria, viruses, and other sources of infection can help prevent skin infections body stores water and nutrients for later use. The body's most vulnerable areas, such as the soles of the feet and the palms of the hands, are the most susceptible. Have a thicker epidermis, which provides better protection for the epidermis's special cells and aids in the protection of your body. The epidermis consists of five layers. The basic stratums are Stratum Corneum, Lucidum, Stratum Ulumusum, and Stratum Spinosum (Geinativum).

I. The keratin-based top layer of the skin is known as the stratum corneum. This layer significantly alters the thickness of various bodily regions when compared to other layers.

II. The Stratum Lucidum is a thin transparent layer found only on thick skin (palm and background).

III. Grain particles in the third layer: This layer secretes chemical substances (glycolipids) that bind the skin cells together.

IV. Stratum Spinosum (also known as a sheet of chip cell): This layer contains dendritic cells. The first line of defense for the skin is this layer.

V. Stratum basale (Stratum germinativum): This is the epidermis's lowest layer. The cells in this layer are constantly creating keratinocytes, which are involved in the production of vitamin D when exposed to sunlight. Keratinocytes produce protein, keratin, and lipids, which act as a protective barrier.

This layer also contains melanocytes, which are responsible for the production of melanin, a natural dark pigment that gives skin its color. When the skin is darker, the epidermis produces more melanin. The pigmentation of human skin varies from person to person. The skin of humans can be dry, oily, or a combination of the two. Because of its diversity, human skin provides a diverse environment for bacteria and other microbes.

Skin types: Classification of the skin based on its reaction to UV radiation [20]

Type	Definition	Description
I	Always burns but never tans	Pale skin, red hair, freckles
II	Usually burns, sometimes tans	Fair skin
III	May burn, usually tans	Darker skin
IV	Rarely burns, always tans	Mediterranean
V	Moderate constitutional pigmentation	Latin American, Middle Eastern
VI	Marked constitutional pigmentation	Black

Table 2. 1 Skin type based on reaction to UV radiation

2.2.2 Dermis

The dermis is connected to the epidermis and is composed of connective tissue that gives the skin elasticity and strength. Sweat glands, sebaceous glands (sebaceous glands), hair, hair follicles, muscles, nerve endings, blood vessels, and dendritic cells are also found there. Each of these parts helps a certain purpose. Pain, touch, pressure, and temperature are all sensed by nerve endings. When heat and pressure are applied to sweat glands, perspiration is produced. Sweat helps to cool the body by evaporating from the skin. Sebaceous glands secrete sebum into the skin. Hair follicles are found all over the body and create numerous types of hair. It's also broken down into two levels. The upper layer, referred to as the papillary region, is made up of loose connective tissue. The second level is the lower layer, which is made of tissue that is more closely packed, called the reticular layer.

2.2.3 Hypodermis

The hypodermis is the skin's deepest layer, made up primarily of fatty acids that regulate temperature, provide insulation, store nourishment, and protect deeper structures from injury. The sub-cutis is another name for this stratum. It is responsible for retaining your body's heat and protecting your important interior organs by containing sweat glands, fat, and collagen cells.

2.3 Fungal skin Diseases

A fungus is a tiny organism, such as mold or mildew. Fungi can be found in the air, water, and in people's bodies. About half of fungi are harmful. If one of the harmful fungi lands on your skin, it can cause a fungal infection. Anyone can develop a fungal rash. Tinea is a superficial fungal infection caused by one of three fungal genera known as dermatophytes: Microsporum, Epidermophyton, and Trichophyton. Dermatophytes are fungi that can penetrate keratinized tissues (skin, hair, and nails) and cause acute and chronic dermatophytosis in humans and other animals. These infections are among the most common diseases in the world, causing serious chronic morbidity. Any red, scaly, pruritic, growing lesion, as well as pruritic scalp lesions with scaling, folliculitis, or an inflammatory reaction, is suspected of being tinea. [21]. The most prevalent type of infection is superficial infections of the skin and nails, which affect up to 20-25 percent of the world's population at any given time [22].

2.3.1 Tinea Pedis

It is one of the skin diseases caused by fungus and it mostly affects the leg and foot. It is also known as athlete's foot. This type of fungal infection is most commonly found between the toes. It's especially common in persons who have sweaty feet from being constrained in tight-fitting shoes. It is characterized by a scaly rash that causes itching, stinging, and burning. Common causes of tinea pedis include T. rubrum, Trichophyton inter digital, and Epidermophyton floccosum. The most common mode of infection is direct contact with the causative organism, which can occur in locker rooms and swimming pools through barefoot contact between the feet and an infected surface. The use of occlusive footwear is more widespread in the winter, which leads to a rise in tinea pedis cases.

Figure 2. 2 sample Tinea pedis image

2.3.2 Tinea Corpories

Tinea corpories is a skin disorder caused by a fungus that affects the whole body like the leg, abdomen, and neck. It's usually an itchy, circular rash with clearer skin in the middle. Ringworm gets its name because of its appearance. Factors that predispose individuals to tinea corporis include warm and humid climates, tight occlusive clothing, diabetes mellitus, atopic dermatitis, and immunosuppressive states.

Figure 2. 3 sample Tinea Corpories image

2.3.3 Tinea Capitis

Tinea capitis is a disease caused by a superficial fungal infection of the scalp, eyebrows, and eyelashes, with a proclivity for attacking hair shafts and follicles. The condition is thought to be a type of superficial mycosis or dermatophytosis. Tinea capitis affects 32.3 percent of school-aged children in Ethiopia [23]. There are several synonyms for ringworm of the scalp, including tinea tonsurans.

Figure 2. 4 sample Tinea Capitis image

2.3.4 Tinea unguium

Tinea unguium, also known as onychomycosis, is a fungal infection of the nail. Pathogens that cause onychomycosis include dermatophytes, the most common of which is Trichophyton rubrum, as well as non-dermatophyte molds and yeasts. Nail discoloration, nail shape distortion, and a foul odor are all symptoms of Onychomycosis. Onychomycosis is more common in the elderly, and its prevalence has recently increased due to the practice of wearing tight shoes, using lockers, and ignoring proper foot care. [21].

Figure 2. 5 sample image of Tinea Unguium

2.4 Digital Image Processing

An image is defined as a two-dimensional function f(x, y), where x and y are spatial (plane) coordinates, and the amplitude of f at any pair of coordinates (x, y) is called the image's intensity or gray level at that point [25]. Digital image processing (DIP) involves processing a digital image with the help of computer algorithms to get an enhanced image by extracting some useful information DIP entails processes at the low, medium, and high levels. Noise reduction, contrast enhancement, and image sharpening are examples of low-level operations. Operations like segmentation, where the input is an image and the outputs are properties retrieved from images, are examples of medium-level processes. To make sense of a set of qualities, high-level processes are used. In general, different image processing applications may take different approaches. However, the fundamental steps that every image processing applications pass through include image acquisition, image preprocessing, image segmentation, feature extraction, and image classification.

2.4.1 Image Acquisition

Unless no processing is possible, image acquisition is the initial or most basic step in digital image processing. It is the process of taking an image using hardware devices like scanners, digital cameras, and smart phone. Image can also be acquired from the database or another source tailored for research purposes. The image is delivered in digital format during image acquisition. Most of the time an image taken is unprocessed and requires further processing and analysis to be used for specific purposes. We collect fungal skin lesion images from patients using smartphone cameras at Dr. Gerbi medium clinic, and JUMC.

2.4.2 Image preprocessing

After capturing images, the images captured should first be transferred onto a computer to convert them into digital images. Once the data is collected, it will be processed in steps called preprocessing. When processing high-resolution images, the image size is needed to be reduced because of the reason that processing on high-resolution images takes a longer time. It is an essential step of detection to enhance the quality of the original image by removing unrelated and unnecessary parts such as noise in the background of the image. By any means the image is acquired there are artifacts to be removed and enhance the contrast for making the border detection easy to the system.

This is an important step in digital image processing because enhancing the quality of the original image enhances the detection of the lesion region. In this stage, the image must be normalized. Normalization is a technique for altering the range of pixel intensity values in image processing. Images with low contrast due to glare, for example, can be used. Histogram stretching or contrast stretching are other terms for normalization. Image normalization is a technique for bringing numerous images into a common statistical distribution in terms of size and pixel values, and it's often used in data preparation for image processing.

2.4.3 Image Segmentation

It refers to the process of partitioning a digital image into multiple segments set of pixels, pixels in a region are similar according to some homogeneity criteria such as color, intensity, or texture, to locate and identify objects and boundaries in an image and also classify pixel until it is possible to extract objects or regions from the background. To begin, the digital image is divided into two parts: background and foreground, with the foreground representing the interesting object and the background representing the rest of the image. All the pixels in the foreground are similar concerning a specific characteristic, such as intensity, color, or texture.

2.4.4 Image Feature Extraction

A functional definition of features is something that can be measured from an image. Those features are the distinguishing primitive characteristics or attributes of an image. Rather than analyzing the image in its original form, extracting the features of the image will minimize the time to analyze it. The goal of image feature extraction is to achieve a better classification rate by extracting new features to represent objects from raw pixel data [22].

Feature extraction is a technique that changes the original feature of data to a new smaller feature that is more informative than the previous. This smaller set of informative features is important for recognition to discriminate among different labels. It is the process of retrieving meaningful information from an image that is used for the classification of images into different categories. It's the process of reducing a raw image to make decision-making easier, including pattern detection, categorization, or recognition. Finding and extracting trustworthy and discriminative features is always an important part of the image recognition and computer vision process. Several image features represent an image for classification systems. For the classification task, an image is represented by several image features. The color, texture, and shape of an image are the most popular.

2.4.4.1Color Feature

Color is an important and the most straightforward feature that humans perceive when viewing an image. Since the human visual system is more sensitive to RGB color information, color is the main parameter used for feature extraction. The primary spectral components of red (R), green (G), and blue (B) are the most often utilized color feature models in image processing. Color features of an object are extracted by examining the R, G, and B levels of each pixel within the object's boundary.

2.4.4.2Shape Feature

Shape features are mostly used for finding and matching shapes, recognizing objects, or making measurements of shapes. Moment, perimeter, area, and orientation are some of the characteristics used for the shape feature extraction technique. The shape of an object is determined by its external boundary abstracting from other properties such as color, content, and material composition, as well as from the object's other spatial properties. The contour methods calculate the feature from the boundary and ignore its interior, while the region methods calculate the feature from the entire region. The most common feature extraction method used recently in medical image detection and classification systems is CNN. There are various layers in the design of Convolution neural network architecture. This layer analysis continued until the network began to train effectively using a convolution layer, pooling layers, and fully connected layers. So different features are understood by these layers and to understand the images it also conceders filter size. Therefore Convolution neural network is a good feature extractor. Transfer learning is a new learning process that can be used in existing machines learned from a single environment and new solutions [23].

VGG (Visual Geometry Group) is a CNN architecture that consists of sixteen learned layers, including thirteen convolutional layers with a 3 x 3 filter size, five pooling layers that follow some of the convolutional layers, and three fully-connected layers with the final 1000-way Softmax that produces a distribution over 1000 class labels.

GoogleNet: is a CNN model, which contains 22 layers with no fully connected layers and only 5 million trainable parameters and decreases 12 times than AlexNet. For the convolutional operation, the model used 1*1, 3*3, 5*5 filter sizes for pooling 3*3 with stride 2 and 224*224-pixel values used to rescale or normalized images. GoogleNet, also known as Inception-V1, was the winner of the 2014-ILSVRC competition. The GoogleNet architecture's major goal was to achieve great accuracy at a low computing cost [24].

ResNet (Residual Network) is the deepest CNN model, with 152 layers, among VGG, AlexNet, and GoogleNet. ResNet took first place in the ILSVRC-2015 classification competition, which required it to classify 1.2 million images into 1000 different classes with a top-5 test error rate of 3.57 percent [25].

MobileNet: The MobileNet network architecture is a type of convolutional neural model that uses depth-wise separable convolutions to construct it and is, therefore, more lightweight in terms of their parameter count and computational complexity [26]. When compared to a network with regular convolutions of the same depth in the nets, it dramatically reduces the number of parameters. This results in lightweight deep neural networks. It is a class of CNN that was open-sourced by Google.

2.4.5 Image Classification

The task of classifying is to approximate a mapping function (f) from discrete input variables (X) to discrete output variables (y) [27]. Image classification is the final phase in digital image processing responsible for making Predictions or decisions about the extracted and selected feature information from the input.

Training and testing are the two most important phases of classification. A training set is used to build a model in a dataset, whereas a test (or validation) set is used to validate the model built during the training phase. Classifiers such as Naive Bayes, K-Nearest Neighbor, Artificial Neural Networks, Support Vector Machine, and CNN are used to process the two phases. These classification methods are divided into two types: supervised learning and unsupervised learning. [28]. Supervised learning the dataset of interest in supervised methods contains both the explanatory variables (also known as the input or features) and the target responses (also known as the output labels). Un Supervised learning unsupervised learning, on the other hand, is a technique for teaching machines to use data that hasn't been labeled or categorized. It signifies that no training data is available, and the machine is programmed to learn on its own.

Semi-supervised learning: Some algorithms can handle partially labeled training data, which typically consists of a large amount of unlabeled data and a small amount of labeled data. This is known as semi-supervised learning.

Naive Bayes Classifier is a classification technique based on Bayes Theorem. The attribute values are assumed to be conditionally independent of one another in Nave Bayes. Bayesian classifiers use the Bayes theorem, which says:-

$$p(c_j \mid d) = \frac{p(d \mid c_j)\, p(c_j)}{p(d)}$$

The following rule can be used to reduce the probability of a classification error:

d is classified to C1,if P(C1/d)> P(C2/d)

d is classified to C2,if P(C2/d)> P(C1/d) [27].

K-Nearest Neighbor: A new sample is classified by calculating the distance to the nearest training case; the sign of that point determines the sample's classification. The k-NN classifier expands on this concept by taking the nearest k points and assigning the majority sign to them. Similar things are assumed to exist nearby by the KNN algorithm. For Classification problems, the K-NN algorithm is commonly used. [28].

Support Vector Machines: SVM is a non-probabilistic binary linear classifier. The non-probabilistic aspect is its key strength. This distinguishes it from probabilistic classifiers like the Nave Bayes. An SVM, in other words, separates data along a decision boundary (plane) determined by only a tiny portion of the data (feature vectors) [29].

Artificial neural network (ANN). Artificial neural networks, also known as neural networks (NNs), are computing systems that are inspired by the biological neural networks that make up human brains. An ANN is built from a network of connected units or nodes known as artificial neurons, which are loosely modeled after the neurons in the human brain. It is a well-known machine learning technique. Input, output, and hidden layers are all part of the neural network model.

Input Layer Assists in the distribution of information to the network. The number of neurons in an input layer is typically the same as the input feature to the network. The main function of the hidden layer is to transform the data received from the input layer into something that can be used by the output layer. One or more hidden layers can be present in an ANN architecture. Information received from the hidden layer is translated to the output layer and is processed to produce the desired results [30].

Deep learning and shallow learning are two types of ANN. In a summary, shallow neural networks are NNs with only one hidden layer, as opposed to deep neural networks, which include multiple hidden layers of varying sorts. A neural network comprises intermediary layers called hidden layers in addition to an input layer and an output layer. Deep learning features are automatically extracted, but shallow learning features are not automatically extracted.

Types of Artificial Neural Networks are the following

Feed-forward Neural Network: This is the most basic type of ANN, with data or input only traveling in one direction. Data flows through the input nodes and out the output nodes. This neural network may or may not have hidden layers. For classification, it employs an activation function.

Back-propagation Neural Network: A back-propagation neural network is identical to a feed-forward neural network except for one minor difference. To feed data from the output layer to the input layer, an algorithm is used.

Radial basis Neural Network: Distances between points are taken into account by this type of ANN. This neural network consists of 2 layers.

Kohonen Self Organizing Neural Network: To discrete maps made up of neurons, a Kohonen map requires an input dimension of the structure. It can organize the training data [31].

2.4.5.1 Deep learning techniques

ANNs, or artificial neural networks, are algorithms that are inspired by the structure and function of the brain. Deep learning is one type of representation learning method that directly processes raw data (e.g., RGB images) and automatically learns the representations [32]. There are many types of deep learning used for a variety of tasks in Artificial intelligence like a deep neural network, deep belief network, recurrent neural networks, Deep Boltzmann Machine, restricted Boltzmann machines, and Convolutional neural network [33].

2.4.5.2 Convolutional neural network (CNN)

Deep learning, specifically Convolutional Neural Networks (CNN), is an image representation and classification technique that has been validated for medical image analysis and applications. We have observed much encouraging work that reports new and newer state-of-the-art performance on quite challenging problems in this domain [32]. The convolutional neural network (CNN) is a classic model produced by the combination of deep learning and image-processing technology [34] as one of the most representative neural networks in deep learning technology, it has made several successes in the field of image analysis and processing. Many improvements in image feature extraction and classification, pattern recognition, and other areas have been accomplished using convolutional neural networks in the standard image annotation set ImageNet, which is extensively used in academics. The convolutional neural network is a deep model with supervised learning.

The main idea is to use spatial relative relationships to reduce the number of parameters and share the weights of feature mapping at different positions of the preceding layer network to improve training performance. CNN is used for classification because the fundamental benefit of CNN is that it automatically finds important features without the need for human intervention [35]. The CNN network can be regarded as a self-learning progression of low, medium, and high-level local image properties. CNN is a pattern recognition and image processing method that is widely used. The goal of CNN is to use spatial information between image pixels. It has several advantages, including a straightforward structure, fewer training parameters, and adaptability. CNN takes images as input directly. CNN is used to learn a hierarchy of features automatically, which can then be utilized for classification.

An input layer, an output layer, and multiple hidden layers make up a CNN. Convolution, pooling, and activation are just a few of the operations performed by each layer in the hidden layer. The input layer is linked to the input image, and the number of neurons in this layer corresponds to the number of pixels in the input image. The middle convolutional layer uses a convolution process to extract features from the input data, resulting in a feature map [36]. Because of this, we use CNN for our classification problem. CNN architecture components include convolution layers, pooling layers, and fully connected layers [37].

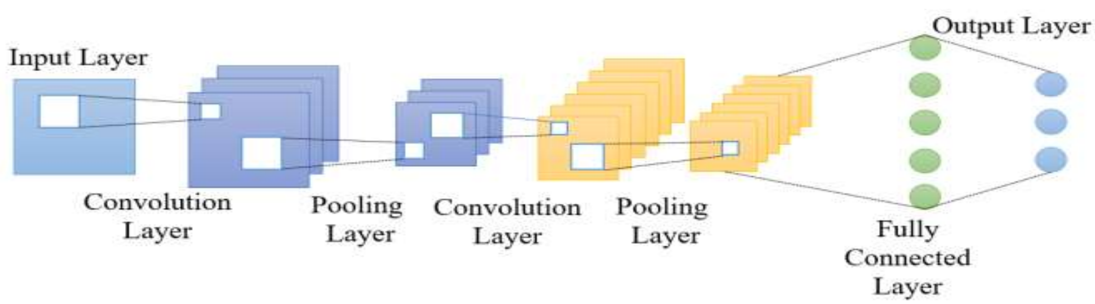


Figure 2. 6 basic CNN architecture

Convolution Layer: It contains a set of convolutional kernels (also called filters), which gets convolved with the input image (N-dimensional metrics) to generate an output feature map. A kernel can be described as a grid of discrete values or numbers, where each value is known as the weight of this kernel [38]. During the starting of the training process of the CNN model, all the weights of a kernel are assigned with random numbers (different approaches are also available there for initializing the weights). Then, with each training epoch, the weights are tuned and the kernel learned to extract meaningful features the value of the windows is obtained through the experimental analysis. With a predetermined step size, the filter moves across the image. This step size is referred to as stride. The output of this operation is the result of the dot product between the entries of the filter and the pixel values of the input image. The result of this operation is called the feature map or activations of a filter. Pooling layers: are used to down sampling the volume spatially, independently in each depth slice of the input. Max is the most common down sampling operation, which results in max pooling. The role of the pooling layer is mainly to extract image features, reduce the input size of the next layer. As a result, the pooling layer can minimize the CNN's computation time and avoid over-fitting.

There are different types of pooling techniques are used in different pooling layers such as max pooling, min pooling, average pooling, gated pooling, tree pooling, etc. The most popular and often used pooling technique is max pooling. The pooling layer's biggest disadvantage is that it can sometimes degrade CNN's overall performance. The reason behind this is that the pooling layer helps CNN to find whether a specific feature is present in the given input image or not without caring about the correct position of that feature [38].Fully Connected Layer: Usually the last part (or layers) of every CNN architecture (used for classification) is consists of fully-connected layers each neuron in a layer is linked to the neuron in the previous layer. The last layer of Fully-Connected layers is used as the output layer (classifier) of the CNN architecture. The Fully-Connected Layers are a type of feed-forward artificial neural network (ANN) and it follows the principle of traditional multi-layer perceptron neural network (MLP). The FC layers take input from the final convolutional or pooling layer, which is in the form of a set of metrics (feature maps) and those metrics are flattened to create a vector and this vector is then fed into the FC layer to generate the final output of CNN.

The output of a neural network is determined by activation functions, which are mathematical equations. The function is associated with each neuron in the network and determines whether or not it should be stimulated based on whether or not the neuron's input is important to the model's prediction. Its purpose is to introduce nonlinearity into the network's modeling capabilities. A neural network without an Activation function is nothing more than a linear regression model with limited power and poor performance. It's used to change a linear neural network into a nonlinear one. It also gives the network non-linearity features. As a result, the neural network can handle more complicated tasks.

Activation that isn't linear Allow the model to build complicated mappings between network inputs and outputs using functions. It's necessary for learning and modeling complicated data including images, video, and audio, as well as non-linear or high-dimensional data sets. Because they have a derivative function that is connected to the inputs, they allow backpropagation. They enable the creation of a deep neural network by stacking multiple layers of neurons. Multiple hidden layers of neurons are needed to learn complex data sets with high levels of accuracy. We need a neural network model to learn and represent a complex function which maps inputs to outputs that is why we need non-linearity.

The main task of any activation function in any neural network-based model is to map the input to the output, where the input value is obtained by calculating the weighted sum of the neuron's input and further adding bias with it (if there is a bias). In CNN architecture, after each learnable layer (layers with weights, i.e. convolutional and FC layers) non-linear activation layers are used. The non-linearity behavior of those layers enables the CNN model to learn more complex things and manage to map the inputs to outputs nonlinearly. The most commonly used activation functions in deep neural networks (including CNN) are described below.

The sigmoid activation function takes real numbers as its input and binds the output in the range of [0, 1]. The following is a mathematical representation of the sigmoid.

$$f(x)_{sigm} = \frac{1}{1+e^{-x}} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 2.1$$

Rectifier Linear Unit (ReLU) is a short form of Rectified Linear Unit. In Convolutional Neural Networks, it is the most widely employed activation function. It's used to turn all of the numbers in the input into positive ones. Activation function adds to the transformation's complexity. This means that the neurons will be silenced only if the outcome of the linear transformation is less than 0. When negative input values are used, the result is zero, indicating that the neuron is not activated. Because just a limited number of neurons are activated, the ReLU function is significantly more computationally efficient than other activation functions. ReLU is represented mathematically as:

$$f(x)\ \mathrm{ReLU} = \max(0,x) \text{ -------------------------------- Equation 2. 2}$$

Equation of Relu activation function

ELU: Exponential Linear Unit, or ELU for short. ELU is a function that corresponds to zero more quickly and produces more precise results. Unlike other activation functions, ELU requires an additional alpha constant to be positive. The ELU is a function for activating neural networks.

Softmax function: A collection of numerous sigmoids is typically used to define the Softmax function. Sigmoid is commonly employed to solve binary classification problems. For multiclass classification issues, the softmax function can be employed. The likelihood of a data point belonging to each class is returned by this function. As a result, we apply our findings to the Softmax activation function in the output layer. The mathematical expression for the same can be found here.

$$\sigma(\mathbf{z})_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}} \quad \text{for } j = 1, \ldots, K.$$

2.5 Related works

In this section, we try to review related research works about skin diseases detection and classification and their contribution to the area as well as their limitation of the research work. Previously, several researchers developed their model for the diagnosis, detection, and classification of human skin disease from images.

"Advanced Skin Diseases Diagnosis Leveraging Image Processing": In this study, the authors proposed a method to detect four skin diseases namely, rosacea, melanoma, psoriasis, and acne using grey-level co-occurrence matrix (GLCM) for feature extraction matrix (GLCM) for feature extraction and SVM for classification [39]. They have got 89% accuracy. Even though their method recognizes four types of skin diseases, they didn't use a good feature extraction technique

"Melanoma Detection by Analysis of Clinical Images Using Convolutional Neural Network" for classification of melanoma and benign lesions CNN was proposed and they got 81% accuracy [40]. Even though they have used powerful classification algorithm, doesn't consider fungal diseases

"A Web-Based Skin Disease Diagnosis Using Convolutional Neural Networks": The Authors used CNN for feature extraction and they classify three skin diseases namely, Atopic dermatitis, Acne vulgaris, and Scabies with evaluation accuracy of 88%, 85%, and 84.7% respectively and the overall accuracy is 88% [8]. Their model recognizes three skin diseases but does not consider fungal diseases like Tinea Pedis, Tinea Captis, Tinea Corpories, Tinea unguium.

“Skin Disease Detection Using Image Processing with Data Mining and Deep Learning”: The Authors proposed a mobile-based system that classifies three skin diseases namely melanoma, eczema, and impetigo. Based on their result CNN performs better classier performance than SVM [41]. Even though their system recognizes skin diseases for what they proposed they did not consider fungal skin diseases like tinea pedies, Tinea Capitis, Tinea Corpories, and Tinea unguium.

“A Smartphone-Based Skin Disease Classification Using MobileNet CNN”: The Authors proposed Smartphone-based skin diseases detection method their system recognized Acne, Eczema, Pityriasis rosea, Psoriasis, Tinea Corporis, Varicella (chickenpox), and Vitiligo. The accuracy achieved was 94% [42]. Even though they include Tinea Corpories, they did not consider other fungal skin diseases like Tinea pedies, Tinea Capitis and Tinea Unguium.

“Studies on Different CNN Algorithms for Face Skin Disease Classification Based on Clinical Images”: In this research work, the Authors compared five pre-trained deep learning frameworks for the diagnosis of six facial skin conditions from a clinical image and using an InceptionResNet_V2 a precision of 77% was claimed [43].

“Using artificial intelligence on dermatology conditions in Uganda”: A case for diversity in training data sets for machine learning. The Authors tried to test one AI application, which is developed for skin disease identification for dermatology. They have used a black color image dataset. The accuracy achieved was low i.e.17% [14]. Finally, they conclude that the designed AI application is poor for fungal infections like tinea infections. In all previous works, Tinea capitis, Tinea pedis, and Tinea Unguium are not considered.

“Automatic skin disease diagnosis using deep learning from clinical image and patient information”, in this work the Authors proposed an automated system based on a pre-trained mobilenet-v2 for the diagnosis of five skin diseases namely, acne vulgaris, atopic dermatitis, lichen planus, onychomycosis, tinea capitis and they have unknown class. They have used black skin images and patient clinical information. The accuracy achieved was 97.5%. In this study tinea corpories is categorized as unknown and Tinea pedis is not considered. To fill this gap we develop a model for classifying skin fungal diseases in to Tinea Pedis, Tinea Capitis, Tinea Corpories, and Tinea Unguium.

Authors &Yea	Title	Major Findings / Contributions /conclusion	Critical Remarks to find out the research gap for the proposed research work
Samuel Akyeramfo-Sam, Acheampong Addo Philip , Derrick 2019	“ A Web-Based Skin Disease Diagnosis Using Convolutional Neural Networks”	The Authors used CNN for feature extraction and they classif three skin diseases namely, Atopic dermatitis, Acne vulgaris, and Scabies with evaluation accuracy o 88%, 85%, and 84.7% respectively and the overal accuracy is 88%	Their model recognizes three skin diseases but does not consider fungal diseases like Tinea Pedis , Tinea Captis, Tinea Corpories
Mrs. Jayashree Hajg Aishwarya Bhavsar, Harsha Achara, Nish Khubchandani 2019	“ Skin Disease Detectio Using Image Processing with Data Mining and Deep Learning”	The Authors proposed a mobile-based system that classifies three skin diseas namely melanoma, eczem and Impetigo. Based on their Comparison result CNN Performs better classier performance than SVM.	Even though their system recognizes skin diseases for what they proposed They did not consider Fungal skin diseases like tinea pedies, Tinea Capitis and Tinea Corpories
Jessica Velasco, Cherry Pascion, 2019	“A Smartphone-Based Disease Classification Using MobileNet CNN”	The Authors proposed Smartphone-based skin diseases detection method their system recognized Acne, Eczema, Pityriasis rosea, Psoriasis, Tinea Corporis, Varicella (chickenpox), and Vitiligo. The accuracy achieved wa 94%.	Even though they include Tinea Corpories, they did not consider other fungal skin diseases like tinea pedies, and tinea Capitis

Louis Henry Kamulegeya Mark Okello, John Mark Bwanika&, Davis Musinguzi&, William Lubega&, Davis Rusoke&, Faith Nassiwa&, Alexander Börve, 2019	"Using artificial intelligence on dermatology conditions in Uganda: A case for diversity in training data for machine learning"	Authors tried to test one AI application, which is developed for skin disease identification for dermatology. They have used a black color image dataset. The accuracy achieved was low i.e. 17%. Finally, they conclude that the designed AI application is poor for Fungal infections like tinea infections.	all previous works, Tinea capitis, Tinea pedis and tinea unguium are Not considered.
Kedir Ali , et al. 2021	"Automatic Skin disease diagnosis deep learning clinical image patient information"	The Authors proposed an Automated system based on a pre-trained mobilenet-v2 for the diagnosis of five skin diseases namely, acne vulgaris, atopic dermatitis, lichen planus, onychomycosis, tinea capitis and Unknown. They have used black skin Images and patient clinical information. The accuracy achieved was 97.5%	In this study tinea corpories is categorized as unknown and Tinea pedis is not considered. To fill this gap we develop a model for classifying skin fungal disease in to four classes including Tinea Pedis, Tinea Corpories

Table 2. 2 Related works simple description

2.4.6 Summary

This chapter covered the basics of human skin structure, skin fungal diseases, digital image processing. Although addressing all related works is difficult, the important literature is provided in this chapter. The majority of the literature presented is in support of automatic skin lesion identification and diagnosis, which is the main goal of this work. We attempted to fill the gap in this thesis work by reviewing the literature.

Chapter Three

Methods and Algorithms

3.1 Introduction

In this study, the system architecture of the proposed work is explained. The steps in image processes such as skin lesion preprocessing, feature extraction, model training, and classification that are used in the system architecture are also explained in detail. The model has two components such as image processing and deep learning. It has two phases training and testing. In this work, our objective is to address the identification problem of skin fungal disease using a convolutional neural network.

3.2 The architecture of the model

This study follows an experimental research design. Experimental research design is a systematic research study in which the researcher manipulated and controlled testing to understand the causal process. An experimental research design includes dataset preparation, implementation, performance evaluation, designing skin fungal diseases classification model. To detect and classify the fungal skin lesion images, it is important to follow a series of image processing steps. Figure 3.1 depicts the details of these steps. In this thesis, we follow the image processing concepts to customize the model for skin diseases images detection and classification model. Accordingly, image analysis and understanding are used to classification skin lesion images into four classes Tinea Pedis, Tinea Capitis, Tinea Corpories, and Tinea Unguium.

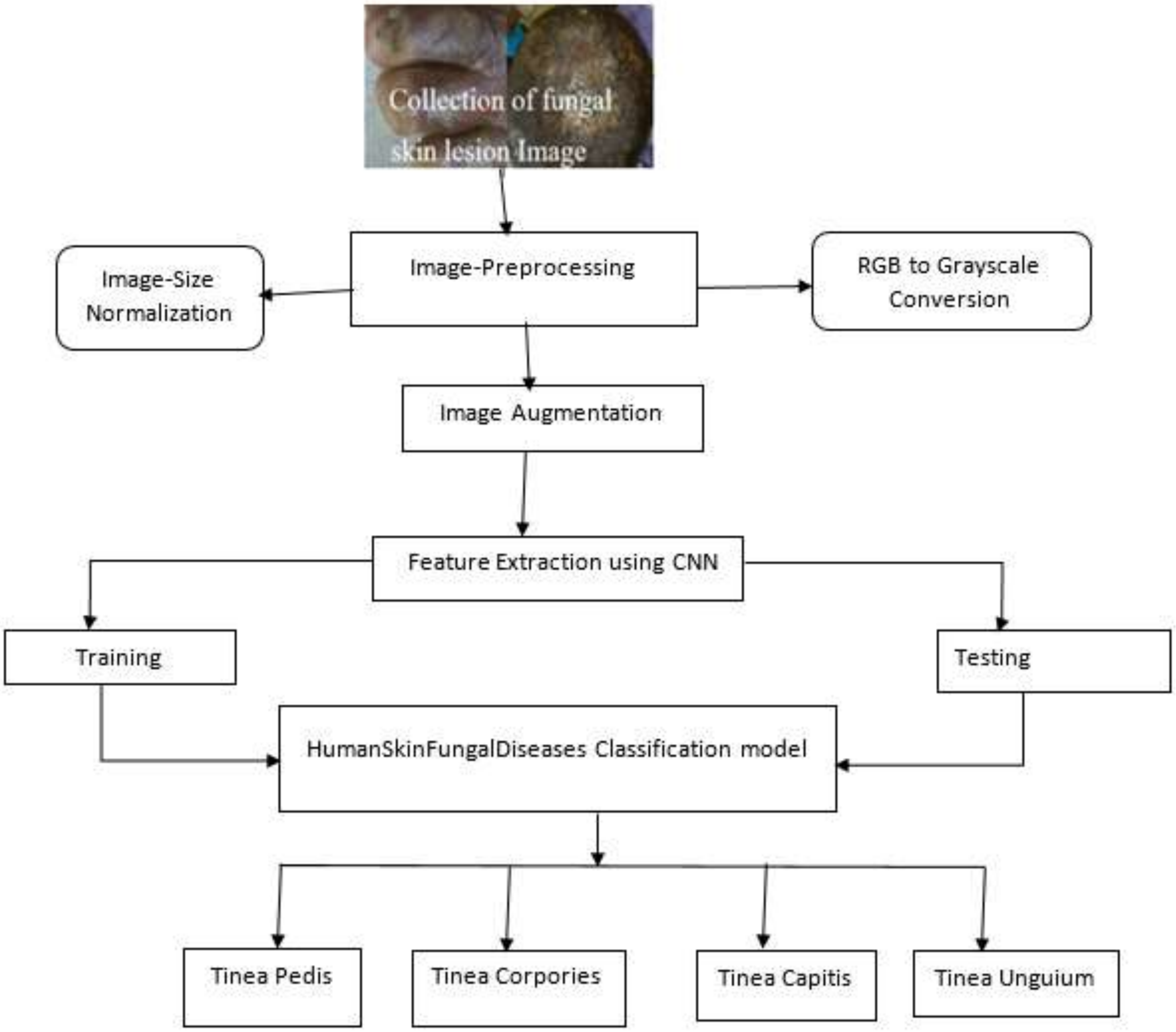


Figure: 3. 1 Research design Block diagram

The detail of the data set description is discussed under chapter 4 subsection 4.2. We use the following Image pre-processing techniques:

3.3 Image pre-processing

In different applications and domains, image processing is a technique to increase the quality of an image by eliminating unwanted image data. The real format of scanned medical images contains a lot of unnecessary and undesired components. Some image preparation techniques are required for better visualization of the images before discovering the diseases in specific, to remove such unwanted components in an image [44]. In comparison to traditional classification algorithms, which rely on hand-engineered filters, CNNs require little pre-processing. The independence of human intervention in learning filters is a good advantage of CNN. Normalization, image color conversation, and image resize were the image preprocessing techniques employed in this investigation.

3.3.1 Image Resize

The image was not uniform in size at first, thus all images have a uniform size to enable image preprocessing algorithms to increase and reduce the specified image size in pixel format. When you need to raise or decrease the total pixel for image standardization, this step is required. Furthermore, shrinking the image cuts down on processing time an d costs. The images gathered are of various sizes. Image resize is the basic step in image preprocess because the data set must have a similar size that is preferable for the proposed method and the large pixel's size consumes too much computational cost and time. We compare three types of image size by resizing the dataset into 120X120, 150X150, and 224X224 pixels.

3.3.2 Image Color Conversion

In this study, after the size of all acquired images becomes uniform, the color is converted from RGB to grayscale. Here is the visualization of color conversion.

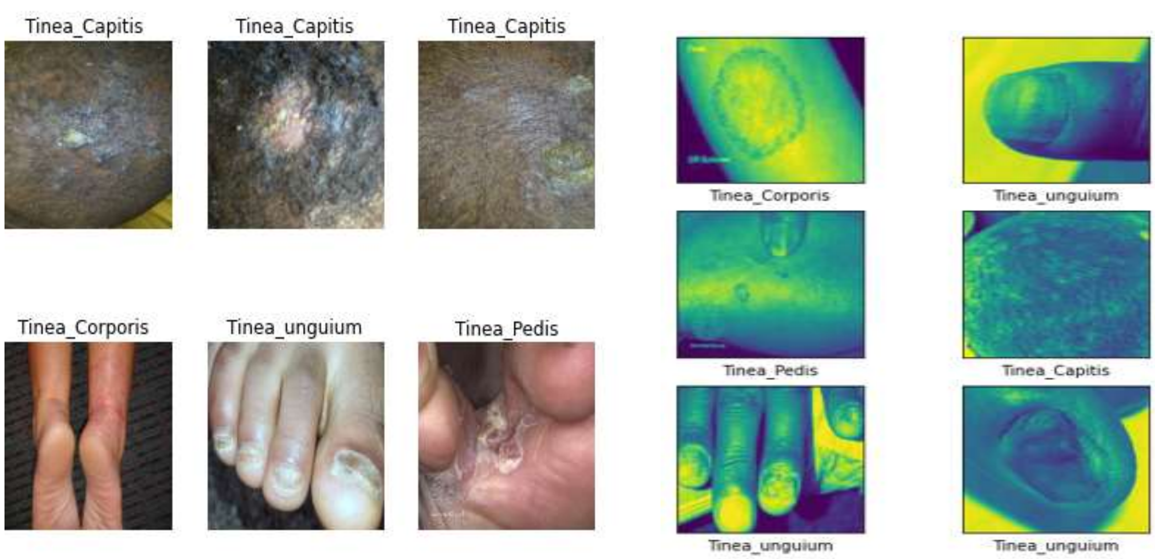


Figure 3. 1 Fig RGB color mode And Gray scale color mode

3.3.3 Feature Extraction

To extract a descriptive feature from images of skin lesions. Generally, extracted features are descriptive and commonly texture features, color feature size or shape feature, etc. This study employed the CNN feature extraction model. This is because the CNN model is the current state of the art in image detection and classification tasks. Deep CNN's great learning ability stems from using many feature extraction stages that can automatically learn representations from data [45].

3.4 Data Augmentation

To train, deep learning normally needs a huge amount of data. A small amount of data often causes over-fitting. But in reality, a large number of labeled medical fungal images are expensive and difficult to obtain, so we need to create data. It is a technique for increasing or expanding the amount of the training dataset artificially. It is important because sometimes there is a very limited-sized training data set is available for most of the real-life complex problems (e.g. medical datasets) and the fact is that more training data samples can result in a more skillful CNN model [46]. In this thesis, we augment the total acquired images which are 407 images labeled into four classes namely, Tinea Capitis, Tinea Corpories, Tinea Pedis, and Tinea Unguium, and after augmentation, we have the total data set of 1069 images. To balance the insufficiency of our data, we applied different operations such as rotating, shifting, and flipping to it.

Image rotation is one of the most often employed augmentation techniques. The information on the image remains the same regardless of how it is rotated. Even if you look at it from a different perspective, the image remains the same. As a result, by making many images rotated at different angles, we may use this strategy to enhance the size of our training data.Image Shifting: Image shifting is another image augmentation technique. We can modify the position of the objects in the image by changing the images, giving the model additional variation. This could eventually lead to a more generic model.Image Flipping: Flipping can be considered as an extension of rotation. It allows us to flip the image in the Left-Right direction as well as the Up-Down direction.

```
datagen = ImageDataGenerator( rotation_range=25,
                              width_shift_range=0.5,
                              height_shift_range=0.5)
```

3.5 Classification

Classification is the final task of this work. In this thesis work, we select CNN for this purpose. Convolutional Neural Network (CNN) is a particular implementation of a neural network used in machine learning that exclusively processes array data such as images, frequently used in machine learning applications targeted at medical images [47].In this study, we discuss a method for developing CNN based skin fungal diseases classification model.

Classification is done by using the knowledge from the learning model, which is constructed by using the training and validation phase. Hence, the features extracted by CNN are used as input for the classifier. Now, in the CNN models, the most common classifier is Softmax. By using the knowledge from the learning model, Softmax is used to classify each image (in the testing dataset) into a specific or predefined class (Tinea Capitis, Tinea pedies, Tinea Corpories, and Tinea Unguium).

3.6 Summary

In this chapter, the design of the CNN-based Skin Fungal Diseases Classification model for human skin disease detection and classification is discussed thoroughly. The components of the model such as preprocessing, feature extraction, data augmentation, and classification are discussed.

CHAPTER FOUR

EXPERIMENTATION AND MODEL RESULT DISCUSSION

4.1 Introduction

The dataset that was used and how the proposed models were implemented are both detailed descriptions in this section. The next sections include details on the implementation, technique, dataset preparation, and experimental outcomes, as well as evaluation metrics

4.2 Experimentation

4.2.1 Implementation Tools

The experimentation process is conducted using a TOSHIBA laptop Computer with Intel(R) Core(TM) i5-5200U CPU @ 2.20GHz Logical Processor speed and 8.00GB (RAM), 500GB hard disk capacity with windows 10 operating system. To implement the skin disease classification model, we have used python programming language for image understanding, image preprocessing, image feature extraction, and image classification purpose. This programming language contains advanced machine learning algorithms for image understanding and identification. To create the algorithms, we chose Python as the programming language. The simplicity and readability of the code are the major reasons for its selection.

- The IDE used is Anaconda 3, Jupyter notebook
- CV2 module is inside this library which is used to read the image, resize the image, change RGB to grayscale, etc…
- Tensor flow is also a free machine learning library used for mathematical operation.
- Keras library used to create layers in the CNN model
- Kernel Size: Filter size to generate feature maps.
- Padding: For keeping the size of output equal to the input of the next layer.
- Pooling Size: Down sampling size of the convolved result.
- Learning Rate: a positive fraction determining the step of learning of the network neurons
- Dropout: a mechanism of regularization of the training to overcome overfitting

4.2.2 Dataset Preparations

The data to conduct this research was collected from the patients in Dr. Gerbi medium clinic of Jimma and Jimma University Medical Center (JUMC) using a smartphone camera (Techno pop 2 power, Techno Spark4, SamsungA20). The images were captured after the diagnosis was confirmed by an expert dermatovenerologist. The images were in various file formats like JPEG, JPG. Tinea Pedis, Tinea Capitis, Tinea Corpories, and Tinea Unguium are the four labels found in the collected image. From those, the total number of skin lesion images were collected from Dr. Gerbi medium clinic (which is found in Jimma), and JUMC was 407 images. We select this Dermatology clinic and JUMC because the selected fungal disease is the common case in these two health centers. I could not get enough data because the dermatologist can see it with the naked eye, so there is no lesion image for a research, which is why I chose to take smart phone camera. It is difficult to collect many images in this way because of the COVID-19 pandemic.

We apply different image preparation techniques to feed for the neural network. Different image formats are converted to the same format, JPG file format. The details quantities and varieties of sample images used in our experimentation are summarized in the following table.

No	Diseases type	No of images before augmentation	No of images after augmentation
1	Tinea Capitis	120	304
2	Tinea Pedis	96	264
3	Tinea Corpories	71	229
4	Tinea Unguium	120	272
Total number of images collected		407	1069

Table: 4. 1 Total collected Dataset

The dataset is divided into training, validation, and testing using the holdout method. This data splitting technique was selected in our study because it is simple and has high speed than k-Fold Cross-Validation to run on a local machine with a CPU processor. Training accounts for 80% of the total images (727), while validation accounts for 10% of the total images (164), and the remaining 10% which is 178 images for testing after the data is augmented. Here the following is the data set distribution.

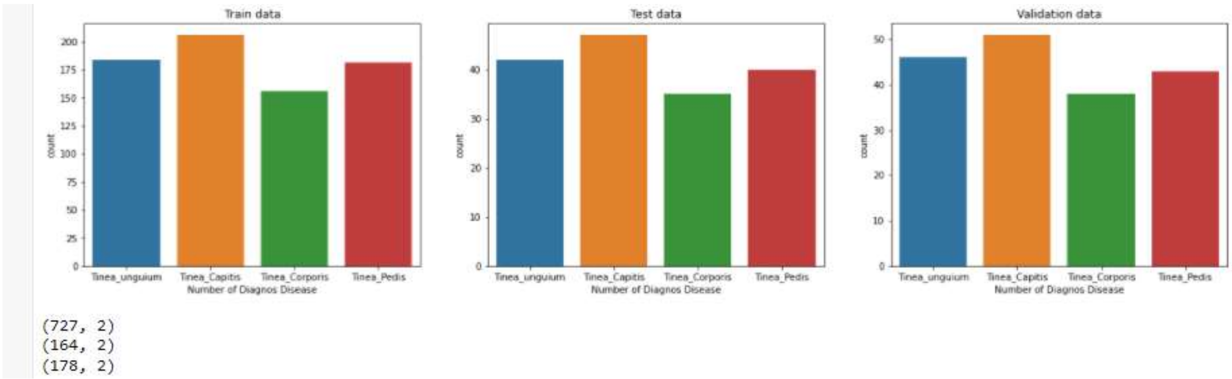


Figure: 4. 1 splited data distribution after augmentation

4.2.3 Evaluation Metrics

In this study, the provided model's performance is measured by the number of test records which the model correctly and wrongly predic ıd error rate can be used to evaluate the classifier's performance. The test model's correctly and wrongly categorized counts are summarized in a table known as a confusion matrix. The commonly used measurement metrics such as precision, recall, f1 score, and support are used to compute the accuracy of the system which is defined as follows.

The recall is the ratio of many correctly predicted over the total number of samples used.

$$\text{Recall} = \frac{\text{Correctly predicted}}{\text{Total number of samples}} \quad \frac{(TP)}{(TP+TN)} \quad \ldots\ldots\ \ldots\ldots 3.1$$

Equation: 3. 1 recall equation

Precision is the ratio of

$$\text{Precision} = \frac{\text{Correctly predicted}}{\text{Total No of positive}} \quad \frac{(TP)}{(TP+FP)} \quad \ldots\ldots\ldots\ldots\ldots\ldots 3.2$$

can be interpreted as a weighted harmonic mean of the precision and recall and is defined as

$$\text{F1- score} = \frac{2\times(\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots 3.3$$

Equation: 3. 3 F1-score equation

$$\text{Accuracy rate} = \frac{Total\ number\ of\ samples\ correctly\ classified * 100\%}{Total\ number\ of\ samples\ used\ for\ testing} = \frac{TP*TN*100\%}{P+N} \quad \ldots\ldots\ldots (3.4)$$

Equation: 3. 4 Accuracy question

Where P: Positives which refer to the total number of positive tuples.

N: Negatives refer to the total number of negative tuples.

TP: True positives refer to positive tuples that were correctly labeled by the classifier.

TN: True negatives refer to negative tuples that were correctly labeled by the classifier.

FP: False positives refer to the negative tuples that were mislabeled as positive.

FN: False negatives refer to the positive tuples that were mislabeled as negative

4.3.1 Experimentation Result

While training the model, some Hyperparameters i.e. variables determine the network structure for the optimized result of training. Those are:

Number of Epoch: How many times the model reads all the data set. Sometimes, just increasing the number of epochs for model training delivers better results, although this comes at the cost of increased Computation and training time.

Batch Size: Parts from all dataset to be visited at a time using a moderate batch size always helps achieve a smoother learning process for the model.

Learning Rate: is a positive fraction determining the step of learning of the network neurons.

Dropout: a mechanism of regularization of the training to overcome overfitting

Hyperparameter	**Taken value for Experiment**
Epoch	30
Batch size	32
Learning rate	0.0001
Droupout	0.5

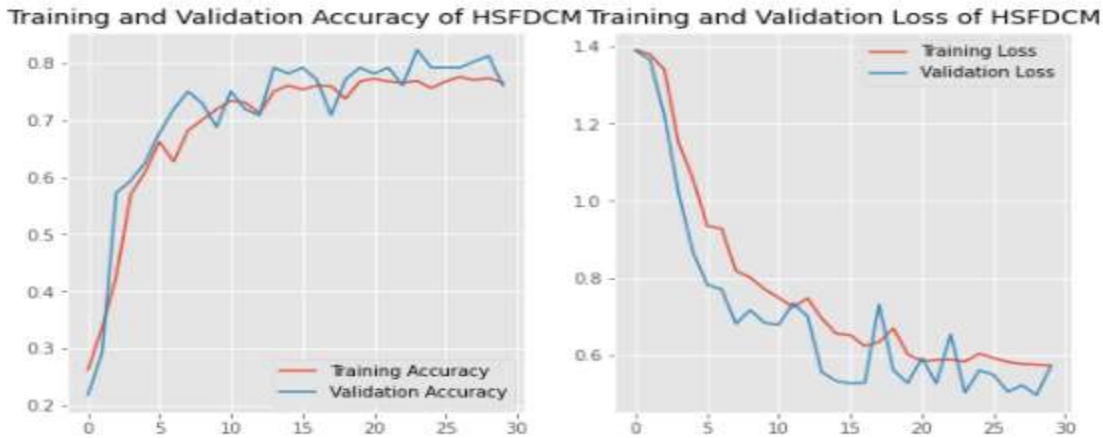
Table: 4. 2 Hyperparameters used in the experiment

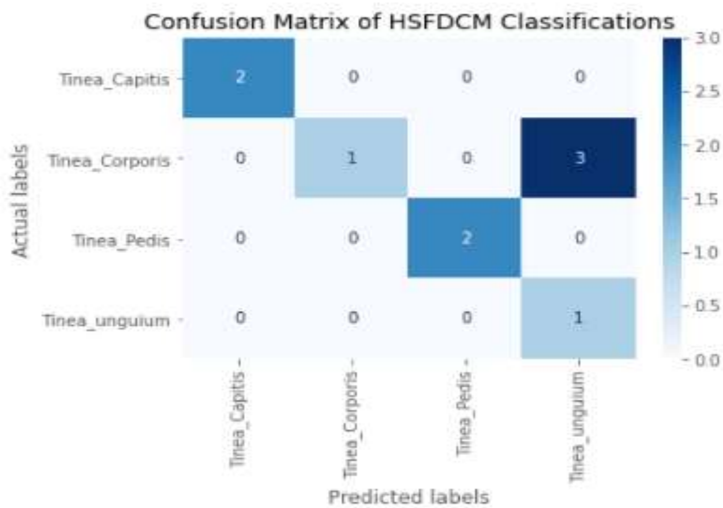
4.3.2 Experimenting to find appropriate Image sizes to achieve maximum accuracy

When you need to raise or decrease the total pixel for image standards, this image resizing is needed. Furthermore, shrinking the image greatly reduces processing time and costs. The collected images have different sizes. Image resize is the basic step in image preprocess because the data set must have a similar size the large pixel's size consumes too much computational cost and time. The collected images have different sizes. We resized to the image size of 120X120, 150X150, and 224X224. In this experiment, 224X224 registered the highest accuracy. As the size of the image increases it needs much computational time. The result is as follows

4.3.1.1Image Size 120 by 120 experiment

In this experiment, the model is trained using an image size of 120X120. From this, we have achieved 77%,76% for training and validation accuracy respectively. The plot diagram shows accuracy and loss result in figure 4.3 below.





	precision	recall	f1-score	support
Tinea_Capitis	1.00	1.00	1.00	2
Tinea_Corporis	1.00	0.25	0.40	4
Tinea_Pedis	1.00	1.00	1.00	2
Tinea_unguium	0.25	1.00	0.40	1
accuracy			0.67	9
macro avg	0.81	0.81	0.70	9
weighted avg	0.92	0.67	0.67	9

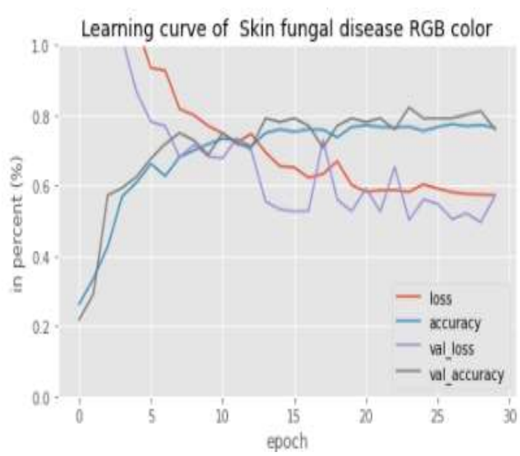
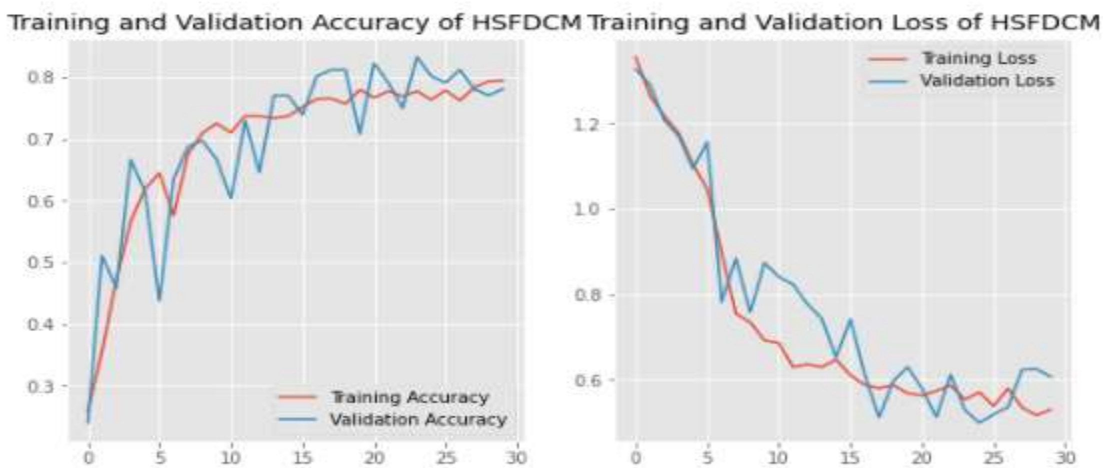


Figure: 4. 2 accuracies and Loss confusion metric's Learning Rate and classification report for 120 X 120 image size

4.3.1.2 Image size 150 by 150 experiment

In this experiment, the model is trained using an image size of 150X150. From this, we have achieved 79%, 78% for training and validation accuracy respectively. This result shows that image 150X150 achieves better performance than image size 224X224 but it requires more time to train. The plot diagram shows the accuracy and loss result in figure 4.4 below.



	precision	recall	f1-score	support
Tinea_Capitis	1.00	1.00	1.00	3
Tinea_Corporis	1.00	0.50	0.67	2
Tinea_Pedis	0.50	1.00	0.67	1
Tinea_unguium	1.00	1.00	1.00	3
accuracy			0.89	9
macro avg	0.88	0.88	0.83	9
weighted avg	0.94	0.89	0.89	9

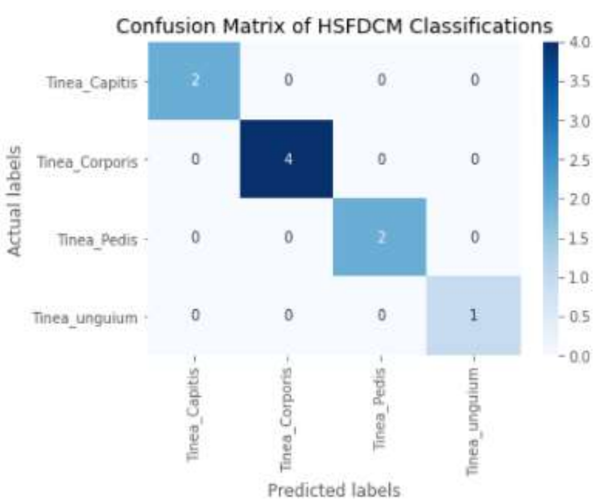


Figure: 4. 3 accuracies and Loss confusion matrix and classification report for 150X150 image size for HSFDC Model

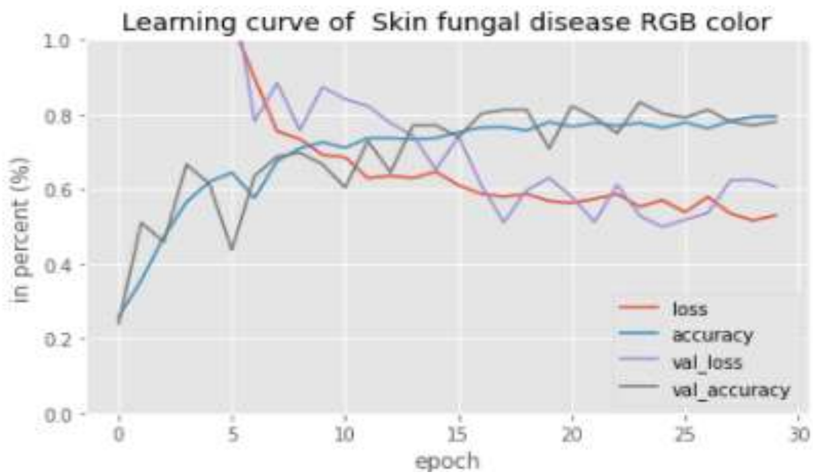
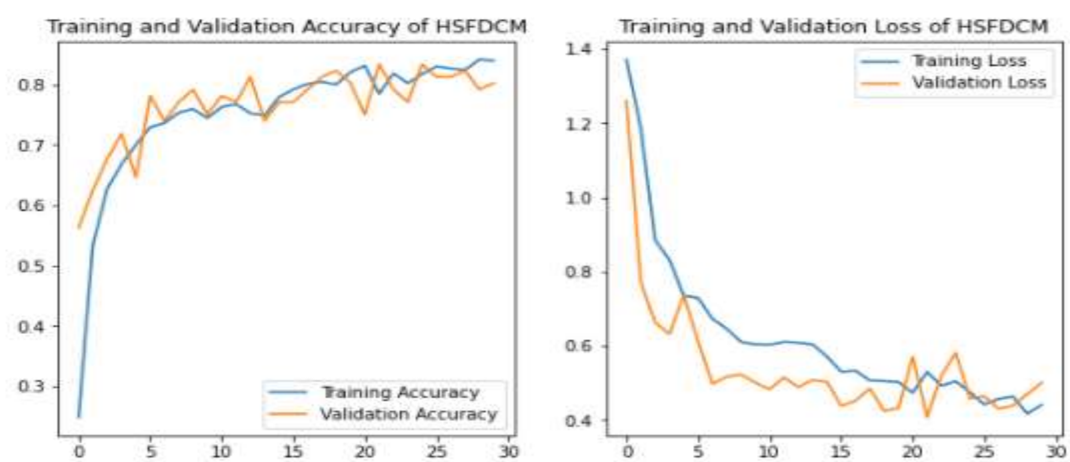


Figure: 4. 4 learning curve for 150X150 RGB using HSFDC Model

4.3.1.3 Image size 224 by 224 experiment

The model is trained with an image size of 224X224 in this experiment. We were able to attain 83 %, 80 %, and 80 % accuracy for training and validation, respectively. This result shows that image 224X224 achieves better performance than image sizes 120X120 and 150X150 but it requires more time to train. The plot diagram shows the accuracy and loss result in figure 4.5 below.



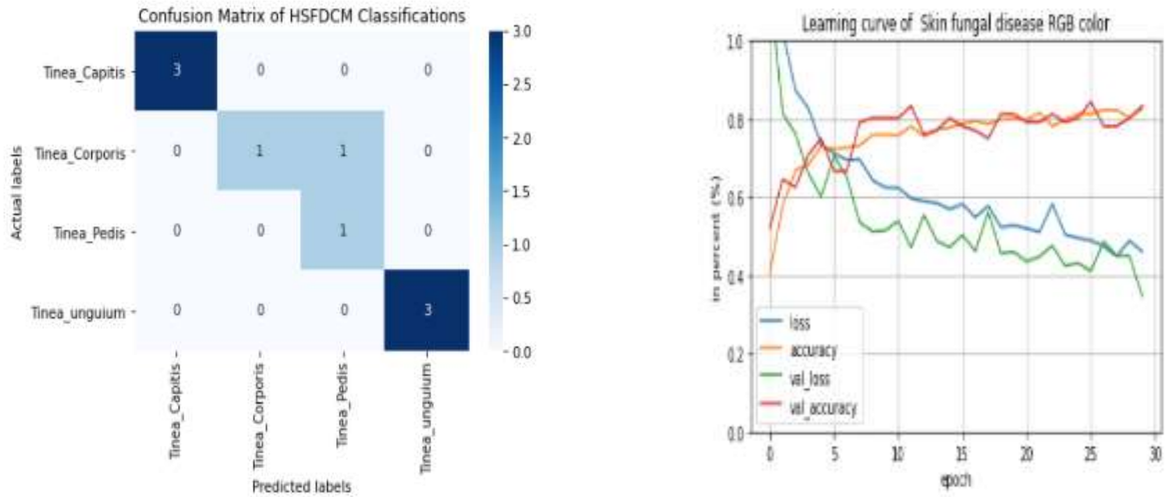


Figure: 4. 5 Accuracy Loss confusion matrix and learning curve for 224 X 224 image size

HSFDC Moc	**Image size**	**Training accuracy i**	**Validation accura %**	**Test accuracy in %**
	120 X 120	77	76	68
	150X 150	79	78	76
	224 X 224	83	80	79

Table: 4. 3 HSFDCModel different image size results

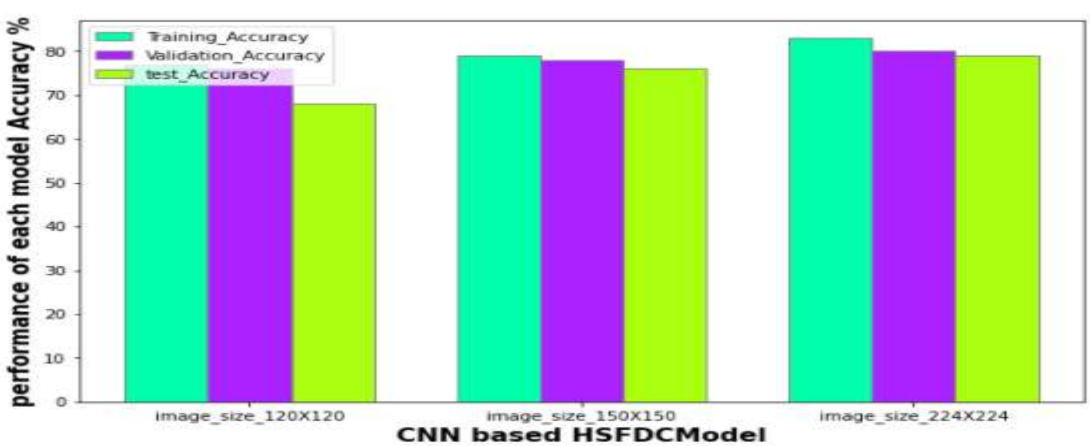


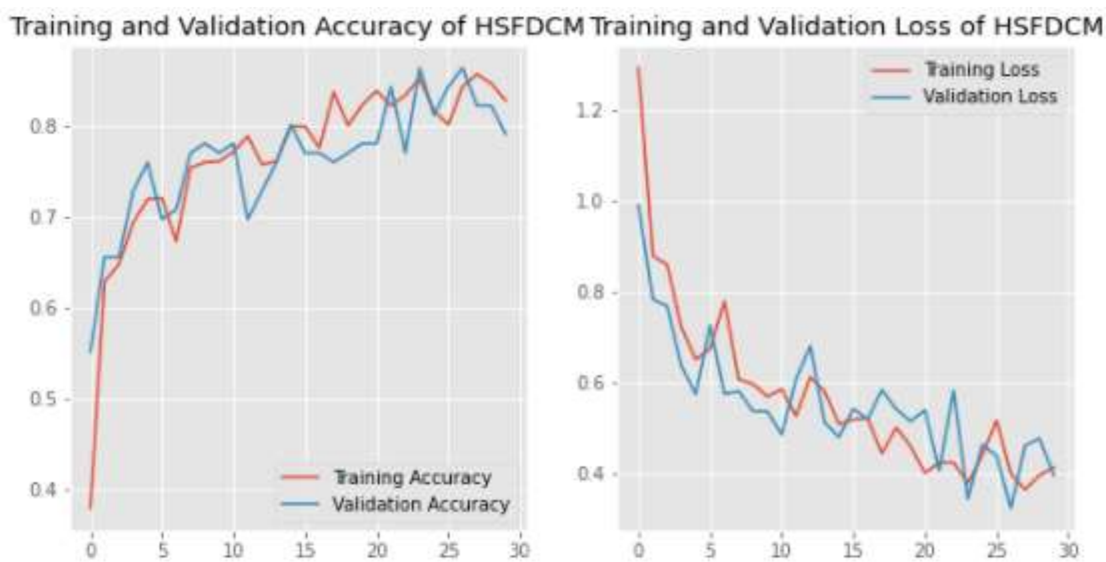
Table: 4. 4 Experimental results of three different image size HSFDCModel

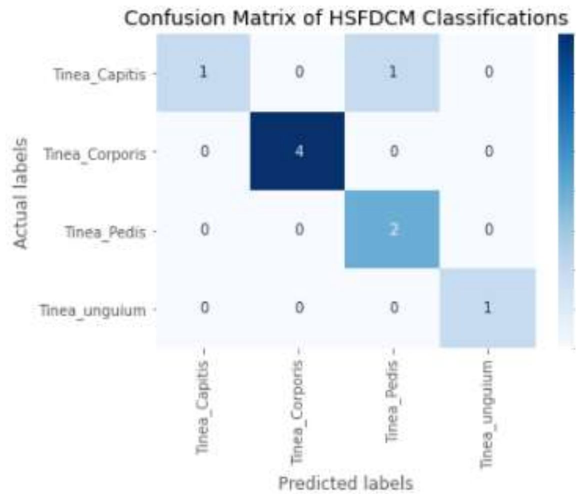
4.3.3 Experimenting to find appropriate Activation function to achieve maximum accuracy

In this experiment, the model is trained using an image size of 224X224, RGB color mode to check the appropriate activation function for HSFDCModel. We conduct this experiment using Relu and ELU separately. The result is as follows.

4.3.2.1HSFDCModel using 224X224 image size and ELU Activation Function

In this experiment, the model was trained using 224X224 image size RGB color mode and with Elu as an activation function. From this, we have achieved 82%, 79% for training and validation accuracy respectively. This result shows that the Elu activation function registered less performance than Relu. The plot diagram shows this accuracy and loss result in figure 4.7.





	precision	recall	f1-score	support
Tinea_Capitis	1.00	0.50	0.67	2
Tinea_Corporis	1.00	1.00	1.00	4
Tinea_Pedis	0.67	1.00	0.80	2
Tinea_unguium	1.00	1.00	1.00	1
accuracy			0.89	9
macro avg	0.92	0.88	0.87	9
weighted avg	0.93	0.89	0.88	9

Figure: 4. 6 Training and validation accuracy loss confusion matrix and classification report of HSFDCModel result using Elu

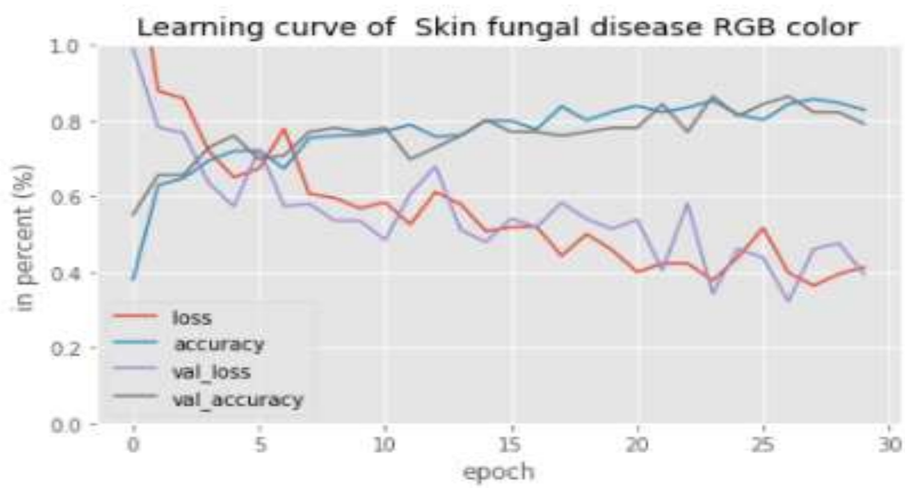


Figure: 4. 7 Learning Curve of HSFDCModel using Elu

4.3.2.2HSFDCModel using 224X224 image size and Relu Activation Function

In this experiment, the model was trained using 224X224 image size, RGB color images, and with Relu as an activation function. From this, we have achieved 83, and 80% for training and validation accuracy respectively. This result shows that the Relu activation function enhances the performance of Elu. The table shows this accuracy and loss result.

HSFDC Model	**Activation functi**	**Training accuracy**	**Validation accuracy in**	**Test accuracy in %**
	Relu	83	80	79
	Elu	82	79	78

Table: 4. 5 HSFDCModel result using Relu and Elu activation function

4.3.4 Experimenting to find an appropriate color mode to achieve maximum accuracy

In this experiment, the appropriate color mode for Skin fungal diseases classification is identified. We have done two experiments using RGB and Grayscale color mode with an image size of 224X224. The result shows that the classification accuracy using RGB color is better than using grayscale color mode.

4.3.3.1Experimenting HSFDCModel using RGB color mode

In this experiment, we have used RGB color mode to identify which color mode achieves better results and as a result using RGB color mode for HSFDCModel achieves the highest accuracy. The result is shown in subsection 4.3.1.2 above.

4.3.3.2Experimenting HSFDCModel using Grayscale color mode

Two-color modes we have examined the performance of the RGB color and Grayscale separately. We have compared RGB and Grayscale color mode using HSFDCModel by using an image size of 224X224. The results suggest that utilizing RGB color mode enhances classification accuracy over using grayscale color mode. The result is as follows.

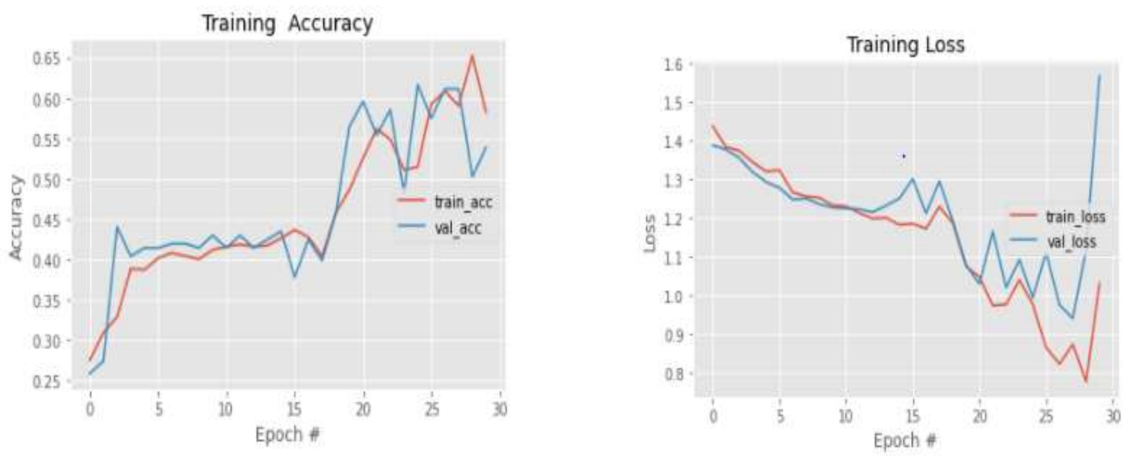
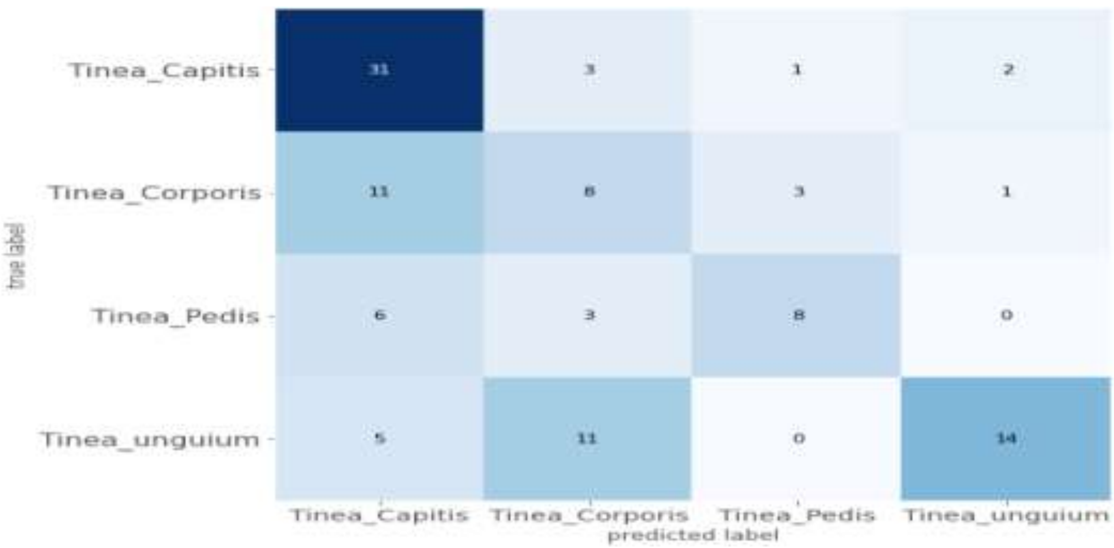


Figure: 4. 8 Training accuracy and training loss using Gray color




```
                precision    recall  f1-score   support

 Tinea_Capitis       0.58      0.84      0.69        37
Tinea_Corporis       0.32      0.35      0.33        23
   Tinea_Pedis       0.67      0.47      0.55        17
 Tinea_unguium       0.82      0.47      0.60        30

      accuracy                           0.57       107
     macro avg       0.60      0.53      0.54       107
  weighted avg       0.61      0.57      0.56       107

classification report for HSFDM gray color image
```

Figure: 4. 9 HSFDCModel result using grayscale confusion matrix and classification report

HSFDCModel	Color mode	Image size	Training accu in %	Validation accu in %	Test accurac in %
	RGB	224 X 224	83	80	79
	Grayscale	224 X 224	58	53	57

Table: 4. 6 HSFDCModel result using RGB and Grayscale color mode

4.3.5 Identification of suitable algorithm for skin disease image classification model

Comparison is done with deep neural networks using the same dataset and parameter with architectural differences in the model. As we described in the methodology section 3.3.4, there are different types of deep neural network models such as AlexNet, ResNet, MobileNet, VGG16, VGG19, and GoogleNet. From these models, we select MobileNet V2 and ResNet 50 to evaluate our model. The reason selects this model is related to hardware dependency, since, this architecture runs on the CPU.

4.3.4.1 Experimentation Result for MobileNetV2 model

In this experiment, the MobileNetV2 model was trained using 224X224 image size, RGB color channel, and Relu activation function because our model (HSFDCM) achieves better results in 224X224 image size, RGB color images, and Relu activation function as shown in the above three experiments. We got 79%, 74% training, and validation accuracy respectively. This shows HSFDCModel achieves better (83%) than the performance of MobileNetV2. As shown in figure 4.11 the training and validation accuracy, training, and validation loss are plotted.

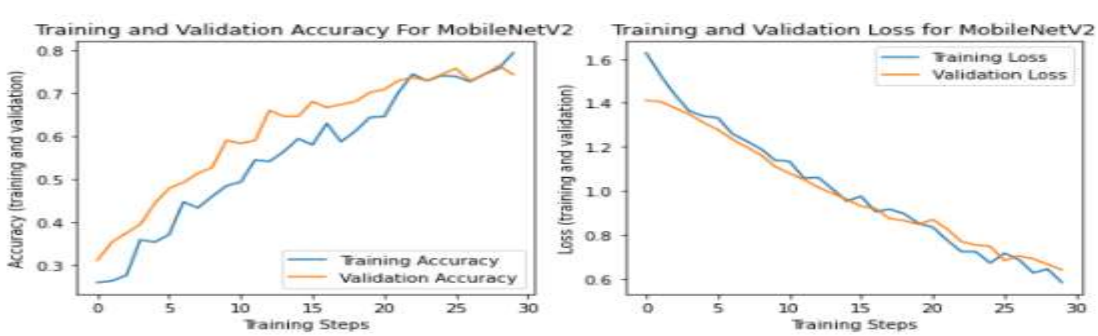


Figure: 4. 10 MobileNetV2 model result

4.3.4.2 Experimentation Result for ResNet 50 Model

In this experiment, the ResNet50 model was trained using 224X224 image size, RGB color channel, and Relu activation function because our model (HSFDCM) achieves better results in 224X224 image size, RGB color images, and Relu activation function as shown in the above three experiments. We got 69%, 66% training, and validation accuracy respectively. This shows HSFDCModel achieves better (83%) than the performance of ResNet50. As shown in figure 4.12 the training and validation accuracy, training, and validation loss are plotted.

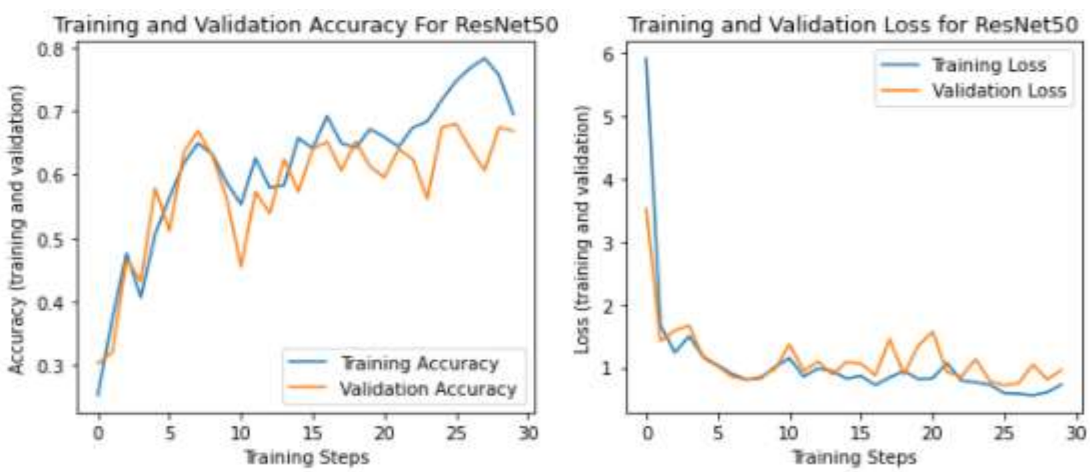


Figure:4. 11 ResNet50 model result

Model	Color mo	Image size	Training accurac %	Validation accuracy in %
HSFDCModel	RGB	224 X 224	83	80
MobileNetV2	RGB	224 X 224	79	74
ResNet 50	RGB	224X224	69	66

Table: 4. 7 Result of HSFDCModel, MobileNetV2 and ResNet 50

4.3.6 Discussion

We examine the different parameters until obtained better results in each technique by examining the different parameters discussed above. The classification process details four experimental scenarios with CNN features to identify the optimal feature classification techniques. The first experiment is focused on classifying the skin fungal diseases by using three image sizes (120X120, 150X150, and 224X224). Under this experiment, we have done each image size separately using CNN-based HSFDCModel. We got an accuracy of 77% for 120X120, 79% for 150X150 and, 83% for 224X224(image size).From this experiment result with an image size of 224X224, the accuracy registered high. And as the size of the image increases the computation time is also increasing.

The second experiment is focused on classifying the skin fungal diseases by using the CNN-based HSFDCModel with Relu activation function and we get 83% performance while scenario two do the same steps for using CNN-based HSFDCModel with Elu activation function and 82 % performance of classification model.

The third experiment is focused on classifying the skin fungal diseases by using the CNN-based HSFDCModel with RGB color space and we get 83% performance while scenario two does the same steps for using CNN-based HSFDCModel with the grayscale of color space and 58 % performance of classification model. In the fourth experiment, the comparison is made between CNN-based HSFDCModel and pre-trained MobileNetV2 and ResNet50 using image size 224X224, RGB color mode, and activation function Relu. The experimental result shows that our model (HSFDCModel) registered the highest accuracy than the pre-trained MobileNetV2 and ResNet50 for our dataset.

4.3.7 Evaluation

Based on the above training result we evaluate our model using deep learning evaluation techniques. The classification report is described based on the experiment result. The overall prediction of the model is measured by accuracy. Because our prepared dataset is balanced in each class distribution.

Model used	Image size	Activation funct	Color Channel	Training Accuracy	Validation Accuracy
HSFDCM	120X120	Relu	RGB	77%	76%
HSFDCM	150X150	Relu	RGB	79%	78%
HSFDCM	224X224	Relu	RGB	83%	80%
HSFDCM	224X224	Elu	RGB	82%	79%
HSFDCM	224X224	Relu	RGB	83%	80%
HSFDCM	224X224	Relu	RGB	83%	80%
HSFDCM	224X224	Relu	Gray	58%	53%
HSFDCM	224X224	Relu	RGB	83%	80%
MobileNetV2	224X224	Relu	RGB	79%	74%
ResNet50	224X224	Relu	RGB	69%	66%

Figure:4. 12 Summary of experiments result

Figure: 4. 13 Sample test result visualization using HSFDC Model

4.3.8 Summary

The whole dataset and the number of images in each class are described in this chapter. The system's implementation tools, as well as the model's evaluation results and comparisons to CNN architectures MobileNetV2 and ResNet50, are reviewed. HSFDCModel, our model, outperforms MobileNetV2 and ResNet50 in terms of classification accuracy.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION'S

5.1Conclusion

Previously many works are done in the area of Diagnosing, detection, and classification of skin diseases. As far as the researcher's knowledge, most research works consider only for white skin color, and tinea pedis and tinea corpories are not identified. In this study, there is an effort made to construct an optimal model for the classification of skin fungal lesion images types.

In this study, we conducted the use of a pre-trained CNN model to classify fungal skin diseases types that are common in developing countries. This is unending research and future work included also not limited to increasing and cleaning the dataset by continuing to collect. Feature extraction of the skin lesion images and use the extracted features in the advanced deep learning algorithms in convolutional neural networks and see how the result compares with the result of this study. The development of the skin diseases classification model supports the health sector experts (Dermatologists) to classify skin lesion images. The datasets were collected from patients at Dr. Gerbi medium clinic of Jimma and JUMC using a smartphone camera. Finally, the model is developed and this model is used to identify and classify the four common fungal skin lesion types the classification is occur after the convolutional neural network extracts the features of the images, then Softmax classifiers classify based on the images features which are extracted by CNN before display the result as tinea capitis, tinea pedis, tinea corpories, and tinea unguium. We register an overall performance accuracy of 83%.

5.2 Contribution

In this thesis work, we contribute a lot to the area of the health stack holder's patients, and the scientific community. the first one is we develop and investigate human skin fungal disease classification model, secondly, we collect and prepare a dataset to feed the convolutional neural network for training model and testing the model, thirdly we also ready to upload our prepared human skin fungal lesion dataset for the public repository for future researchers.

5.3 Recommendations

The suggested work can be further extended to improve performance. Therefore, the following are some notable future work recommendations observed during this study.

- The amount of datasets used in this task is not large. Deep learning requires a large amount of data, so, we recommend increasing the dataset.
- Only four classes are considered in this task. We recommend increasing the number of classes to distinguish normal skin from all common types of skin diseases.

References

[1] S. J. ,. A.-O. a. T. S. John D'Orazio, "UV radiation and the skin," *International Journal of Molecular Sciences,* vol. 14, p. 12222–12248, 2013.

[2] N. V. K. N. a. U. S. Yadav, "Skin diseases detection models using image processing: A survey.," *International journal of computer applications ,* vol. 12 , no. 137, pp. 34-39, 2016.

[3] K. A. Zimmermann, "live science," 22 October 2018. [Online]. Available: https://www.livescience.com/27115-skin-facts-diseases-conditions.html. [Accessed 12 11 2021].

[4] B. R. Gulati S, " Serving the dermatologists: skin diseases detection.," *In Information and Communication Technology for Sustainable Development,* pp. 799-822, 2020.

[5] M. .. S. F. S. T. B. A. B. a. A. Z. L. Tizek, "Skin diseases are more common than we think : screening results of an unreferred population at the Munich Oktoberfest," *Journal of the European Academy of Dermatology and Venereology,* no. DOI: 10.1111/jdv.15494, pp. 1-8, 2019.

[6] R. S. b. R. A. c. T. Shanthi a, "Automatic diagnosis of skin diseases using convolution neural network," *Microprocessors and Microsystems,* vol. 76, pp. 1-7, 2020.

[7] D. D. A. Dagne, "Recognizing neglected skin diseases: WHO publishes pictorial training guide," World Health Organization Global, 8 Jun 2018. [Online]. Available: Available:https://www.who.int/neglected_diseases/news/WHO-publishes-pictorial-training-guide-onneglected-. [Accessed 12 11 2021].

[8] A. A. P. Y. C. N. K. N. Samuel Akyeramfo-Sam, "A Web-Based Skin Disease Diagnosis Using Convolutional Neural Networks," *International Journal of Information Technology and Computer Science ,* vol. 11, pp. 54-60, 2019.

[9] A. O. P. R. A. B. E. W. L. a. D. B. Kelbore, "Pattern of skin diseases in children attending a dermatology clinic in a referral hospital in Wolaita Sodo, southern Ethiopia," *BMC dermatology 19,* p. 1_8, 2019.

[10] WORLDHEALTHRANKINGS, WORLD HEALTH ORGANIZATION , 2018. [Online]. Available: https://www.worldlifeexpectancy.com/ethiopia-skin-disease. [Accessed 20 07 2021].

[11] A. Bewley, "The neglected psychological aspects of skin disease," vol. 3208, 2017.

[12] B. P. ". f. i. Kelly, "Superficial Fungal Infections. skin disorders," *Pediatrics in review,* vol. 4, pp. 1-19, 2012.

[13] A. K. R. R. M. S. G. V. B. M. P. A. T. A. S. M. B. e. a. Gupta, "Global perspectives for the management of onychomycosis," *International journal of dermatology,* vol. 10, p. 1118–1129, 2019.

[14] L. H. M. O. J. M. B. D. M. W. L. D. R. F. N. a. A. B. Kamulegeya, "Using artificial intelligence on dermatology conditions in Uganda: A case for diversity intraining data sets for machine learning," pp. 1-30, 2019.

[15] N. A. S. a. M. A. H. Hameed, "A Computer-aided diagnosis system for classifying prominent skin lesions using machine learning," *Computer Science and Electronic Engineering (CEEC),* pp. 185-191, 2018.

[16] R. B. S. E. C. S. E. R. A. H. M. T. &. M. Hay, "Skin Diseases.," 2016. [Online]. Available: https://www.ncbi.nlm.nih.gov/books/NBK11733/. [Accessed 12 11 2021].

[17] D. S. &. K. C. &. D. B. &. E. E. Freeman, "Global Burden of Skin Disease: Inequities and Innovations," *EPIDEMIOLOGY (R DELLAVALLE, SECTION EDITOR),* vol. 6, no. 3, pp. 204-210, 7 aug 2017.

[18] Y. F. a. H. Z. Yuan Zhou, "Human Fungal Infection Image Classification Based on Convolutional Neural Network," in *In Chinese Conference on Image and Graphics Technologies Springer*, Singapore, 2019.

[19] M. Hoffman, "skin-problems-and-treatments," Picture of the Skin, 7 NOv 2019. [Online]. Available: https://www.webmd.com/skin-problems-and-treatments/picture-of-the-skin. [Accessed 12 Nov 2021].

[20] J. a. Bartlett, "Basic Biology of the Skin," 2020.

[21] A. S. a. M. Babaev, "Fungal Infections (Onychomycosis,Tinea Pedis, Tinea Cruris, Tinea Capitis, Tinea Manuum, Tinea Corporis, different Candida Infections, and PityriasisVersicolor) and Mycological," *Springer International Publishing AG, part of Springer Nature,* pp. 237-242, 2018.

[22] P. K. Gaurav Kumar, "A Detailed Review of Feature Extraction in Image Processing Systems," pp. 1-9, 2014.

[23] S. Mahamd, "A model for identifying Historical Landmarks of Bangladesh from image content using a Depth-wise," in *18th International Conference on Intelligent Systems Design and Applications (ISDA 2018)* , Vellore, 2019.

[24] W. L. Y. J. e. a. Szegedy C, "Going deeper with convolutions," in *In: 2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, 2015.

[25] K. Z. X. R. S. a. S. J. He, " Deep residual learning for image recognition.," *In Proceedings of the IEEE conference on computer vision and pattern recognition,* pp. 770-778, 2016.

[26] A. Pujara, "Analytics vidhya," 14 Jul 200. [Online]. Available: https://medium.com/analytics-vidhya/image-classification-with-mobilenet-cc6fbb2cd470. [Accessed 15 10 2021].

[27] T. Bayes, "Naïve Bayes Classifier.Evidence from a Tunisian commercial bank," vol. 22, pp. 3-24, 2017.

[28] O. Harrison, "Machine Learning Basics with the K-Nearest Neighbors Algorithm," *International Conference on Computational Science and Computational Intelligence.,* 2018.

[29] R. Bridgelall, "Introduction to Support Vector Machines," *Lecture Notes,* pp. 1-18., 2017.

[30] D. K. Narender Kumar, "Classification using Artificial Neural Network Optimized with Bat Algorithm," *nternational Journal of Innovative Technology and Exploring Engineering (IJITEE)ISSN,* vol. 9, no. 3, pp. 2278-3075, 2020.

[31] D. K. Narender Kumar, "Classification using Artificial Neural Network Optimized with Bat algorithm," *nternational Journal of Innovative Technology and Exploring Engineering (IJITEE)ISSN,* vol. 9, no. 3, pp. 2278-3075, 2020.

[32] L. L. •. Y. Z. •. G. C. L. Yang, Deep Learning and Convolutional Neural Network For Medical Image Computing, Switzerland : springer, 2017.

[33] M. I. S. N. a. A. Z. Razzak, "Deep learning for medical image processing: Overview, challenges and the future," *Classification in BioApps,* pp. 323-350, 2018.

[34] Z. W. K. M. S. a. Jiuxiang Gu, "Recent advances in convolutional neural networks pattern recognition," *Elsevier Ltd,* vol. 1, no. 77, pp. 354-377, 2017.

[35] R. a. A. A. Sathya, "Comparison of Supervised and Unsupervised Learning Algorithms for Pattern classification," *(IJARAI) International Journal of Advanced Research in Artificial Intelligence,* vol. 2, no. 2, pp. 34-38, 2013.

[36] L. S. L. a. Y. Z. Xiangbin Liu, "A Review of Deep-Learning-Based Medical Image Segmentation Methods," *journal sustainability 13,* vol. 3, p. 1224, 2021.

[37] H. Y. W. S. H. a. G. G. Gu, "Blind Channel Identification Aided Generalized Automatic Modulation Recognition based on Deep Learning," *IEEE Access ,* vol. 7, pp. 110722-110729., 2019.

[38] A. Ghosh.et.al, "Fundamental Concepts of Convolutional Neural Network," *In Recent Trends and Advances in Artificial Intelligence and Internet of Thing springer,* pp. 519-567, 2020.

[39] K. R. S. B. Ms.Siva S Sinthura, "Advanced Skin Diseases Diagnosis Leveraging Image Processing," in *Proceedings of the International Conference on Electronics and Sustainable Communication Systems*, 2020.

[40] E. N.-E. e. al, "Melanoma Detection by Analysis of Clinical Images Using Convolutional Neural Network," *in Annu Int Conf IEEE Eng Med Biol Soc,* pp. 1-4, 2016.

[41] A. B. H. A. N. K. Mrs. Jayashree Hajgude, "Skin Disease Detection Using Image Processing with Data Mining and Deep Learning," *International Research Journal of Engineering and Technology (IRJET),* vol. 06, no. 04 , pp. 4363-4366, 2019.

[42] C. P. J. W. A. J. A. J. S. C. M. G. B. J. M. L. T. A. T.-a. R. J. J. Jessica Velasco, "A Smartphone-Based Skin Disease Classification Using MobileNet CNN," *International Journal of Advanced Trends in Computer Science and Engineering,* vol. 8, pp. 2632-2637, 2019.

[43] Z. H. E. W. e. al, "Studies on Different CNN Algorithms for Face Skin Disease Classification Based on Clinical Images," *IEEE Access,* vol. 7, pp. 66505-66511, 2019.

[44] S. a. T.Velmurugan, "Preprocessing by Contrast Enhancement," *International Journal of Pure and Applied Mathematics,* vol. 118, pp. 3681-3688, 2018.

[45] 2. A. S. 2. U. Z. a. A. S. Q. Asifullah Khan1, "A Survey of the Recent Architectures of Deep Convolutional Neural Networks," *Published in Artificial Intelligence Review,* 2018.

[46] A. Ghosh.et.al, "Fundamental Concepts of convolutional Neural Network," *In Recent Trends and Advances in Artificial Intelligence and Internet of Thing springer,* pp. 519-567, 2020.

[47] J. S. Lee JG1, "Deep Learning in Medical Imaging: General Overview," *Korean J Radiol,* vol. 17, no. 4, pp. 570-584, 2017.

[48] V. K. D. &. K. V. Sandeep, "Seed image analysis: its applications in seed science research," *International Research Journal of Agricultural Sciences,* vol. 1, pp. 30-36, 2013.

[49] R. E. W. Rafael C. Gonzalez, Digital image processing using matlab, Pearson Education international, 2004.

[50] P. S. Rajeshwar Dass, "Image Segmentation Techniques," *IJECT Vo l. 3, IssuE1, Jan. - March 2012,* 2012.

[51] A. A. Catherine R. Alimboyong, "Classification of Plant Seedling Images Using Deep Learning," in *IEEE Region 10 Conference*, 2018.

[52] Q. G. a. T. J. Li-sheng Wei, "Skin Disease Recognition Method Based on Image Color and Texture Features," *Computational and Mathematical Methods in Medicine,* 2018.

[53] Y. F. e. al, "Deep learning-based, computer -aided classifier developed with a small datasetof clinical images surpasses board-certified dermatologists in skin tumor diagnosis," *” Br. J. Dermatol,* pp. 0-3, 2018.

[54] G. CJ, "Research in Psychology: Methods and Design. USA, Western Carolina University: John Wiley & Sons, Inc.," 1010.

[55] J.-e. L. 1. a. F.-P. An, "Image Classification Algorithm Based on Deep Learning-Kernel Function," *Hindawi Scientific Programming,* vol. 2020, p. 14, 2020.

[56] D. R. Adrian, "Deep Learning for Computer Vision with Python," 2017.

[57] A. P. M. H. a. Berkman Sahiner, "Deep learning in medical imaging and radiation therapy," *American Association of Physicists in Medicine,* 2018.

[58] e. Phooi Yee Lau, "IMAGE CLASSIFICATION FOR DIFFERENT IMAGING MODALITIES EN IMAGE-GUIDED MEDICAL DIAGNOSIS MODEL," *IEEE,* p. 150, 2003.

[59] ∗. N. H. Y. S. S. H. Y. W. Tomoko Maruyamaa, "Comparison of medical image classification accuracy among three machine learning methods," *Journal of X-Ray Science and Technology,* 2018.

[60] U. D. o. H. a. H. Services, "National Institutes of Arthritis and Musculoskeletal and Skin Disease," [Online]. Available: https://www.niams.nih.gov/health-topics/arthritis. [Accessed 25 07 2021].

[61] S. P. Ravishankar Chityala, Image Processing and Acquisition using Python, CRC Press Taylor & Francis Group, 2014.

[62] [Online]. Available: https://ai.stanford.edu/~syyeung/cvweb/tutorial1.html. [Accessed 01 08 2021].

[63] D. U. B. M. R. a. G. K. Alexander Ziller, "Medical imaging deep learning with diferential privacy," natureportfolo, 2021.

[64] J.-R. L. Wang Yang, "Research and development of medical image fusion," *IEEE,* p. 307, 2013.

[65] R. S. b. R. A. c. T. Shanthi a, "Automatic diagnosis of skin diseases using convolution neural network," 2020.

[66] K. R. S. S. C. S. Ghosh, "Skin Disease detection based on different Segmentation Techniques," 2019.

[67] B. R. H. a. R. M.-J. ". d. a. m. o. t. Moriarty, "The diagnosis and management of tinea," 2012.

[68] "skin-fungus," cleve land clinic, 25 Sep 2020. [Online]. Available: https://my.clevelandclinic.org/health/diseases/4276-skin-fungus. [Accessed 8 10 2021].

[69] R. Shy, "Tinea Corporis and Tinea Capitis," *Pediatrics in Review ,* vol. 28, 2007.

[70] T. B. a. D. W. D. Tufa, "The Burden of Fungal Infections in Ethiopia," *Journal of Fungi,* vol. 4, no. 5, p. 109, 2019.

[71] A. S. a. M. A. H. N. Hameed, "A Computer-aided diagnosis system for classifying prominent skin lesions using machine learning," *In2018 10th Computer Science and Electronic Engineering (CEEC) ,* pp. 186-191, 2018.

[72] s. Das, "CNN Architectures: LeNet, AlexNet, VGG, GoogLeNet, ResNet and more…," Analytics Vidha, 16 Nov 2017. [Online]. Available: https://medium.com/analytics-vidhya/cnns-architectures-lenet-alexnet-vgg-googlenet-resnet-and-more-666091488df5. [Accessed 11 2 2021].

[73] I. S. E. H. Alex Krizhevsky, "ImageNetClassificationwithDeepConvolutional NeuralNetworks. Advances in neural information processing systems," pp. 1-9, 2012.

[74] O. G. a. T. Blaschke, "ptimizing Sample Patches Selection of CNN to Improve the mIOU," *GISTAM 2019 - 5th International Conference on Geographical Information Systems Theory Applicatio and management,* pp. 33-40, 2019.

[75] M. R. M. A. S. Hariharan, "Image Classification using Convolutional Neural Networks," *International Journal of Pure and Applied Mathematics,* vol. 119, no. 17, pp. 1307-1319, 2018.

[76] K. D. M. A. T. Z. G. L. S. Kedir Ali Muhaba, "Automatic skin disease diagnosis using deep learning from clinical image and patient information," *Research Square,* pp. 1-22, 2021.

Appendix A: Developed model summary:

```
Model: "sequential_12"
_________________________________________________________________
Layer (type)                Output Shape              Param #
=================================================================
sequential_1 (Sequential)   (None, 224, 224, 3)       0

conv2d_62 (Conv2D)          (32, 222, 222, 64)        1792

max_pooling2d_62 (MaxPooling (32, 111, 111, 64)       0

conv2d_63 (Conv2D)          (32, 109, 109, 64)        36928

max_pooling2d_63 (MaxPooling (32, 54, 54, 64)         0

conv2d_64 (Conv2D)          (32, 52, 52, 64)          36928

max_pooling2d_64 (MaxPooling (32, 26, 26, 64)         0

conv2d_65 (Conv2D)          (32, 24, 24, 64)          36928

max_pooling2d_65 (MaxPooling (32, 12, 12, 64)         0

conv2d_66 (Conv2D)          (32, 10, 10, 64)          36928

max_pooling2d_66 (MaxPooling (32, 5, 5, 64)           0

conv2d_67 (Conv2D)          (32, 3, 3, 64)            36928

max_pooling2d_67 (MaxPooling (32, 1, 1, 64)           0

flatten_10 (Flatten)        (32, 64)                  0

dense_24 (Dense)            (32, 64)                  4160

dense_25 (Dense)            (32, 4)                   260
=================================================================
Total params: 190,852
Trainable params: 190,852
Non-trainable params: 0
_________________________________________________________________
```

Appendix B: Developed model training progress:

```
Epoch 20/30
27/27 [==============================] - 126s 5s/step - loss: 0.5026 - accuracy: 0.8206 - val_loss: 0.4325 - val_accuracy: 0.80
21
Epoch 21/30
27/27 [==============================] - 146s 5s/step - loss: 0.4735 - accuracy: 0.8310 - val_loss: 0.5711 - val_accuracy: 0.75
00
Epoch 22/30
27/27 [==============================] - 133s 5s/step - loss: 0.5301 - accuracy: 0.7847 - val_loss: 0.4076 - val_accuracy: 0.83
33
Epoch 23/30
27/27 [==============================] - 139s 5s/step - loss: 0.4927 - accuracy: 0.8183 - val_loss: 0.5203 - val_accuracy: 0.79
17
Epoch 24/30
27/27 [==============================] - 129s 4s/step - loss: 0.5046 - accuracy: 0.8021 - val_loss: 0.5813 - val_accuracy: 0.77
08
Epoch 25/30
27/27 [==============================] - 129s 5s/step - loss: 0.4751 - accuracy: 0.8171 - val_loss: 0.4583 - val_accuracy: 0.83
33
Epoch 26/30
27/27 [==============================] - 128s 5s/step - loss: 0.4421 - accuracy: 0.8299 - val_loss: 0.4638 - val_accuracy: 0.81
25
Epoch 27/30
27/27 [==============================] - 129s 5s/step - loss: 0.4573 - accuracy: 0.8264 - val_loss: 0.4305 - val_accuracy: 0.81
25
Epoch 28/30
27/27 [==============================] - 118s 4s/step - loss: 0.4636 - accuracy: 0.8241 - val_loss: 0.4389 - val_accuracy: 0.82
29
Epoch 29/30
27/27 [==============================] - 116s 4s/step - loss: 0.4176 - accuracy: 0.8414 - val_loss: 0.4701 - val_accuracy: 0.79
17
Epoch 30/30
27/27 [==============================] - 113s 4s/step - loss: 0.4407 - accuracy: 0.8391 - val_loss: 0.5005 - val_accuracy: 0.80
21
Time: 1:03:55.998589
```

```
scores = HSFDCM.evaluate(test_ds)
```

```
4/4 [==============================] - 3s 760ms/step - loss: 0.5106 - accuracy: 0.7969
```