SKIN CANCER DETECTION WITH MACHINE LEARNING

A Report Submitted to the
Department of Computer Science and Engineering, Daffodil International University
In partial fulfillment of the requirements for the degree of
B.Sc. in Computer Science and Engineering

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Approval

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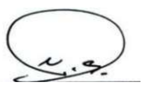

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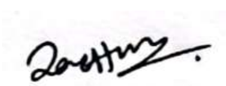

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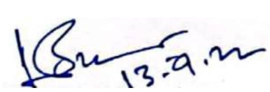

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Declaration

We hereby declare that this project has been done by us under the supervision of Mohammad Jahangir Alam, Lecturer, Dept. of CSE, Daffodil International University. We also declare that neither this project nor any part of this project has been submitted elsewhere for the award of any degree or diploma.

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Abstract

In 2013, 85 million Americans saw a doctor for at least one skin condition, making skin illnesses a widespread problem today. Skin infections are rising at an ever-increasing rate. Additionally, skin conditions are difficult for human eyes to diagnose. Therefore, we suggested using a CNN (Convolutional Neural Network) system to identify and categorize skin diseases. The dataset we are utilizing is HAM10000 and some raw images. 2144 dermoscopic pictures of skin conditions, broken down into 7 classifications, are encompassing. Attributable to this, our CNN system will indeed be able to classify and pinpoint seven different types of skin diseases. In our system, we also do some picture preprocessing and image augmentation. In our system, we also do some picture preprocessing and image augmentation. ResNet50 is the pre-trained CNN models that we are operating. Skin cancer is an alarming disease for mankind. The necessity of early diagnosis of the skin cancer has been increased because of the rapid growth rate of Melanoma skin cancer, it's high treatment costs, and death rate. This cancer cells are detected manually and it takes time to cure in most of the cases. This paper proposed an artificial skin cancer detection system using image processing and machine learning method. The features of the affected skin cells are extracted after the segmentation of the dermoscopic images using feature extraction technique. A deep learning based method convolutional neural network classifier is used for the stratification of the extracted features. An accuracy of 89.5% have been achieved after applying the publicly available data set Dermatological Diseases are one of the biggest medical issues in 21st century due to its highly complex and expensive diagnosis with difficulties and subjectivity of human interpretation. We believe that the application of automated methods will help in early diagnosis especially with the set of images with variety of diagnosis. Hence, in this article we present a completely automated system of dermatological disease recognition through lesion images, a machine intervention in contrast to conventional medical personnel-based detection. Our model is designed into three phases compromising of data collection and augmentation, designing model and finally prediction. We have used multiple AI algorithms like Convolutional Neural Network amalgamated it with image processing tools to form a better structure, leading to higher accuracy of 89%.

Table of Contents

Chapter 1: Introduction

Chapter 2: Background

Chapter 3: Research Methodology

Chapter 4: Experimental Results and Discussion

List of Figures

List of Tables

Chapter 1
Introduction

1.1 Introduction

With a porous structure of roughly 20 square feet and three main purposes—protection, regulation, and sensation, among all bodily organs, the skin is the biggest., involving minerals, liquids, protein, and fat. The skin's ectodermal tissues, which can have up to seven layers, adequately protect organs, muscles, bones, and ligaments beneath. The skin screens the body from the surroundings and microorganisms that enter it help regulate body temperature kill germs, and offer the sensation of touch, freezing, and warmth. The unrestricted proliferation of aberrant skin cells is known as skin cancer. Malignant tumors grow when skin cells undergo apoptosis, which is most frequently brought on by UV radiation from sunburn or tanning beds. UV rays can generate heat or any other source, and moles can cause approximately 25% of malignant cancers. There are many kinds of skin cancer. In this project, we are working on Melanoma, Basal cell, carcinoma, Actinic keratosis, Dermatofibroma, Nevus, Seborrheic keratosis, and vascular lesions. An alteration in our skin, usually a new outgrowth or a modification in a preexisting protrusion or mole, is the most prominent clear signal of skin cancer.[1] As the diagnostic classification does not currently meet the diverse needs of the illness, it is not able to precisely forecast the disease's trajectory or treat it. Furthermore, cancer cells are frequently discovered and treated only after they have spread to other abdominal areas and undergone mutations. Therapies and treatments are not incredibly beneficial at this time. Due to these complications, heart diseases are now the leading cause of mortality globally and have eclipsed skin cancer in measures of the proportion of cases. Other factors that may have contributed to the disease's progression to such a terrible stage include people's misfortune, their use of folk cures without first understanding the complexity of the issue, and the possibility that these remedies might aggravate the ailment outright.

According to recent WHO data, 853 skin cancer deaths—or 0.12% of all deaths—occurred in Bangladesh in 2020. Bangladesh ranks #153 in the world with an adjusted for age, mortality rate of 0.68 per 100,000 people. In the US, skin cancer is the most prevalent type of cancer. According to current projections, one in five Americans may have skin cancer at some point in their lives. In the United States, an estimated 9,500 people receive a skin cancer diagnosis each day.

Hidden convolutional layers and custom filters that look for patterns are used by CNN to analyze input images. The algorithm then separates and ranks the various things in the image according to their relevance. To detect skin cancer we use the Convolutional Neural Network. Recommender Systems also use Convolutional Neural networks. CNN was chosen the fact of the matter, it provides great image processing accuracy. CNN employs four standards.[2] Dermatologists input all of their information into the primary layer, which serves as the input layer. The information is then formed by the input layer and sent to the following levels, which subsequently transmit it to the pooling layer. The integrated model is pooled by the pooling veneer using max pool or min pool. The information is sent from the pooling veneer to the straightening veneer for smoothness, which converts the data during one vector. At that time, the intelligence is thick enough to be altered into the subcategory they desire, perhaps innocuous or malignant.

1.2 Motivation

Skin cancer is a significant stumbling block that needs to be found as soon as viable. The diagnostic is a manual process that takes a lot of hour and money. Nonetheless, machine learning has revolutionized science in today's climate and can be beneficial for many reasons. ways. Consequently, computer learning, especially convolutional neural networks, can make spotting cancerous cells easier. Faster malignant cell detection is achieved using neural networks, and smoothly. We wish to evaluate the widely used Dense Net 201 model, which applies deep convolutional neural networks to the detection of skin cancer. [3] In such case, we could evaluate the use of these models as well as their effectiveness by using this methodology, which is both novel and practical. We will be able to distinguish between skin cancer and other skin problems as a result of this endeavor. Although the evidence suggests that ML is useful in the diagnosis of skin cancer, the main factor determining its applicability will be clinical compliance. Future Perspectives AI has many uses in the healthcare sector, both for therapeutic and diagnostic purposes.

1.3 Rationale of the study

Skin cases of prostate cancer are rising daily. The main risk factor for the majority of skin malignancies is assumed to be exposed to ultraviolet (UV) rays. The environment also has an impact on the prevalence of skin cancer. Skin cancer cases dramatically increased during the period when the ozone hole was at its worst.[4] Unsettlingly, fresh reports indicate that the hole is once again expanding. Experts worry that as a result; people will be exposed to UVB radiation from the sun at never-before-seen levels. This indicates that the impact on the diagnosis of skin cancer could be far higher than the numbers estimated by the World Health Organization if the climate crisis intensifies.

Skin incidence rates are greater in men than women until the age of 50, but beyond that age, skin cancer rates are higher in men, which may be attributed to differences in UV exposure during leisure time and at work. According to predictions, 1 in 27 heterosexual men and 1 in 40 women will get melanoma over their lifespan..[5]

Skin cancer early detection is crucial. Skin cancer is a more frequent cause of death, as we can see. We gather photographs of many types of skin cancer to detect it. Then we go on to the Dense Net 201 model, which uses a convolution neural network to accurately identify skin cancer and determine whether or not the skin is afflicted. We also create an Android app that allows us to snap pictures of our skin, with the app detecting it and displaying the results. People will be more likely to recognize skin cancer as a result.

1.4 Research Questions

- How Does Skin Cancer Implications of Authentication on Our Ordinary Existence?
- Is it feasible to apply deep learning and machine learning models simultaneously??
- What are the difficulties that Skin Cancer Petition for Identification?
- Which the far more appropriate tactic for spotting Skin Cancer?
- What are the areas of skin cancer pick the area of study where my preferences should be courted?

1.5 Expected Output

We are trying to detect skin cancer. Through our project, we can find out whether our skin is infected and if it is infected, we can also take out the percentage of it that is infected. Thinking about the future, we have worked on such a program so that in the future we can detect our skin cancer very early and get good quality treatment for it. Chemotherapy is a topic of extensive exploration in our country. How can we get rid of skin cancer? The main cause of our UV radiation is the factor that causes skin cancer that we get from the sun. Due to this various types of skin cancer diseases are seen in our country. If we can manage our ozone level properly then our ozone level will be fine and also we will be less exposed to the ultraviolet rays of the sun in that case, we will be able to stay away from serious diseases called skin cancer.[6] We worked with a programming language called machine learning in our skin cancer detection project. In this project, we took seven classes. Seven classes after detection with machine learning we received 89 percent above skin cancer.

We worked with a small class of diseases through our project to see if something can be detected through a programming language. We found that it can be detected very easily using a programming language called machine learning. In the future we will work with many more classes of skin cancer and on them we will find out our percentage of skin cancer and from there we will get a better output. And that person will figure out the percentage that can or will be present in a human body.

1.6 Project Management and Finance

To better understand emerging patterns of roles and responsibilities, data from the survey of project management roles and responsibilities was acquired. Project management includes scheduling and planning meetings, facilitating the entire study, and entering data into databases. Study progress was recorded via timely release of meeting agendas and minutes outlining progress and action items. These resources accumulated throughout time to create an archive that is centrally accessible via the Madcaps communication platform. To produce high-quality data that can influence disease prevention and control as well as policy requirements, taking Competent project management is essential for executing health-related research that involves taking into account the local and nationwide political and social situations. This is owing to the fact that efficient project management enables the administration and adherence of the appropriate tools, methodologies, tactics, and predictable approaches. By incorporating project management abilities into efforts to establish health systems in low- and middle-income nations, the population's health may be boosted (LMICs). 2; nevertheless, the research done in an African setting seldom ever offers the development and evaluation of the tools and skills required for successful project management. [7]

Finance bill-paying and account-balancing, money-management, grant administration, and budget creation.

1.7 Report layout:

- The essential ideas of "A machine learning model for predicting plant disease" were covered in chapter 1, along with the purpose, goal, and anticipated results of our study.
- A brief rundown of the summary, the severity of the problem, and the challenges are the main topics of Chapter 2's related works section.
- The research technique is covered in Chapter 3.
- The details of the experimental findings are detailed in Chapter 4.
- Chapter 5 describes our social impact on environmental effects, etc.
- Chapter 6 contains an overview evaluation data as well as a few more insight that can support me in current study efforts for subsequen publications.

Chapter 2
Background

2.1 Preliminaries

This served as the inspiration for developing a descriptive language with an easy-to-understand structure. The main drawback of descriptive language is that it may result in very laborious and lengthy descriptive statements for complicated systems that might be expressed neatly in a metaphor. We arranged a new consensus conference in light of the advantages and disadvantages of metaphoric vs descriptive terminology22–25 and the appearance of a considerable number of new concepts. Our main goals were to build a glossary of standardized words, reach an agreement on term definitions, and unify metaphorical and descriptive vocabulary.[8] Dermoscopic nomenclature, methodology, and working groups were the main topics of the International Skin Imaging Collaboration. The task of creating a dictionary of standardized words was given to the terminology working group to simplify the annotation and markup of reference pictures.

The team leader of the terminology working group (H. K.) chose a group of specialists to debate potential approaches to come to an agreement on terminology standards in dermoscopy during the project's early phase.
The expert group's early deliberations were focused on the benefits and drawbacks of metaphoric vs descriptive vocabulary.

2.2 Related Works

Several works detail various ways to carry out one or more of the aforementioned procedures. As a result, it is crucial to synthesize them in surveys that serve as a reference for upcoming specialists. When looking for better solutions to this issue, this might be daunting. This problem inspired us to create an overview that solely included the feature extraction component of the CAD system. The selection of this block is not random because segmentation and diagnosis both heavily rely on obtaining the right descriptors.[9] Additionally, feature extraction is by far the stage with the greatest variation among comparable research. By handling pigment, Hamad and Asa foresaw skin cancer. For the pigments of skin lesions, they employed a computerized approach based on symmetric color. In this work, two skin lesion adaption techniques were created. First, artificial spectrums of reddish, yellow, brown, and black pigments were used to adapt. The second strategy included modifying a database of healthy and unhealthy hues. 40 photos were compared to the outcomes. The first and second approaches' classification rates were 80 and 92.5 percent, respectively. If skin lesion segmentation or the database of pigments and spectrums is expanded, the results will be better. A strategy to identify skin cancer using local and universal traits was put out by Barata et al. [10]. This study set out to identify the best characteristics and the best approach (local and universal) for diagnosis (color and texture). In investigations, three different classifiers—KNN, SVM, and Ada boost—were employed, and various feature combinations were also looked at. The outcomes demonstrated that a straightforward classifier, like KNN, may be utilized to produce the desired outcome. Additionally, the color function performs better than the texture one. It just takes a small number of attributes to classify with high accuracy and broadens the scope of the system. The results revealed that both strategies could be utilized to get the desired outcome, however, the local method required more time.

2.3 Comparative Analysis and Summary

The World Cancer Research Fund ranks skin cancer as the 19th most prevalent type of cancer. Over the past few decades, diagnoses have expanded most rapidly in the USA, Canada, and Australia. Melanocytic skin cells develop unevenly, which promotes skin cancer. The most lethal types of skin cancer are malignant and benign. A cancerous growth that spreads and grows inside of a patient is called a malignant tumor. They can expand and spread uncontrollably into other vital organs. Many malignant skin growths have antecedent symptoms that can be recognized. A precursor is a collection of abnormal cells that have the potential to become cancerous. Another word for a precursor is malignant. A precursor is a cluster of potentially cancerous aberrant cells cancer. Another word for a precursor is malignant. [11] While certain precancerous skin benign tumors have a very low likelihood of turning into cancer, others have a very high likelihood. Malignant skin growths come in a variety of forms, including skin lymphoma, melanoma, carcinoma, sarcoma, and squamous cell carcinoma. It is crucial to identify and treat cancer in its earliest stages of malignant skin development. Complete excision (surgical removal) frequently results in health. A benign tumor, on the other hand, can evolve but won't spread. Knowing the typical early signs and symptoms of potentially malignant skin growths is crucial when dealing with benign skin growths, as is getting medical assistance when suspicious skin growths emerge. Seborrheic keratosis, cherry Animas, dermatofibromas, skin tags granulomas, and cysts are examples of benign skin growths (epidermal inclusions).[12]

Figure 1 in this article displays cancer cases in men and women of ages ranging. The incidence rates increase gradually between the ages of 20 and 24, and they increase more dramatically in males between the ages of 55 and 59. Males aged 85 to 89 had the lowest rates, whereas females aged 90 and up had the highest.[13] In younger age categories, females are more likely than males to develop cancer, however older generations have much lower cancer prevalence in women. The disparity between males and females is highest between the ages of 20 and 24, when girls have a 2.5-fold greater age-specific occurrence than adolescents.

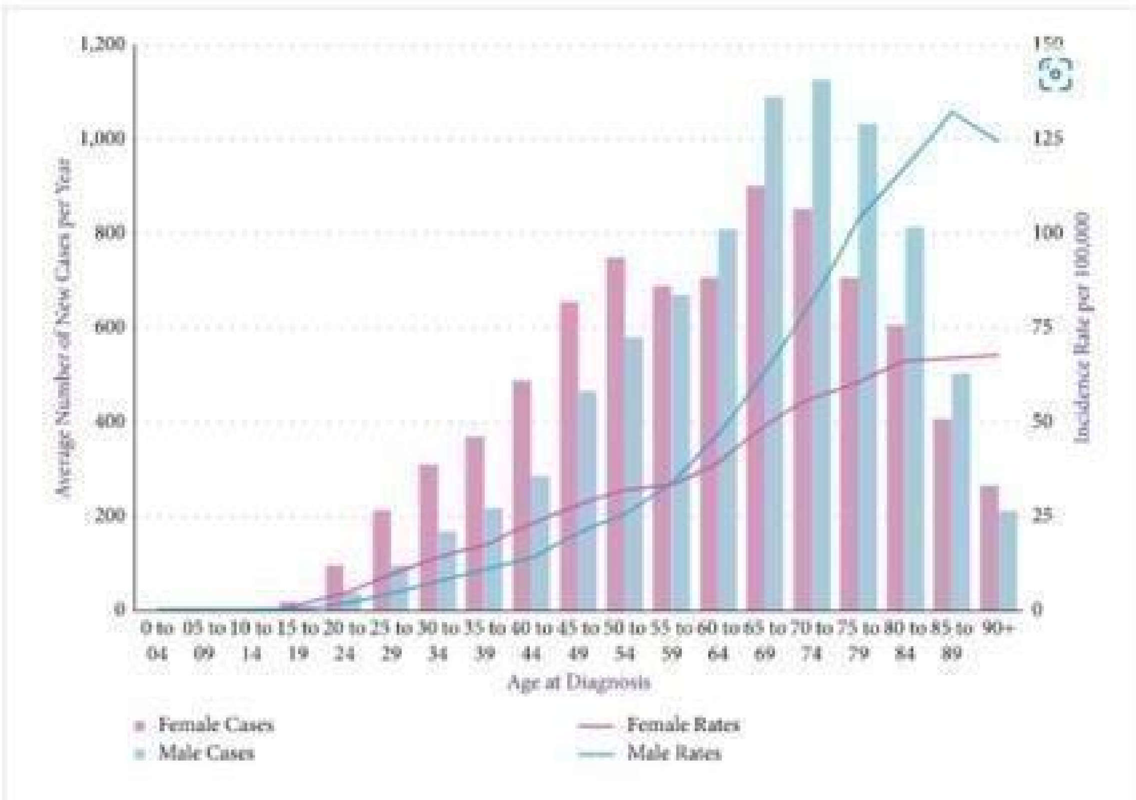

Figure 2.1 Comparative Analysis and Summary

There are many dreadful diseases in the contemporary world. Skin cancer is one of them. In the human body, skin cancer cells develop and spread like tumors. If not treated, this tumor has the potential to spread to other body tissues and organs, which can be fatal. Although expensive and time-consuming procedures are used to treat skin cancer, the mortality rate has not decreased. The risk of death can be decreased by finding skin cancer early. The answer has been discovered via the machine learning (ML) model. Using picture categorization, Deep Learning, particularly the Convolution Neural Network, can be used to promptly and reliably identify skin cancer. For the underprivileged, it has become a lifesaver.[14] When it comes to image classification-based skin cancer detection, these ML models are quicker and more accurate. Today's globe is seeing advancements in medical research. Skin cancer used to be manually detected, which was time-consuming and expensive. However, it has gotten simpler as a result of deep learning's growth in the field of medical science. The CNN is suggested in the systems of this study to identify skin cancer as a result.

2.4 Scope of the Problem

Individuals with persistent actinic damage who are vulnerable are more likely to acquire severe skin malignancies due to the long-term immunosuppressant required for transplantation. The risk factors linked to skin cancer should be assessed in transplant candidates. To reduce the morbidity and mortality from NMSC, those who are at risk should be informed about the precautions for and the significance of attentive UVR protection, frequent skin self-examination, and regular dermatologic evaluation. Skin malignancies should be actively treated, especially SCC. Candidates for retinoid chemoprevention may include those who are actively developing several malignancies.

While a person's risk may be raised by hereditary factors like fair skin or a family history of skin cancer, exposure to UV radiation is also closely linked to the most common types of skin cancer. Additionally, by far avoidable cause of skin cancer is UV exposure.[15] Skin cancer is more likely to occur in some people than in others due to certain hereditary risk factors. Having lighter skin naturally, blue or green eyes, blond or red hair, dysplastic nevi (a type of unusual mole), or a lot of common moles, as well as skin that burns, freckles, or reddens easily, or becomes painful after spending a lot of time in the sun, are all genetic risk factors for developing skin cancer. Melanoma risk may be notably elevated in people with red hair. Additionally, those who have a personal or family history of skin cancer, particularly melanoma, are at a higher risk.[16]

2.5 Challenges

The possibility of skin cancer recurring after therapy can be concerning. It is known as a recurrence. Recurrence of skin cancer is quite typical. Although skin cancer recurrence is frequent, that does not make it simple to treat. In reality, community members tell us that it is a more difficult task than most people know. Although melanoma is less frequent than other forms of skin cancer, it is thought to be more hazardous if left untreated. Those who have had melanoma are more likely to have it again or to get another type of skin cancer. Skin cancer of the most prevalent kind is basal cell carcinoma (BCC).[17] It is typically simple to treat. Although basal cell carcinoma seldom spreads, it can come back in the same spot. BCC patients are more likely to get a recurrence.

The challenges with skin cancer are numerous. Like as

ISIC Challenges

The International Skin Imaging Collaboration (ISIC) is a leading force in offering automated CAD solutions for the early diagnosis of melanoma and other malignancies using digital skin lesion image datasets with expert interpretations globally. By increasing the accuracy, sensitivity, and specificity of early diagnosis of melanoma and other skin cancers, this community's main objective is to decrease the number of biopsies and fatalities associated with skin malignancies.[18] To increase the engagement of researchers and raise awareness of skin cancer, this community also conducts the annual skin lesion challenges. The quantity of skin lesion photos and classifications is growing yearly.

The Segmentation Challenges:

Regardless of the nature of skin lesions, the skin segmentation issue entails segmenting lesion borders. Our paper's scope is restricted to AI solutions for lesion diagnosis, even though segmentation of skin lesions is essential to help dermatologists give insights into the many features and qualities of skin lesions, such as the ABCD rule. Consequently, we excluded any research on the single class segmentation problem [19].

AI Challenges

The benchmarks of well-known Computer vision datasets have recently been surpassed by deep learning techniques; the skin lesion diagnostic issue might follow a similar path. The skin lesion diagnostic problem is more sophisticated than challenges in non-medical areas like ImageNet, PASCAL-VOC, and MS-COCO as we strive to pursue it. There are commonalities within classes and variances throughout categories in terms of appearance, texture, intensity, distribution, and pattern of carious lesions. Deep learning methods frequently require a significant quantity of training information that encompasses each class of skin lesions and is diverse, balanced, and of exceptional quality in order to boost diagnostic accuracy.

Performance of deep learning and unbalanced datasets:

Living with skin cancer may make it difficult to navigate daily life. Self-examinations, testing, medical visits, and recurrent therapy may be exhausting, depleting, and a waste of time. The consequences of skin cancer therapy and its side effects might interfere with everyday activities, employment, and social interactions.[21] As is frequently observed in the various publicly accessible datasets for skin lesions, the effectiveness of deep learning methods depends more on the caliber of picture datasets than on modifying the hyper-parameters of networks. Malignant skin lesions are less common than benign skin lesions overall. The majority of deep learning architectures are developed using balanced datasets, such as ImageNet, which has 1000 classes and 1000 photos per class.[22] Therefore, despite applying tuning techniques like a erroneous negatives are punished discovered in small skin lesion classes during training using bespoke loss functions, the performance of a deep learning algorithm typically does not have balanced datasets.

Chapter 3

Research Methodology

3.1 Research Subject and Instrumentation

Our project concentrates on identifying skin cancers using machine learning, as I've previously indicated. We make use of Google Colab tools for programming. In Google Colab, we applied machine learning to the DenseNet201 model. Seven categories of skin cancer were demonstrated to be sufficiently accurate utilising the DenseNet201 model.[23] We can accurately determine the amount of skin cancer in our bodies as well as its classification. In this session various steps are considered, initial of all, Data pre-processed, noise-reduction, and transfer to TensorFlow appropriate format to train. After the gaining step then take a look at validate images and send images for testing. And we show the test image that we use randomly Python is the language that we used in our research. We use a high-level neural network API Keras as the framework. To work with Keras we need a backend for low-level operations. For this purpose, we had to install Tensor Flow in our anaconda development environment. We used pre-trained CNN algorithms. We used google collab for coding. We used the Matplotlib library for graph and confusion matrix visualization.

3.2 Data Collection Procedure

The International Skin Imaging Collaboration (ISIC) dataset was utilized. Dermatoscopic pictures from various populations that were collected and archived using various modalities are included in the dataset. In particular, in the area of skin cancer diagnosis and malignancy evaluation, the International Skin Imaging Collaboration (ISIC) datasets have emerged as a premier repository for researchers in machine learning for medical image analysis.[24] They include gold-standard lesion diagnostic information together with tens of thousands of dermoscopic images. The International Skin Imaging Collaboration produced 2357 photos of both malignant and benign oncological illnesses for this collection (ISIC). Additionally, we altered 2144 dermatoscopic pictures. The illnesses are nevus, seborrheic keratosis, basal cell carcinoma, melanoma, actinic keratosis, and vascular lesions.

Table 3.1 Detailed statistics of image collection

Label	No Of images	Image Format	Image Size
Actinic keratosis	363	jpg	224*224
Basal cell carcinoma	478	jpg	224*224
Dermatofibroma	130	jpg	224*224
Melanoma	477	jpg	224*224
Nevus	494	jpg	224*224
Seborrheic keratosis	457	jpg	224*224
Vascular lesion	166	jpg	224*224

In our dataset, there have seven categories of diseases and it contains 2144 dermoscopic images. We have divided the dataset into 80%, and 20%, respectively for Training, and Testing.

Table 3.2 The number of training, testing data for each classification

Label	Training set	Testing set
Actinic keratosis	300	63
Basal cell carcinoma	396	82
Dermatofibroma	106	24
Melanoma	405	72
Nevus	422	72
Seborrheic keratosis	385	72
Vascular lesion	130	36

The Whole system works like

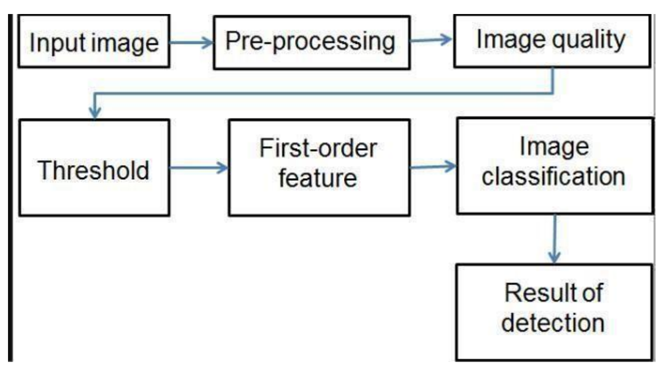

Figure 3.1 System Design

3.3 Statistical Analysis

Along with GLCM parameters contrast, energy, homogeneity, and correlation, the statistical parameters employed are mean, skewness, and kurtosis. The mean will display the average pixel value for the image.

The asymmetry of the pixel distribution will be revealed by the skewness, and the peaking will be revealed by the kurtosis. value of the pixels.[25] A measure of the intensity contrast between a pixel and its neighbor over the entire image is returned by the Contrast function. Using image and homogeneity, a value that gauges how closely the GLCM's element distribution adheres to diagonal GLCM The subsequent functions define these parameters:

$$\text{mean}(\mu)=\frac{\sum_{x=1}^{M}\sum_{y=1}^{N} I(x,y)}{M\times N} \tag{1}$$

$$Energy(e)=\frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N} I^2(x,y) \tag{2}$$

$$Skewness=\frac{\sum_{x=1}^{M}\sum_{y=1}^{N}(I(x,y)-\mu)^3}{M\times N\times\sigma^2} \tag{3}$$

$$Kurtosis(k)=\frac{\sum_{x=1}^{M}\sum_{y=1}^{N}(I(x,y)-\mu)^4}{M\times N\times\sigma^4} \tag{4}$$

Calculations based on the gray-level co-occurrence matrix (GLCM) or gray-level spatial dependence matrix are categorized as second-order statistics. A group of 14 textual features, which may be retrieved from the co-occurrence matrix and contain details regarding image textural properties including homogeneity, contrast, and entropy, were proposed by Haralick et al. Information about the locations of pixels with comparable gray level values is contained in a gray level co-occurrence matrix (GLCM).[26] A collection of potential image values are represented by both the rows and the columns of this two-dimensional array, P. The process of defining a GLCM Pd I j] involves first defining a displacement vector d = (dx, dy) and then counting all pairs of pixels with gray levels I and j that are separated by 'd'. Pd I j] = NIJ, where NIJ is the number of times the image's pixel values I j) located at distance d occur. Dimension n x n is the size of the co-occurrence matrix Pd, where n is the number of gray levels in the image. The co-occurrence matrix allows us to calculate the following statistics:

$$\text{Contrast} = \sum_{i\,j=1}^{n} P_d (i - j)^2 \tag{5}$$

$$\text{Homogeneity} = \sum_{i\,j=1}^{n} \frac{P_d}{1+|i - j|} \tag{6}$$

A measure of how linked a pixel is to its neighbor across the entire image is returned by the GLCM correlation function. For an image that is perfectly positively or negatively correlated, correlation is either 1 or -1.

3.4 Proposed Methodology

Our model is designed in phases as follows:

Input Image: A dataset made up of high-resolution dermoscopic pictures is used by the suggested system. Eight distinct classes from the ISIC 2019 challenge dataset are compressed into 800 photos and applied to the suggested system.

Pre-processing: The method utilized to acquire the images had to be irregular in a number of ways. The major goal of the preprocessing stage is to delete or decrease the undesirable elements of the image or the backdrop in order to enhance aspects like quality, clarity, etc. The highlights the fact techniques are noise reduction, picture enhancement, and grayscale conversion. All of the photographs in this suggested system are first made in grayscale. Thin en, for picture improvement and noise reduction, two filters—the Gaussian filter and the median filter—are applied. The Dull Razor Method is performed in conjunction with filters to get rid of the unwanted hair from the skin lesion.

Augmentation: pictures, such as flipping them horizontally or vertically, rotating them, shifting them horizontally or vertically, and zooming them, new data is created.

There are various alternative uses for this procedure that don't require more data. We can prevent the over-fitting of data by making several copies of the current data. Additionally, using data augmentation, we may balance the data of each class in the data set.

Transfer Learning: We used the data augmentation approach to enhance the volume of data that was processed. A pre-trained algorithm or model is applied to another dataset using the transfer learning approach of machine learning.[27] This method is utilized when there is not enough data to fully train the model. In such an instance, it would be advantageous if we used a trained version of the model. Here, we utilized a model, including DenseNet201, for the main purpose of the training model was to retrain the pre-trained CNN.

Convolutional Neural Networks are a widely used technique for boosting the precision of imagery recognition (CNNs for short). We know CNN (Convolutional Neural Network) is the largest deep AI used in image processing. The term “convolutional neural network” symbolizes that the network operates a mathematical operation called convolution. A convolutional neural network is an algorithm of artificial intelligence that takes images as input, assigns learnable weights to different objects of images, and can classify the images into their corresponding categories. CNN is almost similar to regular neural networks. It's built up of neurons that have learnable weights and biases. The connectivity of neurons is similar to the architecture of the human brain. The goal of despite losing the key qualities that are essential to making a systems are likely, CNN will condense the pictures into a version that is straightforward to interpret. [28] The reason for choosing this method for classifying images is that the pre-processing requirement is very low on CNN. Here’s a look at the key stages that help machines to identify patterns in an image:

Convolutional Layer: It’s the core major building block of a convolutional neural network. These layer parameters build a set of kernels or learnable filters, a small receptive field but stretch by the full depth of input. It is not only used in input data but it is also used for pixel values bandit can also be used in the output of other layers.

Max pooling: Max Pooling layer is used to minimize the size of the neurons. It executes the next operation after every Convolutional Layer. Implementing this layer is mostly done so to lower the amount of processing resources required to look into the information through data preprocessing. The maximal value from the zone of an output that the filter covers is returned by residual blocks.

Fully Connected Layer: Fully connected layer is the last layer of a convolutional neural network. This layer is attached to all preceding neurons. The main objective of this layer is to receive the result from all previous convolution or pooling layers and use them to complete the classification process.

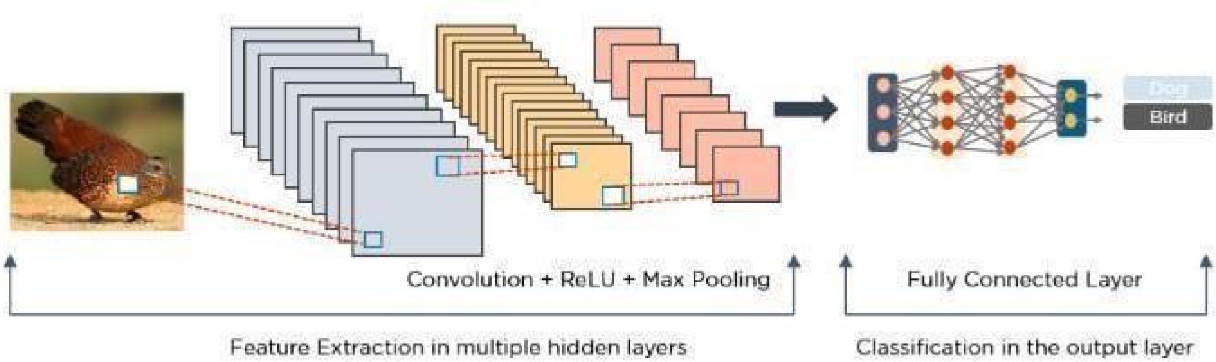

Figure 3.2 Example of an image processed via CNN.

Machine Learning models may be easily built, trained, and deployed thanks to the potent tool Tensor Flow. To process the images in our dataset, we employ the CNN Model. The CNN basics are shown in the image below. Convolutional neural networks are a class of deep neural networks used most frequently to analyze visual vision in deep learning. Multilayer perceptron often refers to fully connected networks, in which every neuron in one layer is coupled to every neuron in the following layer. The fundamental CNN model is shown in Fig.

Sample Architecture

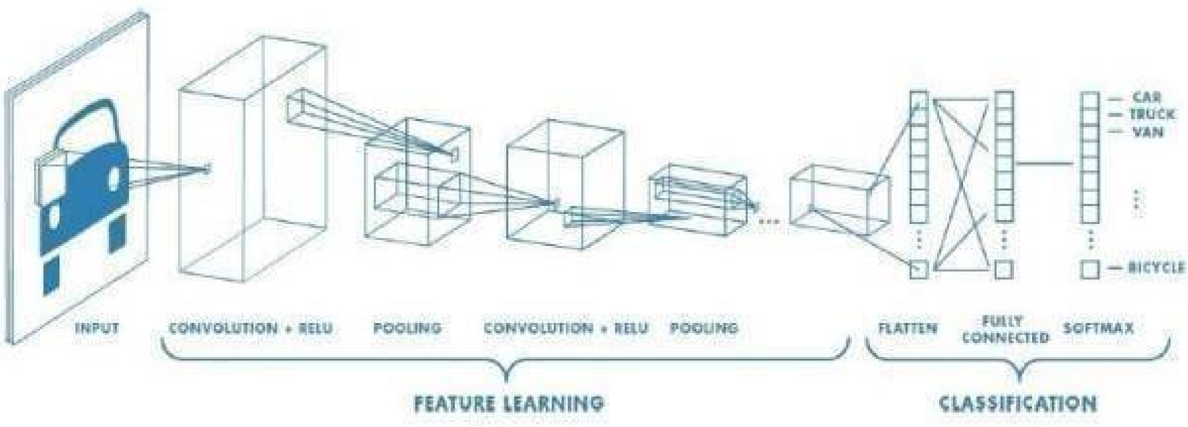

Figure 3.3 Basic CNN model

Model Architecture:

```
model.summary()
```

```
Model: "densenet201"
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==================================================================================================
 input_1 (InputLayer)           [(None, 224, 224, 3  0           []
                                )]

 zero_padding2d (ZeroPadding2D)  (None, 230, 230, 3)  0          ['input_1[0][0]']

 conv1/conv (Conv2D)            (None, 112, 112, 64  9408        ['zero_padding2d[0][0]
                                )

 conv1/bn (BatchNormalization)  (None, 112, 112, 64  256         ['conv1/conv[0][0]']
                                )
```

```
 conv5_block32_2_conv (Conv2D)  (None, 7, 7, 32)     36864       ['conv5_block32_1_relu[0][0]']

 conv5_block32_concat (Concaten  (None, 7, 7, 1920)  0           ['conv5_block31_concat[0][0]',
 ate)                                                              'conv5_block32_2_conv[0][0]']

 bn (BatchNormalization)        (None, 7, 7, 1920)   7680        ['conv5_block32_concat[0][0]']

 relu (Activation)              (None, 7, 7, 1920)   0           ['bn[0][0]']

==================================================================================================
Total params: 18,321,984
Trainable params: 18,092,928
Non-trainable params: 229,056
```

Figure 3.4 Architecture of DenseNet201

In our study, we employed a dataset on Skin cancer. We divided our dataset into two halves, with the training dataset receiving 80% of the data and the test dataset receiving 20%. Preparation and validation take happen at the same time. During training, we examined the influence of parameters [18] and fine-tuned them to build an accurate model. The following are the proposed CNN model assumptions are as follows: After the algorithms were tested on a set of skin malignant tumors, the reliability was assessed on a test set.

Table 3.3 Training Parameter

Batch-Size	16
Epoch	164
Training	80%
Testing	20%
Output Class	7
Input Shape	224*224*3
Train Samples	2144
Test Samples	421

3.5 Implementation Requirements

Follow the recommendations in NICE's guideline on improving outcomes for individuals with skin tumors, including melanoma, on communication, information provision, and support to assist people in making decisions about their care, in particular, the following 5 recommendations:

- All patients should have access to updated textual information that is ideally nationally standardized. Information should be repeated over time and should be suited to the patients' requirements at that moment in their diagnosis and treatment.[29] The provided information must be unique to the histological kind of lesion, the type of therapy, local resources, and any options within them, and it must address both physical and mental difficulties.

- The sharing of bad news and specific communication training should be provided to those who are directly involved in treating patients.

- "Patients should be encouraged to bring a companion to consultations," the statement reads.

- A skin cancer clinical nurse specialist (CNS) who will take the lead in assisting patients and caregivers should be a part of each LSMDT (local hospital skin cancer multidisciplinary team) and SSMDT (specialist skin cancer multifunctional team).

- All LSMDTs and SSMDTs ought to have access to services for patients with skin cancer who need psychological support.

Chapter 4
Experimental Results and Discussion

4.1 Experimental Setup

We go over the consequences of the penultimate step of the process using actual data in this volume. With our calculations, we were able to obtain rather pinpoint efficiency.

Table 4.1 Experimental Result

Serial No	Model	Accuracy
1	DEnseNet21	89%

4.2 Experimental Results & Analysis

Model Evolution:

This part is one of the most important parts of the training process. By evaluating the models, we can understand how our model is performing. We are showing the increasing graphs of training and validation accuracy for the model.

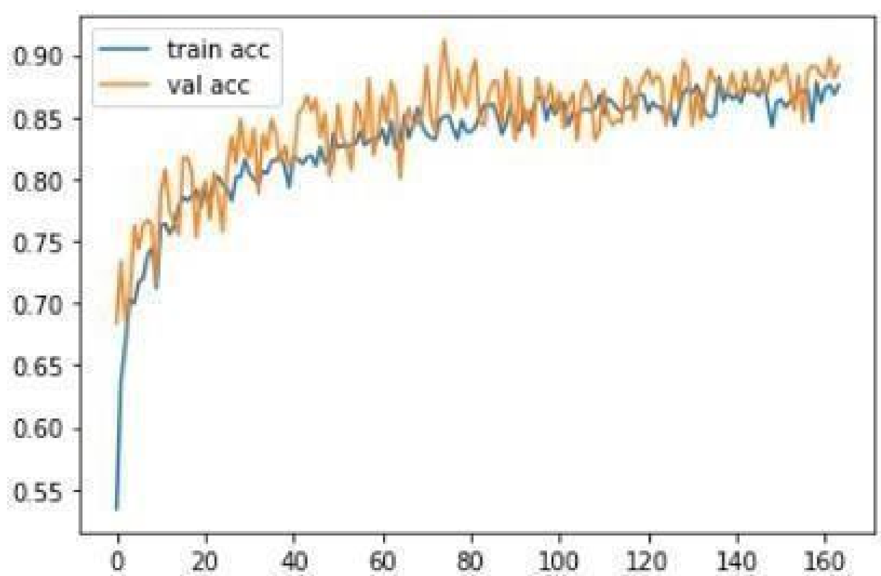

Figure 4.1 Training Accuracy

Below we also show the graph of validation and training loss for the model

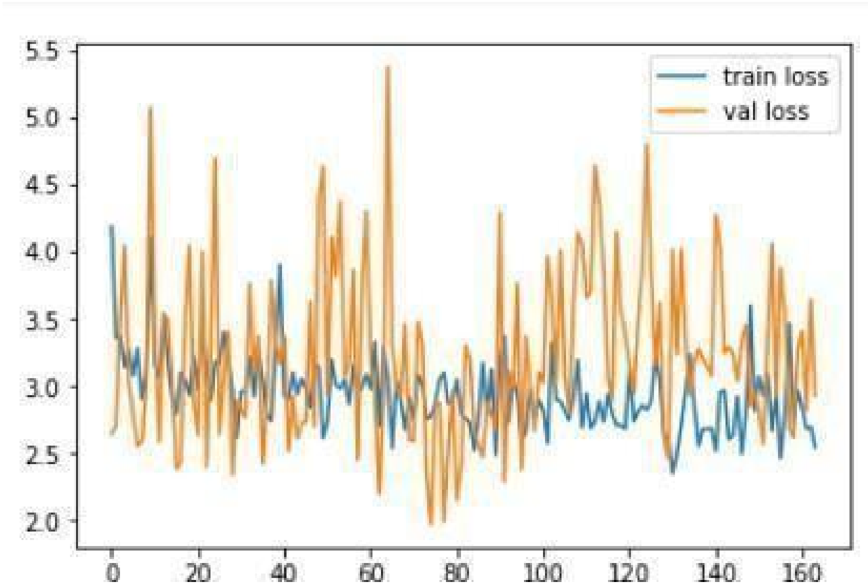

Figure 4.2: Training Loss

Accuracy The precision is stated for each epoch. Increasing the number of epochs enhances accuracy in this scenario.

```
Epoch 1/164
134/134 [==============================] - 67s 304ms/step - loss: 4.1834 - accuracy: 0.5345 - val_loss: 2.6470 - val_accuracy: 0.6841
Epoch 2/164
134/134 [==============================] - 28s 210ms/step - loss: 3.3534 - accuracy: 0.6371 - val_loss: 2.6969 - val_accuracy: 0.7340
Epoch 3/164
134/134 [==============================] - 32s 239ms/step - loss: 3.3688 - accuracy: 0.6674 - val_loss: 3.5080 - val_accuracy: 0.6865
Epoch 4/164
134/134 [==============================] - 29s 218ms/step - loss: 3.1368 - accuracy: 0.7034 - val_loss: 4.0420 - val_accuracy: 0.7078
Epoch 5/164
134/134 [==============================] - 28s 210ms/step - loss: 3.2713 - accuracy: 0.6996 - val_loss: 3.0256 - val_accuracy: 0.7625
Epoch 6/164
134/134 [==============================] - 28s 211ms/step - loss: 3.0785 - accuracy: 0.7174 - val_loss: 2.7878 - val_accuracy: 0.7435
Epoch 7/164
134/134 [==============================] - 28s 208ms/step - loss: 3.2793 - accuracy: 0.7201 - val_loss: 2.5523 - val_accuracy: 0.7625
Epoch 8/164
134/134 [==============================] - 29s 214ms/step - loss: 2.9019 - accuracy: 0.7388 - val_loss: 2.5882 - val_accuracy: 0.7672
Epoch 9/164
134/134 [==============================] - 28s 208ms/step - loss: 3.0892 - accuracy: 0.7444 - val_loss: 2.9848 - val_accuracy: 0.7625
Epoch 10/164
134/134 [==============================] - 28s 207ms/step - loss: 4.1039 - accuracy: 0.7122 - val_loss: 5.0634 - val_accuracy: 0.7173
Epoch 11/164
134/134 [==============================] - 28s 206ms/step - loss: 3.1551 - accuracy: 0.7621 - val_loss: 3.3518 - val_accuracy: 0.7886
Epoch 12/164
134/134 [==============================] - 28s 209ms/step - loss: 3.0644 - accuracy: 0.7640 - val_loss: 2.5828 - val_accuracy: 0.8076
Epoch 13/164
134/134 [==============================] - 28s 206ms/step - loss: 3.5290 - accuracy: 0.7556 - val_loss: 3.5360 - val_accuracy: 0.7743
Epoch 14/164
```

Fig 4.3 Accuracy

```
Epoch 151/164
134/134 [==============================] - 27s 203ms/step - loss: 3.0712 - accuracy: 0.8643 - val_loss: 2.8060 - val_accuracy: 0.8812
Epoch 152/164
134/134 [==============================] - 28s 208ms/step - loss: 2.9268 - accuracy: 0.8577 - val_loss: 2.5653 - val_accuracy: 0.8931
Epoch 153/164
134/134 [==============================] - 27s 203ms/step - loss: 3.0857 - accuracy: 0.8624 - val_loss: 3.3674 - val_accuracy: 0.8741
Epoch 154/164
134/134 [==============================] - 29s 219ms/step - loss: 2.6665 - accuracy: 0.8638 - val_loss: 4.0568 - val_accuracy: 0.8551
Epoch 155/164
134/134 [==============================] - 27s 202ms/step - loss: 2.9507 - accuracy: 0.8711 - val_loss: 2.9115 - val_accuracy: 0.8836
Epoch 156/164
134/134 [==============================] - 27s 203ms/step - loss: 2.4624 - accuracy: 0.8699 - val_loss: 3.8765 - val_accuracy: 0.8456
Epoch 157/164
134/134 [==============================] - 27s 202ms/step - loss: 2.7922 - accuracy: 0.8727 - val_loss: 3.5349 - val_accuracy: 0.8860
Epoch 158/164
134/134 [==============================] - 27s 202ms/step - loss: 3.4634 - accuracy: 0.8465 - val_loss: 2.6867 - val_accuracy: 0.8907
Epoch 159/164
134/134 [==============================] - 27s 203ms/step - loss: 2.7202 - accuracy: 0.8783 - val_loss: 2.6161 - val_accuracy: 0.8907
Epoch 160/164
134/134 [==============================] - 27s 204ms/step - loss: 2.9635 - accuracy: 0.8615 - val_loss: 3.2702 - val_accuracy: 0.8836
Epoch 161/164
134/134 [==============================] - 27s 203ms/step - loss: 2.8388 - accuracy: 0.8731 - val_loss: 3.4055 - val_accuracy: 0.8812
Epoch 162/164
134/134 [==============================] - 28s 208ms/step - loss: 2.6810 - accuracy: 0.8759 - val_loss: 2.8139 - val_accuracy: 0.8979
Epoch 163/164
134/134 [==============================] - 28s 209ms/step - loss: 2.6925 - accuracy: 0.8680 - val_loss: 3.6395 - val_accuracy: 0.8812
Epoch 164/164
134/134 [==============================] - 28s 208ms/step - loss: 2.5419 - accuracy: 0.8755 - val_loss: 2.9279 - val_accuracy: 0.8907
```

Figure 4.4: Accuracy

Here batch size is 16 and epochs are 164.

Confusion matrix: A regression model may be used to assess the effectiveness of the classifier models are executing. We can swiftly see how much information we accurately and erroneously identify. The confusion matrix for each of our three models is therefore illustrated below:

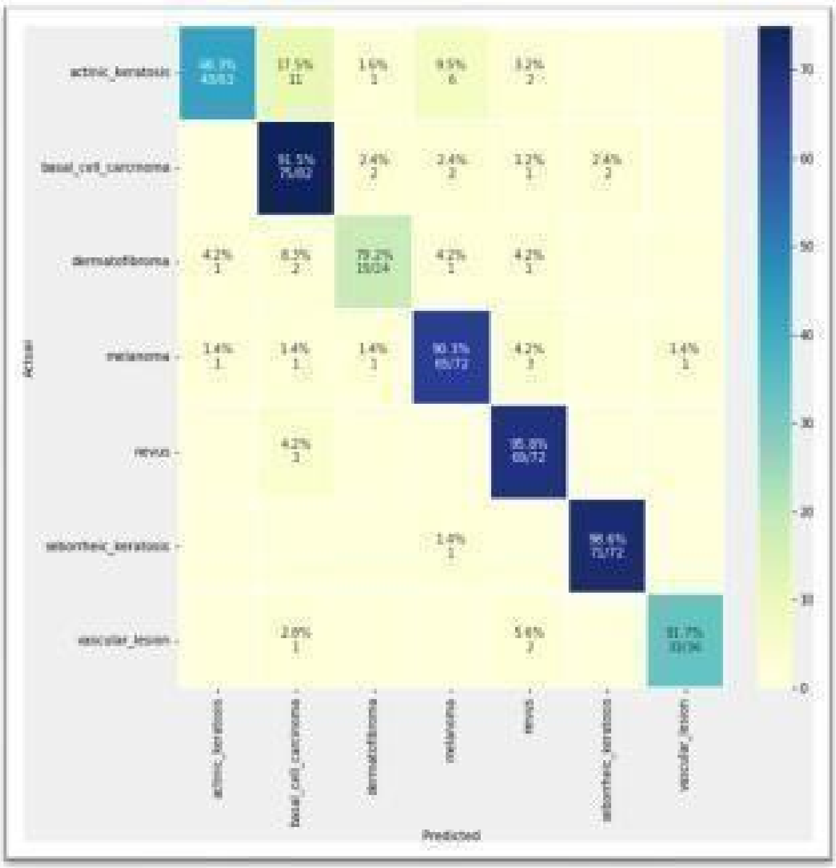

Figure 4.5: Confusion Matrix for DenseNet201

Classification report: The correctness of assumptions made by a categorisation algorithm is examined using a classification report. how many forecasts come true and how many come truer. More explicitly, the metrics of a categorization assessment are predicted using True Positives, False Positives, True Negatives, and Incorrectly Classified as illustrated below: Here is a discussion of how accuracy, recall, and f1-score are ordered before that.

Precision: Precision means out of all the positive classes we have predicted correctly, how many are positive. Precision = True positive / (True Positive + False Positive).

Recall: It represents that out of all the positive classes, how much we predicted correctly. The higher values represent the better quality of the model. Recall = True positive / (True Positive + False Negative).

F1-score: Retention and sharpness are both quantitatively measured by the F-score. Rather than employing Geometric Mean, it employs Waveform Mean. F1-score is proportional to (recall + precision)/(2*recall*precision).

Report on Classification: Between the skin cancer classes, precision, recall, f1-score, and accuracy are shown. With this model, we were able to achieve an 89 percent accuracy rate.

Classification Report:

	precision	recall	f1-score	support
actinic_keratosis	0.96	0.68	0.80	63
basal_cell_carcinoma	0.81	0.91	0.86	82
dermatofibroma	0.83	0.79	0.81	24
melanoma	0.87	0.90	0.88	72
nevus	0.88	0.96	0.92	72
seborrheic_keratosis	0.97	0.99	0.98	72
vascular_lesion	0.97	0.92	0.94	36
accuracy			0.89	421
macro avg	0.90	0.88	0.88	421
weighted avg	0.90	0.89	0.89	421

Figure 4.6: Report on Classification for DenseNet201

View Test Scene Cancer Test Data: Here we have used a graph through which A class of skin cancer can detect the image of a specific class of skin cancer if it can detect then the result will be true, And if it cannot detect then the result will be false.

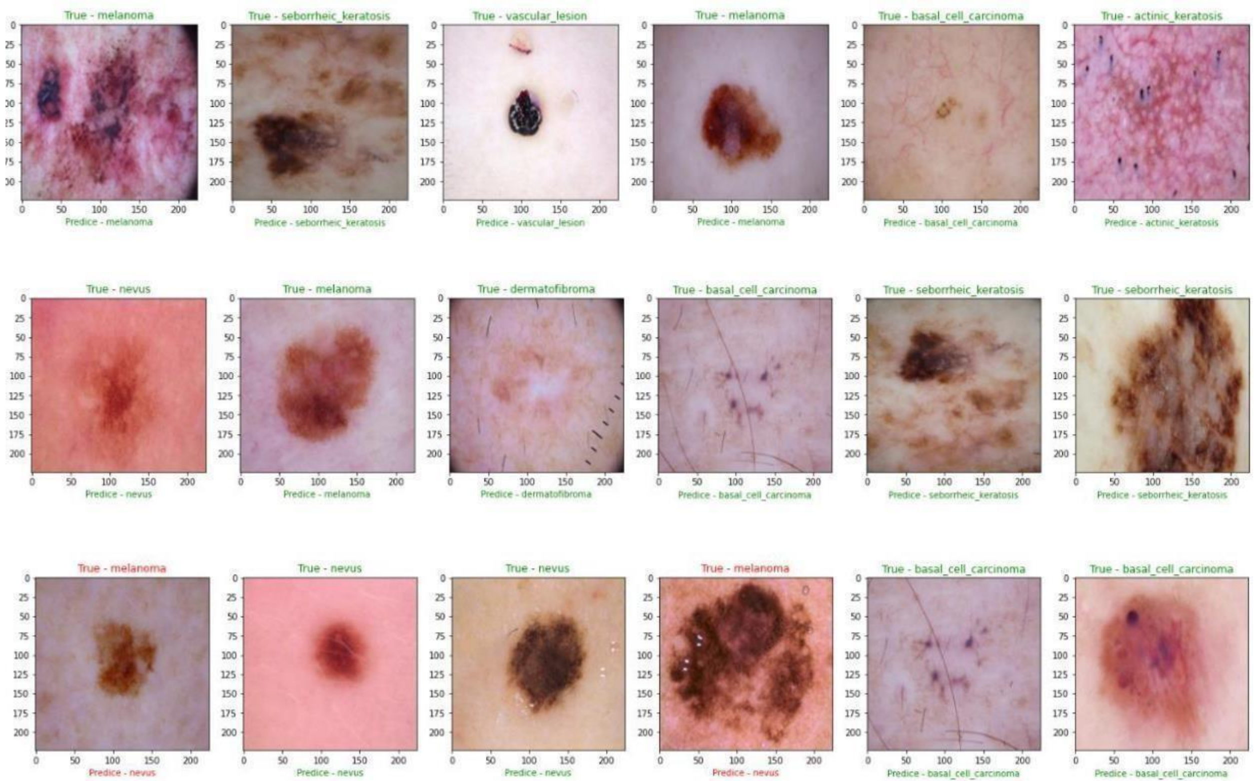

Figure 4.7: Cancer testing data

4.3 : Discussion

Here we divided the dataset into two parts, training and testing, in training we use 80% data and in training, we use 20% data and our accuracy is 89%. We use 16 batches and 164 epochs. We also test the class to find out if the class predicts itself or not. If it predicts then the result will be true otherwise false. Thus we have given a graphical view.

Chapter 5

Impact on Society, Environment, and Sustainability

5.1 Impact on society:

After acquiring a diagnosis of cancer, you could have emotional and social repercussions. This could include decreasing your psychological stress or confronting painful experiences like sadness, concern, or hostility. It might be a challenge for individuals to convey their feelings to their loved ones at times. Some people have discovered that speaking with an oncology social worker, counselor, or clergyperson can help them come up with better coping mechanisms and cancer-related communication strategies.

The cost of cancer therapy might be high. For those who have cancer and their families, it is frequently a significant cause of worry and anxiety. Many patients discover they have additional, unforeseen fees linked to their care on top of the cost of their therapy. Due to the high cost of medical care, some patients are unable to continue or finish their cancer treatment plan. This might endanger their well-being and result in future expense increases.[30]

5.2 Impact on environment:

Melanoma and non-melanoma skin cancer incidence rates are both sharply rising globally. Skin cancers with basal and squamous cells are known to be caused by exposure to UVB radiation in a dose-dependent manner, and the loss of stratospheric ozone may result in an increase in biologically harmful solar UVB radiation reaching the earth's surface.[31] As well as causing lung, bladder, liver, and kidney cancer in people, arsenic is also known to cause skin cancer. In various parts of the world, exposure to high arsenic concentrations in drinking water has been documented.

The first step in preventing skin cancer is to have an improved understanding of the etiological variables. It is generally recognized that the sun's ultraviolet (UV) radiation is the fundamental factor in the development of skin cancer. Cumulative damage from sunburns, excessive sun exposure, and tanning beds result in immunosuppression, which plays a role in the pathogenesis of skin cancer.[32] The amount of UV radiation that reaches the earth's surface is influenced by the ozone hole, latitude, height, UV light levels, and weather. Additionally, skin cancer has been linked to environmental toxins, chemical carcinogens, and occupational carcinogen exposures.

There is worry over the rising rate of skin cancer around the world. Epidemiological research in white populations has shown a link between rising rates of skin cancer and UV radiation exposure. In actuality, Caucasians who live close to the equator accounted for the majority of the population growth. The radiative transfer model TUV was used in Beijing to study the link between surface UV radiation and the number of air pollutants (Tropospheric Ultraviolet-Visible).[33] According to the data gathered for this study, the average total ozone concentration is greater in the winter and spring and lower in the summer and fall. On the other hand, the average total ozone concentration and UV radiation levels at ground level are inversely related.

An important first step in their prevention is to have a better understanding of the causes of melanoma and non-melanoma skin cancer since their incidence rates are significantly rising globally. Sadly, despite the wealth of information available on skin carcinogenesis, prior studies have been unable to identify all of the environmental risk factors for skin cancer. More research is also necessary to determine the potential impact of additional potential risk factors and to implement preventative methods based on avoiding them.

5.3 Ethical aspects:

It takes years, if not decades, for cancer research to go from the lab to clinical trials and then from there to knowledge translation into clinical practice. A novel hypothesis of illness prevention, diagnosis, and therapy frequently has a very low statistical likelihood of being successful. The existing body of knowledge, however, is the result of a vast array of research endeavors.[34] Clinical scientists are required by the ethical standards of biomedical research to inform their study participants about the potential negative effects and potential ineffectiveness of the new intervention being considered. Neither the counselor's nor the client's task is simple.

Additionally, comparable to other disorders, the possibility of partaking in a medication treatment for the treatment of cancer is massively greater. The disadvantaged demographic, who would not otherwise be able to afford the therapy, benefits from this on the one hand, but it also creates a big ethical dilemma when the clinical trial is over and the consumer is unable to acquire the same pharmaceutical.

The method of informed permission and who can consent on behalf of a palliative patient, who is frequently ineligible to assent owing to loss of comprehension, are further ethical issues in research on the terminally ill. Additionally, the patient or family of a terminally ill patient can feel compelled to contact the researcher, which could lead to unintentional or unwillingly forced consent. Due to inadequate funding, palliative care standards of treatment are more likely to be subpar than in other disciplines. Since it might be challenging to treat such issues clinically, this may raise ethical concerns for researchers in the field.

5.4 Sustainability Plan:

A key objective for public health is sustainability, or the maintenance of a program and its core values when financing and outside assistance have ended. Given the substantial resources invested in the creation and assessment of preventive programs, it is crucial to pay more attention to how well evidence-based initiatives translate and maintain their impacts over time in at-risk groups.[15] By concentrating on early identification and prevention, occupational preventive programs can address the rising prevalence of skin cancer. Health professionals advise people to prevent becoming sunburned and tanning, limit their time in the sun during the daytime and use protective caps, clothes, and sunscreen.

Outdoor workers' skin cancer prevention is still a significant public health concern. More than 3.5 million nonmelanoma skin cancer cases and 76,250 melanoma cases were identified in the US in 2012, resulting in 2000 and 9180 fatalities, respectively. Australia, Austria, Brazil, Britain, Canada, Germany, New Zealand, Switzerland, and the United States all performed research in workplace settings. indicating that exposure to ultraviolet (UV) radiation, the main cause of skin cancer, is significant and frequently excessive for outdoor workers.[22]

Chapter 6:

Summary, Conclusion, Recommendation, and Implication for Future Research

6.1 Summary of the study:

Skin cancer occurs unregulated tissue proliferation of aberrant cells in the epidermis, the skin's outermost barrier, as a result of unrepaired DNA damage that produces mutations. These alterations lead to the rapid proliferation of skin cells and the formation of malignant tumors. The majority of skin malignancies are brought on by excessive UV (ultraviolet) radiation exposure.[29] You may shield your skin against UV radiation from the sun and from man-made sources like tanning beds and sunlamps to reduce your chance of developing skin cancer. Cancer is a condition in which the body's cells proliferate unchecked. Skin cancer refers to cancer that first appears on the skin.

In the US, skin cancer is the most prevalent type of cancer. Although some people are more likely to get skin cancer than others, everyone can. Overexposure to ultraviolet (UV) light, whether from the sun or man-made sources like tanning beds, is the greatest avoidable cause of skin cancer. The majority of skin malignancies are brought on by excessive UV (ultraviolet) radiation exposure. [12] You may shield your skin against UV radiation from the sun and from man-made sources like tanning beds and sunlamps to reduce your chance of developing skin cancer.

6.2 Conclusions:

The most prevalent carcinoma, which affects millions of individuals globally, is skin cancer. Skin cancer is becoming a more significant hazard to the public's health as its prevalence rises. Skin cancer is more likely to occur when several endogenous and exogenous risk factors are present. Numerous risk factors might be crucial prognostic indicators and contribute to the illness. A summary of epidemiology and risk elements Identify skin cancer early, keep an eye on patients' skin, have a high index of suspicion about any lesions that might indicate an elevated risk for skin cancer, and work to improve patients' health by lowering modifiable risk factors. Skin cancer is one of the most prevalent cancer in the globe because of variations in the surroundings that exposure skin to UV radiation. Skin mortality rate are on the rise, which is commonly attributed to environmental and hereditary reasons. Basal cell carcinoma, squamous cell carcinoma, and melanoma are the three most prevalent kinds of skin cancer. Depending on the patient's age and location, each variety has a unique dynamic and therapy. Skin malignancies may be treated with anti-cancer drugs, chemotherapy, radiation, and surgery. Nowadays, surgical removal is common, but it needs careful care following the procedure. The prevalence of skin cancer has been steadily rising over time. Early-stage skin cancer can be easily treated with straightforward techniques or procedures, while advanced skin cancer cannot be properly treated with any drugs. Therefore, early illness detection and treatment are necessary. Skin BCC accounts for 80% of all cases of skin cancer, followed by SCC (16%) and melanoma (4%). Skin cancer is mostly caused by UV-A and UV-B rays. Because they are frequently exposed to skin malignancies, outdoor workers are more likely to develop the disease. Therefore, it is necessary to take precautions like using sunscreen lotion.

6.3. Implications for Upcoming Studies:

We can expand the categories in the next studies and concentrate on sub-class categorization. These models may also be used to train using other medical resources because they can distinguish objects in any image. Convolutional neural networks need to be studied more thoroughly. High-dose-rate brachytherapy, a nonsurgical procedure, may be an option for some skin cancer patients, according to recent studies. According to researchers, elderly people and other patients who could have difficulties following surgery may benefit more from this radiation therapy. The sun's UV radiation, which is proven to be the primary cause of 86 percent of skin cancer cases in the nation, is the greatest risk factor for developing skin cancer. Exposure to artificial UV radiation from indoor tanning beds and/or lamps is the second most frequent cause. We will therefore significantly limit UV radiation in the future.

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