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Detection and classification of skin cancer using CNN

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Detection and classification of skin cancer using CNN

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First, thanks to Allah the Almighty who guided and helped us to finish our final project .We would like, also, to thank the supervising doctor "Kifouche Abdessalam" who helped us a lot and admitted to supervise our work, gave us all the precious, valuable directions that could help in preparing this research. Additionally, all the stages it went through, We would like to thank the jury who accepted to judge and evaluate this project. A great thank to our teachers who taught and support us during all the of years at the department and university.

Dedication

My university journey ended after exhaustion and hardship.

And here I am today finishing my graduate research.

I am grateful to everyone who did me a favor in my career, and helped me even if it was by praying for me.

To the one I prefer over myself and why not?

Who spared no effort to keep me happy?

My dear mother,

We walk the paths of life, and those who control our minds remain on every path we take his good face and good deeds.

Throughout his life, my dear father did not abandon

me to my sisters, family, friends, especially my friend Taousse,

my teachers, and especially the one who supervised this work, Dr. KIFOUCHE Abdessalam,

everyone who taught me a letter, and everyone who stood by me and helped me with everything they had.

Today I dedicate my graduation thesis to the soul of my grandmother, and I hope that God will enlighten her grave and that she will be among the people of God and His special ones.

Lehella Karima

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We Thank God Almighty, who succeeded me in completing this memo and who inspired me with

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I dedicate this work to my Mother, the apple of my eye and the first source of encouragement for me (Dear Mom).

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I dedicate this work to you, hoping that it will be in your good opinion.

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Abstract

Recently, Artificial Intelligence (AI) has permeated all areas of scientific study due to the solutions it provides in the field of health.

The most common type of cancer in the world is skin cancer. Because early recognition is crucial for improving patient outcomes, we focused our efforts on developing a skin image classification model that differentiates benign from malignant melanoma. Based on a set of data generated using the CNN model, our model is based. To train our models, we used publicly accessible sites such as Google Colab and Kaggle. In this study, we applied the CNN architecture to a variety of information containing both benign and malignant data.

In this project we have achieved a high accuracy in recognizing and classifying skin cancer with a score of 91%.

Keywords: artificial intelligence, 3D Configurable Model, Fuzzy Logic,CNN, Machine Learning, Deep Learning, Artificial Vision, and health care.

Résumé

Récemment, l'Intelligence Artificielle (IA) a imprégné tous les domaines de l'étude scientifique en raison des solutions qu'elle apporte dans le domaine de la santé.

Le type de cancer le plus répandu dans le monde est le cancer de la peau. Parce que la reconnaissance précoce est cruciale pour améliorer les résultats des patients, nous avons concentré nos efforts sur le développement d'un modèle de classification des images cutanées qui différencie le mélanome bénin du mélanome malin. Basé sur un ensemble de données générées à l'aide du modèle CNN, notre modèle est basé. Pour former nos modèles, nous avons utilisé des sites accessibles au public tels que Google Colab et Kaggle. Dans cette étude, nous avons appliqué l'architecture CNN à une variété d'informations contenant à la fois des données bénignes et malignes.

Dans ce projet, nous avons atteint une grande précision de reconnaissance et de classification des mélanomes avec un score de 91 %.

Mots-clés : intelligence artificielle, modèle configurable 3D, logique floue, CNN, apprentissage automatique, apprentissage en profondeur, vision artificielle et soins de santé.

ملخص

في الآونة الأخيرة، تغلغل الذكاء الاصطناعي (AI) في جميع مجالات الدراسة العلمية بسبب الحلول التي يوفرها في مجال الصحة.

أكثر أنواع السرطانات شيوعًا في العالم هو سرطان الجلد. نظرًا لأن التعرف المبكر أمر بالغ الأهمية لتحسين نتائج المرضى ، فقد ركزنا جهودنا على تطوير نموذج تصنيف صورة الجلد الذي يميز الورم الميلانيني الحميد عن الورم الميلانيني الخبيث. استنادًا إلى مجموعة البيانات التي تم إنشاؤها باستخدام نموذجCNN ، لتدريب نماذجنا، استخدمنا مواقع يمكن الوصول إليها بشكل عام مثل Google Colab و .Kaggle في هذه الدراسة، طبقنا بنية CNN على مجموعة متنوعة من المعلومات التي تحتوي على بيانات حميدة وخبيثة.

لقد حققنا في هذا المشروع دقة عالية في التعرف على سرطان الجلد وتصنيفه بنسبة 91٪ .

الكلمات المفتاحية: الذكاء الاصطناعي، النموذج القابل للتكوين ثلاثي الأبعاد ، المنطق الضبابي ،الشبكات العصبية الالتفافية ، التعلم الآلي ، التعلم العميق ، الرؤية الاصطناعية ، والرعاية الصحية.

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List of Abbreviations

BCC	Basal cell carcinoma
SCC	Squamous cell carcinoma
DFSP	Dermato fibro sarcoma protuberans
CNN	Convolutional neural network
ANN	Artificial neural network
TADA	The Triage method Amalgamated Dermoscopy Algorithm
AI	Artificial Intelligence.
AK	Actimic Keratosis
MLP	Multilayer perceptron
CONV	Convolution Layer
POOL	The pooling Layer
FC	Fully connected
TP	True positive
TN	True negative
FP	False positive
FN	False negative

General Introduction

One of the most prevalent cancers in the world, skin cancer, if not detected early, can have devastating side effects. As a result, it is crucial and significant to pay close attention to the topic of skin cancer identification. It is regarded as one of the largest health issues the world faces today.

The traditional diagnostic process depends on analyzing a patient's sample taken from the skin to send to the laboratory, then costs and a lot of time to perform the analyzes, in addition to that this method is not accurate enough. However, the use of machine learning techniques can help improve the accurateness of diagnosing skin cancer, and this can be achieved by means of artificial neural networks (CNN) technology to classify images containing signs of skin cancer by analyzing temporal and subtle patterns in the pictures. This technique is based on training a neural network to cite different cases of skin cancer, and using the functions of this network to accurately analyze the data and determine whether there is skin cancer or not. It can be used to classify tumors, malignant and benign, and to determine the severity of each type of tumor. This technology is also characterized by high accuracy in detecting skin cancer, and the lack of need for special skills by users.

Artificial intelligence is one of the important topics of interest in medicine. Despite the promising results shown by some studies in this field, there are many challenges facing professionals working in this field, including but not limited to: the difficulty in distinguishing between moles, eczema, wounds and other types of skin, as well as the difficulty in distinguishing between the normal and the abnormal is the problem facing professionals in this field.
This paper is subdivided into three main chapters:

In the first chapter, we discussed skin cancer, its types, how it is detected, and how artificial intelligence (AI) entered the field of medicine.

In the second chapter, we discussed neural networks, both biological and artificial, as well as convolutional neural networks, the topic of our dissertation, and their types.

Finally, the third chapter discusses the outcomes of an experiment conducted in Python using CNN algorithms and the aforementioned convolutional neural networks

This note aims to study and analyze the usage of interconnected neural networks in the discovery and classification of skin cancer using some of the modern techniques used in this field that guarantee better results. The research work aims to reach more accurate follow-up and diagnostic capabilities.

Chapter 1: Skin Cancer

1.1. Introduction

Skin cancers are a major public health problem. In this chapter we will discuss the meaning of cancer, especially skin cancer, which is the field of our research as it has become a major health problem in the whole world, and for this reason we must know what it is? What are its causes? More importantly, how does it spread? In all of this, we will use AI for diagnosis because it has many uses in healthcare as it has the ability to analyze big medical data, work for the patient better, achieve health systems, and so on.

1.2. Cancer

Cancer can appear almost anywhere in the millions of cells that make up the human body. When the body needs new cells, human cells frequently divide (through a process known as cell proliferation and multiplication). When old cells pass away due to aging or damage, new ones take their place.

This methodical procedure occasionally goes wrong, allowing damaged or abnormal cells to proliferate when they shouldn't. These cells have the ability to develop into tumors, which are tissue lumps. Tumors may be malignant or non-cancerous (benign).

1.2.1. Definition

Cancer is a DNA disease, the basic units of the body being the cells that make up tissues and organs. The body is constantly producing new cells to support our growth, replace damaged tissues, and heal wounds [1].

Cells usually divide and die in an orderly manner, with each new cell replacing a dead cell. Sometimes cells can develop abnormalities and continue to grow. These abnormal cells can also develop into cancer [2].

The abnormal cells in solid malignancies, such as melanoma, produce an abnormal mass known as a polyp. In some malignancies, such as leukemia, abnormal cells accumulate in the blood.

Tumors are not always cancerous. Benign tumors are more likely not to spread to other areas of the body or to develop into a malignant tumor or to grow

slowly. Malignant tumors, also referred to as carcinoid tumors, can infect nearby tissues, expand rapidly, and kill healthy cells.

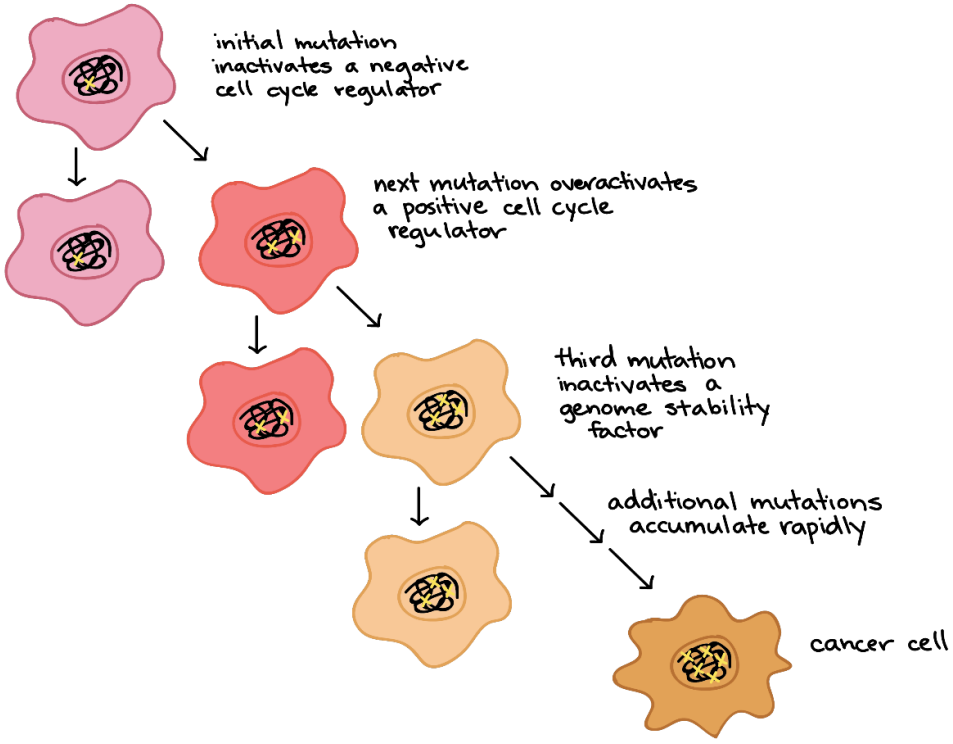


Figure 1.1: Cancer and the cell cycle

Cancer cells have the ability to divide and spread to different areas of the body through lymph vessels or blood vessels. Primary cancer is the one that appears first. If the cancer has not spread to other areas of the body, it is thought to be localized. Secondary cancer, or metastasis, occurs when the original cancer cells multiply and form a new tumor in a different location. The original name of cancer is preserved by metastasis. Metastatic squamous cell carcinoma, for example, is squamous cell carcinoma that has migrated from the epidermis to the lymph nodes [3].

1.3. The skin

The biggest organ in the body is the skin. It serves as a barrier to shield the body from harm, regulate body temperature, and stop fluid loss. The epidermis and dermis are the two primary layers of skin.

1.3.1. Epidermis

The epidermis is a layer on the upper, outside of the skin. It contains three main types of cells:

Squamous cells are the thick epidermal layer which consists of the upper layer of the skin and to form the latter is a close grouping of flat cells.

The lower layer of the epidermis consists of basal cells that look like lumps. The body is constantly producing new basophils. They ascend to the epidermis as they age, flatten, and develop into squamous cells. The basal membrane that divides the epidermis from the rest of the body is supported by basal cells.

Melanocytes - found between basal cells, these cells secrete melanin, a dark pigment that gives skin its color and protects the skin from burns when exposed to ultraviolet light. Moles and birthmarks are benign skin lesions, classified by melanocytes [4].

1.3.2. Dermis

The dermis is a layer of skin located under the epidermis and consists of fibrous tissues. It is rich in lymphatic and blood vessels and nerves. They are supported by collagen, elastin and proteins that give the skin its strength and elasticity.

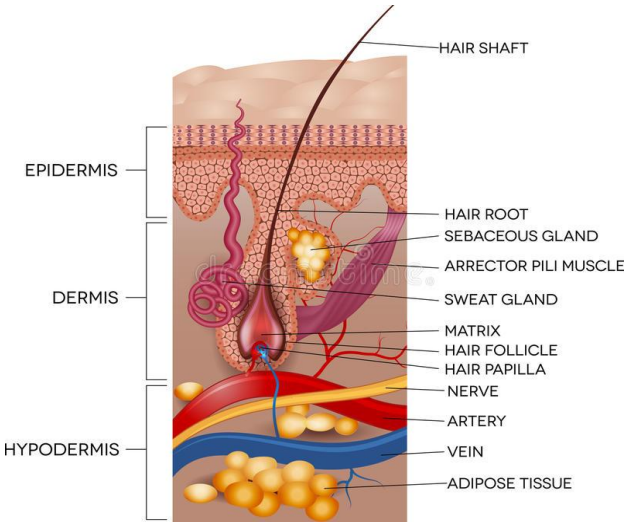


Figure 1. 2: Skin and hair anatomy

1.3.3. The principal action of the skin

The skin is the biggest structure in the frame and has several important functions. Its main role is to guard the body from external issues, such as injury, infection, and dehydration. The skin acts as a physical barrier, preventing harmful substances and microorganisms from entering the body.

The skin not only serves a protective purpose but also controls body temperature through a process known as thermoregulation. The blood arteries in the skin dilate when the body temperature raises too high, allowing heat to escape through the skin's surface. The blood vessels in the skin contract when the body is too cold, preserving heat and keeping the body warm [5].

The skin also plays a role in sensation, allowing us to feel different types of stimuli, such as touch, pressure, temperature, and pain. Nerve endings in the skin pick up on these feelings and relay the information to the brain for interpretation

The skin's ability to produce vitamin D is another critical function. It converts a type of skin cholesterol into vitamin D when exposed to sunlight, which is essential for healthy bones and skin [6].

In general, the skin is a complex and important organ that serves the body in a number of key ways.

Excretion, or removal of waste from the body, is another function of it. Sweat glands in the skin secrete sweat, which helps control body temperature and eliminate waste products such as urea and ammonia [7].

1.4. Skin cancer

Exposure of the skin to the sun leads to skin cancer or abnormal proliferation of its skin cells. However, this predominant type of cancer can also develop in parts of your skin that aren't often exposed to sunlight.

Melanoma, squamous cell carcinoma, and basal cell carcinoma are the three main types of skin cancer.

By reducing your exposure to UV rays, you can reduce your risk of developing skin cancer. Examining your skin for unusual changes might help you find early indications of skin cancer. The earlier skin cancer is discovered, the better your chances of effectively treating it are.

1.4.1. Definition

Skin cancer occurs when skin cells proliferate and elongate erratically , and new skin cells often develop when existing cells die or become infected. When this process is not working properly, cells develop rapidly, and some may be abnormal cells. This group of cells can be malignant, which if not identified and treated early enough can spread to surrounding tissues or other parts of the body, or non-cancerous (benign), which do not spread. Exposure to ultraviolet rays from the sun is a common cause of skin cancer [8].

Skin cells are exposed to a cancer known as skin cancer that occurs as a result of abnormal growth at the level of skin cells. Basal cell carcinoma, squamous cell carcinoma, and melanoma are among the most common types of skin cancer.

The most common type of skin cancer is basal cell carcinoma, as it usually appears on areas of the skin exposed to the sun, such as the arms, neck and face. It is usually slow and rarely spreads to other portions of the corpus [9].

The second most common type of skin cancer is squamous cell carcinoma also typically appears on sun-exposed areas of the skin. It can grow quickly and may if left untreated; it spreads to other parts of the corpus.

The most dangerous and least common form of skin cancer is known as melanoma. It can on the skin appear anywhere, until in areas that are not visible to the sun. Delay in its detection and treatment leads to rapid spread of melanoma to other portions of the body.

Skin cancer risk factors include a family history of skin cancer, a weak immune system, the use of expired cosmetics, and excessive exposure to sunlight [10].

Prevention measures it includes using a sunscreen with a high sun protection factor, all of this with a medical prescription, and wearing protective clothing, avoiding prolonged exposure to the sun, avoiding tanning beds, and regularly checking

Your skin for any changes or abnormalities. If you notice any suspicious changes in your skin, such as new moles or changes to existing moles, you should see a dermatologist for further evaluation [11].

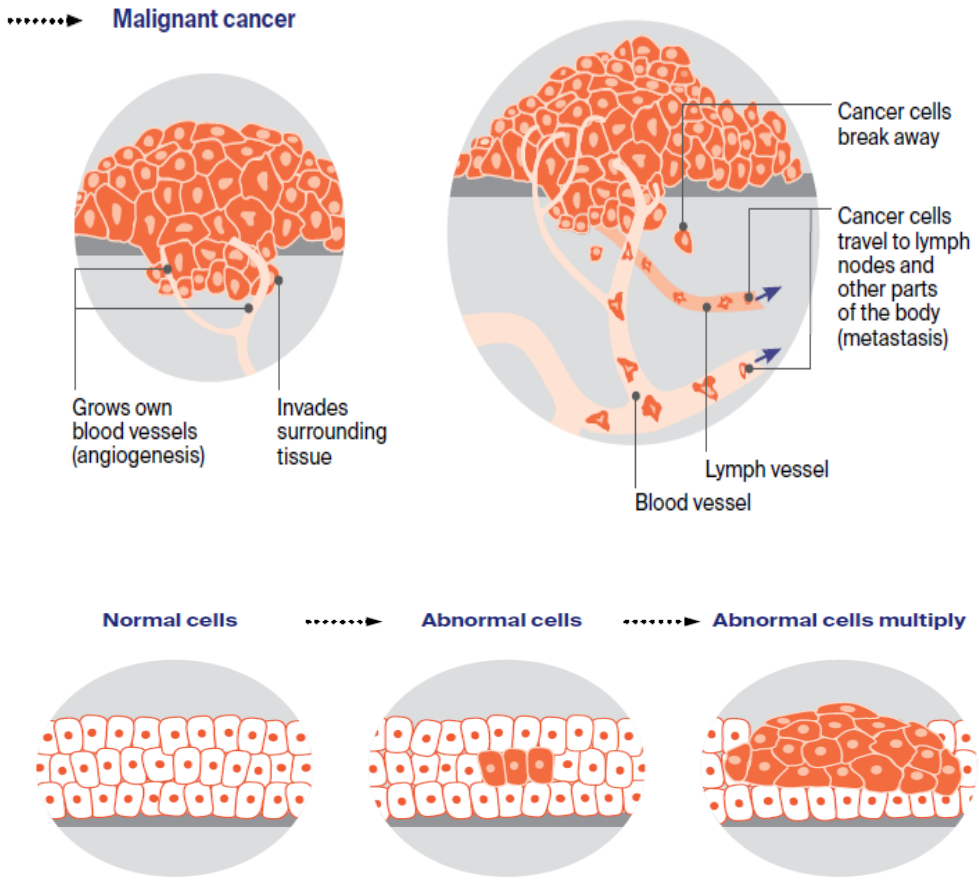


Figure 1.3: How does skin cancer start and how does it spread

1.4.2. The principle of action of skin cancer

Skin cancer is a disease that occurs when skin cells grow abnormally and out of control. The most common cause of skin cancer is exposure to ultraviolet (UV) radiation from the sun or tanning beds.

When the skin is exposed to UV radiation, it damages the DNA in skin cells. This damage can lead to mutations in the DNA that control cell growth, division, and repair. If the mutations affect the genes that regulate cell growth, the affected cells can start to divide and grow uncontrollably. These abnormal cells can form a tumor, which can then spread to other parts of the body [12].

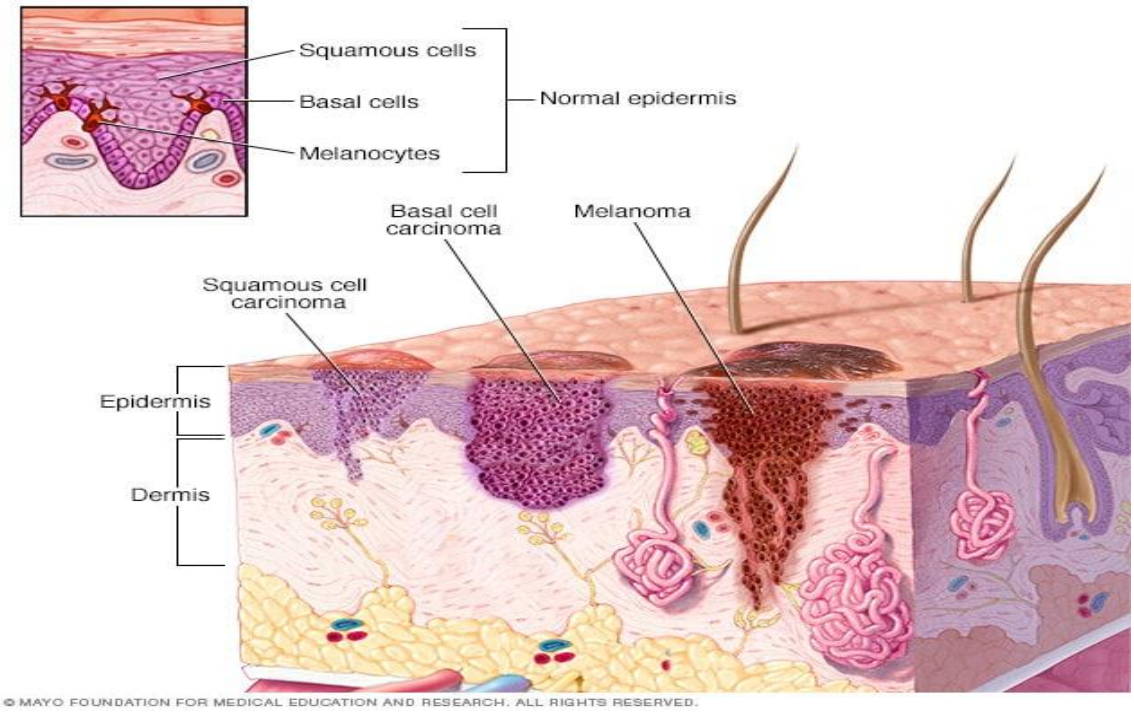


Figure 1.4: Sectional image of skin with cancer

There are three main types of skin cancer: basal cell carcinoma, squamous cell carcinoma, and melanoma. Basal and squamous cell carcinomas are the most common types and are usually caused by exposure to UV radiation. These cancers typically occur on sun-exposed areas of the skin, such as the face, neck, arms, and hands [13].

Skin cancer is a less common but more dangerous form of skin cancer. It arises from the melanocytes, the pigment-producing cells in the skin. Melanoma can develop anywhere on the body, and it often appears as a dark, irregularly shaped mole. Melanoma is more likely to spread to other parts of the body than other types of skin cancer, which can make it more difficult to treat. [14]

14.3. Causes of skin cancer

In summary, DNA damage to skin cells causes skin cancer, which can result in aberrant cell proliferation and tumor formation. Exposure to UV radiation from the sun or tanning beds is the main source of this damage [15].

UV exposure is the main cause of about 95% of skin malignancies. Where cells react when exposed to ultraviolet light on bare skin.

The sun is the main source of UV radiation, although it can also originate from arc welders, glue-curing lights (used, for example, to cure artificial nail glue), and solariums (also known as tanning beds or sun lamps) . Australia has now banned the commercial use of solariums due to evidence that those who use them have a higher chance of developing skin cancer. [16]

Australia experiences high levels of UV radiation throughout the year in some areas. Ultraviolet rays are not affected by temperature and cannot be seen or felt.But they cause skin burns, premature aging of the skin, and damage to skin cells, which can lead to skin cancer.

Your chance of developing skin cancer is affected by a variety of variables, including your lifestyle and certain medical conditions. About 85 in 100 cases of skin cancer in the UK (or 85%) are caused by overexposure to UV rays.

In the UK, skin cancer is the fifth most common type of cancer overall. Over the past few decades, more people have received skin cancer diagnoses.

A risk factor is something that can make you more likely to develop cancer. Protective factors are those that reduce risk.

The presence of one or more risk factors does not guarantee that you will develop skin cancer [17].

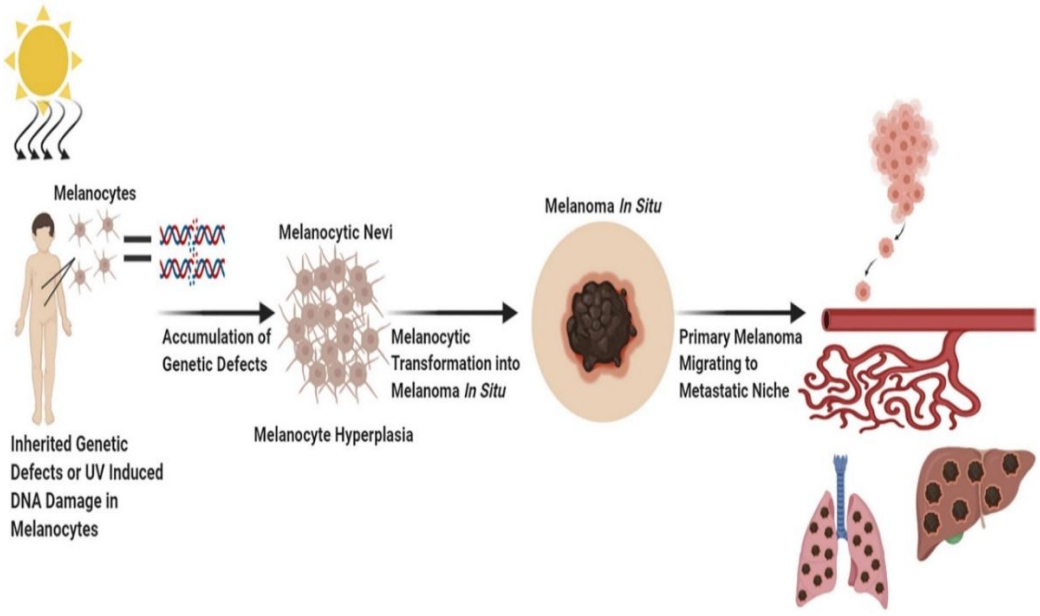


Figure 1.5: Factors Which Contribute to Melanocytic Transformation.

1.4.3.1. The most common causes

- Age
- Ultraviolet light
- Intermittent sun exposure
- Sunburn
- Sunscreen
- Skin color and freckling
- Moles
- Birthmarks
- Family history and genetic factors

1.4.3.2. Less common causes of skin cancer

- Inflammatory bowel disease (IBD)
- Weakened immune system. [18]

1.4.4. Types of skin cancer

The skin's cells are susceptible to cancer development. The sort of cell that skin malignancies originate from is used as their name .

Squamous cell carcinoma and basal cell carcinoma are the two most prevalent kinds of skin cancer [19].

Non-melanoma skin cancer is a term that has been used occasionally. Melanoma, which develops in melanocyte cells, is the third most prevalent form of skin cancer. [20[

Other, more uncommon types of skin cancer include those that develop from hair follicles and sweat glands.

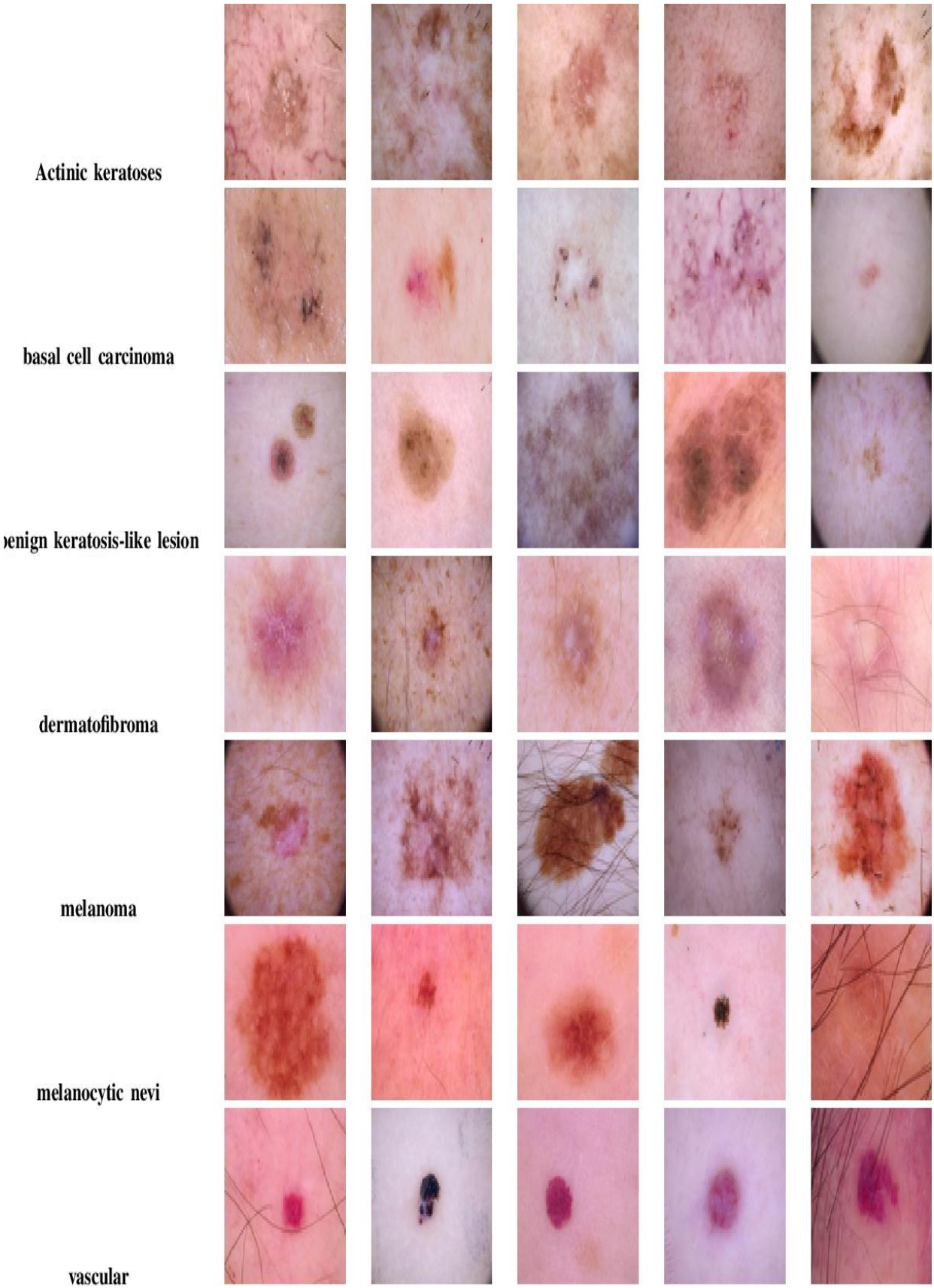


Figure1.6: Types of skin cancer

1.4.4.1. Actinic Keratosis

The precancerous lesion known as actinic keratosis (AK), often referred to as sun keratosis, has the potential to progress into squamous cell carcinoma.

Overexposure to UV rays from the sun or indoor tanning are the two main causes of the illness.

AK may resemble a tiny, dry, scaly, or crusted skin patch. These patches can have a variety of hues, including pink, white, flesh-toned, tan, red, and white.

In the US, almost 58 million individuals own one or more AKs.

Most squamous cell carcinomas begin as AKs, although only 5 to 10% of AKs progress to skin cancer [21].

1.4.4.2. Basal cell carcinoma (BCC)

The most prevalent kind of skin cancer, basal cell carcinoma, also known as basal cell skin cancer, accounts for around 80% of all occurrences.

Basal cell cancer incidence has been rising. According to experts, this is a result of more sun exposure, longer lifespans, and improved skin cancer diagnosis techniques.

Basal cells, which are located in the epidermis, the top layer of the skin, are where this form of cancer first manifests itself. Basal cell carcinomas typically appear on the face, head, and neck because of their sun exposure [22].

They could resemble:

- ✓ a circular, flesh-colored growth
- ✓ A lump like a pearl
- ✓ a reddish spot on the body
- ✓ A wound that bleeds or scabs and then returns after healing [23].

1.4.4.3. Dermatofibrosarcoma Protuberans (DFSP)

An uncommon form of skin cancer called Dermatofibrosarcoma protuberans (DFSP) starts in the middle layer of the skin. Normally, it develops gradually and is contained to one area of the body.

Usually, a little lump that resembles a deep-seated pimple or rough skin is the initial indication of DFSP. It can also mimic a scar; in kids, it could seem like a birthmark [24].

1.4.4.4. Kaposi Sarcoma

The human herpes virus is the cause of kaposi sarcoma, which develops in the blood vessels of the skin.

His particular kind of skin cancer primarily affects patients with compromised immune systems, such as those with AIDS or those who use immunosuppressive medications. Young males in Africa or elderly men with Mediterranean or Jewish ancestry frequently develop other types of Kaposi sarcoma.

On the skin, Kaposi sarcoma manifests as red or purple areas. Additionally, lesions might develop in the digestive tract, lungs, anus, or mouth [25].

1.4.4.5. Keratoacanthoma

Slow-growing tumors called Keratoacanthomas may potentially disappear without any medical intervention. If they develop further, they are managed similarly to squamous cell carcinoma.

These tumors are typically seen on sun-exposed parts of the skin and have a dome-like structure [26].

1.4.4.6. Lymphoma of the Skin

Non-Hodgkin lymphoma that affects the skin is called cutaneous lymphoma. T cells, a kind of white blood cell that ordinarily helps your body fight infection, are where it starts.

This kind of cancer may result in a rash, skin tumors, or raised or scaly areas on the skin.

Cutaneous T-cell lymphomas come in a variety of forms, some of which are more aggressive than others [27].

1.4.4.7. Melanoma

Melanoma is the most dangerous kind of skin cancer because, if left untreated, it has a propensity to spread.

Melanocytes, which produce color in the epidermis, are where this cancer first appears. Each year, over 100,000 new melanomas are identified [28].

Melanoma risk factors include:

- ✓ A history of excruciating sunburns, fair complexion, bright eyes, freckles, or red or blond hair
- ✓ Using tanning beds or being in the sun
- ✓ Residing at a higher altitude or closer to the equator
- ✓ Having several moles or moles with strange appearances
- ✓ Having a weaker immune system
- ✓ Having a family history of melanoma [29].

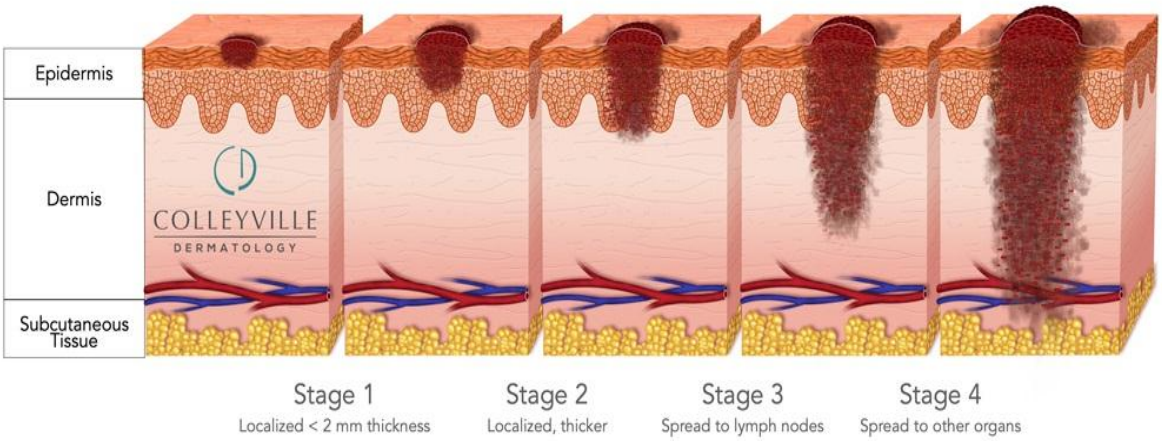


Figure 1.7: Stages of Melanoma

1.4.4.8. Merkel Cell Carcinoma

Approximately 2,000 Americans are diagnosed with the uncommon form of skin cancer known as Merkel cell carcinoma each year.

Merkel cell carcinoma is a rare kind of skin cancer, but during the past two decades, the number of cases has quickly grown. This form of cancer begins when Merkel cells, which are skin cells, begin to proliferate uncontrollably.

Merkel cell carcinomas often develop fast and, if they spread, can be challenging to cure.

Merkel cell carcinomas can begin anywhere on the body, although most frequently affect the face, neck, and arms because of their sun-exposed locations. When you touch them, they could feel hard and have a pink, red, or purple color to them. They may occasionally become sores or ulcers [30].

Risk factors include:

- ✓ Prolonged exposure to UV radiation from the sun or tanning beds Immune system compromised
- ✓ A history of prior cases of skin cancer
- ✓ Reaching the age of 50
- ✓ Possessing fair skin [31].

1.4.4.9. Sebaceous Gland Carcinoma

Sebaceous gland carcinomas begin in the skin's oil glands and are a rare but aggressive type of cancer. Typically, they take the form of brittle, painless nodules. Although they can appear elsewhere, these tumors are most frequently discovered on the eyelid [32].

1.4.4.10. Squamous cell carcinoma (SCC)

About 30% of all skin malignancies are SCCs. It generally affects adults over the age of 50, and it often affects skin that is frequently exposed to the sun, such as the head, neck, hands, and forearms. It can occasionally appear on the legs or upper torso.

SCCs can develop as swollen, scaly, red areas that bleed easily over time and resemble open sores. SCCs can spread to other areas of the body and frequently develop swiftly over several months. The danger of SCCs spreading to the lips or the ears is very significant [33].

1.5. Methods of diagnosing skin cancer

The diagnosis of skin cancer involves a assortment of methods, including visual inspection, dermoscopy, biopsy, and various imaging technologies.

1.5.1. Visual inspection

Visual inspection is a common first step in identifying suspicious skin lesions, and involves a visual examination of the skin for any changes or irregularities in the shape, size, color, or texture of the lesion. While this method is generally quick and non-invasive, it can be subjective and relies heavily on the experience of the examiner [34].

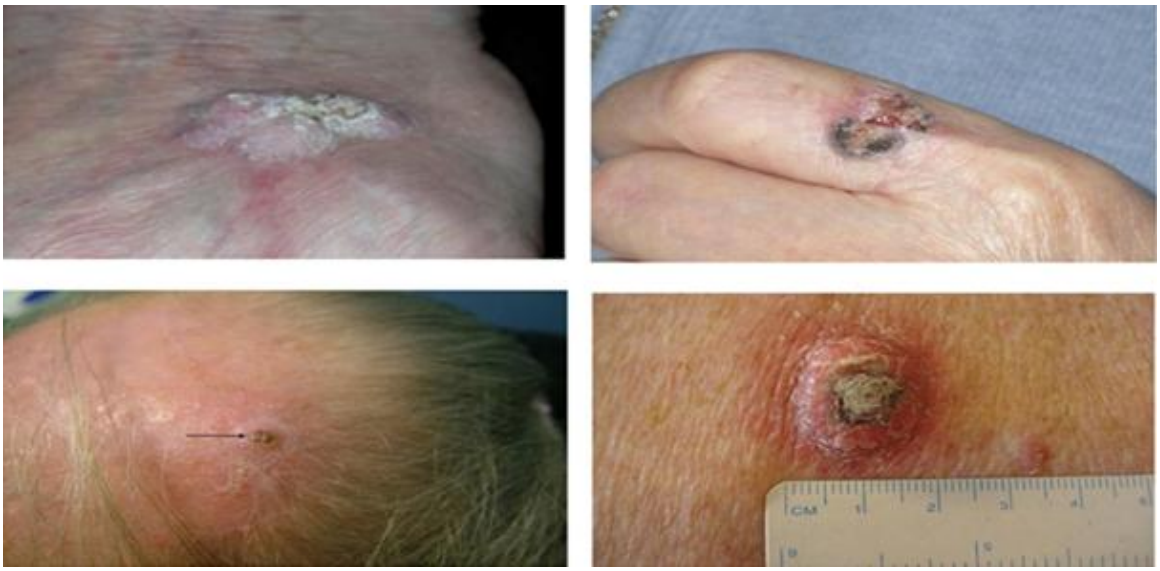


Figure 1.8: Diagnosis with the naked eye of various types of skin cancer.

1.5.2. Dermoscopy

Dermoscopy is a neuter imaging technique that does not prevent for a more detailed examination of skin lesions, and involves the use of a handheld device with a magnifying lens and a light source, which is used to examine the skin surface [35].

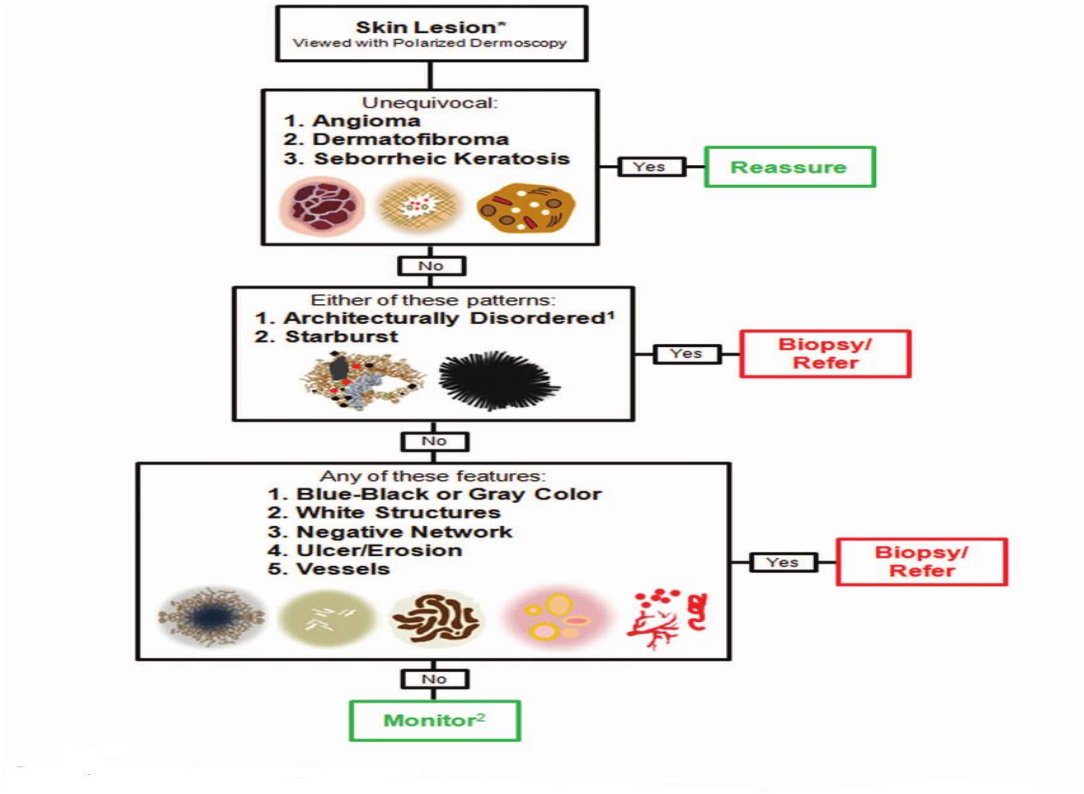


Figure 1.9: The Triage Amalgamated Dermoscopy Algorithm (TADA)

Dermoscopy can help distinguish benign from malignant lesions by identifying characteristic patterns or structures in the skin lesion, and is useful in diagnosing early-stage melanoma [36].

1.5.3.Biopsy

Biopsy is a commonly used method for diagnosing skin cancer, and involves removing a sample of tissue from the lesion for microscopic examination. Biopsies can be performed using various techniques, including excisional, punch, or shave biopsy, depending on the location and size of the lesion [37].

Excisional biopsy is the most invasive technique and involves removing the entire lesion along with a margin of normal tissue, while punch biopsy involves using a circular tool to remove a small piece of skin, and shave biopsy involves shaving off the surface of the lesion.

Biopsy is the most accurate method for diagnosing skin cancer, as it allows for microscopic examination of the tissue, but it is invasive and may leave scarring. In addition to these traditional diagnostic methods, newer technologies are emerging as non-invasive methods for imaging skin lesions with high diagnostic accuracy [38].

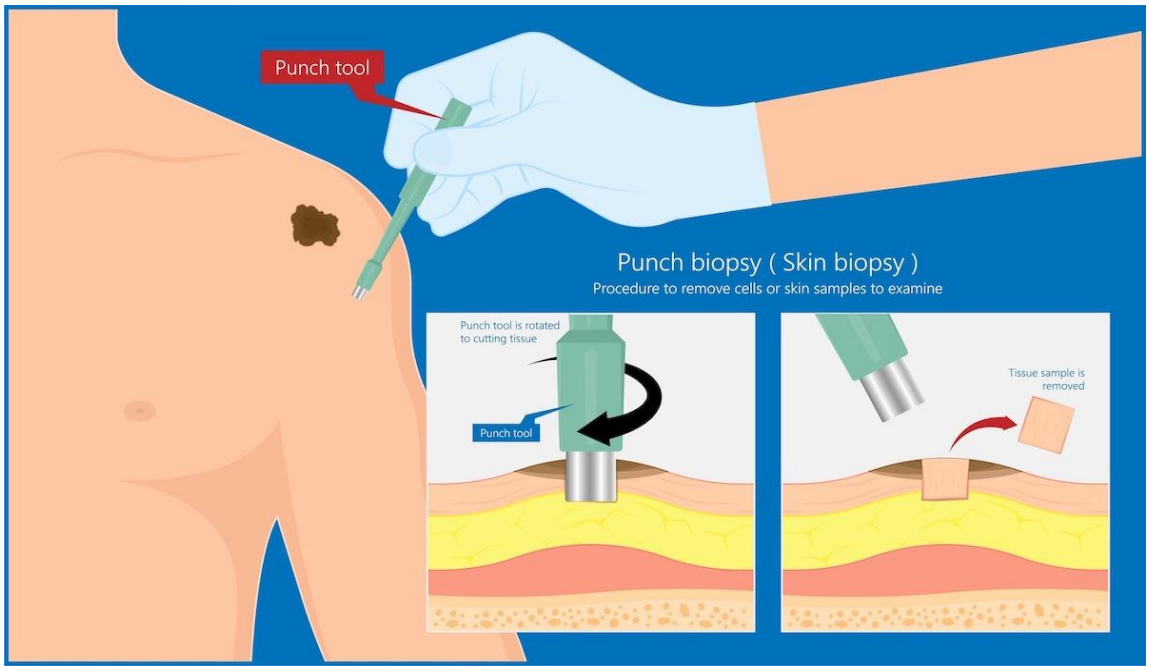
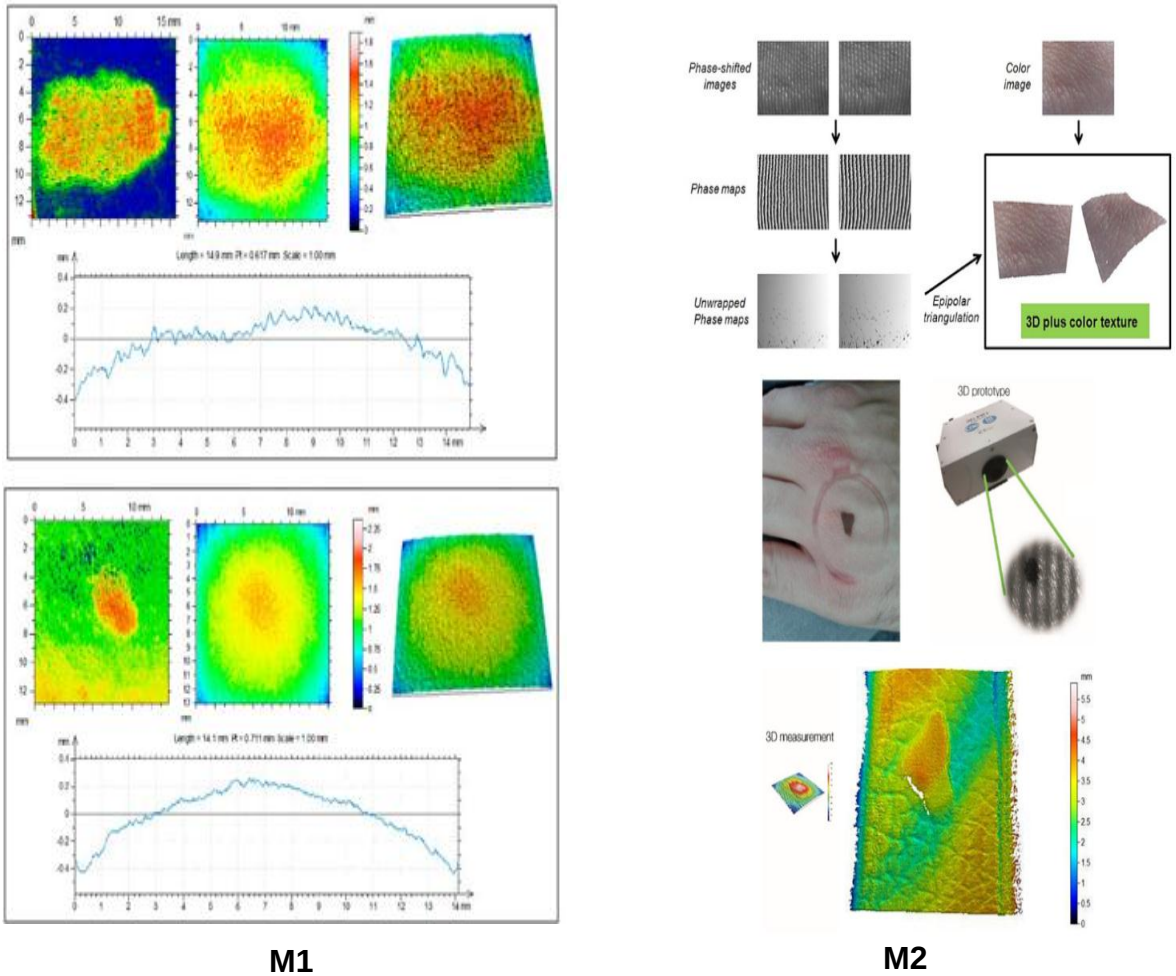


Figure 1.10: Biopsy method for skin cancer detection

1.5.4. Confocal microscopy

Confocal microscopy uses a laser beam to create a 3D image of the skin at the cellular level, allowing for the identification of individual cells and structures .Optical coherence uses light waves in tomography to produce a detailed picture of the layers of the skin, allowing for the identification of structural abnormalities in the skin [39].

Reflectance microscopy is a less invasive imaging technique, which uses light to create images of the layers of the skin, allowing the identification of structural changes in the skin associated with melanoma. These imaging techniques have the potential to improve the accuracy of melanoma diagnosis and reduce the need for invasive biopsy [40].



M1 **M2**

Figure 1.11: Microscopy (M1) to obtain 3D images with superimposed color texture and (M2) is three-dimensional (3D) topographical images of a melanoma (top) and nevi (bottom).

1.5.5.Convolutional Neural Network

Skin cancer is the most common type of cancer worldwide, and early detection is crucial for successful treatment. One emerging method for diagnosing skin cancer is the use of convolutional neural networks (CNNs), a type of artificial intelligence that has shown promise in accurately identifying skin lesions. CNNs are a type of deep learning algorithm that use multiple layers of artificial neurons to learn features and patterns from images. In the case of skin cancer diagnosis, a CNN can be trained on a large dataset of skin lesion images, learning to identify patterns and features associated with different types of skin cancer [41].

The use of CNNs for skin cancer diagnosis has been demonstrated in several studies, with promising results. In one study, a CNN was trained on a dataset of over 130,000 skin lesion images, and was able to achieve a diagnostic accuracy of 91% for melanoma, the deadliest form of skin cancer. In another study, a CNN was trained on a dataset of over 10,000 images and was able to achieve a diagnostic accuracy of 96.4% for melanoma, which was comparable to the accuracy of dermatologists [42].

The use of CNNs for skin cancer diagnosis has several advantages over traditional diagnostic methods. First, CNNs are non-invasive and can provide a diagnosis without the need for a biopsy. This can save patients from the discomfort and scarring associated with biopsy, as well as reduce healthcare costs. Second, CNNs are highly accurate and have the potential to improve the accuracy of skin cancer diagnosis, particularly in cases where traditional diagnostic methods may be subjective or inconclusive.

However, there are also limitations to the use of CNNs for skin cancer diagnosis. One challenge is the need for large and diverse datasets to train the network, which may be difficult to obtain in some settings. Additionally, the interpretation of the output of a CNN can be challenging, as it may not always be clear which features or patterns the network is using to make a diagnosis. This can be particularly concerning in cases where a misdiagnosis could have serious consequences [43].

Overall, the use of convolutional neural networks for skin cancer diagnosis is an exciting area of research with great potential for improving patient outcomes. While more research is needed to fully evaluate the accuracy and safety of this

technology, early results suggest that CNNs may be a valuable addition to the diagnostic toolkit for skin cancer [44].

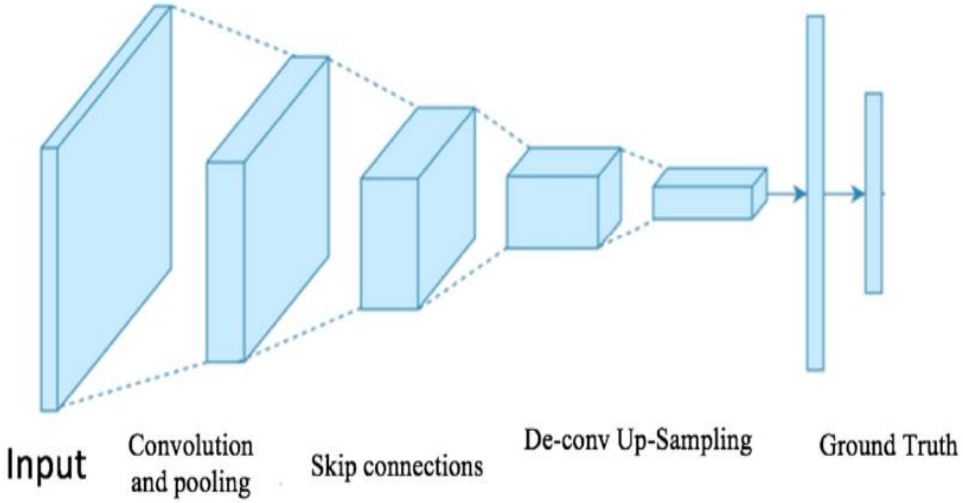


Figure 1.12: Structure of convolution neural network

In addition to these diagnostic methods, various laboratory tests can be used to identify genetic mutations or protein markers associated with skin cancer, which can aid in diagnosis and treatment. However, these tests are not yet widely available or routinely used in clinical practice

A combination of these methods may be used to improve the accuracy of skin cancer diagnosis and improve patient outcomes. Overall, the diagnosis of skin cancer is a complex process that requires a thorough understanding of the various diagnostic methods available, as well as the patient's individual characteristics and medical history.

1.6. Conclusion

In conclusion, early diagnosis and treatment of cancer is the most important element in combating it. Its main goal is to cure or significantly extend the life of cancer patients, ensuring a good quality of life. In order for the treatment to succeed, the patient should not be isolated from society, because the psychological factor is the biggest motive for treatment. Artificial intelligence should also be used because it is important for early detection. This is what we will discuss in the coming chapters.

Chapter 2: Convolutional Neural Network

2.1. Introduction

We shall discuss neural networks, neural networks Convolution, and its applications in this chapter Formal neural networks are structures that are mostly mimicked by algorithms running on general-purpose computers, occasionally on devices or even specialized circuits, and which draw their inspiration from how basic nerve systems function. They are mostly employed to address issues related to identification, association, pattern recognition, classification, and extraction of characteristic. One of the most popular types of deep neural networks is the Convolutional neural network (CNN). A CNN uses Convolutional layers to extract features directly from the data. Its architecture is perfectly suited to the processing of raster data such as images. Convolutional neural networks eliminating the need for the laborious and time-consuming manual feature extraction process. The network learns the attributes by itself when training on images because they are not pre-trained.

2.2. Neural Network

Artificial neural networks (ANN), named also neural nets or neural networks NNs are à computing tools stirred from the dynamic of biological neural nets that control the animal bodies. Artificial neural networks make a mimic of the information traffic in the biological nervous systems.

An ANN creates a network of interconnected artificial neurons that resemble biological brain neurons. Similar to synapses in biological brain neurons, each link has the ability to send a signal to nearby neurons. An artificial neuron can signal neurons that are connected to it after processing signals that are sent to it. A connection's "signal" is a real value, and each neuron's output is calculated using a non-linear function of the sum of its inputs. Edges refer to the connections. The weight of neurons and edges often changes as learning progresses. The weight alters a connection's signal intensity by increasing or decreasing it .Neurons may have a threshold and only send a signal if the combined signal crosses it.

Neurons frequently group together into layers. Different layers may modify their inputs in different ways. Signals move through the layers, perhaps more than once, from the first layer (the input layer) to the last layer (the output layer).

2.2.1. Biological Neural Network

The brain is the control unit of the neural network of living beings, and it has several components that handle vision, sensing, movement, and hearing. The brain is linked to the rest of the body's sensors and actors by a complex network of nerves. The brain has around more than 86 billion neurons, which serve as the foundation for the whole central nervous system of the living body.

a. Biological Neurons

A neuron is a cell that consists of a cell body and a nucleus. The cell body branches off to form what are called dendrites. Through dendrites information is transmitted from the outside to the soma, the body of the nerve cell. The information processed by the neuron then travels along the axon to be relayed to other neurons. Transmission between two neurons is not direct. The junction between two neurons is called a synapse.

Briefly, a biological neuron is a cell that is characterized by:

- ✓ Points of contact with other nerve cells, nerve fibers or muscles.
- ✓ The dendrites or inputs of neurons.
- ✓ Axons, or neuron outputs, to other neurons or muscle fibers [45].

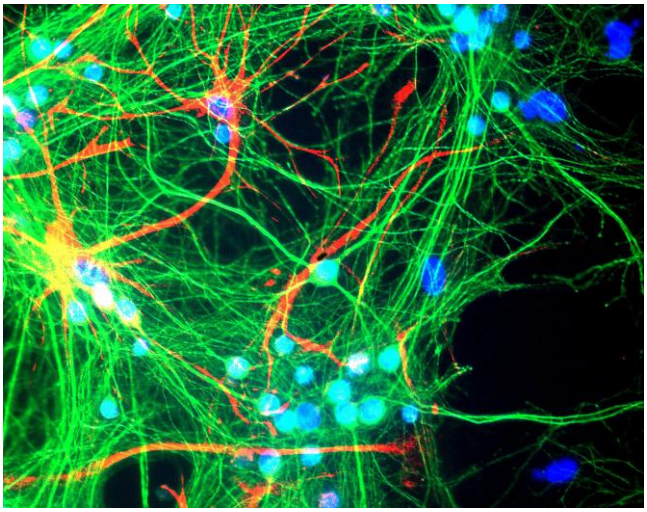


Figure 2.1: Neural Network in Human body

b. Biological Neural Network

Billions of biological neurons are arranged and formed into biological neural systems. As seen in Figure 2.2, a basic biological neuron is made up of a cell body with several branching protrusions called dendrites and a single branch known as the axon. Signals from nearby linked neurons are received by neurons through their dendrites. The neuron fires an impulse that goes along an axon to the other neurons linked when the sum of these excitations exceeds a certain threshold. The synapses, which link to the dendrites of other neurons, are formed by branches at the end of the axons Neurons connect to one another through synapses, which can either be excitatory or inhibitory. Signals reaching a cell are increased by an excitatory synapse and decreased by an inhibitory synapse. The total number of signals that are received by a cell is increased by excitatory synapses and decreased by inhibitory synapses. Although it is fairly brief, this description covers all the details necessary for mimicking biological brain systems using artificial neural networks [46].

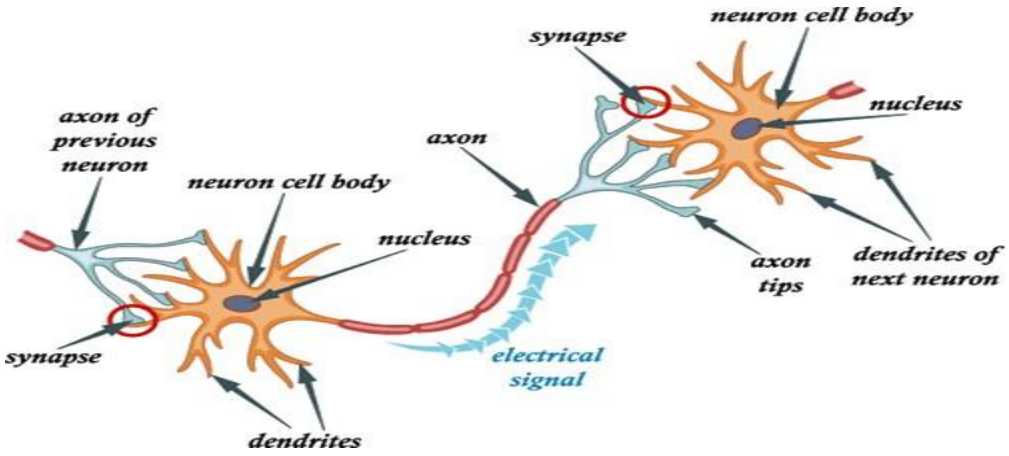


Figure 2.2: A Schematic view of the biological neuron

2.2.2. Artificial Neuron

The mathematical equivalent of a genuine neuron is an artificial neuron. The idea of a real neuron is quite complex. It operates using biological principles. Numerous factors are involved, including hormones, the speed of conduction, the chemical makeup of neurons, and the existence of substances in the body. Artificial neurons operate by fairly simple principles. Dendrites are multiplication structures that multiply an incoming signal by a weight that is constantly changing as a result of learning, replacing the nucleus with a simple mathematical function known as "activation function." No transformational operations exist in Axon.

There are several activation functions utilized in programmed neurons, but the sigmoid function is the most fundamental and efficient one. Signals of any range can be entered into a sigmoid, but it can only produce signals between -1 and 1. That makes using a network much simpler. Moreover, another property that improves the function's efficacy was discovered only after the sigmoid was applied. Because there are so many mathematical calculations involved, neural network learning is incredibly costly for the computer. The technique is made simpler by the sigmoid function since it is relatively simple to calculate its derivative [47].

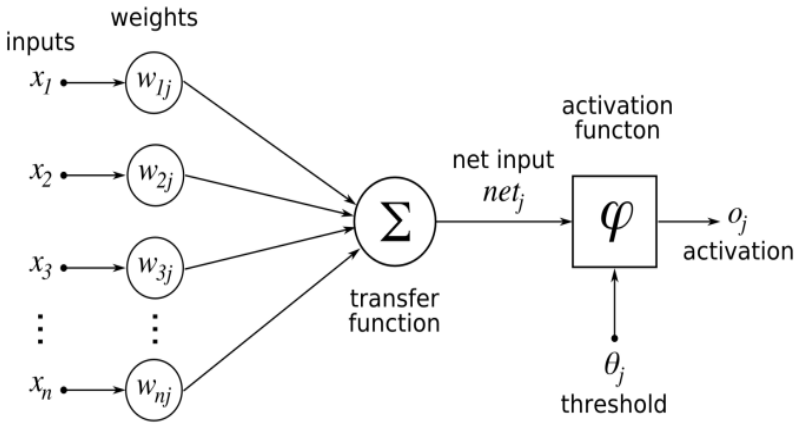


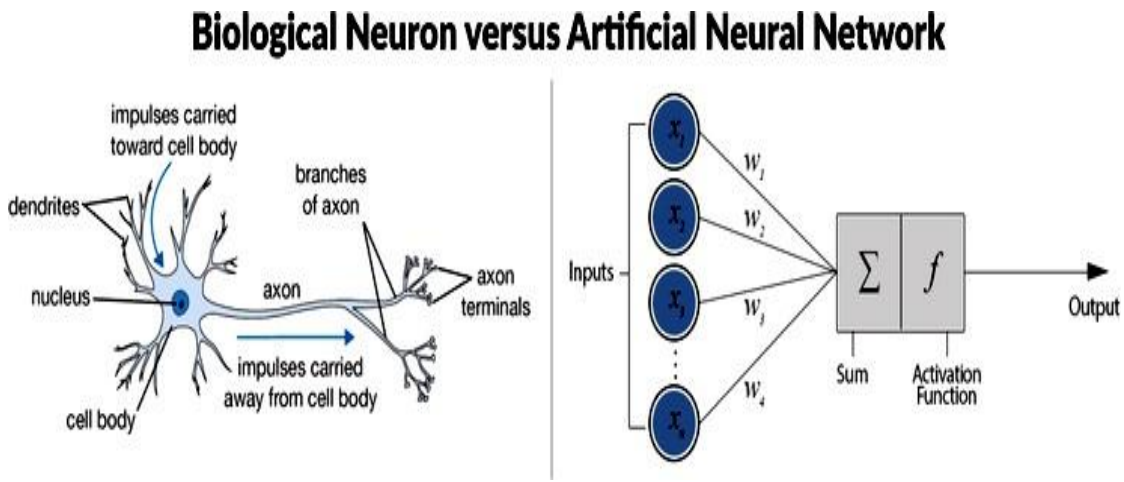
Figure 2.3: Artificial Neuron

2.2.3. Artificial Network networks

Creating a new method of calculation and using artificial neural networks in general to create a new generation of computers. This concept is distinct from the typical approach employed on computers since it was inspired by the biology of the human brain. This novel method appears to be more human than machine. The man, who constantly daydreams about the machine that speaks, thinks, forgets, and remembers the objective is to mimic and duplicate the human brain's natural approach to research rather than creating a human machine, which is unachievable [48].

We are unable to create a complete model of the real neural network due to its complexity. It would be difficult to address the difficulty of creating a model that replicates all of the mechanisms affecting the neurons. Even if the models now in use for speech or image recognition are rather basic in comparison to the brain of the

tiniest being, they nevertheless demand a lot of processing power from an operating system. The way that lets us use neural networks is quite simple. First of all, neural network programmers do not consider neurons to be computational units. The weights are important in artificial neural network programming. Because they are the only ones that are constantly changing as neural networks learn, weights that represent dendrites in natural neurons are the most crucial component. Except for weights, everything required to build a network after learning remains the same. Although the learning rate can occasionally be altered, this is not a requirement in order to use the network that has been trained. Second, the network is often merely software. As mentioned earlier, weights are how a network stores its memory. Most current neural networks have connections between neurons in two distinct layers rather than just one layer. Each-to-Each connections are this kind of relationship. This connection type's intriguing characteristic is that all weights may be conveniently stored as huge. For instance, each of the 10 neurons in the first layer would have 10 connections to the second layer's 5 neurons if the two layers were connected one to the other. They are simple to store as a set of two dimensions, 5 and 10 correspondingly, and handle them like matrices [49].



Human	Artificial
Neuron	Processing Element
Dendrites	Combining Function
Cell Body	Transfer Function
Axons	Element Output
Synapses	weights

Figure 2.4: Model representation of a biological neuron with multiple inputs

2.2.3.1. Main Architectures of Artificial Neural Networks

An artificial neural network may often be split into three sections known as layers, which are as follows:

- LAYERS

a) Input layer: This layer is in charge of acquiring data (information), signals, characteristics, or measurements from the outside world. The limit values generated by activation functions are often used to normalize these inputs (samples or patter-

ns). The mathematical operations carried out by the network are more numerically precise as a result of this normalization.

b) These layers, which might be hidden, intermediate, or undetectable, are made up of neurons that are responsible for extracting patterns connected with the process or system being studied. These layers handle the majority of a network's internal operations.

c) Final layer the final network outputs, which come from the processing carried out by the neurons in the preceding layers, are produced and presented by this layer, which is likewise made up of neurons. With regard to neuron arrangement, connectivity, and layer composition, the primary artificial neural network designs may be categorized into the following categories: Single-layer feed forward networks, multilayer feed forward networks, recurrent networks, and mesh networks are among the options [50].

2.2.3.2. Training of Artificial Neural Networks

When a network has been configured for a specific application, it is ready for training. The starting weights are picked at random at the start, and then the training or learning occurs. There are two types of training methods supervised and unsupervised:

a. Supervised learning

Information is incorporated into learning under the supervision of an external signal known as the teacher.

Each input vector must be paired with a target vector that represents the expected output during supervised training; this combination is referred to as a training pair. A

network is typically trained using a number of these training pairs. The network's output is generated after applying an input vector, compared to the matching goal vector, and the difference—or error—is supplied back into the network. Weights are then adjusted in accordance with an algorithm that aims to reduce the error. Up until the error for the complete training set is at the acceptable low value, the training set's vectors are applied progressively, with errors computed and weights changed for each vector[51]**.**

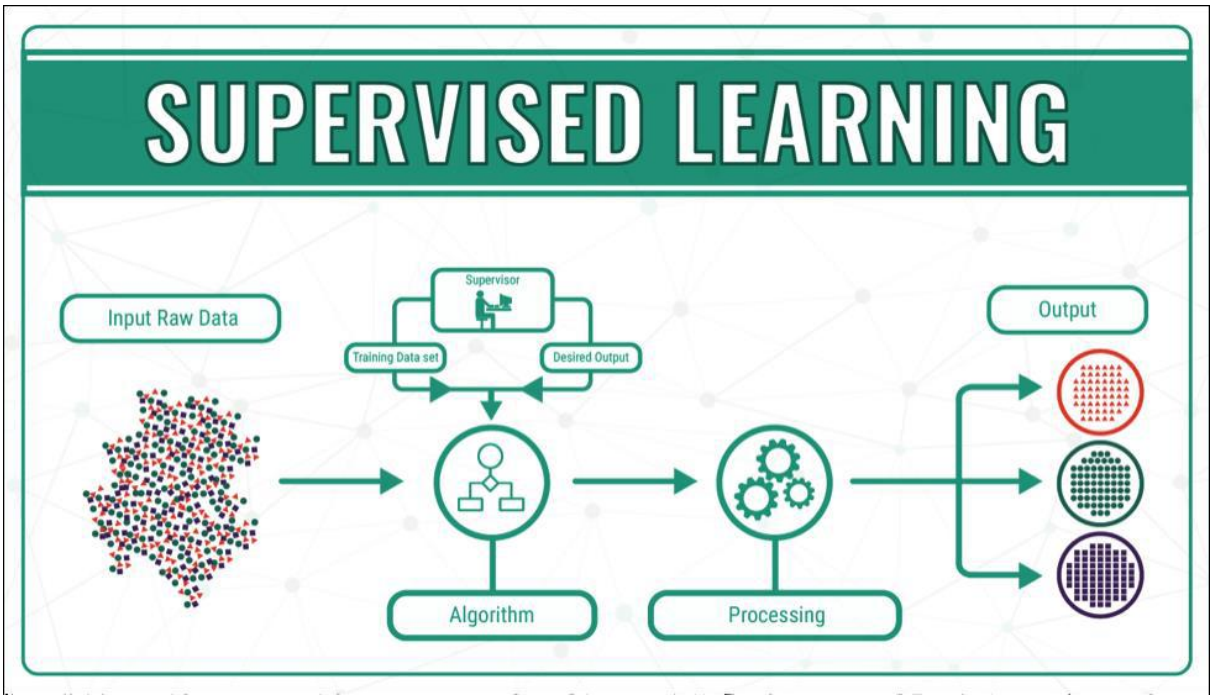


Figure 2.5: An Ultimate Guide to Understanding Supervised Learning

b. Unsupervised learning

Unsupervised learning relies solely on the characteristics of the patterns; there is no a priori knowledge present. This is also referred to as self-organization at times. To ensure that comparable inputs result in similar outputs, the neural network modifies its own weights. Without help from outside sources, the network finds patterns and differences in the inputs. In order to train the network when it is in online mode, just the bare minimum of data is used. The Hebbian and competitive learning rules are the unsupervised learning techniques that are the most effective. Using several sets of input patterns, the learning process was repeated over numerous cycles, or epochs, until the network produced acceptable outputs for all inputs [52].

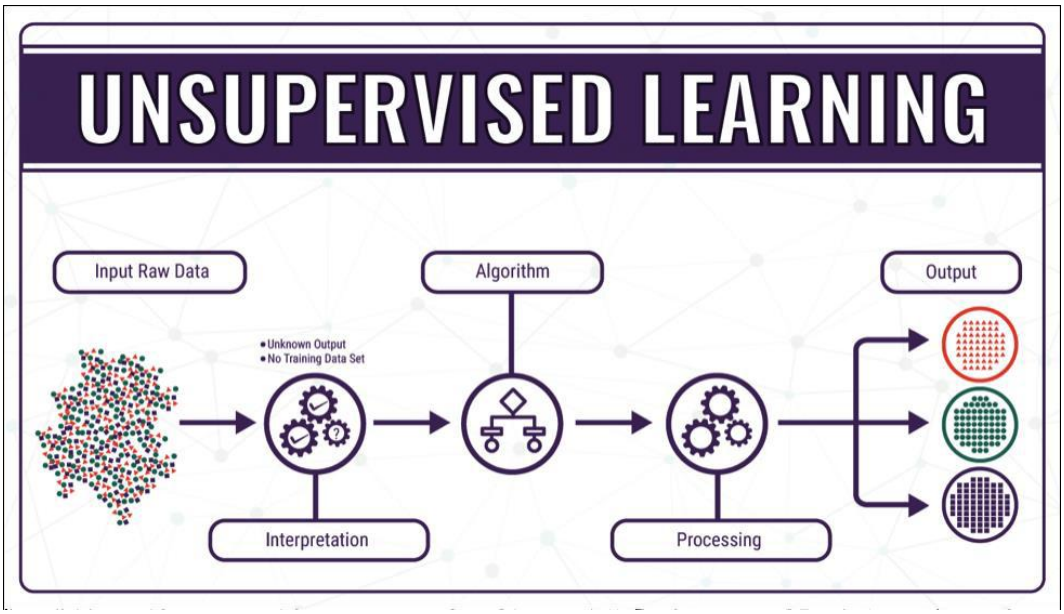


Figure 2.6: classification unsupervised learning

2.2.4. Classification of images CNN instead of ANN

To use ANN, specific data points must be provided. For example, in a model where we are trying to distinguish between dogs and cats, the length of the ears and the width of the nose should be explicitly presented as data points. When using CNN, these spatial features are extracted from the image input. This makes CNN ideal when you need to extract thousands of features. Instead of having to measure each feature separately, CNN collects these features on its own. With ANN, image classification problems become difficult because two-dimensional images need to be converted into one-dimensional vectors. This greatly increases the number of trainable parameters. Increasing trainable parameters requires storage and processing capabilities. In other words, it will be expensive. Compared to its predecessors, the main advantage of CNN is that it automatically detects important features without any human supervision. This is why CNN will be an ideal solution to computer vision and image classification problems[53].

2.3. Convolution Neural Network (CNN)

Convolution neural network is a more sophisticated kind of neural networks. Instead of a single layer, neural networks have hidden layers. CNN are regularized forms of multilayer perceptions; typically, multilayer perceptions relate to completely linked networks, in which each neuron in one layer is coupled to every other neuron

in the subsequent layer. Since this network has complete connection, it is predicted that the data would be over fit [54].

Convolutional layers, which are what make up CNNs, distinguish convolutional neural systems from more typical neural systems in that they feature a rare kind of layer known as a convolutional layer. Edge recognition is often applied in the first layer [55].

Later, layers are able to recognize increasingly complicated elements. Towards the system's conclusion, these element maps are added to a huge rundown of highlights that is used to finally organize the image. CNNs include a few distinct layers in addition to convolutional layers, including pooling and characterization layers [56].

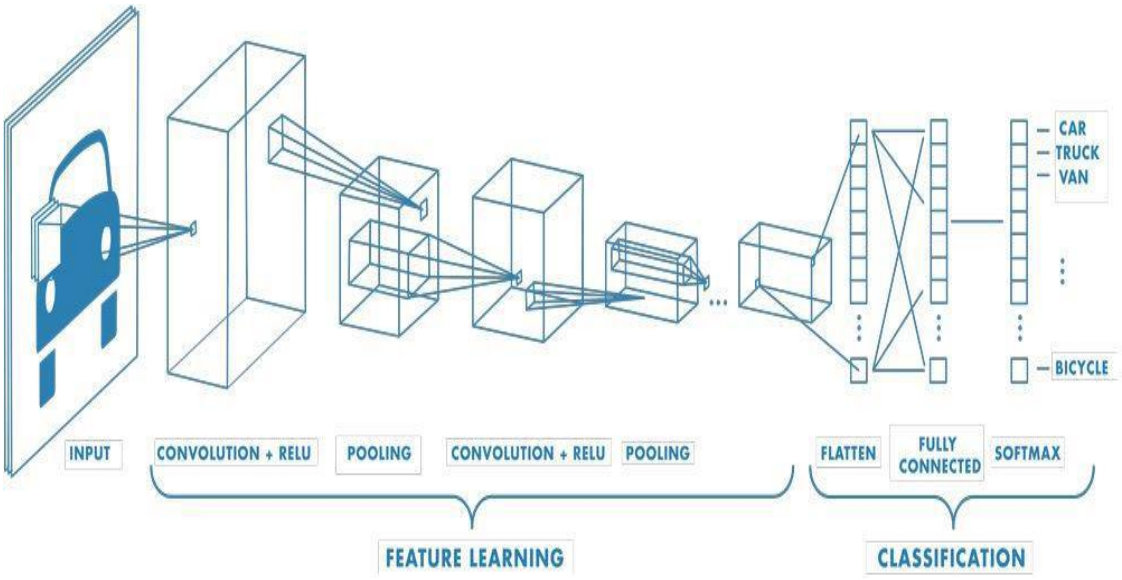


Figure 2.7: Example of a network with many Convolutional layers

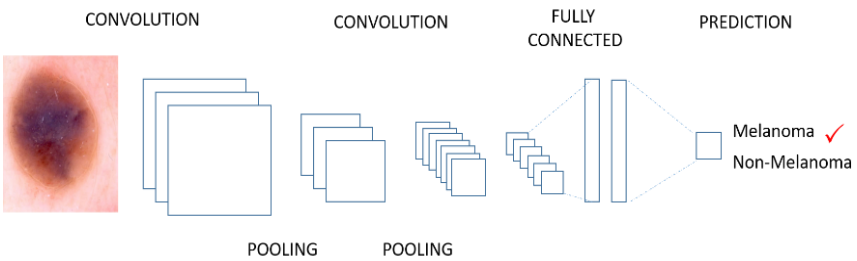


Figure 2.8: Diagnosis of melanoma with a simple CNN model

CNN architecture includes components like as convolution layers, pooling layers, and fully connected layers. A popular architecture is the recurrence of a stack of several convolution layers and a pooling layer, followed by one or more completely connected layers.

2.3.1. Types of Artificial Neural Networks

A. Hopfield

Hobbs's rule (1949), which states that a synapse improves its activity if and only if the activity of its two neurons is correlated (i.e., the weight of a connection between two neurons increases when both neurons are activated at the same time), applies to this network of neurons with two states (-1 and 1, or 0 and 1), and this rule is the learning law of the system [57].

a. Kohonen

In contrast to Hopfield networks, where neurons are described as simply as feasible, we are searching for a neuron model that is more accurate. These networks were developed as a result of scientific investigations of how mammalian perception nerve systems operate. For learning, a modified version of Hobbs's law that takes forgetting into account is employed. When the linked neurons are active at the same time, the connection is strengthened, and when they are not (as opposed to the prior situation), it is weakened. There are uses for each of these networks in decision support, classification, image processing, and optimization.

b. Adeline

The Adaptive Linear Element has the same architecture as a perceptron, but on the other hand, it has values of continuous activations. A linear activation function is a learning rule that is a little more advanced than a perceptron, and it is known as the rule of WIDROW & HOFF. This law does indeed minimize the quadc error using the gradient method. Contrary to the perceptron rule, the latter always optimizes the coefficients of the separating hyper planes and acts on both correctly and incorrectly categorized case [58].

2.3.2. Architecture of Convolutional Neural Network

Convolutional neural networks are based on the multilayer perceptron (MLP) and were developed as a result of research into the function of vertebrate visual cortex. MLPs are efficient for processing photos, but they struggle to handle huge images since the number of connections grows exponentially with the size of the image. As seen in Fig., a convolutional neural network has several layers.

2.3.3. CNN Layers

A stack of independent processing layers makes up CNN architecture.

- The convolution layer (CONV), which handles information from a receiving field.
- The pooling layer (POOL), which enables data compression by shrinking the size of the intermediate picture (typically by down sampling).
- The correction layer (ReLU), also known as the activation function (Linear grinding unit) or simply "ReLU," is frequently mispronounced.
- The "fully connected" (FC), a layer resembling a perceptron. LOSS or the Loss layer [59].

a. Convolution layer

The convolution layer is a critical component of the CNN architecture that provides feature extraction. It generally comprises of a mix of linear and nonlinear operations, namely the convolution operation and the activation function [60].

Convolution layers are the key component of every CNN design. It consists of a number of highly integrated convolution kernels (filters) that combine to create an output feature map from the input data (N-dimensional parameters). A convolution network receives data from an input and outputs it in Figure.9.

An input volume exists for a single convolution layer. Some data segments are removed from the input source, and the activation value is saved for those. (End) After processing, the activation value is transferred to the output activation volume.

Every form of communication makes use of kernel-level trickery. A kernel is an assortment of continuous or integer values, where each value represents the weight of the kernel. When a CNN model is being trained, each kernel weight is first initialized with a random number (alternative methods of initialization are also

possible). The kernel then learns to extract important information when the weights are adjusted with each training period [61].

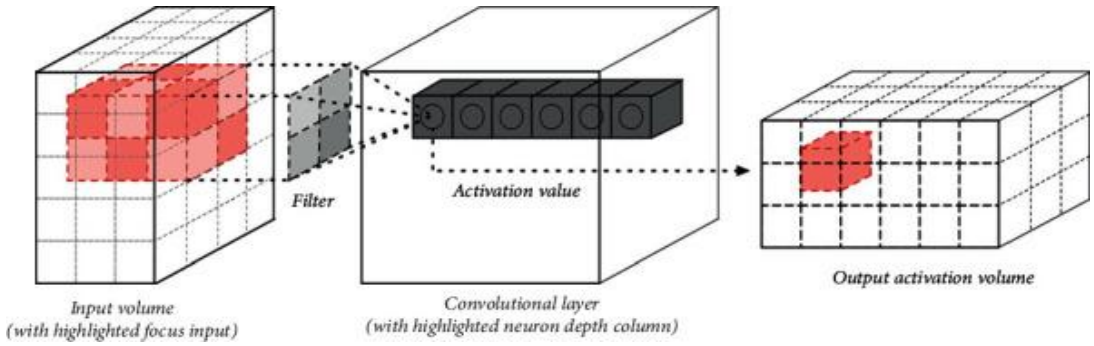


Figure 2.9: One convolution layer

b. Pooling Layer

The notion of pooling, which is a type of picture down sampling, is another crucial one in CNNs. The input picture is divided into a number of n pixel side rectangles that do not overlap each other (pooling). You may think of each rectangle as a tile. The values selected by the various tile pixels determine the output signal for the tile.

Pooling reduces an intermediate image's spatial dimensions, which lowers the number of parameters and utilizing a network to compute. Therefore, it is typical to periodically add a pooling layer between two A CNN designs uses consecutive convolution layers to control over fitting.

A type of translational invariance was also produced by the pooling procedure the pooling layer only resizes at the surface level and operates independently on each input depth slice. A highlighting layer is the most typical type.

Common 2x2 tiles (width/height), with the maximum output value next to the entrance. We refer to this as a "Max-Pool 2x2" in this instance. Big increases in computer power are possible with pooling. However, the current trend is to use small filters (2x2 types) due to the aggressive reduction of the size of the representation (and consequently the associated loss of information). The pooling layer can potentially be avoided, although doing so increases the danger of over learning [62].

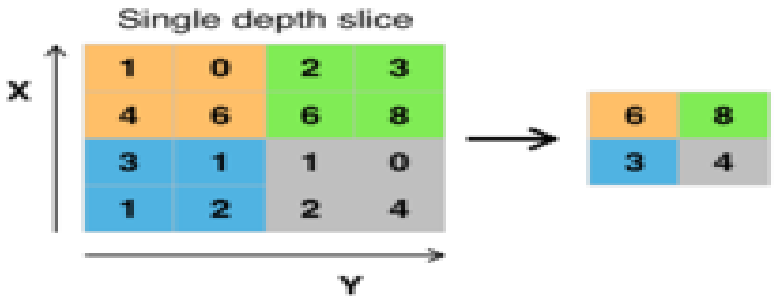


Figure 2.10: Pooling with a 2x2 filter and a step of 2

c. Fully Connected

The final layer of a neural network is always the fully-connected layer. This kind of layer produces another vector from an input vector. It applies a linear combination and maybe an activation function to the input data in order to achieve this.

In order to categorize the input picture of the network, the final fully-connected layer is employed. In our picture classification problem, there are N classes; hence the algorithm generates a vector of size N. The probability that the input image falls into a certain class is represented by each component of the vector.

For instance, the final vector will be of size 2 if the task is to distinguish between cats and dogs. The first element (respectively, the second) provides the likelihood of falling into the category of "cat" (respectively, "dog"). Consequently, the vector [0.9 0.1] indicates that there is a 90% likelihood that the picture is of a cat. The fully-connected layer consequently multiplies each input element by a weight, sums them all together, and then applies function activation (logistic if N=2, softmax if N>2) to determine the probabilities: The input vector is multiplied by the weights matrix during this step. The phrase "fully-connected" refers to the fact that each input value is connected to each output value [63].

2.3.4. Training CNN

To use this method effectively for cancer diagnosis, deep neural network training (CNN training) is required. A vast library of medical pictures is used for training (typically, the model is too sophisticated for great performance) and is then uploaded to a CNN. In order to get the best picture classification performance at the needed level, network weights are distributed throughout training processes. Huge and powerful computational resources are needed for CNN training, particularly if there is a huge amount of medical data accessible. While certain CPUs can manage training effectively, stronger GPUs are favored since they can train deeper networks more thoroughly and more quickly. Additionally, numerous model alterations must be made in order to train the CNN, as well as choosing the ideal configuration for the network [64].

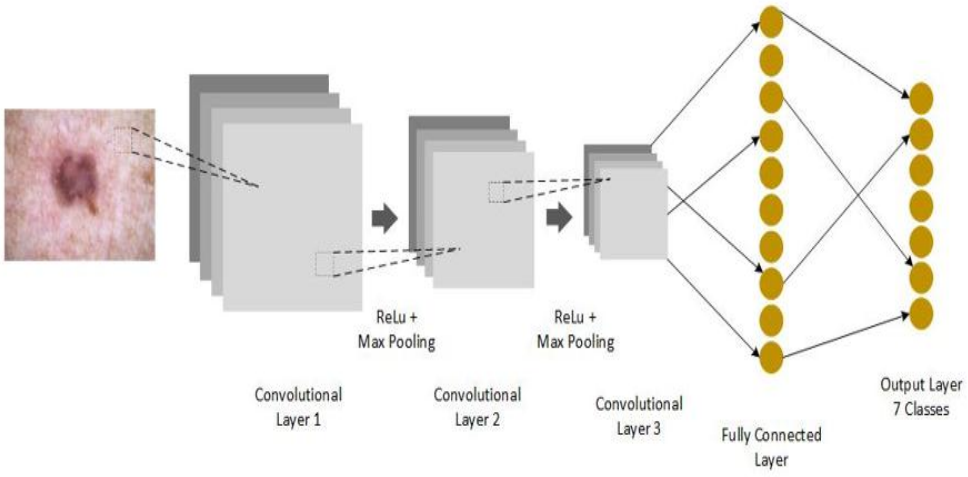


Figure 2.11: Skin lesion classification based on deep ensemble convolution neural network.

2.4. Conclusion

In the modern world, there are numerous dangerous diseases. A case in point is skin cancer. Early diagnosis is the best course of action. In the modern world, medical knowledge has advanced.

Skin cancer was formerly identified manually, which was time-consuming and expensive. But it has gotten considerably simpler as a result of the development of deep learning in the field of medical science. Rapid skin cancer detection is simple and inexpensive when deep learning, more specifically CNN, is applied. This study suggests using the CNN to find skin cancer because of this.

Chapter 3: Skin Cancer Diagnosis Using CNN

3.1. Introduction

Many studies have focused on the diagnosis of skin cancer in recent years, and as a result of the fast development of machine learning and deep learning algorithms, as well as successful applications in this field, deep convolutional neural networks have shown beneficial in a variety of domains. Skin cancer is frequently diagnosed manually utilizing photos of trained doctors, dermatoscopy examination results, and its compliance with medical sciences. The problem of manual detection is that it is heavily impacted by human subjectivity, which causes it to be inconsistent in some situations. As a result, developing a machine learning model that can determine if a mole is cancerous or benign based on pictures leads me to believe that artificial intelligence will bring about inconceivable changes in our lives in the next decades or years.

3.2. Software

This section discusses the software used to develop and train the machine learning model based on a CNN including cloud-based platforms such as Colab and Kaggle, as well as the programming language Python.

3.2.1. Cloud (Colab, Kaggle)

To circumvent storage constraints and processing complexity, cloud computing has been utilized in every aspect of human existence, particularly healthcare. To give diagnostics, data should preferably be stored on the cloud rather than restricted storage and computer resources. Furthermore, real-time monitoring is a critical area of healthcare that requires a fast reaction time and minimal latency [65].

a. Colab

Created a Google Colab Python notebook. We utilized an approach to run over the pandas Data frame column from the sequences and obtain all k-mers of a certain length using slicing and list Understanding before adding the k-mers to the FASTA file. For this, we leveraged Colab's form field functionality. Create a simple panel where you may enter parameters like k-mer length, output file name, and The file column where the entry sequence is found. Users must submit a CSV file

containing one sequence in each row and one sequence in one of the columns. Other columns may be included in the CSV file. Users upload CSV files to Colab using the Upload to file window on the left side. We've included a link to a YouTube instructional by Chanin Nantasenamat that describes the uploading process [66].

Google Colab is a Google Research product. Colab allows anybody to develop and run arbitrary Python code in the browser, making it ideal for machine learning, data analysis, and teaching.

When utilizing Google Colab, code is run on a virtual machine. Virtual machines are regenerated after a period of inactivity.

b. Kaggle

Kaggle is a platform that hosts competitions in data science and machine learning. Kaggle, which has around half a million data scientists on its platform, was founded by Gold bloom and Ben Hammer in 2010. The service got its start early and despite having a few competitors like DivenData, Top Coder and Hacker Rank, it has managed to survive. Long ahead of them by focusing on his specific niche. The service is essentially the de facto home to run data science - and machine learning – competitions [67].

3.2.2. Python

Python is an object-oriented language of programming, executed in an interpreted way and interactive. It delivers higher-level data constructions like associative and list arrays (named dictionaries), dynamic linking and dynamic typing, Classes, modules, exceptions, automatic memory management, etc. It has ordinarily elegant and simple structure. So far it is a dominant, general purpose programming language. Guido van Rossum designed in 1990.

As other scripting languages, it is open for free use, either for commercial purposes, and is practically runnable on any kind of computers. The interpreter compiles all Python programs automatically into independent platform byte code which is interpreted [68].

Python is cleaner, which makes any code simple to read and execute. It is an open source completely and is constantly being developed on all systems, with its own robust user base. Founded bugs and incompatibilities are generally fixed as

faster as possible, because of the full source code is available, users can troubleshoot or modify Python (if they are suitably qualified programmers). Another significant advantage for the developer (although not necessarily the user) is that Python currently has a large range of libraries, including a complete interface for OpenGL calls. This decreases the requirement for platform-specific C code significantly. In reality, PsychoPy is nearly entirely built in native Python code [69].

3.3. Data Organization

Data was collected and regrouped into two parts, one for the benign images which represent the non-dangerous cells on the skin, on the other side, the second group of the malignant images of the dangerous skin cancer.

3.3.1. Dataset collection

We gathered dermatoscopy pictures from various populations, which were obtained and archived in various methods. The resulting dataset includes 10,015 dermatoscopy pictures that may be used as a training set for academic machine learning. The examples offer a cross-section of all key diagnostic categories in the area of pigmented lesions, with the most important of them, benign and malignant, distinguished. This stage involves loading the photos and converting them into unordered arrays containing RGB values. Because the photos have already been reduced to 255x255 pixels

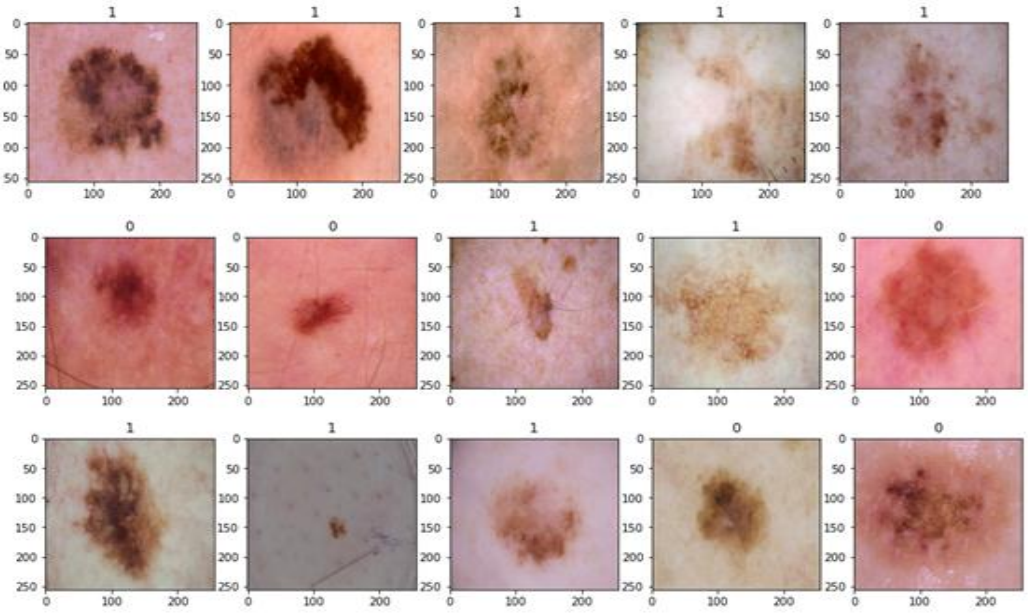


Figure 3.1: type of skin cancer

3.3.2. Importing Essential Libraries

Core libraries are very important because they provide pre-built functionality and tools that can save time and effort when developing software applications.

```
import os                       # for working with files
import numpy as np              # for numerical computationss
import pandas as pd             # for working with dataframes
import seaborn as sns
import torch                    # Pytorch module
import matplotlib.pyplot as plt # for plotting informations on graph and images using tensors
import torch.nn as nn           # for creating  neural networks
from torch.utils.data import DataLoader # for dataloaders
from PIL import Image           # for checking images
import torch.nn.functional as F # for functions for calculating loss
import torchvision.transforms as transforms   # for transforming images into tensors
from torchvision.utils import make_grid       # for data checking
from torchvision.datasets import ImageFolder  # for working with classes and images
from torchsummary import summary              # for getting the summary of our model
import tensorflow as ts
from  tensorflow import keras
import itertools
from sklearn.metrics import precision_score, accuracy_score, recall_score, confusion_matrix, ConfusionMatrixDisplay

%matplotlib inline
```

Figure 3.2: Importing the libraries necessary for the program

3.3.3. Malignant and benign

In this kernel I will try to detect two different categories of moles using Convolution Neural Network in the background and then analyze the result to see malignant from benign.

a. Model of number of image benign and malignant model

In this part, we calculate the number of skin cancer malignant and benign

```
# Number of images for each disease
nums_train = {}
nums_val = {}
for s in skin:
    nums_train[s] = len(os.listdir(train_dir + '/' + s))
img_per_class_train = pd.DataFrame(nums_train.values(),
index=nums_train.keys(), columns=["no. of images"])
print('Train data distribution :')
img_per_class_train
```

Figure 3.3: model of number of image benign and malignant

We obtained the number of malignant and benign tumors and classified them in Table 3.1

Classes	Number of image
Benign	**1082**
Malignant	**610**

Table 3.1: number of image benign and malignant

a. Data distribution

This code places previously obtained results into a bar chart

```
plt.figure(figsize=(10,10))
plt.title('data distribution ',fontsize=30)
plt.ylabel('Number of image',fontsize=20)
plt.xlabel('Type of skin cancer',fontsize=20)

keys = list(nums_train.keys())
vals = list(nums_train.values())
sns.barplot(x=keys, y=vals)
```

Figure 3.4: model of Data distribution

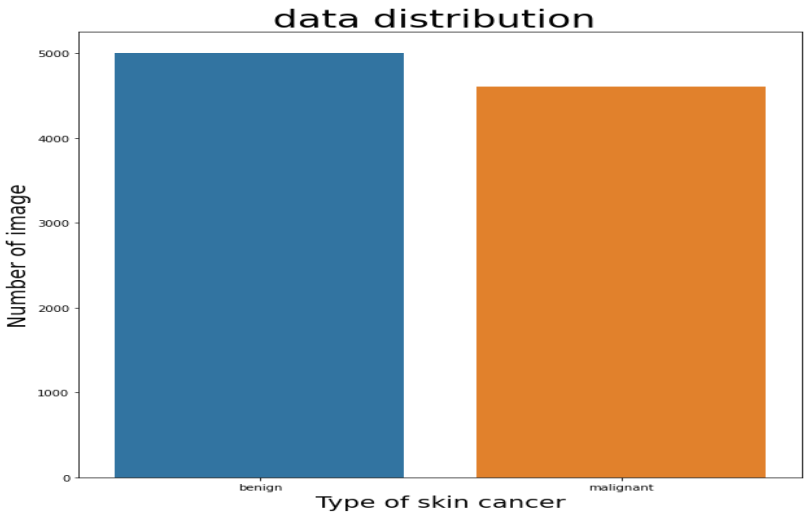


Figure 3.5: Data distribution

3.3.3.1. Benign

A benign tumor is a noncancerous growth that is unlikely to spread or cause health problems.

```
fig, axs = plt.subplots(2, 3,figsize=(12,10))
fig.tight_layout(pad=0)
axs[0,0].imshow(show_image(*train[1]))
axs[0,1].imshow(show_image(*train[260]))
axs[1, 0].imshow(show_image(*train[850]))
axs[1,1].imshow(show_image(*train[930]))
axs[0,2].imshow(show_image(*train[1250]))
axs[1,2].imshow(show_image(*train[1380]))
```

Figure 3.6: benign model

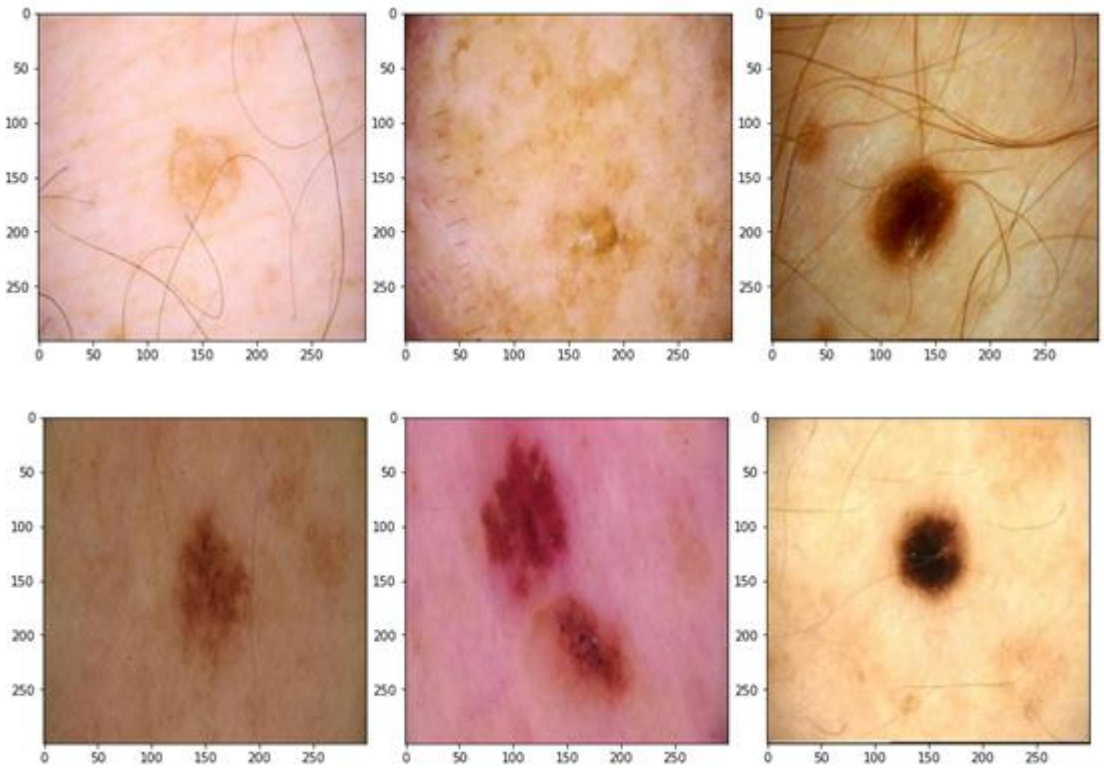


Figure 3.7: image of benign

3.3.3.2. Malignant

Malignant is a type of cancer that is aggressive and has the ability to spread and invade nearby tissues and organs**.**

```
fig, axs = plt.subplots(2, 3,figsize=(12,10))
fig.tight_layout(pad=0)
axs[0,0].imshow(show_image(*train[6000]))
axs[0,1].imshow(show_image(*train[7000]))
axs[1, 0].imshow(show_image(*train[8000]))
axs[1,1].imshow(show_image(*train[9000]))
axs[0,2].imshow(show_image(*train[9500]))
axs[1,2].imshow(show_image(*train[9600]))
```

Figure 3.8: malignant model

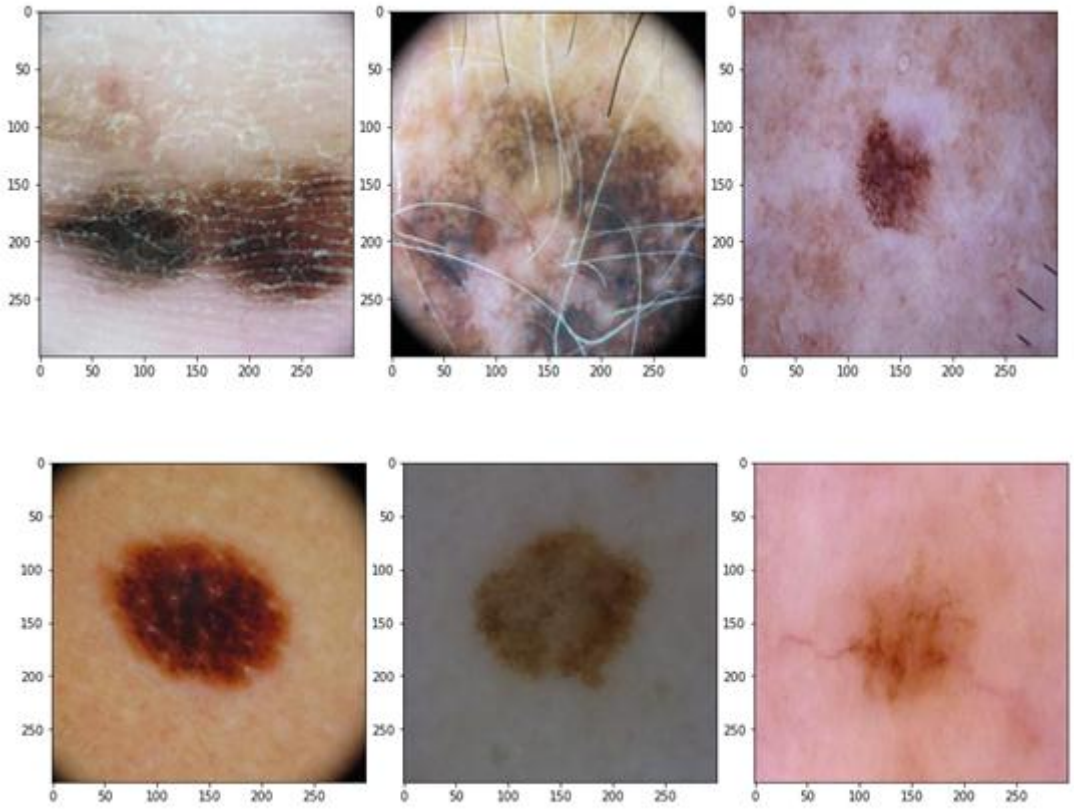


Figure 3.9: image of malignant

3.3.4. Data Visualization

	lesion_id	image_id	dx	dx_type	age	sex	localization
0	HAM_0000118	ISIC_0027419	bkl	histo	80.0	male	scalp
1	HAM_0000118	ISIC_0025030	bkl	histo	80.0	male	scalp
2	HAM_0002730	ISIC_0026769	bkl	histo	80.0	male	scalp
3	HAM_0002730	ISIC_0025661	bkl	histo	80.0	male	scalp
4	HAM_0001466	ISIC_0031633	bkl	histo	75.0	male	ear

Table 3.2: data visualization

3.3.5. Normalization

I opted to normalize x_train and x_test by removing their mean values and dividing them by their standard deviation.

Because all data are pictures, and images are made up of pixels, we divide all pixel values by 255 - each pixel can have a value of [0, 1].

```
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
```

Figure 3.10: Normalization model

CNN model

This is a simple exposition of the used CNN explains how the CNN extract information from images and decide the kind of the skin cancer

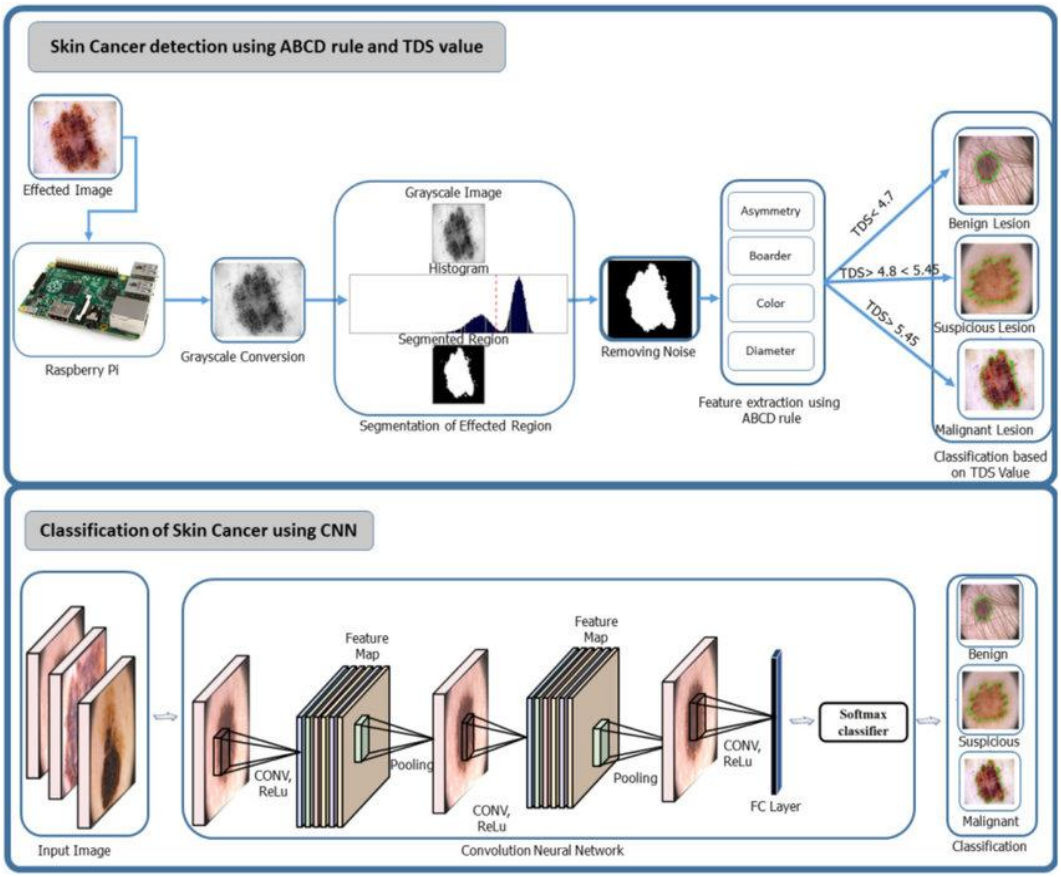


Figure 3.11: CNN Model

3.4.1. Training model

This model is made up of many convolutional layers, two completely connected layers with dropout regularization, two max pooling layers, two fully connected layers with softmax activation output layer, and so forth.

```
model1 = Sequential()

model1.add(Conv2D(32, (3, 3), input_shape=(128,128,1), activation="leaky_relu"))
model1.add(MaxPool2D(2,2))
model1.add(Conv2D(64, (3, 3), activation="leaky_relu"))
model1.add(MaxPool2D(2,2))
model1.add(Conv2D(128, (3, 3), activation="leaky_relu"))
model1.add(MaxPool2D(2,2))
model1.add(Conv2D(256, (3, 3), activation="leaky_relu"))
model1.add(MaxPool2D(2,2))
model1.add(Flatten())
model1.add(Dense(256, activation="relu"))
model1.add(Dense(1, activation="sigmoid"))
```

Figure 3.12: training model

3.4.2. Sequential model

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 28, 28, 16)        448
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 26, 26, 32)        4640
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 13, 13, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 13, 13, 32)        9248
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 11, 11, 64)        18496
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 6, 6, 64)          0
_________________________________________________________________
flatten (Flatten)            (None, 2304)              0
_________________________________________________________________
dense (Dense)                (None, 64)                147520
_________________________________________________________________
dense_1 (Dense)              (None, 32)                2080
_________________________________________________________________
dense_2 (Dense)              (None, 7)                 231
=================================================================
Total params: 182,663
Trainable params: 182,663
Non-trainable params: 0
_________________________________________________________________
```

Figure 3.13: summary model

3.5. Resultant

```
Epoch 20/20
235/235 [==============================] - 30s 129ms/step - loss: 0.029(
- accuracy: 0.9902 - val_loss: 0.3708 - val_accuracy: 0.9049

Epoch 00020: saving model to best_model.h5
```

Figure 3.14: Saving best model structure Dataset

As seen in results after 20 epoch, the accuracy of the training part go to 99,02% but on the test database it go to 90,49% because of the total data can't cover all kinds of skin cancer, but with an adaptive CNN we can train more and obtain better results with time.

3.5.1. Accuracy and Loss

Accuracy and loss are two important metrics used to evaluate the performance of machine learning models, including those developed for skin cancer detection.

A. Accuraccy

Accuracy is calculated using the TP, TN, FP, and FN values from the Confusion matrix.

One of these measures is accuracy, which is defined as the percentage of forecasts that are correct.

The model's accuracy on the total number of predictions is as follows:

$$\mathbf{Accuraccy} = \frac{\boldsymbol{TP} + \boldsymbol{TN}}{\boldsymbol{TP} + \boldsymbol{TN} + \boldsymbol{FP} + \boldsymbol{FN}}$$

A.1. Accuracy model

```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()
```

Figure 3.15: Accuracy model

A.2. plot Accuracy

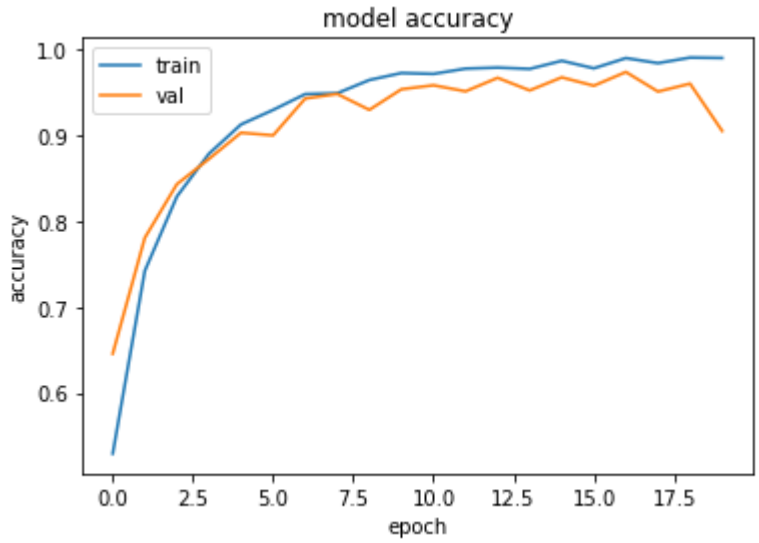


Figure 3.16:plot Accuracy

We have obtained a high classification accuracy of approximately 99.02 %, and this is a development in the field of skin cancer classification

B. Loss

Loss quantifies how accurately each image's correct label can be predicted by the model for the entire data set.

B.1. Loss model

```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()
```

Figure3.17: loss model

B.2. plot Loss

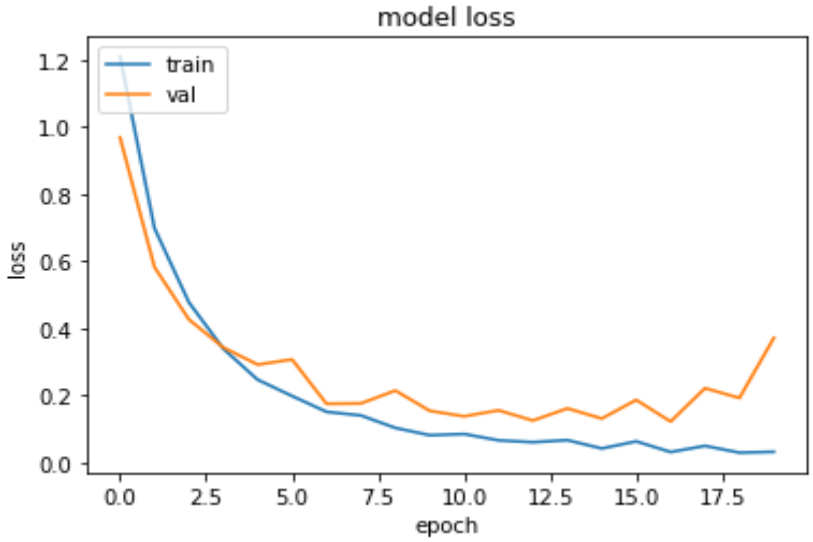


Figure 3.18: plot loss

3.5.2. Testing model

We have developed this code to ensure that the results obtained are correct in terms of accuracy and loss

```
loss, acc = model.evaluate(X_test, Y_test, verbose=2)
```

Figure 3.19: model testing

3.5.3. Resultant final

In the end, the final result after the test 91%

```
294/294 - 3s - loss: 0.3502 - accuracy: 0.9132
```

Figure 3.20: resultant final

3.5.4. Matrix confusion

A confusion matrix is a table that is used to assess the effectiveness of a classification model by contrasting its predicted and actual outcomes. Actual values appear in the rows of a confusion matrix, whereas forecasted values appear in the columns. True positives (TP) are situations in which the model properly anticipated a positive result, true negatives (TN) are cases in which the model correctly predicted a negative outcome, and false positives (FP) are cases in which the model incorrectly predicted a positive outcome. Negative, false negatives (FN) are situations in which the model predicted a negative outcome while the actual result was positive.

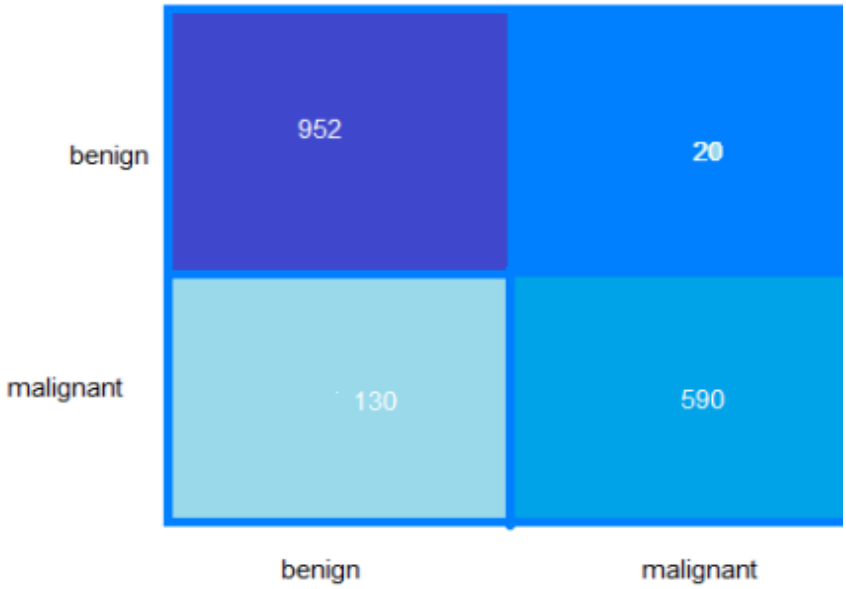


Figure 3.21: matrix confusion

This part explain how the CNN classify and misclassify some cases, it can be seen in the confusion matrix where we can see

From 1082 benign cases the CNN detect and well classify 952 cases and lose 130

And from 610 malignant cases the CNN detect and well classify 590 cases and lose 20 cases.

3.6. Conclusion

In this chapter, we explored the idea of identifying and categorizing skin disorders using computerized techniques, namely machine learning and deep learning-based approaches. As a primary and fundamental prerequisite for computer-aided systems, we began by classifying algorithms for skin illness recognition. From there, we discussed ways to get photos of skin diseases and readily accessible datasets. Is divided into two primary categories (benign and malignant).

After all, establishing a direct and conclusive link is still difficult. For melanoma, further epidemiological research is required to determine a causal link.

General Conclusion

In conclusion, research efforts in this area should be strengthened to improve and develop the use of CNN for skin cancer screening, improve patient care services, improve chances of early treatment, and improve overall health outcomes for patients. For example, CNN can identify various small skin lesions that are difficult to examine manually. CNN can also be used to distinguish between precancerous and noncancerous skin lesions and to determine whether the lesion develops and changes abnormally over time. In addition, CNN can perform faster and more efficient disease detection and classification than traditional manual screening. Improving the accuracy of diagnosis and classification of skin cancer with CNN technology will contribute to improving patient care and health care services in general. The applicability of CNN technology in clinic-like settings and remote areas where medical expertise is not sufficient should also be studied. CNN technology could also be an important step towards improving patient care around the world, saving time and effort for doctors and patients alike.

It helps improve the accuracy and speed of diagnosis and early detection of cancer. It can reduce health risks that occur due to lack of early diagnosis and delayed treatment. It is undeniable that CNN technology constitutes a huge advance in the world of medicine and health, as it can improve methods of diagnosis and treatment and contribute to improving people's lives, which helps in improving chances of recovery and avoiding treatments. excessive or ineffective. In addition, CNN can be used to analyze images of injuries and measure their change and growth over time, which facilitates follow-up of treatment and evaluation of its results. Thus, it can be said that the use of CNN enhances the chances of early detection of skin cancer and improves health care for patients.

Reference

1. Amrish, K., et al. "Sachin k, Nishant K, SK Gupta. Diagnosis and Immunotherapy Strategies for Melanoma: A Review. LOJ Med Sci 2 (1)-2018." LOJMS. MS. ID 128.

2. Cooper GM. The Cell: A Molecular Approach. 2nd edition. Sunderland (MA): Sinauer Associates; 2000.

3. Oppenheimer, S. B. (2006). Cellular basis of cancer metastasis: A review of fundamentals and new advances. Acta histochemica, 108(5), 327-334.

4. Erik B. Schiferle, Se Yun Cheon, Seokjin Ham, Heehwa G. Son, Jonathan L. Messerschmidt, Donald P. Lawrence, Justine V. Cohen, Keith T. Flaherty, James J. Moon, Christine G. Lian, Ryan J. Sullivan, Shadmehr Demehri Sci Adv. 2021 Jun; 7(26): eabg4498.

5. Chuong CM, Nickoloff BJ, Elias PM, Goldsmith LA, Macher E, Maderson PA, Sundberg JP, Tagami H, Plonka PM, Thestrup-Pederson K, Bernard BA, Schröder JM, Dotto P, Chang CM, Williams ML, Feingold KR, King LE, Kligman AM, Rees JL, Christophers E. What is the 'true' function of skin? Exp Dermatol. 2002 Apr; 11(2):159-87.

6. Aumailley, M., & Krieg, T, A family of diverse multifunctional molecules of basement membranes, Journal of Investigative Dermatology, 1996, p 106. Investigative Dermatology.

7. Quijada-Rodriguez, A. R., Treberg, J. R., & Weihrauch, D. (2015).

8. Gandhi, S., & Kampp, J, Skin cancer epidemiology, detection and management. Medical Clinics of North America, 2015, p 99.

9. Gilaberte, Yolanda, nEvaluation of a health promotion intervention for skin cancer prevention in Spain: The SolSano program. Health Promotion International, 2008, p 23.

10. Saladi R, the Causes of Skin Cancer: A Comprehensive Review. Drugs of Today, 2005, p 41.

11. Swartz, R. D., Crofford, L. J., Phan, S. H., Ike, R. W., & Su, L. D. (2003). Nephrogenic fibrosing dermopathy: a novel cutaneous fibrosing disorder in patients with renal failure. The American journal of medicine, 114(7), 563-572.

12. D'Orazio J, Jarrett S, Amaro-Ortiz A, Scott T. UV radiation and the skin. Int J Mol Sci. 2013 Jun 7; 14(6):12222-48.

13. Bruce K Armstrong, Anne Kricker, The epidemiology of UV induced skin cancer, Journal of Photochemistry and Photobiology B: Biology, Volume 63, Issues 1–3, 2001, Pages 8-18.

14. Melanoma Treatment – for health professionals". National Cancer Institute. 26 June 2015.

15. F. R. de Gruijl, Skin cancer and solar UV radiation, Eur. J. Cancer, 1999, 35, 2003-2009.]

16. Katalinic, A., A. Waldmann, M. Weinstock, A. C. Geller, N. Eisemann, R. Greinert, Breitbart, Does skin cancer screening save lives? Cancer, 2012, p 118.

17. Sta, M. C. (2018). Cancer https://www. Mayo clinic. Org/diseases conditions/cancer/symptoms-causes/syc-20370588.

18. Oliveria SA, Saraiya M, Geller AC, Heneghan MK, Jorgensen C. Sun exposure and risk of melanoma. Arch Dis Child. 2006 Feb; 91(2):131-8

19. Miller, S. J., Alam, M., Andersen, J., Berg, D., Bichakjian, C. K., Bowen, G. ... & Zic, J. A. (2010). Basal cell and squamous cell skin cancers. Journal of the National Comprehensive Cancer Network, 8(8), 836-864.

20. J. Larry Jameson, Anthony S. Fauci, Dennis L. Kasper, Stephen L. Hauser, Dan L. Longo, Joseph Loscalzo, Harrison's Principles of Internal Medicine, p4, ch 76.

21. Rosen T and Lebwohl MG. “Prevalence and awareness of actinic keratosis: barriers and opportunities.” J Am Acad Dermatol. 2013; 68(1 Suppl 1):S2-9.

22. Tan ST, Ghaznawie M, Heenan PJ, Dosan R. Basal Cell Carcinoma Arises from Interfollicular Layer of Epidermis. J Oncol. 2018 Sep 26; 2018:3098940.

23. Neff R, Collins R, Backes F. Dermatofibrosarcoma protuberans: A rare and devastating tumour of the vulva. Gynecol Oncol Rep. 2019 May; 28:9-11.

24. Coggshall K, Tello TL, et al. “Merkel cell carcinoma: An update and review Pathogenesis, diagnosis, and staging.” J Am Acad Dermatol. 2018; 78:433-42.

25. M.L., Siegal F.P., Geller S.A. Outbreak of an acquired immunodeficiency syndrome associated with opportunistic infections and Kaposi’s sarcoma in male homosexuals: An epidemic with forensic implications. Am. J. Forensic Med. Pathol. 1982; 3:259–264.

26. Juhász MLW, Marmur ES, A Multiple Recurrent Keratoacanthoma of the Lower Leg after Repeated Wide-Excision and Mohs Micrographic Surgery, Dermatol Surg, 2018; p 45.

27. R.Willemze and others, Annals of oncology, 2013, volume 24 (Supplement 6), pages 149– 154.

28. Gupta AK, Bharadwaj M, Mehrotra R. Skin Cancer Concerns in People of Color: Risk Factors and Prevention. Asian Pac J Cancer Prev. 2016 Dec 1; 17(12):5257-5264.

29. Lasithiotakis KG, Petrakis IE, Garbe C. Cutaneous melanoma in the elderly: epidemiology, prognosis and treatment. Melanoma Res 2010 Jun; 20(3):163-70.

30. Watson M, Holman DM, Maguire-Eisen M. Ultraviolet Radiation Exposure and Its Impact on Skin Cancer Risk. Semin Oncol Nurs. 2016 Aug; 32(3):241-54.

31. Sims, J. R., Grotz, T. E., Pockaj, B. A., Joseph, R. W., Foote, R. L., Otley, C. C., ... & Price, D. L. (2018). Sentinel lymph node biopsy in Merkel cell carcinoma: the Mayo Clinic experience of 150 patients. Surgical Oncology, 27(1), 11-17.

32. Fania L, Didona D, Di Pietro FR, Verkhovskaia S, Morese R, Paolino G, Donati M, Ricci F, Coco V, Ricci F, Candi E, Abeni D, Dellambra E. Cutaneous Squamous Cell Carcinoma: From Pathophysiology to Novel Therapeutic Approaches. Biomedicines. 2021 Feb 9; 9(2):171.

33. Dasgupta T, Wilson LD, Yu JB. A retrospective review of 1349 cases of sebaceous carcinoma. Cancer. 2009 Jan 01; 115(1):158-65.

34. Dinnes J, Deeks JJ, Grainge MJ, Chuchu N, Ferrante di Ruffano L, Matin RN, Thomson DR, Wong KY, Aldridge RB, Abbott R, Fawzy M, Bayliss SE, Takwoingi Y, Davenport C, Godfrey K, Walter FM, Williams HC; Cochrane Skin Cancer Diagnostic Test Accuracy Group. Visual inspection for diagnosing cutaneous melanoma in adults. Cochrane Database Syst Rev. 2018 Dec 4; 12(12):CD013194.

35. ASHFAQ A. M, NATALIA J, Dermoscopy for the Family Physician, American Academy of Family Physicians, 2013, p 88-89.

36. Senel E. Dermatoscopy of non-melanocytic skin tumors. Indian J Dermatol Venereol Leprol 2011; 77:16-22.

37. Wet J, Steyn M, Jordaan HF, Smith R, Claasens S, Visser WI. An Analysis of Biopsies for Suspected Skin Cancer at a Tertiary Care Dermatology Clinic in the Western Cape Province of South Africa. J Skin Cancer. 2020 Jan 27; 2020:9061532.

38. Krišto M, Šitum M, Čeović R. Noninvasively Imaging Techniques for the Diagnosis of Nonmelanoma Skin Cancers. Acta Dermatovenerol Croat. 2020 Dec; 28(3):157-165.

39. Longo, C.; Ragazzi, M.; Rajadhyaksha, M.; Nehal, K.; Bennassar, A.; Pellacani, G.; Malvehy Guilera, J, In Vivo and Ex Vivo Confocal Microscopy for Dermatologic and Mohs Surgeons, Dermatol Clin, 2016, p 497-504.

40. Ahlgrimm-Siess, V.; Laimer, M.; Rabinovitz, H.S.; Oliviero, M.; Hofmann-Wellenhof, R.; Marghoob, A.A.; Scope, A. Confocal, Microscopy in Skin Cancer, 2018, p 108.

41. Refianti, R.; Mutiara, A.B.; Priyandini, R.P, Classification of melanoma skin cancer using convolutional neural network, International Journal of Advanced Computer Science and Applications, 2019, p 411.

42. T.J. Brinker, A. Hekler, J.S. Utikal, N.Grabe, D. Schadendorf, J. Klode, C. Berking, T. Steeb, A.H. Enk, C.von Kalle, Skin Cancer Classification Using Convolutional Neural Networks: Systematic Review Journal of Medical Internet Research, Journal of Medical Internet Research, 2018, p 20-22

43. Refianti, R.; Mutiara, A.B.; Priyandini, R.P, op. cit, p 413.

44. Morgan A., Nair S.A.H., Preethi A.A.P., Kumar K.P.S. Diagnosis of skin cancer using machine learning techniques. Microprocess. Microsyst. 2020; 81:103727.

45. MALKI NARIMENE, classification automatique des textes par Les réseaux de neurones à convolution, Mathématique et Informatique, Université LARBI ben M'HIDId'Oum El Bouaghi 2018/2019 p.16

46. Farook Azam, Biologically Inspired Modular Neural, networks, Dissertation submitted to the Faculty of the Virginia Polytechnic Institute and State University, May, 2000, p.3.

47. DaniilNaumetc, Artificial Neural Networks in plane control, Automation Engineering ValkeakoskiYear2016. p.3.

48. Gridi Adel,Un Outil de Deep Learning pour les données textuelles, MEMOIRE de fin d'étudePrésenté pour l'obtention du Diplôme Master 2, Domaine : Mathématiques et Informatique, UNIVERSITE L'ARBI BEN M'HIDI-OUM EL BOUAGHI, Faculté des sciences de la Nature et de la vie DépartementMI, p.30.2019 -2020.

49. DaniilNaumetc, Artificial Neural Networks in plane control, Automation Engineering ValkeakoskiYear2016. p.3.

50. Ivan Nunes da Silva • Danilo Hernane SpattiRogerio Andrade FlauzinoLuisa Helena BartocciLiboni Silas Franco dos Reis Alves., Artificial Neural Network © Springer International Publishing Switzerland 2017 p.21.

51. Zainab Falah Artificial Neural Network- Babylon University-Science College for Women- Advanced Intelligent Application

52. SEKKILHichamMohamed, MEBROUKI Mahmoud, Etude comparative entre les différentesarchitectures des réseaux de neurones convolutés (CNNs) pour la détection de la fatigue du conducteur Higher School In Applied Sciences –Tlemcen- p.34. 26 / 09 / 2021.

53. Kareem, S., Hamad, Z. J., & Askar, S. (2021). An evaluation of CNN and ANN in prediction weather forecasting: A review. Sustainable Engineering and Innovation, 3(2), 148-159.

54. Shudipto Sekhar Roy, Mel NET: A Deep Learning Based Model for Melanoma Detection.p.16. January 2019.

55. Y.LeCun, Y. Bengio, and G. Hinton, “Deep learning,” Nature, vol. 521, no. 7553, pp. 436–444, May 2015.

56. Hazrat Aliclassification Of Skin Cancer Image Using Convolutional Neural Networks, The Graduate School Of Applied Sciences Of Neareast University Nicosia, P.20. 2019.

57. Tiernan Ray |, « EXCLUSIF : YannLeCun (Meta) explore la frontière énergétique de l'apprentissage profond » [archive], sur ZDNet France (consulté le 13 avril 2023.

58. Hadjila F., Bouabdellah R, Reconnaissance des visages par les réseaux de neurones, Mémoire de PFE, Université de Tlemcen, 2003.

59. Gridi Adel, Un Outil de Deep Learning pour les données textuelles, MEMOIRE de fin d’étudePrésenté pour l’obtention du Diplôme Master 2, Domaine : Mathématiques et Informatique, UNIVERSITE L’ARBI BEN M’HIDI-OUM EL BOUAGHI, Faculté des sciences de la Nature et de la vie Département MI, p.30.2019 -2020

60. Rikiya Yamashita1, 2& Mizuho ishio1, 3 & Richard KinhGian Do2 & Kaori Togashi1Convolutional neural networks: an overview and application in radiology 2018.

61. N. Aljaafari, “Ichthyoplankton classification tool using Generative Adversarial Networks and transfer learning,” Master of senescing Abdullah University of Science and Technology, thuwal, Kingdom of Saudi Arabia, 2018.

62. Mr. Mokri Mohammed Zakaria Mémoire de fin d’études Pour l’obtention du diplôme de Master en informatique Classification des images avec les réseaux de neurones convolutionnels Université Abou Bakr Belkaid Tlemcen .03/07/2017 p.25.

63. K. Eremenko, “Deep learning A-Z™: convolutional neural networks (CNN) - step 4: full connection,” Super Data Science [Online]. Available.

64. Yamashita, R., Nishio, M., Do, R.K.G. et al. Convolutional Neural Networks: An Overview and Application in Radiology. Insights Imaging 9, 611-629 (2018).

65. A. Rehman, T. Sadad, T. Saba, A. Hussain and U. Tariq, "Real-Time Diagnosis System of COVID-19 Using X-Ray Images and Deep Learning," in IT Professional, vol. 23, no. 4, pp. 57-62, 1 July-Aug. 2021, doi: 10.1109/MITP.2020.3042379.

66. Nantasenamat, Chanin. “How to Upload Files to Google Colab.” Www.youtube.com, 24 Apr. 2020.

67. "Google buys Kaggle and its gaggle of AI geeks". CNET. 2017-03-08. Retriever 2018-06-01.

68. SANNER, Michel F., et al. Python: a programming language for software integration and development. J Mol Graph Model, 1999, 17.1: 57-61.

69.Jonathan W. Peirce, PsychoPy—Psychophysics software in Python,Journal of Neuroscience Methods,Volume 162, Issues 1–2,2007,Pages 8-13,ISSN 0165-0270.