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Detection and Classification of Skin Cancer Using Image Processing and Deep Learning

BY:

DEGAREGE AMARE DEMESSIE

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Detection and Classification of Skin Cancer Using Image Processing and Deep Learning

By:

Degarege Amare Demessie

Advisor: Dr. Tebebe Beshah (PhD.)

A Thesis Submitted to Technical and Vocational Training Institute, School of Graduate Studies, Faculty of Electrical Electronics and Information Communication Technology in Partial Fulfilment of the Requirements for the Degree of Masters of Science in Information Communication Technology.

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DECLARATION

I, the undersigned, declare that this thesis entitled: "**Detection and Classification of Skin Cancer Using Image Processing and Deep Learning**" is my original work. I have undertaken the research work independently with the guidance and support of the research advisor. This study has not been submitted for any degree or diploma program in this or any other institutions and that all sources of materials used for the thesis has been duly acknowledged.

Declared by:

Name of the student: Degarege Amare Demessie

Signature: ______________

Date: ______________

Place: Technical and Vocational Training Institute, Addis Ababa, Ethiopia

This thesis has been submitted for examination with my approval advisor.

Advisor's Name: Dr. Tebebe Beshah (PhD.)

Signature ______________

Date: ______________

Place: Addis Ababa University (6 kilo, FBE Campus), Ethiopia

CERTIFICATION

This is to certify that the thesis prepared by Degarege Amare Demessie, entitled "**Detection and Classification of Skin Cancer Using Image Processing and Deep Learning**" and submitted in partial fulfillment of the requirements for the Degree of Masters in MSC in Information Communication Technology complies with the regulations of the university and meets the accepted standards with respect to originality and quality.

Name of the student: Degarege Amare Demessie

Signature: ________________

Date: ________________

Name of advisor: Dr. Tebebe Beshah (PhD.)

Signature: ________________

Date: ________________

Signature of Board of Examiner's:

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Internal Examiner	Signature	Date
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Dean, SGS	Signature	Date

Faculty of Electrical Electronics and ICT

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ABSTRACT

Skin cancer is one of the most serious malignancies today, and it kills so many individuals all over the world. It develops in the skin tissue and can harm nearby tissues, result in disability, or even result in death. Furthermore, in today's technologically advanced world, it is crucial that machines, not people to fix the issue. One of the finest approaches to address the issues with skin cancer is deep learning. A recent topic of research in contemporary technology that makes use of large data, virtual and augmented reality, and micro services is deep learning.

In this thesis work, skin cancer detection and classification using deep learning and convolutional neural network is used to detect and classify dermoscopic images. The field of medicine might greatly benefit from this because early identification and classification could lead to more accurate diagnostic outcomes. So several algorithms, including the convolutional neural network and pre-trained convolutional neural network model algorithms are used in this learning method.

In this study we have followed by data collection, image preprocessing, feature extraction and classification. Firstly, the data is collected from Alert comprehensive specialized hospital and Black Lion specialized hospital within local area and additionally ISIC repository sites. We have collected a total of 3380 images with 1077 images for melanoma, 1062 images for basal cell carcinoma, 1052 images for squamous cell carcinoma and 189 images for healthy. Image preprocessing tasks like histogram equalization, label encoder is done and data augmentation techniques were applied to produce large number of images for each class. Secondly, we have used the combination of the automatic feature extraction technique called CNN are used. Finally, we have applied classification using CNN with softmax classifier. We have got a test accuracy of 96.623% in softmax classifier using CNN model and 92% test accuracy in softmax classifier using VGG19, 87.56% test accuracy in softmax classifier using MobileNet and 85.33% test accuracy in softmax classifier using DenseNet121 pre-trained models.

Keywords: Skin cancer images; Deep learning; Image preprocessing; CNN; Feature extraction techniques; Image detection; Image classification.

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List of Acronyms

AI Artificial Intelligence

DNA Deoxyribonucleic Acid

CT Computed Tomography

CE-CT Contrast Enhanced-Computed Tomography

LDCT Low-Dose Computed Tomography

PET Positron Emission Tomography

MRI Magnetic Resonance Imaging

CAD Computer-Aided Detection

ML Machine Learning

SVM Support Vector Machine

NN Neural Network

ANN Artificial Neural Network

KNN K-Nearest Neighbor

CNN Convolutional Neural Networks

DNN Deep Neural Network

ISIC International Skin Imaging Challenge

FCRN Complete Convolutionary Residual Network

DRN Deep Residual Network

CPU Central Processing Unit

GPU Graphical Processing Unit

ABCDE Asymmetry, Boarder irregularity, Color, Diameter, and Elevation

SCC Squamous Cell Carcinoma

BCC Basal Cell Carcinoma

Chapter One

1. Introduction

1.1. Background of the Study

Skin cancer is the abnormal growth of cells in the outermost layer of the epidermis of the skin due to DNA damage that causes mutations. Rapid growth of skin cells leads to the formation of tumors. Skin cancer is easier to treat when detected early, especially before it develops into full-blown skin cancer or reaches the inner layers of the skin [1].

We have study on melanoma, basal cell carcinoma and squamous cell carcinoma skin cancer types, because those are the most common skin cancer in our country [2]. Basal cell carcinoma is a non-melanoma type cancer that starts with various sized nodules. The second type of skin cancer is squamous cell carcinoma that creates scaly red masks, open inflammations, uneven clots or lumps in the skin. The third type of skin cancer is melanoma, this is a serious one among others and it occurs when pigment cells grow without any control.

Now a day there is lack of effective and accurate automatic diagnosis of skin cancer towards detecting and classifying of skin cancer. Therefore, many people are dying in the world by skin cancer because skin cancer is not diagnosed at early stage [3].

There are different methods to diagnose skin cancer, of which physical examination, biopsy microscopy and dermoscope is considered to be the gold standard. This method of diagnosis is time consuming and may lead to inconsistency. The proposed approach of an automated method for skin cancer detection and classification based on a deep learning approach once digitized will reduce the time taken for screening the disease, and also improves consistency in diagnosis when compared with the previous[4]. The proposed procedures for automatic skin cancer detection and classification system must be equipped with functions to perform are imaging acquired, preprocessing, features extraction and classification tasks [5].

There are so many diseases that affect various parts of the human body, but among them, cancer is the most lethal and can cause death. Cancer refers to a collection of conditions where abnormal cells grow and spread uncontrollably. If left unchecked, it can prove fatal.

The global burden of skin cancer is estimated to 18.1 million cases and 9.6 million people deaths in 2018 [6]. One from five men and one from six women worldwide develop cancer in their life time, and one from eight men and one from 11 women die the disease. The 5- year prevalence estimation in the world is to 43.8.

[7] In Ethiopia specifically Alert comprehensive specialized hospital pathology laboratory from 2173 skin disease diagnosed inflammatory dermatoses cover 632, Infectious diseases 560 and malignant neoplasms 517 and benign neoplasms 464 disease incidence is recorded. In percentage 27, 24, 22 and 20 percent respectively. From 517 of malignant neoplasms 99s are melanoma skin cancers it covers 19.15%.

The skin is a vital component of the human body, covering the largest surface area. Its primary function is to safeguard the internal organs against harmful external factors such as UV radiation, infections, and toxic substances and other enemies that come from the environment. The skin comprises three distinct layers - the epidermis, dermis, and hypodermis. The outermost layer, the epidermis, is composed of three main cells squamous cells, basal cells, and melanocytes cells. The dermis, located beneath the epidermis, contains nerves, blood vessels and sweat glands. The hypodermis, which is the deepest layer of the skin, serves several crucial purposes, such as energy storage, connecting the dermis to muscles and bones, insulation, and protection against injury.

Skin cancer is a widely recognized fatal cancer that arises from an irregular multiplication of cells in the skin tissues, often referred to as a "tumor." It is the primary reason for human fatalities worldwide, surpassing other cancer-linked illnesses such as prostate, colon, and polyps [8]. Skin cancer mainly groups into two those are non-melanoma and melanoma [9].

Non-melanoma cancer is divided into two types of basal cell carcinoma and squamous cell carcinoma. They are originating from epidermal cells and have common epidemiological and carcinogenic features. Basal cell carcinoma covers 80% of non-melanoma skin cancers.

Melanoma cancer is divided into two types of melanocytic nevus and melanoma. Melanoma has increased in the world and is currently the highest incidence in Australia, with 40 new cases per 100,000 populations per year [9].

Timely identification of cancer and appropriate management of this ailment can help lower the mortality rate caused by skin cancer. Up to 20% of deaths from skin cancer are estimated to be preventable with early detection and treatment [10]. To facilitate such detection and treatment, human dermatologist use CT (Computed Tomography) scans.

Accurate diagnoses of skin cancer depend upon image acquisition and image interpretation. Image acquisition devices have improved substantially over the recent few years i.e. currently we are getting dermatological images (X-Ray, CT, dermoscopic and MRI scans etc.) with much higher resolution. The various commonly known imaging modalities are computed tomography (CT), contrast enhanced computed tomography (CE-CT), low dose computed tomography (LDCT) and positron emission tomography (PET) for detection and diagnosis of skin cancerous cell. The use of CT scan in patients is employed to anticipate the type of malignancy in skin cancer for the purpose of non-invasive, early detection and treatment. Nevertheless, the interpretation of numerous images by a dermatologist can be a demanding task. So that, the use of a computer-aided detection (CAD) system can provide an effective solution by assisting dermatologists in increasing the scanning efficiency and potentially improving cancer detection and classification [11].

Automated skin cancer detection and classification by using a CAD system mainly consists of three steps: **Image preprocessing:** used to standardize the data, restrict the search space, and reduce noise and image artifacts (i.e. CT images could smart with intensity variability and high frequency signals). To minimize the effect of those artifacts with CT images, preprocessing is used via median filter and histogram equalization to obtain enhanced images from the input data. This step may contain DICOM specific operation, format and window size identification and thorax part extraction (i.e. image preprocessing is essential and critical to find the accurate object from the portion of the skin) [12].

Cancer detection: detect the cancer from skin and classified into different classes on the basis of shape, growth, texture and appearance analysis. A large number of cancers are rapidly screened throughout the whole volume using a variety of criteria, e.g. intensity, shape curvedness and mathematical morphology [13].

Cancer classification: In classification track the input is set of cancer resulted from cancer detection, but in cancer detection raw dermoscopic images are used as an input. Effective classifiers together with discriminative features are required to reduce a large number of false positive cancers [14].

Over the past few years, Machine Learning and AI have become increasingly significant in the field of medicine. These technologies are being utilized for medical image analysis, computer-assisted diagnosis, interpretation of medical images, fusion of images, registration of images, segmentation of images, and image-guided medical procedures. ML methods extract data from the images and present information with great effectiveness and efficiency. Previously, machine learning methods composed of conventional algorithms (i.e. SVM, NN, KNN, etc.) these methods enhance the abilities of doctors and researchers to understand that how to analyze the generic variations which will lead to disease, but they are not capable to handle complex problems efficiently [15].

Deep neural networks were brought about by the introduction of deep learning techniques, which utilize architectures with multiple layers, including input layers, output layers, and one or more hidden layers. These neural networks are highly effective in solving computer vision challenges such as object detection and classification, particularly when trained on extensive benchmark data sets [15].

These days, convolutional neural networks (CNN) have been known as the most effective deep learning algorithm for visual recognition tasks. The remarkable successes of deep convolutional neural networks (CNN) in image processing have been shown to outperform the state-of-the-art in several computer vision applications; it is providing an exciting solution in medical image analysis with an excellent accuracy. The representation capability of the high-level features which are learned from large amounts of training data has been broadly recognized and inspired some researchers to employ CNNs in automated skin cancer detection and classification. In computer vision, deep convolutional neural networks (CNNs) have been announced because they can be able to achieve a good performance and simulate like the behavior of the human vision system and learn hierarchical features, allowing object local invariance and robustness to translation and distortion in the model. In skin cancer classification, effective classifiers together with categorized features are compulsory to maintain a high accuracy. In this regard, in this thesis we propose to use a CNNs framework for skin cancer detection and classification from dermoscopic images [16][17][18].

1.2. Statement of the Problem

Skin cancer detection and classification is primarily done by trained skin cancer dermatologists with the help of computer aided diagnosis systems. But still accurate detection and classification of skin cancer remains a technical challenge due to complexity of images, extensive variations exist across various interpreters, and fatigue as well as it takes more time to diagnose. To overcome this problem effective detection and classification methods are used to detect and classify the skin cancer.

Previous researchers have studied various type dermatology disease detection, melanoma skin cancer stage identification, melanoma skin cancer segmentation and skin disease and detection and classification of skin cancer as shown in related works section.

Existing researchers are not applied preprocessing techniques to improve accuracy performance and it was used small number of datasets. So, skin cancer detection and classification is an active research area because accuracy must be improved using a robust algorithm. Therefore, a lot must be done to improve accuracy performance of skin cancer detection and classification because it is a fatal public health issue related to skin cancer [19].

Based on the clinical diagnosis problems like time consuming to diagnose and accuracy performance, this thesis proposed detection and classification of skin cancer using image processing and deep learning from dermoscopic skin cancer images. Deep learning convolutional neural network is used for detection and classification of skin cancer.

In computing technology image processing techniques have an energetic role in different application areas. From those in the health area most of the disease can be diagnosed using imaging techniques and those images should be classified or identified accurately as soon as possible[17][20].

1.3. Research Questions

By considering those problems this study include detection and classification model of different skin cancer types using CNN model and pre-trained CNN models by applying appropriate preprocessing techniques.

This thesis is intended to answer the following questions:

Research question 1: What appropriate preprocessing techniques are applied for detects and classify of skin cancer?

Research question 2: Which feature extraction technique is better to identify the detection and classification of skin cancer?

Research question 3: How to develop an optimum convolutional neural network model that is better than pre-trained models?

1.4. Objectives of the Study

1.4.1. General Objective

The main objective of this thesis is to develop a model that can automatically detect and classify skin cancer using image processing and deep learning.

1.4.2. Specific Objectives

The specific objectives of this research work are:-

- To study and identify different classes and attributes of skin cancer.
- To identify image processing algorithms for skin cancer detection and classification.
- To conduct experiments and identify CNN model in order to correctly detect and classify different skin cancer.
- To evaluate models for better performance.

1.5. Scope and Limitation

The scope of the thesis is emphases only the detection and classification of skin cancer images on the designing and implementing of our CNN model to reduce the ineffective skin cancer detection and classification. This approach framework proposed solution should have to be detected and classified images using deep learning algorithms integrated with preprocessing technique. This study has provided essential features regarding detection and classification systems. However, there are some limitations recognized in this study.

The limitations include the following:

- This study didn't include the determination of skin cancer stage level.
- This study didn't cover the survival rate of cancer.

1.6. Significance of the Study

The incidence of skin cancer has been increasing through time and it became a reason for the death of many people globally. The usual clinical practice of skin cancer diagnosis is a visual inspection by the dermatologist and then taking a biopsy invasively. However, this diagnostic technique lacks visualization of morphological features, which are not discernible by examination with the naked eye.

In addition, the high cost of examinations and the lack of specialists prevent many patients from receiving effective treatment. Because of these challenges, developing an accurate image based automatic or computerized detection and classification system becomes very important and a lot is being done. In this research work, the development of detection and classification of skin cancer using image processing and deep learning techniques is carried out.

The importance of this research are:

- It provides a research output for skin cancer detection and classification researchers in the improvement of skin cancer detection and classification systems from dermoscopic images.
- The research plays a great role in understanding the steps and challenges of skin cancer detection and classification from dermoscopic images with deep learning.
- The study helps to initiates researchers to do skin cancer detection and classification with different approaches such as SVM, KNN, Naïve Bayes, DT and RF algorithm classifiers [21].

About the importance of the study output:

Dermatologists: In order to detect the skin cancer and identify the type, he/she take high amount of time as well as have not confidence for decision making ability because of human necked eye is less focusing vision than computer. For this case these study gives time consuming and give best accuracy result for decision making in skin cancer detection and classification.

Patients: The patient have got beneficiary, in the case of fast diagnosis and fast decision about his/her health status as well as to facilitate treatment mechanism.

To the researcher: To have deep knowledge about deep learning, algorithms for images, machine learning of steps and challenges of how skin cancer detection and classification from the study. Even if there is a moral satisfaction from the study that looks patients has treated easily using computer aided diagnosis within a short time.

To other researchers: To initiates other researchers to do more on skin cancer detection and classification on different approaches of deep learning using robust algorithms to perform best accuracy. Other researchers used as a base paper to literature review (related work) to do more on detection and classification.

To the organization: In this thesis the organizations are government hospitals that specially work on skin cancer treatment. So the importance of this study to the organization is to deliver the treatment of automatic detection and classification of skin cancer efficiently, accurately within a short time using computer aided diagnosis. If the organization deploy the thesis in project manner it gets benefit to give better service to customers and attract new customers.

To the country: The country to grow economically the key element is human labor. So that decreasing the death of people by skin cancer.

1.7. Organization of the Thesis

This thesis is prepared into five different chapters. The first chapter represents a preliminary introduction to this study. It offers the overall structure included in this study. It thus delivers enough background of information to help the reader understand the reason behind the study and what the researcher plans to accomplish by carrying out the research. The chapter offers an overview of the whole study.

Chapter two part I defines about the basic ideas, concepts and different topics related with skin anatomy, skin cancer and its types, skin cancer detection and classification, CAD system, deep learning, CNN, diagnosing skin cancer and digital image processing, etc. for better kind of our research domain. Chapter two part II describes about related works that has been done on skin cancer detection and classification based on different approaches and techniques. Chapter three articulates a detailed description of research approach, design, population, sampling and methods experimentation approaches of our system. In Chapter four, the implementation of the proposed system architecture and experimental results are discussed.

Finally, Chapter five discuss about the conclusion from the study, recommendation for users of the research and provide the future work of this study.

Chapter Two

2. Literature Review and Related Works

2.1. Overview

The purpose of this study is to develop a model that is capable of automatically detecting and classifying of skin cancer on human skin using neural networks. In this Chapter, we have discussed theoretical background related to our work by reviewing the literature and related works that are done surrounding our work in the field skin cancer detection and classification using image processing and deep learning techniques. As we have said in the above line, we have started from the science principles or guidelines of diagnosis of skin cancer detection and classification using a dermatoscope machine of it with the existing image processing algorithms. The steps in digital image processing for skin cancer detection and classification are also described by a survey by reviewing previous works.

Examination of existing articles written by other scholars or authors which are relevant for the study will also be summarized. Finally, by revising several techniques, the merit and demerit of different method and their characteristic for skin cancer detection and classification will be presented.

2.2. Medical Anatomy of Skin

Skin is the exterior part of body for vertebrates, with a superior part of cover. It is like an interface for the body part with the environment, used for shield. The skin of our body makes up to between 3.5 and 10 kilograms (7.5 and 22 pounds) and 1.5 to 2 square meter areas so that skin is the important portion of body that plays a great role for body organs and their metabolism [22][23]. This chapter explains about the skin structure, common types of skin layers, skin cancer, clinical skin cancer diagnosis methods and computer aided diagnosis.

The skin anatomy has three division layers those are: epidermis, dermis and hypodermis or deeper subcutaneous tissue [24]. Figure 2.2-1 shows anatomy of skin layer with the contained tissue.

2.2.1. Epidermis

Epidermis is the outside cover of skin structure, which is the skin layer that acts the function of barrier with the environment. Epidermis layer does not have homogeneous thickness all over the body; its thickness is different for different body types. This layer of skin contains inner epidermis layers and tissues. The layers of epidermis from bottom to top are stratum basal, stratum spinosum, stratum granulosum, stratum corneum and stratum lucidum [25][26].

Stratum basal layer produce skin color melanin. The damage of this layer exposes to the deadliest form of skin cancer melanoma. Stratum basal is the place of melanocyte cells that prevent the skin from being damaged by preventing from ultraviolet rays and tumors created by them. Stratum spinosum is the second inner layer and thickest layer containing keratinocyte cells that are responsible for producing a protein called keratin used for keeping the safety of skin, Langerhans cells that get access to attach external or foreign substance and also it regulates the immune system by synthesizing a protein called cytokines. The third inner layer of epidermis is stratum granulosum responsible for strength of skin by producing keratin protein. The fourth inner layer or top of the inner layers is stratum corneum contains dead keratinocytes; it prevents the entrance of foreign things to the inner layers of skin. The fifth layer is stratum luciduma layer which is found on the palms of hand and feet of leg part of body skin.

Generally, epidermis is a layer of skin which are visible in different color those lesions can be infections allergies and other related damages. This layer is the origin of skin cancer that can be melanoma or non-melanoma skin cancers [27].

2.2.2. Dermis

Dermis is the second outside coat of skin layers, found in between epidermis and hypodermis and it is the thickest layer of skin as shown in figure 2.2-1. Dermis contains highly connected tissues divided into two layers: papillary region, which is the upper and contains loosely connected tissues; reticular layer the lower layer of dermis contains a strongly packed tissues [28]. Dermis contains different structures such as hair follicle, sweet gland, lymph vessels and nerve endings. The dermis layer has many responsibilities in the skin biology. Some of the roles dermis layers' play are: producing sweet in controlling the body temperature, produce oil to protect bacteria growth over the skin, growing hair, distribute blood and protecting the inner body since it is composed of strongly connected tissues. Therefore, dermis is considered as a central or most important layer of skin anatomy. Most of the skin damages that come from this layer [29][30].

2.2.3. Hypodermis

Hypodermis is the innermost layer or subcutaneous tissue of skin containing most of our body fat and connective tissues [31]. This innermost layer of skin is used for protection of insulation of the body from heat and cold, as a protective absorbent and used as for storage of energy [32]. From all cells of skin, melanocytes which are found in epidermis are responsible for skin color and protection. Melanocytes are the cause of skin cancer when they are not working properly. Ultraviolet damages melanocytes when there is a lack of DNA repair enzyme genes, genetic mutations caused by heredity or environmental factor [33][34]. If the melanocyte cells are not functioning as expected they may not produce melanin, there will be a different shape and color appearance on the normal skin which gradually grows so that incidence must be taken in to consideration towards detecting skin cancer [35].

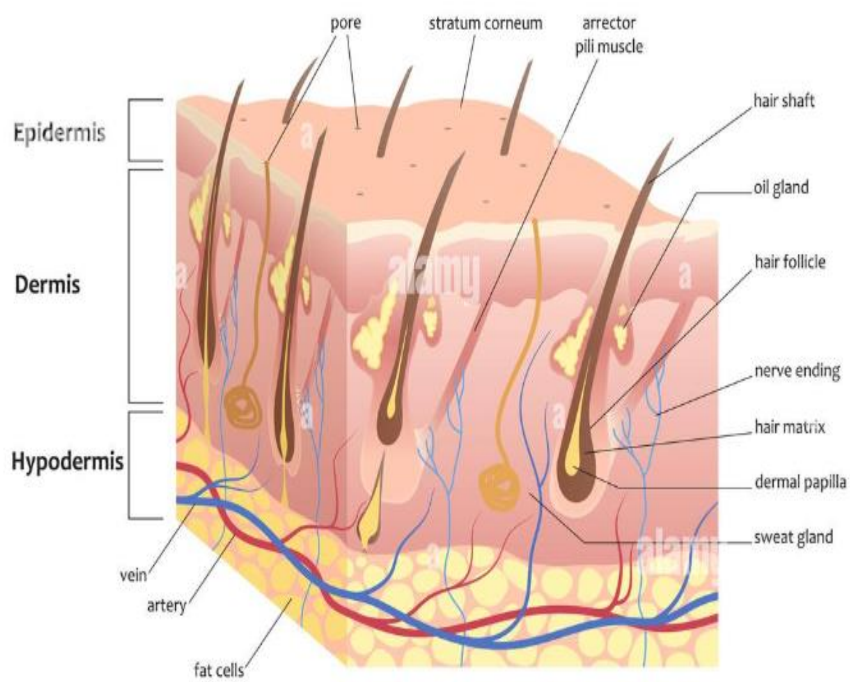

Figure 2.2-1. Skin anatomy showing the epidermis, dermis and hypodermis layers.

2.3. Skin Cancer

Skin cancer is the uncontrolled irregular growing in skin cells. It happened when unrepaired DNA injury to skin cells, (most of the time produced by electromagnetic energy from sunshine or tannings beds) activity changes, or inherited faults. As a result the top of the skin cells grow fast and procedure malignant tumors. Here are two main kinds of skin cancer, melanoma and non-melanoma. Melanoma is a type of skin cancer that begins in your skin's pigment control cells (melanocytes). Melanoma cells that extend to the deeper layers of the skin from the surface of the skin. Non-melanoma skin cancer refers to a group of cancers in the upper layers of the skin that grow slowly. The incident rate of skin cancer continues to increase for melanoma and non-melanoma skin cancer; squamous cell carcinoma an estimated 1.8 million cases are diagnosed each year in the U.S [36]. Basal cell carcinoma with approximately 3.6 million cases diagnosed in the United States each year. In 2023, an estimated 186, 680 new cases of melanoma are expected to occur in the U.S of those, 89,070 cases will be in situ (noninvasive), confined to the epidermis (the top layer of skin) and 97,610 cases will be invasive, penetrating the epidermis into the skin’s second layer (the dermis) [36].

2.3.1. Melanoma

This is the incident of uncontrolled organic process of melanocytes that eventually opened up into the encircling layers of the skin. It is often called "the most serious skin cancer" because it has a tendency to spread. There are four types of skin melanoma, the nodular melanoma, superficial spreading melanoma, acral melanoma and nodular lentigomaligna melanoma [37]. The lentigomaligna skin cancer principally affects older people on the portions of the skin that are over visible to the sun over the years, the acral skin cancer is seen on the feet or palms of the hands and has be determined to be gift in afro Caribbean origin. The nodular variant of melanoma develops inside the superficial spreading type and infiltrates the deeper layers of the skin and has a bleak outlook due to its vertical growth pattern that penetrates deep into the skin and is usually diagnosed at a later stage when it becomes thick. The superficial spreading type appears as a level patch of pigmented skin resembling either a flat mole or a freckle. The risk factors related to skin cancer are skin sort, reduced immunity and genetic science.

2.3.1.1 Melanoma Signs and Symptoms

Melanoma may arise in any part of your body, whether in normal skin or in a pre-existing mole that transforms into cancerous. Typically, melanoma emerges on the face or trunk of men affected by it. Women are more prone to developing this cancer on their lower legs. Irrespective of gender, melanoma can manifest on skin that has not been exposed to sun.

Melanoma has the potential to impact individuals of all skin hues. In individuals with deeper skin tones, melanoma commonly arises on the hands' or feet's undersides or beneath the fingernails or toenails.

Melanoma sign includes:

- A large brown spot with darker speckles.
- A mole that changes in shade, magnitude or texture or that bleeds.
- A small lesion with an irregular boarder and sections that seem red, pink, white, navy or navy-black.
- An aching sore that creates an itching or smoldering sensation.
- Obscure sores on your palms, soles, fingertips or toes, or on mucous membranes coating your mouse, nose and rectum.
- Knowing the ABCDE warning signs of melanoma can help you find an early melanoma.

2.3.2. Non-melanoma skin cancer

Non-melanoma skin cancer refers to all kinds of skin cancer not melanoma that occur in the skin[43][44]. The wider category of non-melanoma skin cancer includes several types of skin cancer, but in my study focus only on BCC and SCC skin cancer because of in our country the most urgent skin cancer [45].

2.3.2.1. Basal Cell Carcinoma (BCC)

BCC is a danger to the epidermis basal cells. It is vital in the United Kingdom and documents 75% of all non-melanoma skin threatening developments. Fortunately, the incidence of metastatic BCC is estimated to be less than 0.1%.

2.3.2.1.1. Basal Cell Carcinoma Signs and Symptoms

Basal cell carcinoma commonly arises in regions of your body that are frequently exposed to sun, like your face, neck, and scalp, and are generally held to hair bearing skin.

Basal cell carcinoma can manifest as:

- A bump that looks waxy or pearly.
- A lesion that is flat and resembles the color of flesh or brown scar.
- A sore that bleeds or scabs and then heals, only to return again.

2.3.2.2. Squamous Cell Carcinoma (SCC)

This type of carcinoma is a dangerous development of keratinocytes on the epidermis which makes about 20% of non-melanoma skin cancers, squamous cell carcinomas appear on domains of the skin exposed to the sun. This carcinoma appears as a red swelling or sometimes a non- recovering damage, which can cause depletion and ulceration. They are normally incredible treatment for this regardless about 5-10% often metastasize at the starting time after affecting the lymph center points. Other hazardous elements are associated with previous skin malignancies, previous radiotherapy.

2.3.2.2.1. Squamous Cell Carcinoma Signs and Symptoms

Frequently, squamous cell carcinoma arises on sun-drenched regions of your body, like your face, ears, head, mouth, lung and hands. Individuals with a darker skin have a higher probability of developing squamous cell carcinoma in areas that are not frequently exposed to sun.

Squamous cell carcinoma can manifest as:

- A solid, red nodule.
- A level injury with a rough, flaky exterior.

2.4. Clinical Diagnosis Method of Skin Cancer

A visual examination is typically the first step in skin cancer diagnosis. In order to check for potential skin cancer, the Skin Cancer Foundation and the American Cancer Society advise monthly self-examinations and yearly doctor appointments. Your doctor will initially inspect the region if a suspicious spot is discovered, taking note of the size, shape, color and texture of the lesion as well as any bleedings or scaling. Additionally, your doctor might check the adjacent lymph nodes for enlargement. A dermatologist can do more specialized testing and provide a diagnosis if you are being treated by a primary care physician.

Dermatoscopy, a procedure used by dermatologists to inspect worrisome spots more carefully, may involve the use of a specialized microscope or magnifying lens. The removal of skin cancer frequently takes place at the dermatologist’s office. More aggressive therapy may be necessary if a dermatologist believes the skin cancer is melanoma or non-melanoma. The two most common types of tests used in diagnosing skin cancer are biopsies and imaging tests.

2.4.1. Biopsy

A skin biopsy is a procedure in which a small sample of skin is taken for testing. This procedure helps diagnose skin lesions (abnormal areas of the skin). Skin samples are examined under a microscope to determine whether skin cancer, various skin disorders, or skin infections are present.

2.4.2. Imaging Tests to Diagnose Skin Cancer

In the medical field, there are various diagnostic methods to cure people's diseases. This imaging is an important diagnostic technique. Imaging or computational design techniques play an important role in diagnosing basic human health problems. Computer-aided design techniques used in human organ diagnosis include the following [11][46]:

CT-scan: A computed tomography scanning device that allows doctors to observe and analyze the organ systems inside the body.

X-ray: This is the primary diagnostic for quick display and analysis techniques. It is used to acquire images of dense tissue and is primarily used for bone and tooth diagnostics. This is because bones and teeth absorb radiation better than other soft tissues.

MRI: magnetic resonance imaging is a medical imaging technique used in radiology to create images of the human anatomy and the body’s physiological processes. MRI uses powerful magnetic gradients, magnetic fields and radio waves to create images of organs inside the body.

Dermatoscope: Also known as dermoscopy or epiluminescence microscopy, it is an imaging technique that allows you to see a magnified view of a skin area of the human body from the base of a lesion to help identify a specialist. A derma scope consists of components: a light source, a magnifying glass, a transparent plate and a liquid medium between the device and the skin. In our study, the images are taken from this type of imaging technique [47][48][49].

Figure 2.4.2-1 Dermoscope machine.

2.5. Digital Image Processing

In signal processing discipline, there are two major fields that are sound and image processing. From those two major fields image processing is done based on the given image based on different image file formats, it can be analyzed using matrix with its value or by its own directly with image. In image processing there are two major types of techniques to process or manipulate images for some tasks that are analog image processing and digital image processing. Analog image processing is an image processing paradigm concerned that the images are manipulated by electrical means by varying at time T the electrical signal, an example of this is the television image. Whereas digital image processing is the modern new paradigm of image processing that dominates the previous analog image processing paradigm that deals with digital forms that was created in the base of digital images that is created based on pixels[50].

Firstly we have defined the image processing actions and techniques; we need to describe the image. Image is a two or more-dimensional signal in mathematics having f(x, y) function with x, y represents the two co-ordinates of the signal which is commonly called pixel values of a specific point in the image which can represent the specific feature of an image. In this study we have used the correct ways for digital image processing as image acquisition, image preprocessing, feature extraction and image classification with their algorithms and select the state-of-the-art techniques for our work. Finally, we have described the evaluation metric techniques and summarize the concepts as follows.

2.5.1. Image Acquisition

In medical sector there are different medical equipment’s that used to acquire the image for diagnosis the human body from those some of them are, MRI, dermatoscope, ultrasound, x-ray, and CT-scan[47]. In digital image processing, to acquire the image the first thing that should be considered is the type of file format and resolution or pixel size of the image. In digital image processing there are different image file format types: Joint photographic experts’ group, bitmap file format, graphics interchange format, tagged image file format and portable network graphics.

2.5.2. Digital Image Preprocessing

Digital image preprocessing is the most important activity besides enhancing the quality of the image for further processing; its activity is starting from normalizing the given image to removing the artifacts of images to moderate the task as baseline[51].

To enhance the image quality, we need to pass different image preprocessing tasks, which leads to accurate results for the image classification task. In digital image processing there are so many artifacts that act as noise and should be preprocessed before it extracts as a feature. In this section we have illustrated histogram equalization for contrast enhancement and noise removal techniques[52].

The improvement of contrast is a technique that highlights the characteristics of an image by utilizing the available colors on the display or output device to their fullest potential. Adjusting the range of values in an image to heighten the contrast is referred to as contrast modification. Histogram equalization is the fundamental technique for contrast enhancement, and it should be used to equalize the image before enhancing it.

Histogram equalization: - it is a visual representation of the distribution of pixel intensities in an image. It displays the frequency of pixels for each individual intensity value. Histogram equalization is a technique utilized in image processing to enhance contrast by utilizing the image histogram. There are two methods of performing histogram equalization in digital image processing tasks the first is by utilizing gray scale images that have a single channel, and the second is by utilizing RGB color images that have three channels.

Median filtering: - Non-linear noise removal technique called median filtering is commonly used to eliminate impulse noise, particularly in medical images. It operates on a pixel-by-pixel basis, replacing each cell's values with the median intensity level of its neighboring pixels with a high degree of accuracy.

Wiener filter: - its aims are to remove noise from images with corrupted signals. It employs a statistical approach to clean up each pixel in an image, utilizing various angles to modify the corrupted signal.

Gaussian filter: - it is utilized to eliminate speckle noise, which is frequently seen in MRI brain images as a result of internal or external factors. This technique replaces the noisy pixel in the image with the average value of its surrounding pixels based on Gaussian distribution.

2.5.3. Digital Image Segmentation

Segmentation of an image refers to the process of breaking down a digital image into smaller subsets known as image segments. This approach simplifies the image and facilitates the analysis or processing of each image segment. In technical terms, segmentation involves assigning labels to pixels with the aim of identifying crucial elements or objects in the image.

A common use of image segmentation is in object detection. Instead of processing the entire image, a common practice is to first use an image segmentation algorithm to find objects of interest in the image. Then, the object detector can operate on a bounding box already defined by the segmentation algorithm. This prevents the detector from processing the entire image, improving accuracy and reducing inference time[53][54].

2.5.3.1. Image Segmentation Techniques

a. **Edge-Based Segmentation:**

Edge-based segmentation is a common image processing technique that identifies the edges of various objects within a given image. Information from edges can be used to help identify features of linked objects in images. Edge detection helps remove redundant information in images, reducing their size and making them easier to analyze.

Algorithms for edge-based segmentation detect edges by examining alterations in contrast, texture, color, and saturation. An edge chain is created to precisely depict the edges of objects in an image.

b. **Threshold-Based Segmentation:**

Thresholding is the humblest method of image segmentation, separating pixels based on their relative intensity to a certain value or threshold. Upright for segmenting objects that have a greater intensity than other objects or the background.
The threshold T acts as a constant for low noise images. In some cases, dynamic thresholds can be used. Threshold divides the gray scale image into two segments based on their relationship to T to produce a binary image.

c. **Region-Based Segmentation:**

Region-based segmentation splits an image into sections with similar characteristics. Each section is a group of pixels that the algorithm identifies from a starting point. Once the algorithm finds a starting point, it can grow the area by adding pixels or by shrinking the area and combining it with other points.

d. **Cluster-Based Segmentation:**

Clustering algorithms are unsupervised classification algorithms that help identify hidden information in images. They augment human vision by separating clusters, shadings, and structures. The algorithm divides images into clusters of pixels with similar characteristics, separating data elements and grouping similar elements into clusters.

e. **Watershed Segmentation:**

A watershed is a change in a gray scale image. The watershed segmentation algorithm treats the imagery like a topographic map, as pixel brightness determines elevation (elevation). This technique detects lines that form ridges and basins and marks areas between watersheds. Watershed technology has several important use cases, such as medical imaging. For example, it can help identify the difference between bright and dark areas in an MRI scan, which can aid in diagnosis.

2.5.4. Feature Extraction

Feature extraction is reducing the dataset by taking certain parameters or features that mainly distinguish one input from the other on the preprocessing image. The feature extraction is performed by the measurements that are taken on the pixels [22]. Feature selection is selecting the features that are important, illuminate redundancy of extracted features and it is a crucial step of CAD analysis.

CNN: - It is a type of artificial neural network with deep neurons and deep layers used to extract features automatically and classify to the given predefined classes. It consists of one input layer, number of convolutional and pooling layer, activation functions and output or fully connected layer using ReLu or sigmoid functions. In CNN mostly there are two basic functions which are feature extraction and classification, convolutional layer with its activation function and pooling layer are used to extract features that take from input layer and compute it in multiple layers as the model prepared, CNN model specifically feature extractions in multiple hidden layers section, it is designed to do for feature extraction tasks. In this convolutional and pooling layer (max pooling and average pooling) it has other important parameters like stride and padding attributes. Stride attribute uses, when we apply a pooling layer it determines the number of pixels to jump for minimizing the feature size of the image. As you see in figure 2.6.4-1 the image below pooling stride, the max pooling size is 2*2 and stride size are 2*2 and as the image size is 4*4 and the first 2*2, the second 2*2, the third 2*2 and the fourth 2*2 will be separated and computed each one by one to find the maximum value from the separated matrix then it will concatenate after all separated matrices have been computed in the form of maximum representation by value. Whereas padding is determining the number of outer pixels added to prevent losing of edge feature in the outermost information. It is mostly useful when the edge feature is needed as you see below in figure 2.6.4-2 convolutional padding it adds surrounding of 0 value pixels as we determine in x, y coordinate value[54][55].

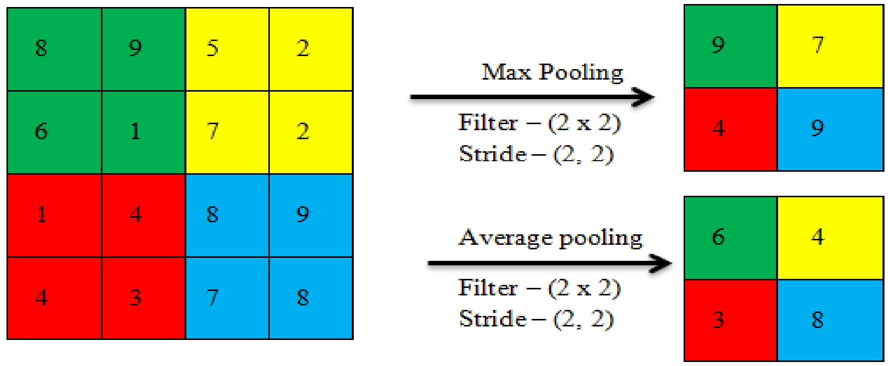

Figure 2.5.4-1 convolutional max pooling layer with 2*2 strides.

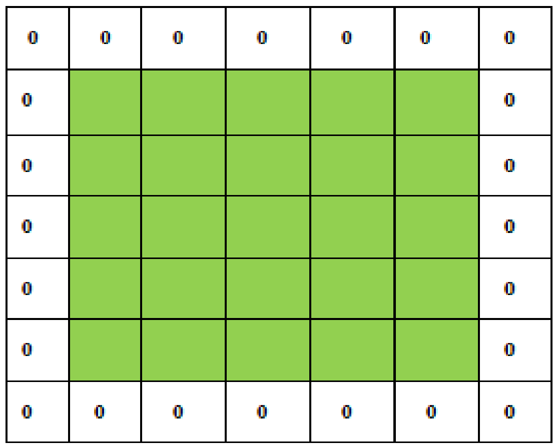

Figure 2.5.4-2 convolutional padding with padding size 1.

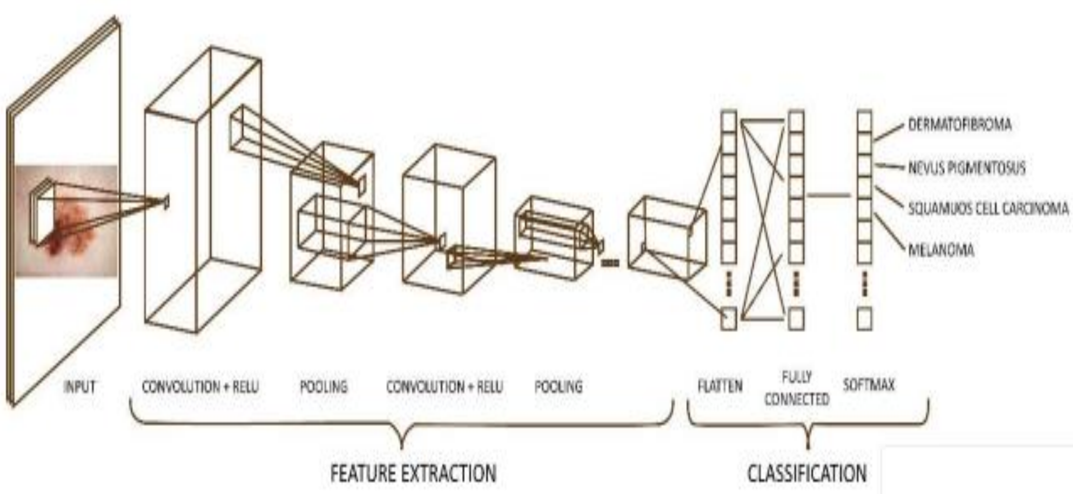

Figure 2.5.4-3 CNN model for feature extraction and classification.

2.5.5. Image Classification

In deep learning approach image classification is the main task in digital image processing that is used to label the given image into correct class using the likeness matching approach. Image classification refers to the labeling of images into one of a number of predefined categories. There are different types of image classification algorithms [56] some of those are KNN, artificial neural network, decision tree, Naïve Bayes, support vector machine, softmax classification and convolutional neural network. The following image classification algorithms are described:

KNN: - it is an instance-based learning algorithm that works based on the distance function a simple, supervised machine learning algorithm that can be used as both classification and regression problems. The distance function is used to calculate the distance between the new input data and all data in the training data. Then, k nearest or most correlated data are selected from the training data and the new input data is assigned the most common class amongst the K-nearest neighbor instances. The Euclidean distance, Makowski distance, Manhattan distance, and Canberra distance are some of the distance functions used by KNN.

ANN: - Artificial neural network is a classification algorithm; it is designed as the human brain architecture. It has the ability to learn from previous knowledge. It consists of a sequence of layers each layer consists of a set of neurons. All neurons of every layer are linked by subjective connections to all other neurons on the preceding and subsequent layers. The performance is basically determined by the structure of the neurons. ANNs have three interconnected layers; input layer, hidden layer and output layer as shown in figure 2.6.5-1. The input layer consists of the input neurons which accept input features, X1, X2… Xi and sends them into the hidden layer neurons which again forwards their output into the output layer neurons. The interconnection between neurons has some weight value W which is initially set with random values. The outputs of each neuron are the function of the sum of weighted inputs. The function is called activation function. The ANN can be trained with different learning algorithms such as back propagation learning algorithm. In back propagation algorithm, the network's predicted output is compared with actual output and the output error is calculated. Then, the error fed back into the network to adjust all weights in the net so that the network's output values are closer to the actual value. After the network converges, the weights of all connections are fixed and the network can determine the classes of a set of new data.

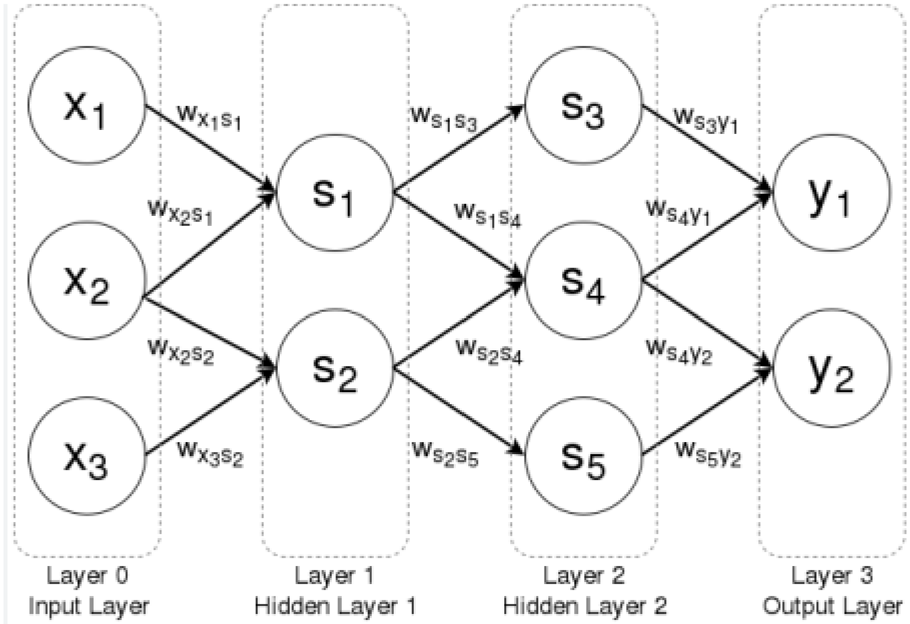

Figure 2.5.5-1 Artificial neural network architecture.

Decision Tree: - it calculates class association by frequently partitioning a dataset into uniform subsets hierarchically classified documents the acceptations and rejection of class labels at each middle stage. It has three parts: Partitioning the nodes, finding the terminal nodes and allocation of class labels to terminal nodes. Decision Tree is based on hierarchical rule-based methods and uses a nonparametric approach.

Naïve Bayes Algorithm:- it is a probabilistic or statistical classification algorithm based on the Bayes theorem with the assumption of independency among predictors. A Naïve Bayes approach is based on the probability that a given predictor belongs to a class. The Naïve Bayes creates a directed acyclic graph or tree based on the computed conditional probability. The tree is called the Bayesian Network. The main advantage of the Naïve Bayes algorithm is its simplicity, requires a small dataset and works for both linearly separable and inseparable dataset. The disadvantage is unable to learn relationships among features/ predictors because of its feature independency.

Support Vector Machine: - it builds a hyper plane or set of hyper planes in a high or infinite dimensional space, used for classification. Good separation is achieved by the hyper plane that has the largest distance to the nearest training data point of any class (functional margin), generally large the margin lowers the generalization error of the classifier. It uses non parametric with binary classifier approach and can handle more input data very efficiently. Performance and accuracy depend upon the hyper plane selection and kernel parameter. Firstly, SVM was designed to work on linearly separable datasets by finding a hyper plane that divides the two classes separately. Now, multiclass SVM classification is available.

Multiclass SVM basically works by mapping the input data into a high dimensional (more than two) space H as Rd → H and defining a separating hyper plane there using a kernel function $\Phi(x)$ such that $x \rightarrow \Phi(x)$. Then, the predefined kernel function $\Phi(x)$ is again used for mapping the new data point into the high dimensional feature space for classification. The kernel function is the first parameter in multiclass SVM, used for mapping the non-linear input vector into a set of linearly separable maps. Thus, the kernel function changes the input vector from a non-linearity separable data to linearly separable. The kernel function measures the similarity between two input samples x and y which allows the SVM classifiers to make a separation in between with a complex boundary. There are different kernel functions used by SVM. Linear kernel, polynomial kernel, radial basis function and sigmoid are the commonly used kernel functions.

Softmax classifier: - it gives you probabilities for each class label while hinge loss gives you the margin. It's much easier for us as humans to interpret probabilities rather than margin scores (such as in hinge loss and squared hinge loss).

CNN: - It is a deep learning application mostly for image detection and classification as well as computer vision tasks in the base of large amounts of data using feed forward approaches. The CNN approach is based on the idea that the model functions properly based on a global understanding of the image. It uses fewer parameters compared to a fully connected network by reusing the same parameter numerous times. It generates enough weights to scan a small area of the image at any given time. This approach is beneficial for the training process the fewer parameters within the network, the better it performs. Additionally, since the model requires fewer amounts of data, it is also able to train faster[57].

CNN has a higher learning rate because of its multiple feature extraction layers that learns representations automatically from the data. It has the ability to determine the spatial or temporal relationship between data points. The most useful characteristics of the CNN are hierarchical learning ability, multi-tasking, automatic feature extraction, and weight sharing. Typically, CNN architecture consists of arbitrary repetition of stack of convolution and pooling layer followed by one or more fully connected layers in between of its input and output layer. The convolution and pooling layers of CNN are used for extracting important features of an image; the fully connected layers receive the extracted features from all previous neurons as input to map them into the output layer. Moreover, activation function, batch normalization and dropout operations are incorporated within the CNN architecture to optimize the performance of CNN. Most common CNN layers are discussed below:

a. Convolution Layer

Convolution layer is the first layer which receives the input image called input tensor. The layer comprises a set of neurons, each neuron acts as a kernel, called convolutional kernel. The convolutional kernel starts working by splitting the image into smaller slices called receptive fields. The size of the slices is similar to the size of the kernel.

The kernel convolves in the entire images with a specific set of weights, by multiplying the kernel elements with the corresponding image receptive field elements and lastly sums up the product to obtain the output value of the corresponding position of the output tensor called feature map. The convolution operation is repeated to create a number of feature maps, which represent different features of the input tensors.

The Convolution operation is used to extract useful features from the locally correlated data points. The key property of convolution operation is weight sharing, i.e., a single kernel is shared across the entire image or for each receptive field. The weight sharing ability allows a set of features extracted by the kernel convolution to be invariant while the kernel travels across the entire image positions.

There are three hyper parameters (depth, stride, and padding) to optimize or control the output of the convolution operation[57]. The depth represents the size of filters which shows the number of neurons in this layer which represents the number of feature maps. Setting this hyper parameter with a small value significantly minimizes the number of neurons in the network and reduces the performance of the model. The stride is the distance between the positions of the kernel to place the receptive fields. Setting the stride as 1 makes the next receptive field jump one row or column to the left or down from its current position makes the one to overlap to the others. On the other hand, setting the stride to greater than 1 reduces the volume of overlapping and used for down sampling feature maps. Padding, commonly used zero padding, is a technique for adding rows and/or columns of zeros on each side of the input tensor so as to fit it with the center of a kernel and have same in-plane dimensions over the convolution operation.

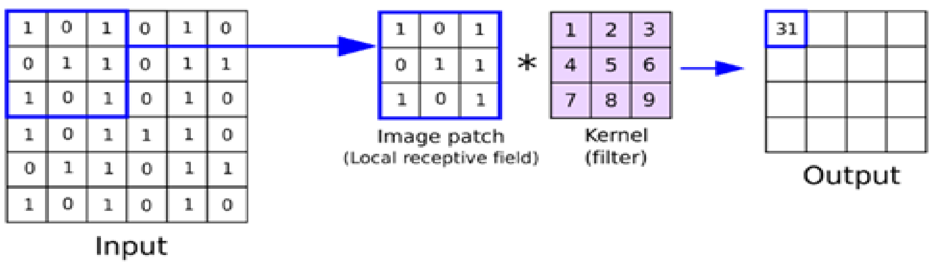

Figure 2.5.5-2 convolution operation example with kernel size of 3 x 3.

b. Pooling Layer

Pooling layer used for down sampling the input image. It receives the convolutional output as input and sub-samples it to reduce the representation dimensionality, number of parameters and computational complexity of the model. The pooling layer has three common parameters; pool size, stride and padding. The concept of pool size, stride and padding in the pooling layer is similar to the kernel size, stride and padding respectively in the convolution layer. Although, the stride of the pooling layer must be more than 1 to down sample the volume of the input matrix. There are different pooling methods, like max pooling, average pooling and sum pooling etc.[57]. Max pooling takes the maximum value of the filtering window as shown in figure 2.6.5-3. Average pooling takes the average value of the window values.

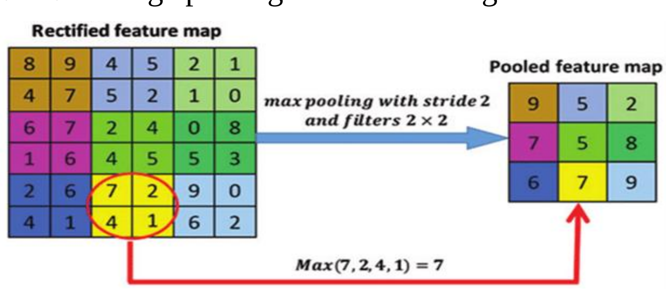

Figure 2.5.5-3 Down sampling feature using 2x2 max pooling with strides 2.

c. Activation Layer

The output of the convolution operation is given to a non-linearity processing unit called activation function. Activation function can be implemented either as other convolution parameters in the convolution layer or as a single layer below the convolution or pooling layer. This function used to transform the linearity in the convoluted feature in to non-linear and to accelerate the learning process. Sigmoid function, hyperbolic tangent (tanh) function and rectified linear unit (ReLU) function shown in Figure 2.6.5-4 are some of the neural network activation functions. However, ReLU is the most popular non-linearity activation function which demonstrated to be more efficient than the tanh and sigmoid activation functions[58].

Sigmoid activation function: used to normalize the outputs of the neuron to the range in between of one and zero. This activation function has a vanishing gradient problem because of that the derivative becomes close to zero when the input value is very large and very small. Sigmoid activation function g(x) is given as the following equation.

$$\frac{1}{1+e-x} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. Equation\ 1$$

Where x is the input value.

Hyperbolic tangent (tanh) activation function: used to normalize the outputs of the neuron to the range in between of positive one and a negative one. Since it allows negative value, it is better than the sigmoid activation function. But like sigmoid function, it also has a vanishing gradient problem. Tanh activation function g(x) is given as follows.

$$\mathrm{g(x)} = \frac{2}{1+e-2x} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. Equation\ 2$$

Rectified linear unit (ReLU) activation function: This normalizes the output of the neuron to either 0 or the input value itself if it is greater than zero. ReLU prevents the vanishing gradient problem. The ReLU activation function g (x) is defined as in the following manner.

$$g(x) = max\ (0, x) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \, Equation\ 3$$

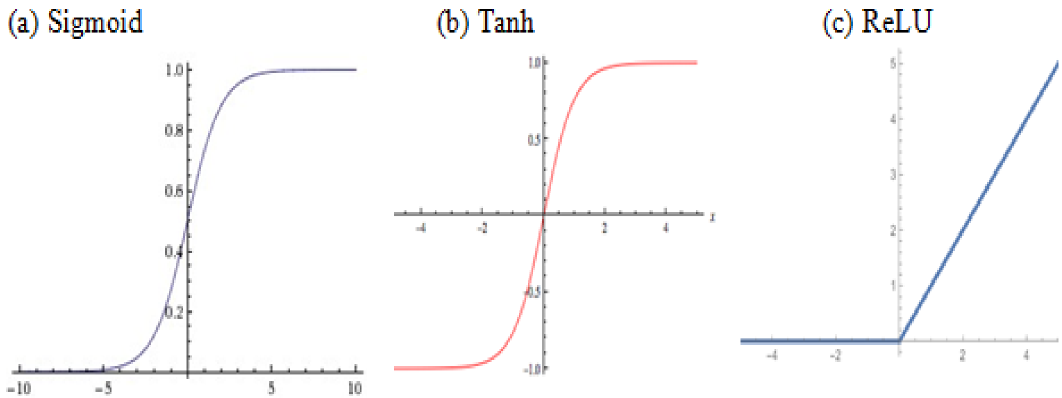

Figure 2.5.5-4 Common activation functions used in neural network.

d. Batch Normalization Layer

Batch normalization is used in order to decrease the convergence time of the network. Batch normalization controls the internal covariance shift between feature-maps. Internal covariance shift is the change between hidden units' values distribution that may slow down the convergence time by compelling the learning rate to smaller value[59].

e. Dropout

Dropout introduces a regularization parameter to improve the generalization ability by randomly skipping some fraction of units or connections using a certain probability during training. During neural network training, multiple neurons which learn non-linear relation may sometimes co-adapt that causes over fitting. But the dropout layer randomly drops some connections or units to overcome the over fitting problem[60].

f. Fully-connected Layer (Flatten Layer)

The Fully-connected Layer changes the feature maps extracted in the final convolution or pooling layer into a one-dimensional (1D) array of numbers. Every fully connected layer is followed by a non-linear activation function[61]. The activation function of the last fully connected layer is different from the top fully connected layers. The activation function used in the last fully connected layer for a multiclass classification problem is a soft-max function which normalizes the last fully connected layer output values in to target probabilities. As a result, every input of the input vector impacts every output of the output vector, and all layer-to-layer relationships are present.

2.6. Pre-Trained CNN Architectures

2.6.1. DenseNet

DenseNet121 also known as Dense Convolutional Network, is a type of convolutional neural network design that emphasizes the ability of deep learning networks to delve even deeper while simultaneously enhancing their training efficiency through the utilization of briefer connections between the layers.

DenseNet121 comprises of 120 Convolution layers and 4 layers of Average Pooling. Each layer, including those present in the dense block and transition layers, distributes its weights across numerous inputs, enabling the deeper layers to utilize features extracted at the initial stages.

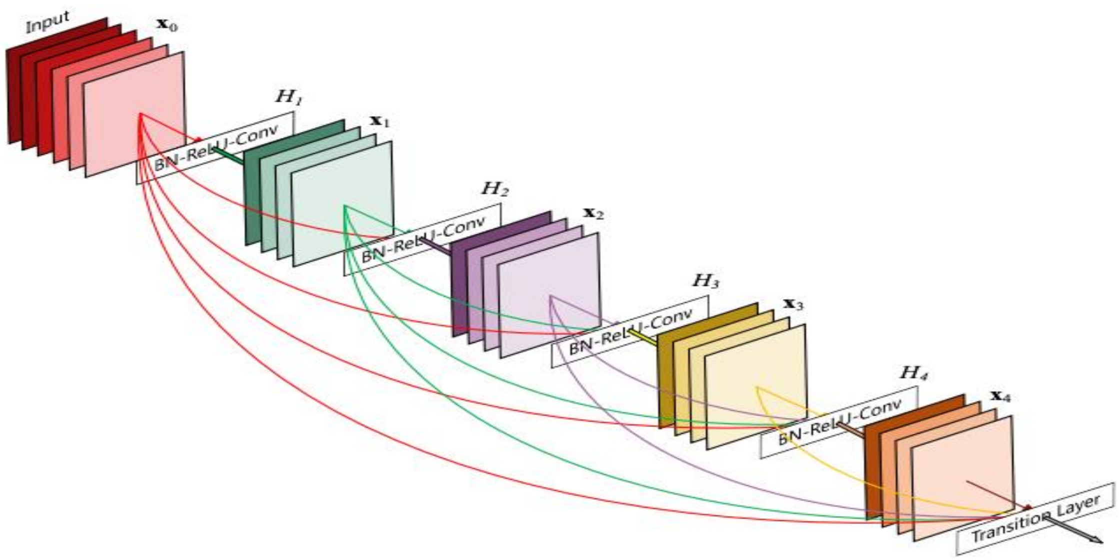

Figure 2.6.1-1 DenseNet121 convolutional neural network architecture.

2.6.2. MobileNet

MobileNet is an efficient and easily transportable CNN architecture that is widely applied in practical settings. Instead of the conventional method employed in earlier models, MobileNet mainly utilize depth wise separable convolutions to create more lightweight structures.

MobileNet are a category of compact, high-speed, energy-efficient models that are suitable for tasks such as detection, classification and other typical tasks that convolutional neural networks are good for.

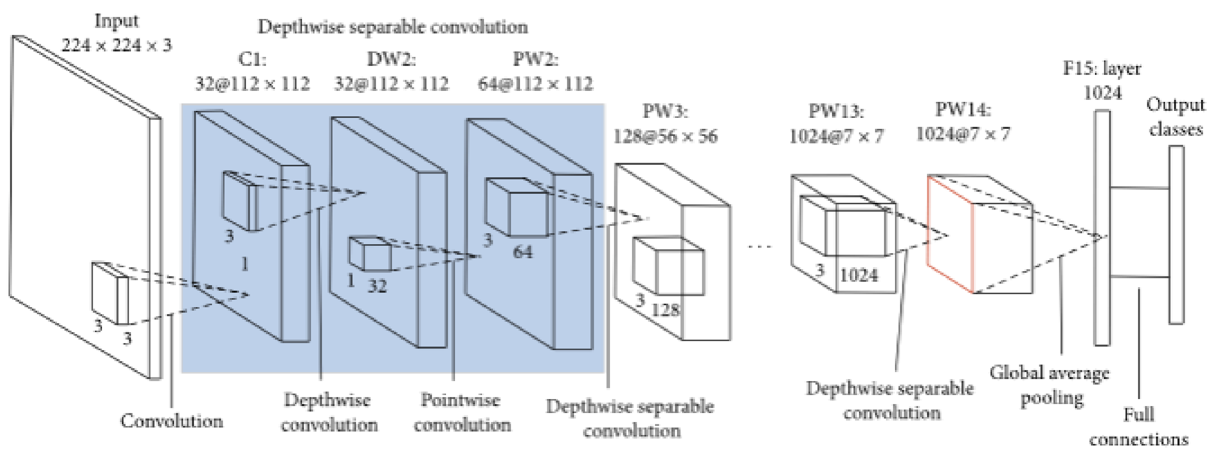

Figure 2.6.2-1 MobileNetV2 convolutional neural network architecture.

2.6.3. VGGNet

The fruitful use of deep CNNs in image recognition problem has accelerated the CNN architectural design research works. Due to this, the authors Simonyan et al. proposed an effective CNN architecture design called Visual Geometry Group (VGGNet). VGGNET was the run-up of the 2014 ILSVRC[64]. The main contribution of this work is that it shows that the depth of a network is a critical component to achieve better recognition or classification accuracy in CNNs. The VGG architecture consists of a number of consecutive two convolutional layers with ReLU activation function followed by single max pooling layer. After the last max pooling layer, several fully connected layers with ReLU activation function are installed. The final output layer of the model is with a Softmax layer for classification. It experimentally proved that the placement of concurrent small sized (3 x 3) filters could bring the performance of large sized (5 x 5) filters. Moreover, the small sized filters offer additional benefit to decrease the computational complexity of the model by reducing the number of trainable parameters. VGGNet investigate a new trend for researchers to work in small sized filters of CNN[65].

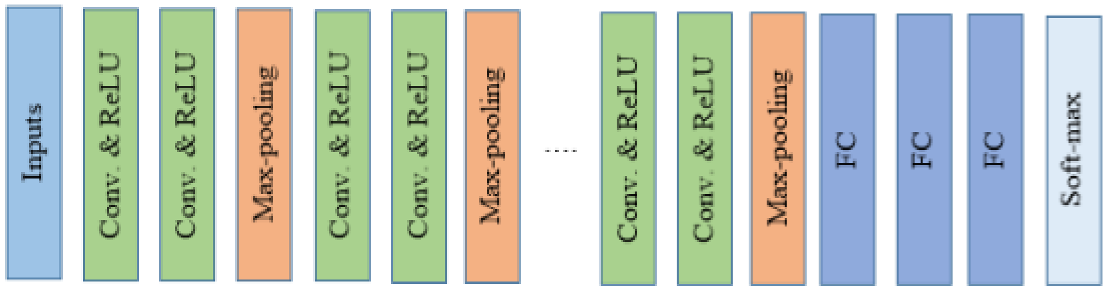

Figure 2.6.3-1 The basic building block of VGG network.

2.7. Model Performance Evaluation Techniques

In order to evaluate the performance of the model different performance evaluation techniques are used. The performance evaluate techniques that are used for evaluating the model include accuracy, confusion matrix, precision, recall, and f1-score. In order to calculate the values of the above performance evaluate technique, parameters like true positive, true negative, false positive and false negative must be known[66].

- True positive (TP):- is an outcome where the model correctly predicts the positive class.
- True negative (TN):- is an outcome where the model correctly predicts the negative class.
- False positive (FP):- is an outcome where the model incorrectly predicts the positive class.
- False Negative (FN):- is an outcome where the model incorrectly predicts the negative class.

Accuracy: is calculated as the sum of correct classifications divided by the total number of classification. Mathematical expression is given below:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots. Equation\ 4$$

Confusion Matrix: is a clear and explicit way to present the prediction results of a classifier for each and every class. It is represented by a matrix of the true class labels versus the predicted class labels. It contains the number of truly predicted instances and misclassified instances for each class.

Precision: is a measure of the true positive among all positives. Mathematical expression is given below:

$$\text{Precision} = \frac{TP}{TP + FP} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \mathit{Equation}\ 5$$

Recall: commonly called sensitivity, corresponds to the true positive rate of the considered class. Mathematical expression is given below:

$$\text{Recall} = \frac{TP}{TP + FN} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ \mathit{Equation}\ 6$$

F1-score: is the weighted average the precision and recall. Mathematical expression is given below:

$$\text{F1} - \text{score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots .. \mathit{Equation}\ 7$$

2.8. Related Works

2.8.1. Introduction

Deep learning is a system of data examination algorithm that programs analytical model building. It is a one mode of machine learning based on the idea that systems can learn from data, identify patterns and make decisions with minimal human intervention. In this image processing is one part of deep learning that is used to manipulate images for further processing in different sectors. From those different sectors the medical sector is the main challenging area that needs computerized techniques to be made quicker to serve different users.

Digital image processing is a computer visual processing technique used to analyze pixels of the given image and apply them to specific domain areas. In medical sectors, image processing tasks are a vital role to diagnosis, detect and identify the healthy and unhealthy parts of the body. There are so many research works are done and we have reviewed those of research works related to skin cancer detection and classification as follows:

(Sasikala et al., 2018) propose one of the most popular articles that uses CNN for the recognition and classification of malignant growth. They state that the accuracy of their proposed CNN is more efficient than most of the neural systems. Thus CNN can be a good alternative for classification malignancy grouping and the accuracy of the CNN method is 96% but the dataset for this scheme was reasonably small 1000 images.

In (Refianti, Mutiara, & Priyandini, 2019), they conduct a research work to classify the image as melanoma and non-melanoma cancer using CNN. They acquire 220 2D images in JPG format which are 110 of melanoma and 110 of non-melanoma, they are done rescaling as 32*32 image size then they have done augmentation by applying flipping horizontally, zooming and rotating it to increase the dataset size. Finally, they have used learning rate and batch size parameters as 0.001 and 32 respectively. Finally, the testing result obtained 91% accuracy for using 154 images and 50 epochs in training, then 93% accuracy for using 154 images and 100 epochs in training. The training conducted on 176 images and 50 epochs resulted in a 95% accuracy of testing result, while for the training using 176 images and 100 epochs resulted in 100% accuracy of testing result. They can perform 100% accuracy in their own deep learning model; however, it may consume a high amount of computation time because there are not any preprocessing tasks applied.

In (Rezvantalab, Safigholi, & Karimijeshni, 2018), they conduct a research work to classify 8 types of skin diseases such as melanoma, melanocytic nevi, actinic keratosis and intraepithelial carcinoma, benign keratosis, dermatofibroma, vascular lesions, and atypical nevi using different pre-trained state-of-the-art architectures like Dense Net 201, Resents 152, Inception v3 and Inception Resents v2 are used and applied on 10135 dermoscopy skin images from HAM10000: 10015 and PH 2: 120 online dataset and compare each other. From all state-of-the-art pre-trained models, Dense Net 201 has given the best result as 96.79%, however there are not applied any preprocessing techniques to simplify the computation of the image.

(Hosny et al., 2019) study on skin injury techniques (melanoma and so on) using a pre-prepared CNN model using transfer learning with AlexNet. They use ph2 dataset and the accuracy is (98.61%), affectability (98.93%), explicitness (98.93%) and accuracy (97.73%).

(Mahbod et al., 2019) they conduct a research work to classify skin lesions from Dermoscopic images. Their approach is created on a novel ensemble scheme for CNNs that combine intra architecture. The recommended method consists of multiple sets of CNNs of different architectures that represent different feature abstraction levels; they used on the 600 test images of the ISIC 2017, the accuracy of melanoma is 87.3% and seboeeheic keratos is 95.5%.

Author (year)	Title/ Topic	Objective	Methodology	Key Findings	Remark
Sasikala et al., 2018	Recognition and classification of malignant growth	Classification of malignancy grouping	CNN	dataset was reasonably small 1000 images	This study presents on classification of malignant growth using CNN
Refianti, Mutiara, & Priyandini, 2019	Classify the image as melanoma and non-melanoma cancer using CNN	Classify the image as melanoma and non-melanoma	CNN	Low dataset and not any preprocessing tasks applied	This paper provides on melanoma and non-melanoma using CNN
Rezvantalab, Safigholi, & Karimijeshni, 2018	Classify 8 types of skin diseases using different pre-trained state-of-the-art architectures	classify 8 types of skin diseases	Dense Net 201, Resents 152, Inception v3 and Inception Resents v2	not applied any preprocessing techniques	This paper gives on skin disease classification using dermoscopy images
Hosny et al., 2019	Skin injury techniques using a pre-prepared CNN model using transfer learning with AlexNet	Identifying melanoma skin cancer	pre-prepared CNN model and transfer learning with AlexNet	Used dataset and feature parameters are not specified	This article reviews the dev[t] of pre-prepared CNN model for skin injury techniques
Mahbod et al., 2019	Classify skin lesions from Dermoscopic images	classify skin lesions	CNN with ensemble architecture	Low dataset and low performance accuracy	This paper provides on skin lesions classification using Dermoscopic images

Table 2.8.1-1 Summary of related work.

2.8.2. Theoretical Framework

In this topic we will discuss about theoretical background and current state of knowledge on topics related with our study. We try to survey, analyze and present papers published by accredited scholars and researchers focusing on skin cancer, skin cancer types, image processing, CAD system, fundamental of deep learning methods, the theory behind the neural networks and convolutional neural networks have been explained.

2.8.3. Conceptual Model

The conceptual framework of this study is based on Department of Systematic Pathology, Division of Dermatology, University of Naples Federico II, and Naples, Italy: Epidemiology of skin cancer. Determinants observed environmental determinants, behavioral/ individual determinants, clinical determinants and health outcomes. Main research focused on the detection and classification of skin cancer, based on a model developed by Department of Systematic Pathology, Division of Dermatology, University of Naples Federico II, and Naples, Italy studied the Epidemiology of skin cancer.

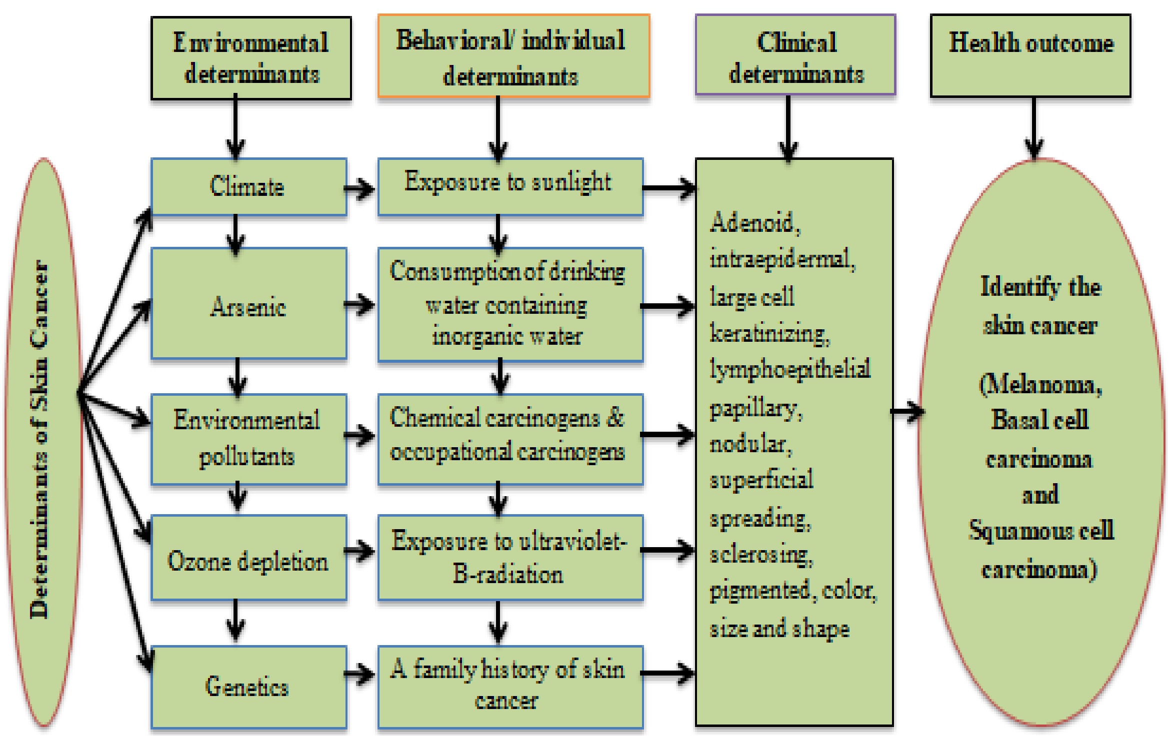

Figure 2.8.3-1 Conceptual model architecture.

2.8.4. Related Work Gap

Many researches attempt to increase the detection and classification accuracy of skin cancer by performing different image processing techniques and deep learning approaches. Some researches designed their system on the basis of image processing technique like DenseNet201, Resents152, InceptionV3, Inception Resents V2 architecture. Others try to design their model by using deep learning approaches for classification, such as CNNs, AlexNet classifiers. Recently, some researchers tried to propose their system on the basis of deep learning algorithms, such as CNNs, using different configuration and fusion methods both in 2D and 3D.

Many researchers have achieved high sensitivity levels by using different image processing techniques but still with many challenges and not applied any preprocessing techniques to simplify the computation of the image. Recently, with the remarkable successes of deep convolutional neural networks in image processing, the representation capability of the high level features which are learned from large amounts of training data has been broadly recognized. This also inspired some researchers to employ CNNs in automated skin cancer detection and classification. According to recent papers, detection and classification of skin cancer using deep learning algorithms can be able to achieve a promising result to obtain a high sensitivity rate by reducing a large number of challenges. So, we inspired to design our model on top of CNNs, which is a deep learning algorithm that achieved successful results in skin cancer image detection and classification.

Generally, number of researchers has been done in the detection and classification of skin cancer, however accurate detection and classification of skin cancer is still a challenging task.

Chapter Three

3. Methodology

3.1. Overview

This chapter focuses on the methodology that the study followed in the research. It begins with a brief description of the research approach, design, population, sampling and methods experimentation used to recruit follows. The chapter also makes a brief description of the experimentation approach techniques and model performance evaluation metrics. In the end, the developing tools, validity and reliability issues are presented.

3.2. Research Approach

In this thesis mixed (quantitative and qualitative) research approach is used to involve collecting and analyzing quantitative and qualitative data to understand a phenomenon better and answer the research questions. And a researcher used research methods that are specific procedures for collecting skin cancer images by using smart phone camera and analyzing data on anaconda software using python programing language and Microsoft excel for creating metadata attribute in .CSV file are used.

3.3. Research Design

The experimental research design is used in this thesis. Image acquisition, data preprocessing, feature extraction, and classification are steps in the application of experimental research. The process for the research experiment is shown in the following figure.

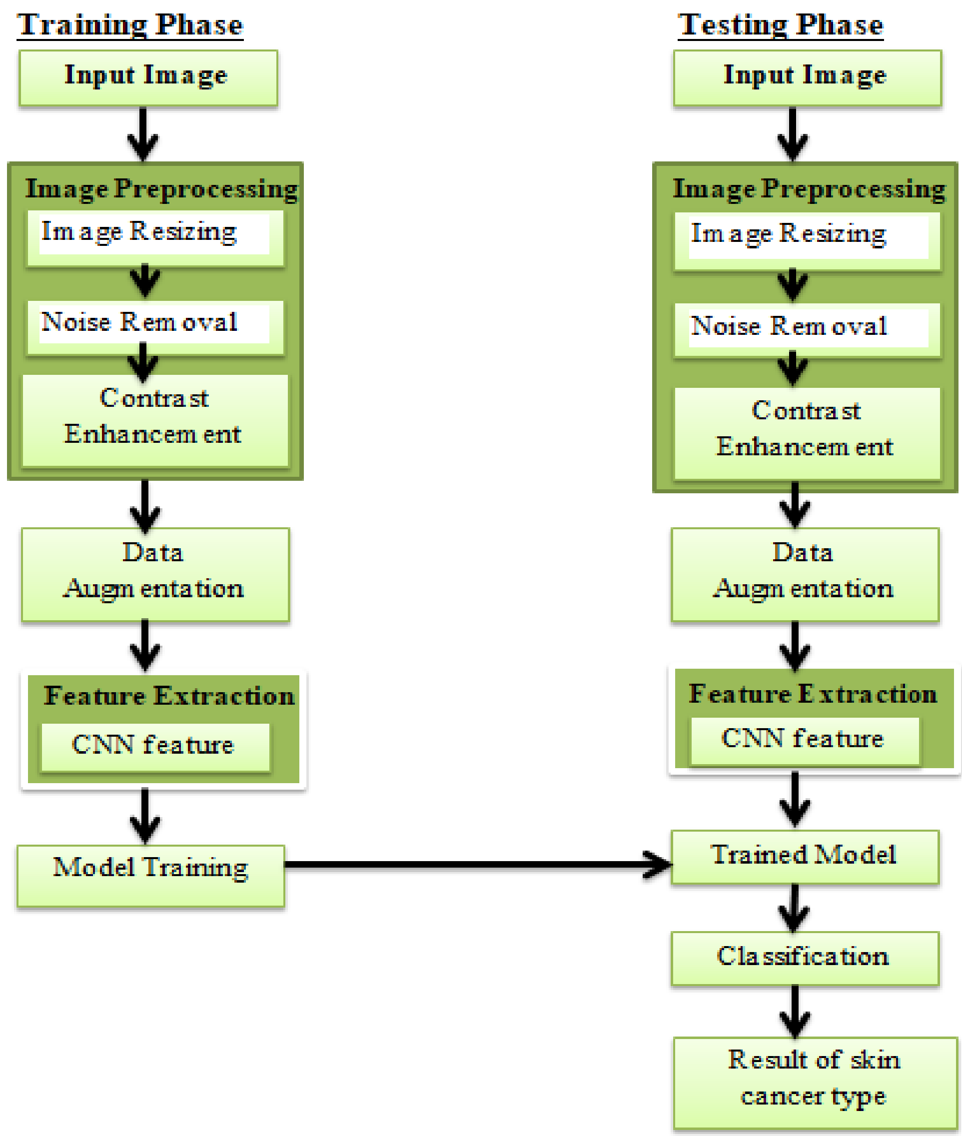

Figure 3.3-1 System architecture.

3.4. Population

Target population (it is the entire collection of people or things).

The study's target population has skin cancer images that have cancer detection and classification capabilities.

The term "**accessible population**" refers to the chosen individuals or components of the target population.

Images of skin cancer with cancer detection and classification are available for the study's accessible population thanks to the attending dermatovenerology departments at government hospitals in Addis Ababa (Alert comprehensive specialized hospital and Black Lion specialized hospital) and ISIC repository sites.

3.5. Sampling

In this study the sample size 3380 skin cancer images are required for the detection and classification of skin cancer experimentation work and collecting the dataset images from attending dermatovenerology department at government hospitals (Alert comprehensive specialized hospital and Black Lion specialized hospital) in Addis Ababa and additionally from ISIC repository sites who fulfilled the detection and classification criteria.

3.6. Experimental Tools

We have used software tools like anaconda 3.10 navigator for python programing language and Microsoft excel to prepare a metadata attribute in .CSV file for experimentation methods.

Python: A researcher conducts experimentation using the easy-to-understand, write, and maintain python programming language. Excellent machine learning libraries are maintained for python include numpy, pandas, matplotlib, tensor flow and keras. Python’s ability to be built on any platform, including a mongo DB database, an SQL browser, or JSON, is another advantage feature.

Microsoft Excel: A researcher uses metadata attribute .CSV files by using excel. It is a common, fundamental, and frequently used analytical tool in almost all thesis. Excel is useful because it has many rows and columns and can be used for analytics on patient data in .CSV file format. In order to help the client filter the data to meet their needs, it analyzes the labor-intensive process of summarizing the data with a preview of pivot tables.

3.7. Experimentation Approach Techniques

The experimentation approach technique consists of each step from image acquisition up to the image classification.

3.7.1. Image Acquisition

Image processing is considered to be one of the most rapidly evolving areas of information technology, with growing applications in all fields of knowledge. It constitutes a core area of research within the computer science and engineering disciplines given the interest of potential applications ranging from image enhancing, to automatic image understanding, robotics and computer vision. The performance requirements of image processing applications have continuously increased the demands on computer power, especially when there are real time constraints. Image processing applications may consist of several low level algorithms applied in a processing chain to a stream of input images.

In most research works one major task is collecting the given proposed data based on their categories, it is challenging but the basic for all tasks. In image processing the input for the proposed task is image. In this case for our scenario, we need skin cancer images. Image acquisition is the process of collecting images from different websites or machine repository sites and government hospitals in a given file format with pixel size.

In medical sectors one mechanism to diagnosis is imaging techniques to diagnose different disease from these there are so many machines to create image of the specific body part some of them are X-ray, ultrasound, CT-scan, dermatoscpoe and others. So our concern is focused on the images that are created by dermatoscpoe. A dermatoscpoe is a noninvasive machine that allows the assessment of constrictive colors and micro structures of the skin, the dermo epidermal connection, and the papillary dermis not visible to the naked eye.

These arrangements are specifically linked to histologic features. In the study we are proposing skin cancer detection and classification and we have on the way to conduct research work on cancer detection and classification. So, the first phase shown in our architecture is image acquisition. In the image acquisition step, we have collected various images from various sources that are locally and machine repository sites that are captured by a dermatoscope machine. From the local context we have found at Alert comprehensive specialized hospital and Black Lion specialized hospital as JPG file format in the size of 320*320 and in machine repository sites we have collect from ISIC in 750*720 image size in the form of .BMP image file format.

Figure 3.7.1-1 Image size 320*320.

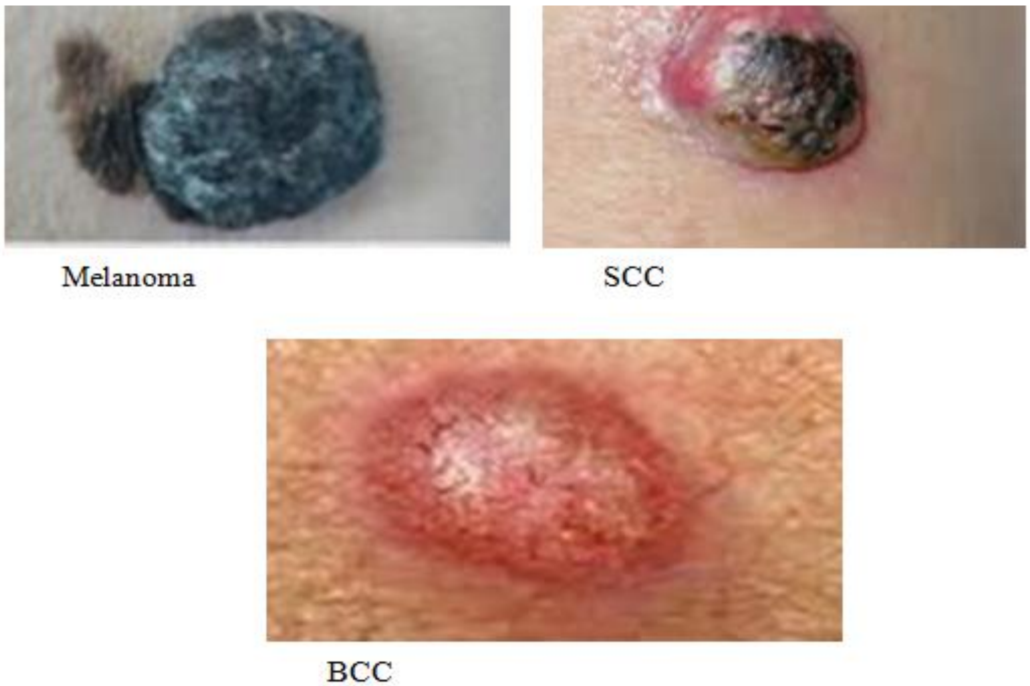

Figure 3.7.1-2 Image size 750*720.

3.7.2. Image Preprocessing

A method for preparing datasets for the model's training and testing is image preprocessing. Before designing and training a model, it is an improvement of the image data that enhances some image features important for subsequent processing and analysis tasks. We applied various techniques to our datasets for image resizing, noise reduction, and contrast enhancement. The following figure 3.7.2-1 clearly explains the dataset's preprocessing flow:

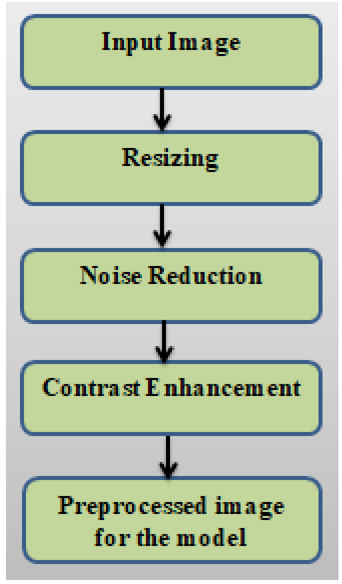

Figure 3.7.2-1 Preprocessing flow.

a. Image Resizing:

Since deep learning models train more quickly on smaller images, image resizing is one of the frequent tasks in the preprocessing stage of computer vision and is done on various pixel sizes. Resizing involves changing the image's size without cropping it. Resizing an image does not add or remove details from the original image or information from the cropped image. When resizing, we must specify the new image's width and height. In this study, 224 x 224 pixels were resized in order to train and test the model. This was done in order to compare the model's performance to the state of the art and to make training easier than with larger images.

b. Noise Reduction:

It is a quick change in an image's pixel values. There are various filtering techniques available to remove noise, but they must be chosen in accordance with the type of noise present in the datasets. There are various types of filtering methods available to them. When compared to the alternatives, the Gaussian filtering technique performs exceptionally well in terms of noise removal with small variances. The Gaussian filter is used by the bilateral filter, but it also has an additional multiplicative component that depends on the difference in pixel intensities. The only pixel intensity that is similar to the central pixel is included in the computation of the blurred intensity value in this type of filter, which also preserves histogram equalization, adaptive median, and edges filtering. This bilateral filtering technique has been used to lessen noise and smooth the image datasets.

c. Contrast Enhancement:

To improve the separation of pixel intensity variations into a more visually distinct structural distribution, image pixels are manipulated and redistributed in a linear or non-linear manner. Contrast is the visual quality that distinguishes between two objects or an object and its background. An image manipulation known as contrast enhancement is defined by a function f, also referred to as the transformation function that maps an input pixel to its corresponding output. The function f, which is also in charge of changing the input image's histogram, determines how the pixels in the final image are modified. Histogram equalization is one of many techniques used to improve the contrast of images. Since the contrast and intensities in our image datasets vary, histogram equalization is used to improve the images.

d. Data Augmentation:

Enhancing the data is one strategy for avoiding over fitting. The process of modifying training data through arbitrary transformations is known as data augmentation. The size of our dataset should be increased in order to improve the performance of our models.

3.7.3. Feature Extraction

Convolutional neural network feature extraction is a type of dimensionality reduction of the image pixels to make the raw data more manageable for processing by reducing the amount of data that must be processed, while still accurately and completely describing the original data set. In this study, the features are extracted using the consecutive convolutional layers followed by max-pooling and activation layers. We have used CNN for feature extraction with several layers including convolutional and pooling layers with ReLu activation function.

The model accepts 224 x 224 resized images, and it has 5 convolutional layers with 16, 32, 64, 128 and 256 filter sizes on 3 x 3 kernel size. We have used max pooling for reduce dimension of the data on 2 x 2 size. The following diagram shows the CNN feature extraction of the model.

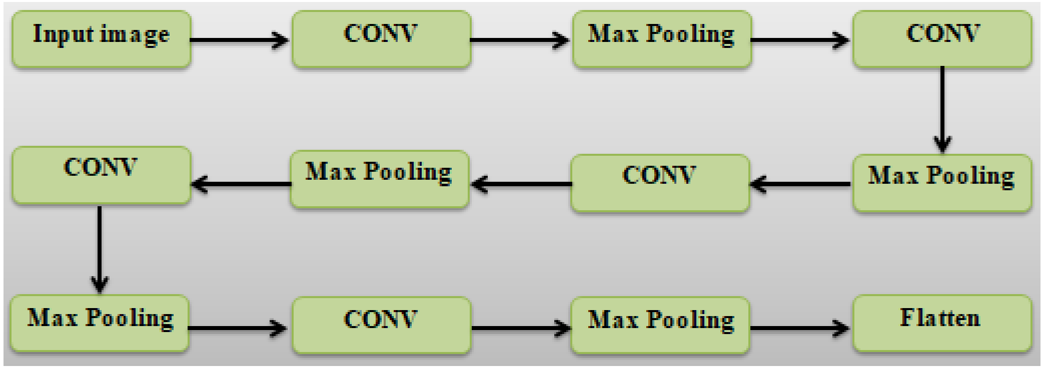

Figure 3.7.3-1 CNN feature extraction of the model.

3.7.4. Image Classification

Image classification refers to the task of extracting information classes of the given image and label to predefined class based on the learning algorithms. For this purpose, there are so many classification algorithms as discussed in literature review section chapter two, but the latest classification with CNN and state-of-the-art image classification techniques have been selected for our work this are deep convolutional neural network and pre-trained CNN architectures of VGG19, MobileNet and DenseNet121 models. In digital image processing task CNN have two functions that are feature extraction and image classification. CNN and pre-trained CNN models uses softmax function as classifier in output fully connected layer. In this study, the image classification is done by classifying into 4 classes (melanoma, basal cell carcinoma, squamous cell carcinoma and healthy) using softmax classifier.

3.7.4.1. Feature Parameters of the Model

To train of our model and to learn set of features to the model, the input datasets are labeled into four distinct categories. Our model comprises multiple layers, each with unique properties. Below are brief descriptions of the layers employed in our model.

Convolution Layer: is the fundamental unit of the CNN model for computing the output of neurons connected to local regions in the input is the convolution layer. The convolution layer comprises a collection of trainable filters with filter size, and there are 5 convolution layers with filter sizes of 16, 32, 64, 128, and 256. The filters have kernel sizes of 3 x 3 for each convolutional layer. To decrease the image dimension by half vertically and horizontally, we used a stride size of two (2, 2). We applied the same padding as the stride size to ensure that the input image is entirely covered by the filter and the specified stride.

Activation Layer: is a crucial layer in a neural network that utilizes an activation function to facilitate the learning of intricate patterns within the data. The activation function determines the conversion of the weighted sum of inputs into an output from one or more nodes in each layer of the network. Our model incorporates the ReLu activation function as it has a reduced computational burden and is less prone to vanishing than other activation functions. ReLu activation function is linear and returns the input value if it is positive; otherwise, it returns zero. Mathematically it is defined as:

$$(x) = \mathrm{ma}(0, \mathrm{x}) \dots\dots.\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots .8$$

Pooling Layer: is used to reduce the feature map dimensions, thereby decreasing the quantity of parameters that the model must learn and the computation carried out in the network. After every convolutional layer, we have utilized the max pooling technique with a polling size of (2, 2) and stride size of two. The max pooling layer lessens the image's dimensionality by extracting the highest value of the area it convolves with the polling size of (2, 2), thereby decreasing the number of pixels in the output from the previous convolutional layer.

Fully Connected Layer: is a dense layer in which all the inputs from a previous layer are linked to each activation unit in the following layer. Prior to implementing the classifier, we employed a dense layer.

Softmax Layer: is used to categorize multiple classes by allotting decimal probabilities to each category. In this research, we have four categories (melanoma, basal cell carcinoma, squamous cell carcinoma and healthy). Therefore, to accomplish a multi-class categorization, we have implemented a softmax classifier subsequent to the fully connected layers.

3.7.4.2. Model Parameters

The model encompasses various parameters that necessitate careful selection to enhance model accuracy and reduce losses. The ensuing are a few of the model's parameters are:

Epoch: is a hyper parameter that denotes the number of times the entire training dataset is iterated by the deep learning algorithm. It signifies the neural network's training process with all the training data for one cycle. During an epoch, each data is utilized exactly once, and both the forward pass and backward pass are considered as one pass. Our model is trained using an epoch size of 50.

Batch size: is a hyper parameter that specifies the quantity of samples to process before adjusting the internal model parameters. By employing a batch size, the number of all samples is reduced, resulting in less memory usage since the network uses fewer samples, and the overall training process necessitates less memory. We have maintained a batch size of 64 for our model.

Learning Rate: is a changeable hyper parameter that is utilized in the training of neural networks. It has a minor positive value, typically ranging between 0.0 and 1.0. The rate of learning oversees how quickly the model conforms to the problem. It is a tuning parameter in an optimization algorithm that determines the size of the step taken at each iteration while advancing towards minimal loss function. If the learning rate is too low, the training will progress slowly. Conversely, if the learning rate is too high, it can lead to undesirable divergent behavior in the loss function. After experimenting with different learning rates, the most famous optimizers, such as ADAM optimizer, were evaluated. It was discovered that the model gave better results with a learning rate of 0.001. Therefore, it was selected.

3.8. Model Performance Evaluation Metrics

The evaluation of classification can be measured using various performance metrics that are suitable for assessing the suggested system. The commonly employed metrics for measuring classification performance include accuracy, recall, precision, F1-score and confusion matrix.

Accuracy: is determined by dividing the total number of accurate classifications by the overall number of classifications made. Mathematical expression is given below.

$$\text{Accuracy} = \frac{Number\ of\ correct\ classification}{Total\ number\ of\ classsification\ made} \ldots\ldots\ldots\ldots\ldots\ldots Equation\ 9$$

Recall: is commonly called sensitivity indicates the proportion of actual positives in the relevant class. Mathematical expression is given below.

$$\text{Recall} = \frac{TP}{TP + FN} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ Equation\ 10$$

Precision: is a measure of the true positive among all positives. Mathematical expression is given below.

$$\text{Precision} = \frac{TP}{TP + FP} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \, Equation\ 11$$

F1-score: is the weighted average the precision and recall. Mathematical expression is given below.

$$\text{F1} - \text{score} = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots .. \, Equation\ 12$$

Confusion Matrix: is a pure and clear way to present the prediction results of a classifier for each and every class. It is represented by a matrix of the true class labels versus the predicted class labels. It contains the number of truly predicted instances and misclassified instances for each class.

Four important confusion matrix terms are described below:

- True Positives: The model predicted true and the actual output also true.
- True Negatives: The model predicted False and the actual output False.
- False Positives: The model predicted true and the actual output False.
- False Negatives: The model predicted False and the actual output true.

	Actual Positive (1)	**Actual Negative (0)**
Predicted Positive (1)	**True Positives (TPs)**	**False Positives (FPs)**
Predicted Negative (0)	**False Negatives (FNs)**	**True Negatives (TNs)**

Figure 3.8-1 Confusion matrix.

In this study, for CNN Softmax classifier, we use categorical cross entropy loss metrics as it is common in multi class classification while the binary cross entropy is used in binary classification.

3.9. Developing Tools

This study is about detection and classification of skin cancer using image processing and deep learning. The implementation of the thesis is done by using the following tools.

- **Python Programing Language**: a power full high level programing language that is used for experiment work and supports various modules to evaluate performance.
- **Tensor Flow**: open source machine learning module used for image classification and it is a symbolic math library based on the data flow and the programing that enables also to run efficiently on the CPU and GPU.
- **Keras**: is a deep learning framework and it is a python API that runs on other libraries like tensor flow and it supports most modules of the neural network.
- **Microsoft Excel**: is a software tool and it is used for creating the metadata attributes in the comma separated values (.CSV) file.
- The experiment was performed by using Intel(R) core(TM) i5-1135G7 CPU with 2.42 GHZ and 8 GB RAM laptop computer and by using Google collab.

3.10. Validity

Experts in the field of skin cancer and dermatologists have been given access to the content and tool in order to assess its validity. They are evaluating the items based on their clarity, relatedness, meaning, and appropriateness of content. To ensure language validity, tools are translated into English.

3.11. Reliability

A key factor in determining a measuring device's quality and sufficiency is its reliability. The accuracy with which it measures the intended attribute is its reliability. The test method is used to determine the tool's dependability. As a result, the tool is regarded as trustworthy and is utilized in this study.

Chapter Four

4. Experimentation and Results

4.1. Overview

This chapter describes the implementation of the proposed model and the outcomes of the experimentation. The primary finding of this study was the detecting and classifying of skin cancer types, including basal cell carcinoma, squamous cell carcinoma and melanoma. The model employed various implementation configurations and experimental results were obtained using CNN model and pre-trained CNN architectures of VGG19, MobileNet and DenseNet121 models using softmax classifier and we have conducted a comparison of various experimentations and evaluated classifier performance based on our dataset. Lastly, we conducted a discussion in order to answer the research questions.

4.2. Data Presentation

In this experimentation work, a researcher has compiled dermatoscopic skin cancer images from various origins including Alert comprehensive specialized hospital and Black Lion specialized hospital located within the local area. Additionally, we have obtained images from the International Skin Imaging Collaboration (ISIC) datasets available on machine repository sites.

The dataset consists of four categories (melanoma, basal cell carcinoma, squamous cell carcinoma and healthy images). To balance the number of datasets in each category and increase the dataset size, data augmentation techniques were applied. In addition for enhancement and regularization data augmentation by rotation is applied. The dataset was divided into two sets: 80% for training and 20% for testing. All images were saved in the .jpg format with resize of 224 x 224.

No	Category/ class	Image format	Quantity
1	Melanoma	Jpg	1077
2	Basal Cell Carcinoma	Jpg	1062
3	Squamous Cell Carcinoma	Jpg	1052
4	Healthy	Jpg	189

Table 4.2-1 Dataset presentation.

4.3. Experimentation Setup

The experiment is done using python programming language through maintained libraries for image manipulation such as numpy, pandas, matplotlib and keras with tensor flow as a backend package on Intel(R) core(TM) i5-1135G7 CPU with 2.42 GHZ laptop with 8 GB RAM. The CNN model and other pre-trained CNN architectures of VGG19, MobileNet and DenseNet121 models are used for experimentation work. During the CNN model and pre-trained CNN architectures of VGG19, MobileNet and DenseNet121 models of training process the trained models are 0.001 learning rate for 50 epochs are used.

Lastly we have done accuracy, precision, recall and f1-score for validating model performance. In addition, we have also used macro-average, weighted-average, and confusion matrices for measuring the model performance.

4.4. Experimentation Datasets

The experiment focuses on the detection and classification of melanoma, basal cell carcinoma, squamous cell carcinoma and healthy dataset classes. The following figure 4.4-1 shows the sample python code to retrieve skin cancer dataset images for each class.

```python
# Reading the data from thesis_metadata.csv

base_skin_dir = 'D:/ETU/Thesis/Final_Thesis/FinalCNN'
# Merge images from both folders into one dictionary
imageid_path_dict = {os.path.splitext(os.path.basename(x))[0]: x
                     for x in glob(os.path.join(base_skin_dir, '*', '*.jpg'))}
df = pd.read_csv('D:/ETU/Thesis/Final_Thesis/FinalCNN/thesis_metadata.csv')
lesion_type_dict = {
    'bcc': 'Basal cell carcinoma',
    'mel': 'Melanoma',
    'scc': 'Squamous cell carcinoma',
    'hea': 'Healthy'
}
n_samples = 5
fig, m_axs = plt.subplots(4, n_samples, figsize = (4*n_samples, 3*4))
for n_axs, (type_name, type_rows) in zip(m_axs,
                                         df.sort_values(['cell_type']).groupby('cell_type')):
    n_axs[0].set_title(type_name)
    for c_ax, (_, c_row) in zip(n_axs, type_rows.sample(n_samples, random_state=2023).iterrows()):
        c_ax.imshow(c_row['image-pixel'])
        c_ax.axis('off')
fig.savefig('category_samples.jpg', dpi=300)
```

Figure 4.4-1 sample python code to retrieve sample dataset images.

As you see the above figure 4.4-1 python code runs and shows the below sample dataset images on each category/ class.

Figure 4.4-2 Sample datasets for each class.

4.5. Pre-Processing and Data Augmentation

We used various preprocessing techniques like histogram equalization, label encoder, label binarizer and Image Data Generator were applied to improve the dataset contrast enhancement.

Data augmentation uses existing data to create modified copies of datasets, which are then used to artificially increase the training set. It involves making small adjustments to the dataset or creating new data point. Finally to improve the dataset size using rotation, flipping, height, width and zoom. We have applied 0.2 as random rotation, height, width and zoom. After applying all the transformations, each image is normalized. The following figure 4.5-1 and 4.5-2 shows preprocessing and data augmentation python code and augmented image experiment task.

```
from sklearn.preprocessing import LabelBinarizer, LabelEncoder
from keras.preprocessing import image
from keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.preprocessing import image_dataset_from_directory

label_binarizer = LabelBinarizer()
image_labels = label_binarizer.fit_transform(label_list)
pickle.dump(label_binarizer,open('label_transform.pkl', 'wb'))
n_classes = len(label_binarizer.classes_)
print(label_binarizer.classes_)

data_augmentation = tf.keras.Sequential([
  tf.keras.layers.RandomFlip("horizontal"),
  tf.keras.layers.RandomRotation(0.2),
  tf.keras.layers.RandomZoom(0.2),
  tf.keras.layers.RandomHeight(0.2),
  tf.keras.layers.RandomWidth(0.2),
])
for image, _ in train_dataset.take(1):
    plt.figure(figsize=(10, 10))
    first_image = image[0]
    for i in range(9):
        ax = plt.subplot(3, 3, i + 1)
        augmented_image = data_augmentation(tf.expand_dims(first_image, 0))
        plt.imshow(augmented_image[0] / 255)
        plt.axis('off')
def Dataset_loader(DIR, RESIZE):
    IMG = []
    read = lambda imname: np.asarray(Image.open(imname).convert("RGB"))
    for IMAGE_NAME in tqdm(os.listdir(DIR)):
        PATH = os.path.join(DIR,IMAGE_NAME)
        _, ftype = os.path.splitext(PATH)
        if ftype == ".jpg":
            img = read(PATH)
            img = cv2.resize(img, (RESIZE,RESIZE))
            IMG.append(np.array(img))
    return IMG

train = np.array(Dataset_loader('D:/SkinCancer/SkinCancer_Datasets/train',224))
test = np.array(Dataset_loader('D:/SkinCancer/SkinCancer_Datasets/test',224))
```

Figure 4.5-1 Sample python code for preprocessing and data augmentation.

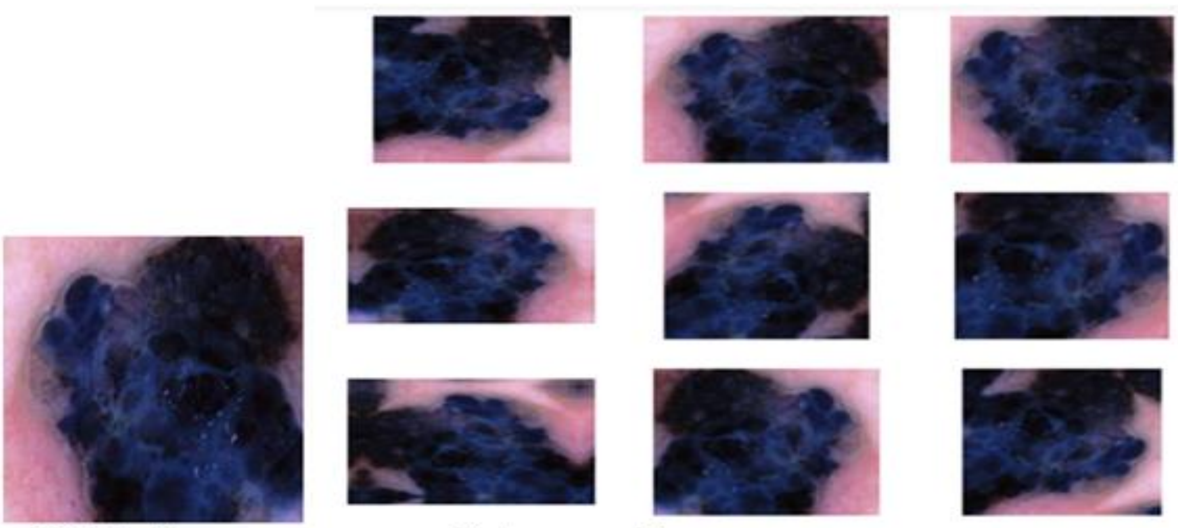

Figure 4.5-2 Sample augmented image.

4.6. Experimentation and Findings

4.6.1. CNN Model

The CNN model involves on five convolution layers that extract the feature the size must fit the model to extract features to the deepest. In this CNN model experimentation various parameters can influence the model performance. For this stimulus we have try to make best by creating various standards for those parameters and lastly we have used batch size 64, epoch 50, optimizer “Adam” with 0.001 learning rate of the model, activation function “ReLu”, classifier “softmax” in the output two dense layers of “categorical cross entropy”. Finally we have developed the following training and validation accuracy with validation model performance in each iteration.

```
Epoch 10/50
39/39 [==============================] - 192s 5s/step - loss: 0.0726 - accuracy: 0.9772 - val_loss: 0.1508 - val_accuracy: 0.94
97 - lr: 0.0010
Epoch 11/50
39/39 [==============================] - ETA: 0s - loss: 0.0788 - accuracy: 0.9736
Epoch 11: ReduceLROnPlateau reducing learning rate to 0.00010000000474974513.
39/39 [==============================] - 212s 5s/step - loss: 0.0788 - accuracy: 0.9736 - val_loss: 0.2046 - val_accuracy: 0.94
64 - lr: 0.0010
Epoch 12/50
39/39 [==============================] - 216s 6s/step - loss: 0.0333 - accuracy: 0.9878 - val_loss: 0.1619 - val_accuracy: 0.95
94 - lr: 1.0000e-04
Epoch 13/50
39/39 [==============================] - 204s 5s/step - loss: 0.0206 - accuracy: 0.9939 - val_loss: 0.1671 - val_accuracy: 0.96
27 - lr: 1.0000e-04
Epoch 14/50
39/39 [==============================] - 200s 5s/step - loss: 0.0183 - accuracy: 0.9943 - val_loss: 0.1714 - val_accuracy: 0.96
10 - lr: 1.0000e-04
Epoch 15/50
39/39 [==============================] - 191s 5s/step - loss: 0.0160 - accuracy: 0.9963 - val_loss: 0.1746 - val_accuracy: 0.96
43 - lr: 1.0000e-04
Epoch 16/50
39/39 [==============================] - ETA: 0s - loss: 0.0147 - accuracy: 0.9947
Epoch 16: ReduceLROnPlateau reducing learning rate to 1.0000000474974514e-05.
Restoring model weights from the end of the best epoch: 6.
39/39 [==============================] - 189s 5s/step - loss: 0.0147 - accuracy: 0.9947 - val_loss: 0.1801 - val_accuracy: 0.96
10 - lr: 1.0000e-04
Epoch 16: early stopping
```

Figure 4.6.1-1 CNN model training and validation performance per each epoch.

As you see the above figure 4.6.1-1 accuracy and validation model performance of the CNN model, it shows that the number of epoch increases the performance of the model accuracy also increased because of the epoch have determined the number of knowing the image character, when the model knows the image character iteratively the learning accuracy have been increased. Finally we have got 99% training accuracy and 96% validation accuracy. The loss of CNN model was 0.01 for training and 0.18 for validation loss.

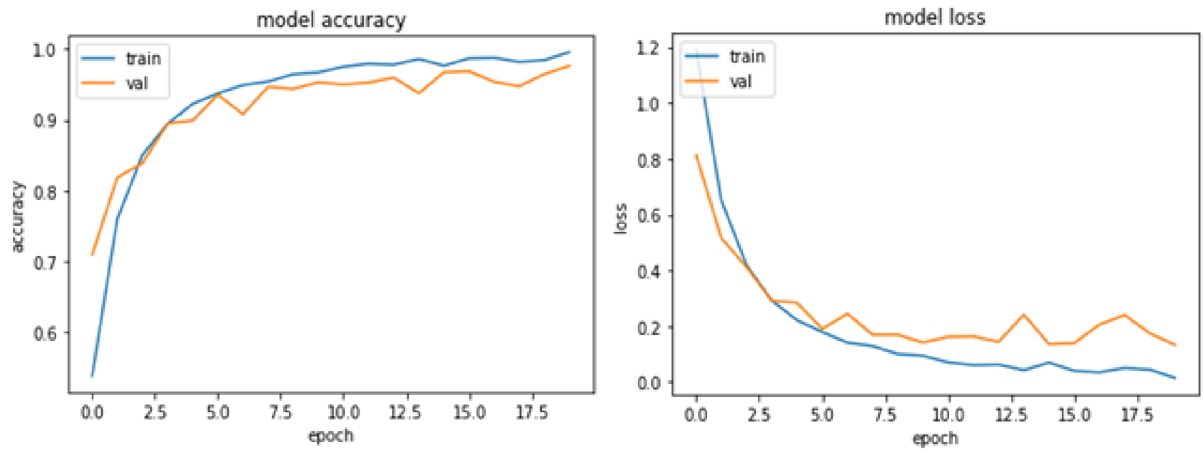

Figure 4.6.1-2 Training and validation accuracy and training and validation loss.

In the above figure 4.6.1-2 of CNN model performance we have shown the model test accuracy and validation and training accuracy of the model in graph. In this test result we have achieved 96.623% test accuracy.

In the below figure we have strained to demonstration the accuracy of the CNN model using precision, recall and f1-score measures and we have achieved 97% average accuracy.

```
Test Accuracy: 96.623%
25/25 [==============================] - 18s 705ms/step
              precision    recall  f1-score   support

         mel       1.00      0.35      0.52        23
         bcc       0.95      0.92      0.93       135
         scc       0.88      1.00      0.94       126
         hea       1.00      1.00      1.00       486

    accuracy                           0.97       770
   macro avg       0.96      0.82      0.85       770
weighted avg       0.97      0.97      0.96       770
```

Figure 4.6.1-3 Precision, recall and f1-score performance measure of CNN model.

4.6.2. Pre-Trained CNN Models

4.6.2.1. VGG Model Performance

VGG (Visual Geometry Group) is a typical deep convolutional neural network design with several layers. The term deep refers to the number of layers, with VGG16 or VGG19 having 16 and 19 convolutional layers.

VGG19 is one of the well-known pre-trained convolutional neural network model in the deep convolutional neural network architecture models that is used for classify images of large image of ILSVRC challenge. This architecture has 19 layers (16 convolution layers, 3 fully connected layers with 5 max-pooling and softmax layers).

The experiment has trained the VGG19 model on the dataset and gives score 97% training accuracy, 92% validation accuracy and 92% classification accuracy. The loss of VGG19 model was 0.08 for training and 0.78 for validation loss. So the CNN model has better accuracy and low loss when compared with VGG19 model and training time is short in CNN.

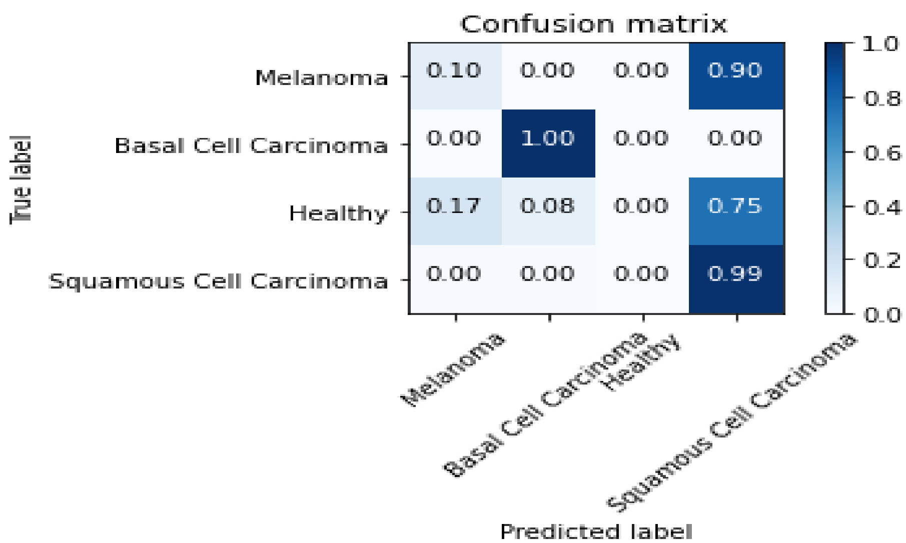

Figure 4.6.2.1-1 VGG19 Model Performance classification confusion matrix.

The model precision, recall, f1-score, micro, macro and weighted average of each category/ classes are plainly showed on the below figure.

	precision	recall	f1-score	support
Melanoma	0.50	0.10	0.17	10
Basal Cell Carcinoma	0.91	1.00	0.95	20
Healthy	0.00	0.00	0.00	12
Squamous Cell Carcinoma	0.93	0.99	0.96	237
micro avg	0.92	0.92	0.92	279
macro avg	0.58	0.52	0.52	279
weighted avg	0.87	0.92	0.89	279
samples avg	0.92	0.92	0.92	279

Figure 4.6.2.1-2 Precision, recall and f1-score performance measure of VGG19.

4.6.2.2. MobileNet Model Performance

MobileNet is a class of light weight pre-trained CNN model in deep convolutional neural networks that are vastly smaller in size and faster in performance than many other popular models. It is also low latency model that can be used for detection and classification and other common tasks convolutional neural network are good for. We have trained MobileNet model on the dataset in 50 epochs and give scores 87.56% classification accuracy, 99% training accuracy and 87% validation accuracy of the model.

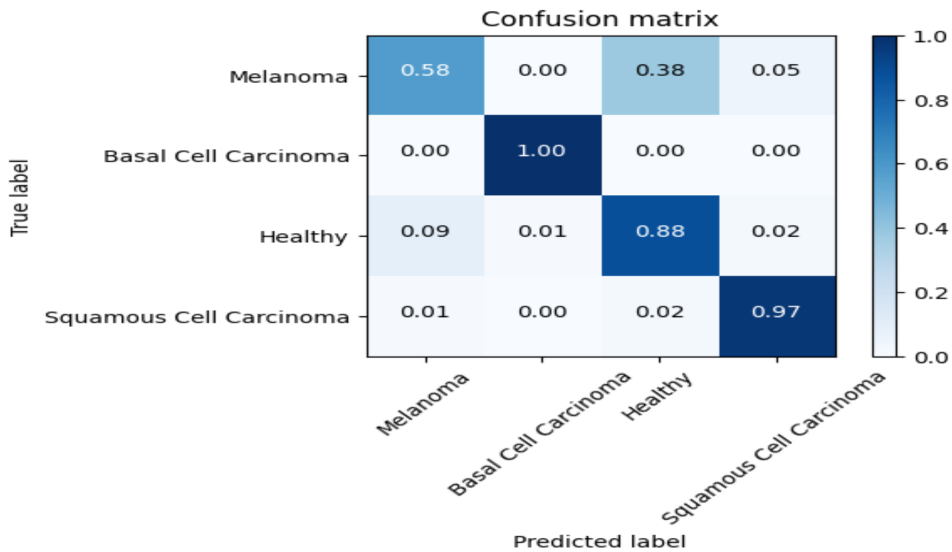

Figure 4.6.2.2-1 MobileNet Model Perform classification confusion matrix.

The model precision, recall and f1-score of each category/ classes are plainly showed on the below figure and the model scores of micro, macro and weighted average of the model are showed on the below figure.

	precision	recall	f1-score	support
Melanoma	0.73	0.68	0.70	84
Basal Cell Carcinoma	0.95	1.00	0.97	18
Healthy	0.78	0.83	0.80	106
Squamous Cell Carcinoma	0.98	0.97	0.98	235
micro avg	0.88	0.88	0.88	443
macro avg	0.86	0.87	0.86	443
weighted avg	0.88	0.88	0.88	443
samples avg	0.88	0.88	0.88	443

Figure 4.6.2.2-2 Precision, recall and f1-score performance measure of mobilenet.

4.6.2.3. DenseNet Model Performance

Densenet121 (Dense Convolutional Networks) is an architecture that focuses on making the deep learning networks go even deeper, but at the same time making them more efficient to train, by using shorter connections between the layers. It has 120 convolutions and 4 averages pool. All layers i.e. those within the same dense block and transition layers spread their weight over multiple inputs which allow deeper layers to use features extract early on. We have trained DenseNet121 model on the dataset in 50 epochs and give scores 85.33% classification accuracy, 99% training accuracy and 85% validation accuracy of the model.

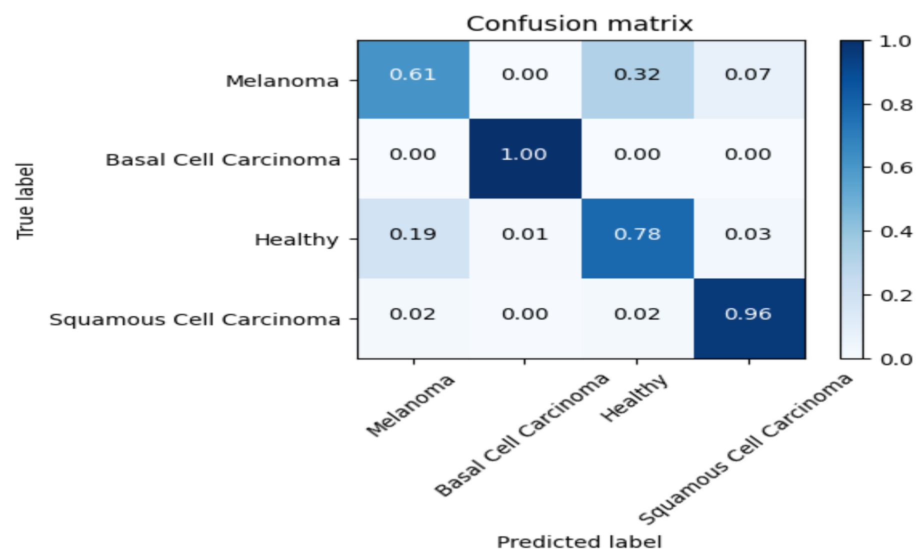

Figure 4.6.2.3-1 DenseNet121 model performance classification confusion matrix.

The model precision, recall, f1-score, micro, macro and weighted average of each category/ classes are plainly showed on the below figure.

	precision	recall	f1-score	support
Melanoma	0.69	0.61	0.65	85
Basal Cell Carcinoma	0.91	1.00	0.95	20
Healthy	0.73	0.78	0.75	108
Squamous Cell Carcinoma	0.96	0.96	0.96	237
micro avg	0.86	0.85	0.85	450
macro avg	0.82	0.84	0.83	450
weighted avg	0.85	0.85	0.85	450
samples avg	0.85	0.85	0.85	450

Figure 4.6.2.3-2 Precision, recall and f1-score performance measure of DenseNet121.

4.6.3. Comparison of Experiments

We have made more than 24 experimentation works using various feature parameters on CNN model and pre-trained CNN architecture of VGG19, MobileNet and DenseNet121 models using different image sizes, optimizer, classifier, batch size, epochs and learning rate. But the best performance accuracy gives on 224 x 224 image size, optimizer “Adam”, classifier “softmax”, batch size 64, epochs 50 and learning rate 0.001 are used for all models. The following table 4.6.3-1 describes the comparison of the above experiments on training and validation accuracy and training and validation loss and their classification accuracy.

Models	Metrics				Classification Accuracy
	Accuracy		Loss		
	Training	Validation	Training	Validation	
CNN model	99%	96%	0.01%	0.18%	97%
VGG19	97%	92%	0.08%	0.78%	92%
MobileNet	99%	87%	0.00%	4.43%	87.56%
DensNet121	99%	85%	0.01%	1.72%	85.33%

Table: 4.6.3-1 comparison of experiments.

As you see the above table 4.6.3-1 comparison of experiments, CNN model has better detection and classification accuracy than the pre-trained CNN architectures of VGG19, MobilNet and DenseNet121 models and the training time of our model are relatively low since the complexity of the model is very low compare to other pre-trained CNN models.

4.7. Discussion/ Answers to Research Questions

In the first chapter of this thesis, three research questions are listed and answered after completing this thesis.

Thus the first research question was about appropriate preprocessing techniques for detecting and classifying skin cancer. Based on the result histogram equalization; label encoder; label binarizer and Image Data Generator found useful to enhance the contrast of the images.

The second research question was about feature extraction technique that are better to identify the detection and classification of skin cancer. The research revealed that CNN model is found good. Based on the result shown in table 4.6.3-1, performance evaluations on CNN model give scores 99% training accuracy, 96% validation accuracy, 97% classification accuracy and the test accuracy is 96.623%. So under the four experiment feature extraction models the CNN model gives better performance accuracy than the pre-trained CNN architectures of VGG19, MobileNet and DenseNet121 models to detect and classify of skin cancer.

The last question was about how to develop an optimum convolutional neural network model that is better than pre-trained models. It is found that the convolutional neural network model develops on five convolutional layers 16, 32, 64, 128 and 256 on the 3 x 3 kernel size followed by max pooling layers on 2 x 2 pool size, three dense layers and activation “ReLu”, padding “same” and classifier “softmax” for better detection and classification of skin cancer.

Most of the existing works perform on classification of skin cancer types using small number of images without any preprocessing techniques and used most of pre-trained CNN architecture models which is quite low and time consuming to detect and classify for its small number of skin cancer images. On the current study, three skin cancer types and healthy images are used with applied of different preprocessing techniques and achieved the best performance classification accuracy 97%, which can help doctors to diagnose the right cancer type. Furthermore CNN model is more effective considering the faster processing capability and better detection and classification of the skin cancer.

Chapter Five

5. Conclusion and Recommendation

5.1. Conclusion

In this study, the detection and classification of skin cancer using image processing and deep learning is proposed and implemented. We have done reviewing of various related works to propose a better method for the problem of skin cancer detection and classification. And one of the problems is enhancing the datasets since the images can have different contrasts so in order to maximize the accuracy of the model the dataset images are enhanced to make them appropriate to the model training. So that deep learning and image processing approach incorporation method is taken into action of the thesis study to success overcoming the limitation of skin cancer detection and classification in computer aided system.

The three main steps of the suggested methodology are pre-processing, feature extraction, and classification. Pre-processing involves carefully enhancing the images to make them more suitable for the model, and data augmentation is used to add more images from the original dataset because we have over fitted. We used flip and rotation in various angle augmentation techniques to solve that issue. Features are extracted using convolutional neural networks with various convolutional layers and filter sizes. A softmax layer with four classes (basal cell carcinoma, squamous cell carcinoma, melanoma and healthy) will be used for the classification portion of the model.

We applied a CNN network architecture consists of five convolutional layers followed by maximum pooling layers and fully connected layers and a softmax layer. The model classification can classify the skin cancer into 4 types and we have achieved good classification performance with accuracy of 97%. When we compare our CNN model with the pre-trained CNN architectures of VGG19, MobileNet and DenseNet121 models, CNN model has better performance accuracy and the processing time of the model is lower than the pre-trained model.

5.2. Contribution

This study is about the detection and classification of the skin cancer types using convolutional neural network and we have used image datasets and improved image enhancement on those datasets to make the model training and classification more accurate. This study work has a lot to offer the scientific community as a contribution, some of which are as follows:

- Performance enhancement: The suggested model produced better outcomes or enhanced its functionality. Accuracy, model loss, training time, and model size or complexity all saw improvements as a result of the study. 99% training accuracy, 97% classification accuracy and 96.623% testing accuracy were attained. The study outperforms pre-trained CNN models due to the model's training time, which is about 160 seconds per epoch.
- By taking into account image datasets with various conditions, such as the variance of noise, background conditions, shadow and others, and enhancing the image datasets with better image enhancement methods histogram equalization; label encoder; label binarizer and Image Data Generator are applied, the CNN model can address issues with the existing systems.

5.3. Recommendation

In this thesis work we attempted to identify the different types of skin cancer as basal cell carcinoma, squamous cell carcinoma, and melanoma detection and classification using image processing and deep learning. This was primarily motivated by some limitations of previous work. According to the problem statement, the issue is one of public health. Solving problems involving public health is primarily concerned with performance enhancement, which should be carried out continuously until the highest level of accuracy is attained. Therefore, while implementing this thesis work, the following noteworthy future work recommendations were discovered:

- There are still additional types of skin cancer that can close this gap.
- In order to achieve better performance, we have not compared our method with other feature extraction and image segmentation techniques.
- The following researcher will determine the stage level for each type of skin cancer.
- Create a system that performs more accurately than this research work.

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Appendix

Here are sample python codes for training and testing of the CNN model

Import necessary libraries

```
import os
import CV2
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from PIL import Image
from glob import glob
import itertools
from keras.utils import to_categorical
from sklearn.preprocessing import LabelEncoder, StandardScaler, ImageDataGenerator
import plotly.graph_objects as go
import plotly.express as px
from plotly.subplots import make_subplots
import pydot
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix
import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, Flatten, BatchNormalization, Dropout, Dense, MaxPool2D
from tensorflow.keras.callbacks import ReduceLROnPlateau, EarlyStopping
from IPython.display import display
```

giving the paths for datasets

```
base_skin_dir = os.path.join('D:/ETU/Thesis/Final_Thesis/Simulation_Datasets')
skin_df = pd.read_csv(os.path.join(base_skin_dir, 'thesis_metadata.csv'))
imageid_path_dict = {os.path.splitext(os.path.basename(x))[0]: x
                     for x in glob(os.path.join(base_skin_dir, '*', '*.jpg'))}
lesion_type_dict = {
    'mel': 'Melanoma (mel)',
    'bcc': 'Basal cell carcinoma (bcc)',
    'scc': 'Squamous cell carcinoma (scc)',
    'hea': 'Healthy (hea)'
}
label_mapping = {
    0: 'mel',
    1: 'bcc',
    2: 'scc',
    3: 'hea'
}
reverse_label_mapping = dict((value, key) for key, value in label_mapping.items())
```

adding image pixels, partition dataset into training and testing datasets and prepare data for training and testing the model.

```
# Adding image pixels
skin_df['image_pixel'] = skin_df['path'].map(lambda x: np.asarray(Image.open(x).resize((224,224))))

def prepare_for_train_test(X, Y):
    # Splitting into train and test set
    X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=0.2, random_state=1)

     # Prepare data for training and testing the model
    train_datagen = ImageDataGenerator(rescale = 1./255,
                                       rotation_range = 10,
                                       width_shift_range = 0.2,
                                       height_shift_range = 0.2,
                                       shear_range = 0.2,
                                       horizontal_flip = True,
                                       vertical_flip = True,
                                       fill_mode = 'nearest')
    train_datagen.fit(X_train)
    test_datagen = ImageDataGenerator(rescale = 1./255)
    test_datagen.fit(X_test)
    return X_train, X_test, Y_train, Y_test
```

Image noise removal

```
def noise_removal(image):
    grayScale = cv2.cvtColor(image, cv2.COLOR_RGB2GRAY)
    kernel = cv2.getStructuringElement(1,(17,17))
    blackhat = cv2.morphologyEx(grayScale, cv2.MORPH_BLACKHAT, kernel)
    ret,threshold = cv2.threshold(blackhat,10,255,cv2.THRESH_BINARY)
    final_image = cv2.inpaint(image,threshold,1,cv2.INPAINT_TELEA)
    return final_image
```

Image Normalization

```
x_train = np.asarray(x_train_o['image'].tolist())
x_test = np.asarray(x_test_o['image'].tolist())

x_train_mean = np.mean(x_train)
x_train_std = np.std(x_train)

x_test_mean = np.mean(x_test)
x_test_std = np.std(x_test)

x_train = (x_train - x_train_mean)/x_train_std
x_test = (x_test - x_test_mean)/x_test_std
```

Histogram equalization

```
import numpy
import cv2
import os
base_skin_dir = os.path.join('D:/ETU/Thesis/Final_Thesis/Simulation_Datasets')
path1 = 'D:/ETU/Thesis/Final_Thesis/Simulation_Datasets/thesis_metadata.csv'
path2 = r'D:/ETU/Thesis/Final_Thesis/Simulation_Datasets/Histogram_equalization'
listing= os.listdir(path1)
num_samples = size(listing)
print (num_samples)
for file in listing:
    img = Image.open(path9 + '\\' + file)
    img=numpy.asarray(img)
    hist,bins = np.histogram(img.flatten(),256,[0,256])
    plt.hist(img.flatten(),256,[0,256], color = 'r')
    plt.xlim([0,256])
    plt.show()
    r,g,b = cv2.split(img)
    h_r, bin_r = np.histogram(r.flatten(), 256, [0, 256])
    h_g, bin_g = np.histogram(g.flatten(), 256, [0, 256])
    h_b, bin_b = np.histogram(b.flatten(), 256, [0, 256])
    # calculate cdf
     cdf_r = np.cumsum(h_r)
     cdf_g = np.cumsum(h_g)
    cdf_b = np.cumsum(h_b)
    # mask all pixels with value=0 and replace it with mean of the pixel values
    cdf_m_b = np.ma.masked_equal(cdf_b,0)
    cdf_m_b = (cdf_m_b - cdf_m_b.min())*255/(cdf_m_b.max()-cdf_m_b.min())
    cdf_final_b = np.ma.filled(cdf_m_b,0).astype('uint8')
    cdf_m_g = np.ma.masked_equal(cdf_g,0)
    cdf_m_g = (cdf_m_g - cdf_m_g.min())*255/(cdf_m_g.max()-cdf_m_g.min())
    cdf_final_g = np.ma.filled(cdf_m_g,0).astype('uint8')
    cdf_m_r = np.ma.masked_equal(cdf_r,0)
    cdf_m_r = (cdf_m_r - cdf_m_r.min())*255/(cdf_m_r.max()-cdf_m_r.min())
    cdf_final_r = np.ma.filled(cdf_m_r,0).astype('uint8')
    img=numpy.asarray(img1)
    hist,bins = np.histogram(img_out.flatten(),256,[0,256])
    plt.hist(img_out.flatten(),256,[0,256], color = 'r')
    plt.xlim([0,256])
    # merge the images in the three channels     img_r = cdf_final_r[r]
    img_g = cdf_final_g[g]
    img_b = cdf_final_b[b]
    img_out = cv2.merge((img_r,img_g,img_b))
    # validation
    equ_r = cv2.equalizeHist(r)
    equ_g = cv2.equalizeHist(g)
    equ_b = cv2.equalizeHist(b)
     equ = cv2.merge((equ_r, equ_g,equ_b ))
    #print(equ)
    img1=Image.fromarray(equ,"RGB")
    img1.save(path3 +'\\' +  file, "JPEG")
```

CNN model design

```
import os
import numpy as np
import pandas as pd

from PIL import Image
from glob import glob
from keras.utils import to_categorical
from sklearn.preprocessing import LabelEncoder, StandardScaler

import plotly.graph_objects as go
import plotly.express as px
from plotly.subplots import make_subplots
import matplotlib.pyplot as plt
import pydot

from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix

import tensorflow as tf
from tensorflow.keras.preprocessing.image import ImageDataGenerator
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Conv2D, Flatten, BatchNormalization, Dropout, Dense, MaxPool2D
from tensorflow.keras.callbacks import ReduceLROnPlateau, EarlyStopping

from IPython.display import display
def create_model():
    model = Sequential()
    model.add(Conv2D(16, kernel_size = (3,3), input_shape = (224, 224, 3), activation = 'relu', padding = 'same'))
    model.add(MaxPool2D(pool_size = (2,2)))

    model.add(Conv2D(32, kernel_size = (3,3), activation = 'relu', padding = 'same'))
    model.add(MaxPool2D(pool_size = (2,2), padding = 'same'))

    model.add(Conv2D(64, kernel_size = (3,3), activation = 'relu', padding = 'same'))
    model.add(MaxPool2D(pool_size = (2,2), padding = 'same'))

    model.add(Conv2D(128, kernel_size = (3,3), activation = 'relu', padding = 'same'))
    model.add(MaxPool2D(pool_size = (2,2), padding = 'same'))

    model.add(Conv2D(256, kernel_size = (3,3), activation = 'relu', padding = 'same'))
    model.add(MaxPool2D(pool_size = (2,2), padding = 'same'))

    model.add(Flatten())
    model.add(Dense(64, activation = 'relu'))
    model.add(Dense(32, activation='relu'))
    model.add(Dense(4, activation='softmax'))

    optimizer = tf.keras.optimizers.Adam(learning_rate = 0.001)

    model.compile(loss = 'categorical_crossentropy',
                  optimizer = optimizer,
                   metrics = ['accuracy'])
    print(model.summary())

    return model;
```

Train the model

```
def train_model(model, X_train, Y_train, EPOCHS=50):
    early_stop = EarlyStopping(monitor='val_loss', patience=10, verbose=1,
                               mode='auto', restore_best_weights=True)

    reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.1, patience=5,
                                  verbose=1, mode='auto')

    history = model.fit(X_train,
                        Y_train,
                        validation_split=0.1,
                        batch_size = 64,
                        epochs = EPOCHS,
                        callbacks = [reduce_lr, early_stop])
    return history
```

Model training curve

```
def plot_model_training_curve(history):
    fig = make_subplots(rows=1, cols=2, subplot_titles=['Model Accuracy', 'Model Loss'])
    fig.add_trace(
        go.Scatter(
            y=history.history['accuracy'],
            name='train_acc'),
        row=1, col=1)
    fig.add_trace(
        go.Scatter(
            y=history.history['val_accuracy'],
            name='val_acc'),
        row=1, col=1)
    fig.add_trace(
        go.Scatter(
            y=history.history['loss'],
            name='train_loss'),
        row=1, col=2)
    fig.add_trace(
        go.Scatter(
            y=history.history['val_loss'],
            name='val_loss'),
        row=1, col=2)
    fig.show()
```

Test the model

```
def test_model(model, X_test, Y_test):
    model_acc = model.evaluate(X_test, Y_test, verbose=0)[1]
    print("Test Accuracy: {:.3f}%".format(model_acc * 100))
    y_true = np.array(Y_test)
    y_pred = model.predict(X_test)
    y_pred = np.array(list(map(lambda x: np.argmax(x), y_pred)))
    clr = classification_report(y_true, y_pred, target_names=label_mapping.values())
    print(clr)

    sample_data = X_test[:15]
    plt.figure(figsize=(22, 12))
    for i in range(15):
        plt.subplot(3, 5, i + 1)
        plt.imshow(sample_data[i])
        plt.title(label_mapping[y_true[i][0]] + '|' + label_mapping[y_pred[i]])
        plt.axis("off")
    plt.show()
```