

**A DEEP LEARNING-BASED APPROACH FOR MELANOMA SKIN CANCER
DISEASE**

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This Report Presented in Partial Fulfillment of the Requirements for the
Degree of Masters of Science in Computer Science and Engineering.

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APPROVAL

This Project/Thesis titled “**A DEEP LEARNING-BASED APPROACH FOR MELANOMA SKIN CANCER DISEASE**”, submitted by **Quazi Zayed Bin Hasan**, ID No: **213-25-055** to the Department of Computer Science and Engineering, Daffodil International University has been accepted as satisfactory for the partial fulfillment of the requirements for the degree of M.Sc. in Computer Science and Engineering and approved as to its style and contents. The presentation has been held on **21st September 2022**.

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I hereby declare that, this project has been done by me under the supervision of **Dr.Md Zahid Hasan, Associate professor, Department of CSE**, Daffodil International University. I also declare that neither this project nor any part of this project has been submitted elsewhere for award of any degree or diploma.

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ABSTRACT

Skin cancer is the maximal rapid cancer in the white pool worldwide. Incidence of basal cell carcinoma (BCC), squamous cell carcinoma (SCC) and malignant melanoma (MM) is nevertheless thriving. This bias can be remedied by sake of elemental and accessory forbearance forasmuch as the principal gamble multiplication for skin cancer UV-radiation is known and express unearth, skin cancer can be cured practically. This paper dosage with a metering on a several computerized exploration dilution for diagnosing melanoma.

These dilution gist several parameters, for example shape, size, surface, shading and diverse belongings of lesions which is take advantage of superfluous battue. The accurate skin influenced territory which is the skin lesion or bounds of conspiracy will be aching out for automated medical mode.

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CHAPTER 1

Introduction

1.1 Introduction

Melanoma is much less not unusual place than different forms of pores and skin cancer, however it's far much more likely to develop and spread. If you've got cancer or had been round a person with cancer, understanding what to anticipate assist you to preserve it beneath neath control. Here, you could examine all approximately cancer, which includes hazard factors, symptoms, detection methods, and treatments.

Melanoma is most cancers that start inside melanocytes. Other names for this cancer include melanoma and skin cancer. However, because most cancer cells produce the pigment melanin, cancerous tumors are usually brown or black. However, some melanomas no longer produce melanin and may appear pink, brown, or white. Melanoma is most cancers that start inside melanocytes. Other names for most of these cancers include melanoma and skin cancer. However, most cancer cells produce melanin, so cancerous tumors are usually brown or black. However, some melanomas no longer produce the pigment melanin and may appear pink, tan, or white. Melanoma can occur anywhere on the skin, but is more common on the trunk (chest and back) in men and on the legs in women. The neck and face are in different positions, nothing special. Dark skin reduces the risk of cancer in these most common areas, but anyone can get cancer on the hands, soles, or under the nails. Melanoma in this region has a much higher rate of melanoma in African Americans than in Caucasians. Melanoma can also form in other parts of the body, including the eyes, mouth, genitals, and anus, but is much less common than skin cancer.

The most common signs of cancer are the appearance of new moles or replacement of existing moles. It can appear anywhere on the body, but it most commonly affects the lower back in men and the legs in women. Melanoma rarely develops in areas that could be covered by the sun's rays, including the buttocks and scalp.

In most cases, melanoma is irregular in shape and comes in more than one color. Moles may become larger than usual and may sometimes itch or bleed. Look for moles that can gradually change shape, length, or color.

About 16,000 new cancer cases are registered each year. More than a quarter of skin cancers are diagnosed under the age of 50, which is surprisingly early compared to most other cancers.

Although melanoma is not always preventable, avoiding sunburn (and even sunburn in some cases) can reduce the chance of developing melanoma.

1.2 Problem Statement

Peak skin cancer is the fastest growing cancer among Caucasians worldwide. The incidence of basal cell carcinoma (BCC), migratory squamous cell carcinoma (MCC), and malignant melanoma (MM) is independent of treatment success. This bias can be adjusted for baseline and random gains for large volumes due to the fact that the product of significant risk for skin cancer is maximal. It is known and accurate and can actually cure the largest number of skin cancers. This article includes automated testing of multiple probe dilutions for the diagnosis of melanoma. This dilution is required for several parameters such as shape, size, surface, color tone, and the diverse arrangement of lesions that benefit from excessive rhythm. The precise areas are defined as pores and skin, which are the actual damaged skin or area boundaries that can be compromised in self-clinic therapy.

1.3 Research Objectives

- a) To review the shortcomings of purely vision-based structural studies of superior devices for efficient classification of single skin cancers and most skin cancers within their classes .
- b) Practice a technique based entirely on the honesty system's vision to improve accuracy to keep them clear on their caste.

1.4 Research Questions

- a) How can we test for defects in the governing system with only the idea of a structure that can successfully classify special types?
- b) How can systems vision-only methods be improved to improve the accuracy of successfully distinguishing specific mold varieties from types?

1.5 Report Layout

Chapter 1 provides an introduction to the study, the purpose of the study, and the main questions.

Chapter 2 A thorough review of the relevant literature is emphasized.

Chapter 3 the proposed method is described with a detailed description.

Chapter 4 Describe evaluation of the end result and compare it to your current work.

Chapter 5 Study Fate to complete the same effect study.

CHAPTER 2

Literature Review

2.1 Related works

In the past, many researchers have repeatedly tried patented methods for melanoma skin cancer, with no good results. Melanoma is the most unstable form of skin cancer of the upper jaw. Most cancers are the most localized, with 4% of the most common cancers. However, it accounts for 75% of all skin cancer deaths. Melanoma should be treated early and [01] will recover easily by now. However, if not diagnosed early, it spreads deep into the pores and skin. It is also independent of all individual elements of the body. Melanoma is also known as the most malignant neoplasm. It produces colors like pink, red, black or white, blue, etc. Most cancers, mostly black or brown, can occur [02] anywhere on the body. It is mainly localized on the head, neck, soles of the feet and near the nails. It grows faster than various menopausal cancers. This article claims the effectiveness of detecting and analyzing this type of melanoma skin cancer [03]. The disease is characterized by the use of an unstable gene pool and the accumulation of many alternative molecules. Current diagnostic categories no longer reduce tumor heterogeneity. This is not enough to expect effective treatment. Lesions were extracted to classify the lesions as malignant features. This is done using segments. Most patients in the world suffer from cancer of the upper jaw. Treating cancer of the upper jaw can be very painful. All cancers of the upper jaw have stages. At each stage, the maximum arm changes.

Most skin cancers today are considered the deadliest form of cancer found in humans. Most skin cancers are identified into several categories, including melanoma, basal cell carcinoma, and squamous cell carcinoma, of which melanoma Unpredictable peaks. Early detection of most melanomas can help with treatment [04]. It may play an important role in medical imaging, and this has been demonstrated in many modern systems.

We propose a computerized approach to the detection of skin melanoma using imaging equipment. An image of the skin lesion is put into the camera and then analyzed using a

new image processing method. It puts an end to pores and most skin cancers. Imaging equipment examination for lesion evaluation of multiple malignancies Evaluate texture, length and shape for shooting to evaluate[05] parameters such as asymmetry, contour, color, diameter (ABCD), etc. Segment and Characteristic Steps. The extracted feature parameters are used to classify the image into normal skin and skin with pores. Melanoma is the most cancerous lesion.

To distinguish between benign and malignant pigmented skin lesions, automated techniques have been improved to capture images with a single device that is at most a traditional virtual camera. In this study, a completely new method to detect malignant cancer from benign pigmented lesions using macroscopic imaging is presented. Images are captured through a traditional virtual camera with a spatial resolution greater than one megapixel and through the medium of unconstrained thinking and unique situations at a certain stage of imaging[06]. As suggested, new strategies to minimize the effects of uneven illumination, modulate the effects of thick hairs and large luminescence in the lesion area, as well as a whole new set of segmentation rules based on above the threshold shown. 187 features representing asymmetry, contour irregularities, color variations, diameters and textures were extracted from the lesion site and after feature diversity reduction using analysis. In primary factor analysis (PCA), lesions were determined as malignant or benign using a classification aid vector device. Depending on the dermatologist's diagnosis, the proposed treatment strategies are capable of detecting the location of the lesions with high accuracy. The type evaluation measurements show that thirteen features extracted by PCA technique lead to higher consequences than all extracted features[07]. These consequences were accuracy 82.2%, sensitivity 77%, and specificity 86.93%. The proposed technique can also help dermatologists detect first-degree internal malignancies due to minimal limitations at a certain imaging stage, the advantage of using these means orthodox and non-expert, and high accuracy in lesion type detection.

2.2 Scope of the Problem

Researchers have tried for decades in various ways to detect skin cancers, with most cancers relying solely on skin's shape, color, odor, and secretions, but they did not produce any quality results. There are more than 200 special forms of most cancers found in the world as melanoma. Several studies have noted that to identify most cancers, this tool relies on an understanding of the past history that people take in, and it has so far been a completely ineffective process. Results in time. Some of the works documented the software entirely on web or mobile platforms that they did not have enough information to successfully classify most of their cancers. Some researchers point to the prevalence of toxic levels in some types of cancer and the use of the device for research methods. Some studies specifically aim to classify most cancers using service-learning methods, and some have identified distinct class predictors as benign and malignant.

2.3 Challenges

There are several research projects focused on this study.

- a) **Data Collection:** There are no reference data sets available online for classification. Therefore, establishing a photographic record in the field of skin cancer has become a very difficult task.
- b) **Raw Image Processing:** The full image of the special reagent is sometimes inflated, which makes it really clean. So it's your business to collect the most complete images and improve your categories through scores and noise.
- c) **Select Machine Learning Approach:** Some researchers use unique systems to know strategies for easily completing tasks. Therefore, by choosing the system that is most advantageous to the knowledge of the method, one can effectively classify one of the types of pore and skin cancer.
- d) **Accuracy Improvement:** Another difficult problem is to improve the accuracy of the system through version knowledge along with the choice of Gaussian noise.

CHAPTER 3

Materials and Methods

3.1 Working Process

There are 5 exclusive qualifications to complete the entire task. Here's what's next:

- a) Get organized images and datasets
- b) Image Pre-processing
- c) Apply Machine Learning Algorithm
- d) Classify Melanoma skin cancer
- e) Result Analysis

The entire workflow from image acquisition to image analysis is shown in Figure 1 and detailed in the next section.

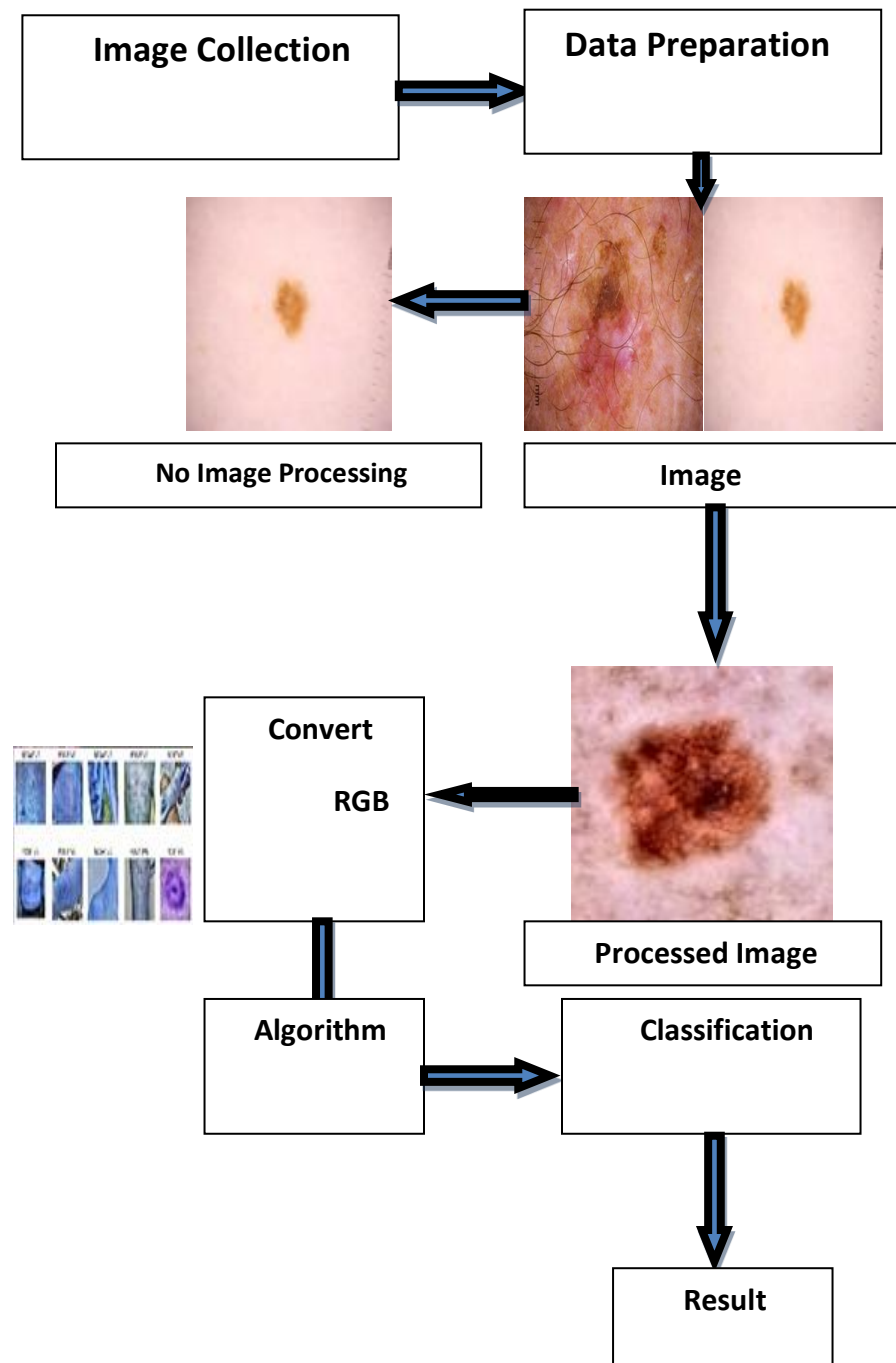


Figure 1: Working Process of the Proposed Model

3.2 Dataset Preparation



Benign



Benign



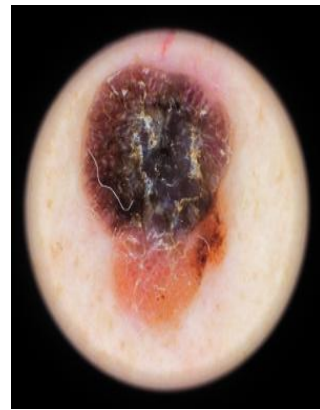
Benign



Malignant



Malignant



Malignant

Figure 2: Different Classes of Melanoma Skin Cancer

[<https://drive.google.com/drive/folders/1WaQv4kHqbOOfpD94pJrtbJdxkKXsxix-?usp=sharing>]

Accumulated photos are of appropriate length and color. The various data sets became the training version, and the accumulated records were sufficient. For this reason, we want noise from the fact that all records have been trained. Therefore, various strategies were used to enlarge the record, such as rotating, moving, resizing, and cropping.

Figures 2-4 randomly show 06 types of exclusively cancerous pores and most cancerous skin types

3.3 Image Pre-processing

Preprocessing is a phenomenon considered for mirror image minimal-level imaging techniques, where the input and output are equally penetrating images. Credentials collected through the sensor containing the dominant image are usually taken by the values of the image matrix characteristics (brightness) represented using the output photos. Improved image information beyond distortion protection through up scaling more or less critical picture functions for additional processing. Although mathematical adjustments of the image (e.g. rotate, scale, translate) are taken into account among the pre-processing strategies, the comparison strategies still apply here.

3.3.1 Contrast Limited Adaptive Histogram Equalization

The CLAHE technique is used to overcome the noise problem with limited clips. One possible development would be to truncate the histogram at the given values before determining the cumulative distribution function (CDF). CLAHE precompiles the CDF, limiting graph extractor development to predefined severity levels. This limits the slope of the CDF and thus limits its receptive function. The clipping limit, or value at which the histogram is clipped, is set according to the normalization measure and grid area of the graph. CLAHE uses important factors such as blocking gaps and clip limits. Peak frames are processed using this setting. in the picture. on figs. Figure 5 shows the BGR-to-grayscale-converted user-taken underestimated images observed using the CLAHE technique with a crop limit of 0.1 and a time interval of 8X8 blocks.

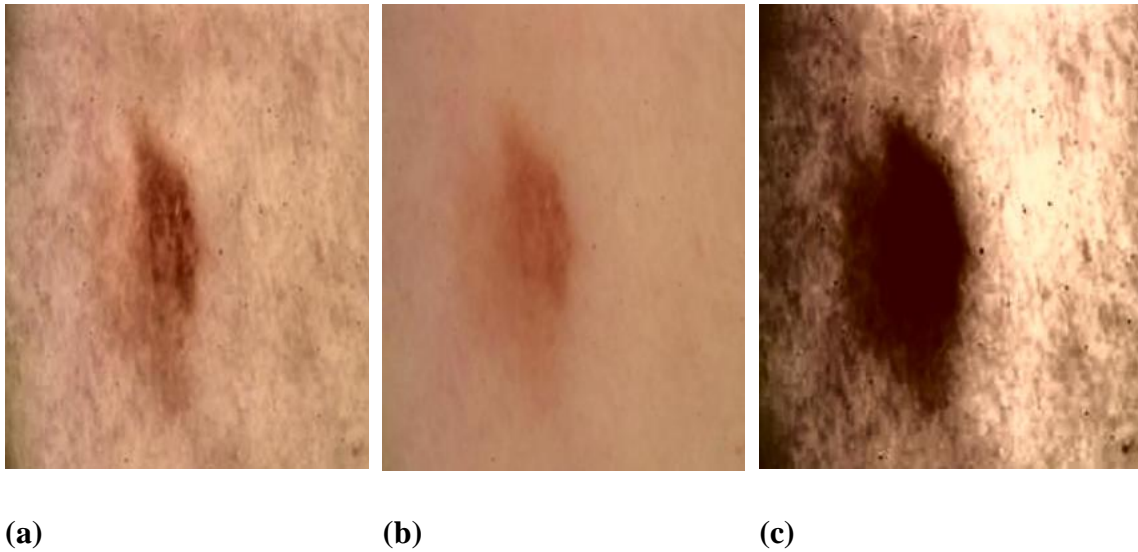


Figure 3. (a) Original low contrast image (b) Converted the image BGR to greyscale and (c) Apply Contrast-enhanced technique CLAHE (CL=0.1, BS=8x8)

3.4 Convolutional Neural Network

CNNs are considered one of the most commonly used types of synthetic neural networks [05]. In theory, CNNs are very similar to Multilayer Perceptron (MLPs). Activation attributes used in MLP map weighted inputs to outputs. MLP acts as a deep neural community, although there are several hidden layers within this community. Therefore, CNNs are considered MLPs with a proprietary architecture [06]. This great employer allows transform-rotation-invariance thanks to the model's architecture. Transformation layer, clustering layer, and fully[07] associative layer are considered the main Rectified Linear Activation (ReLU) layers of CNN structure[08]. A CNN includes three types of layers and a synthetic class that groups layers in the same way as fully connected layers.

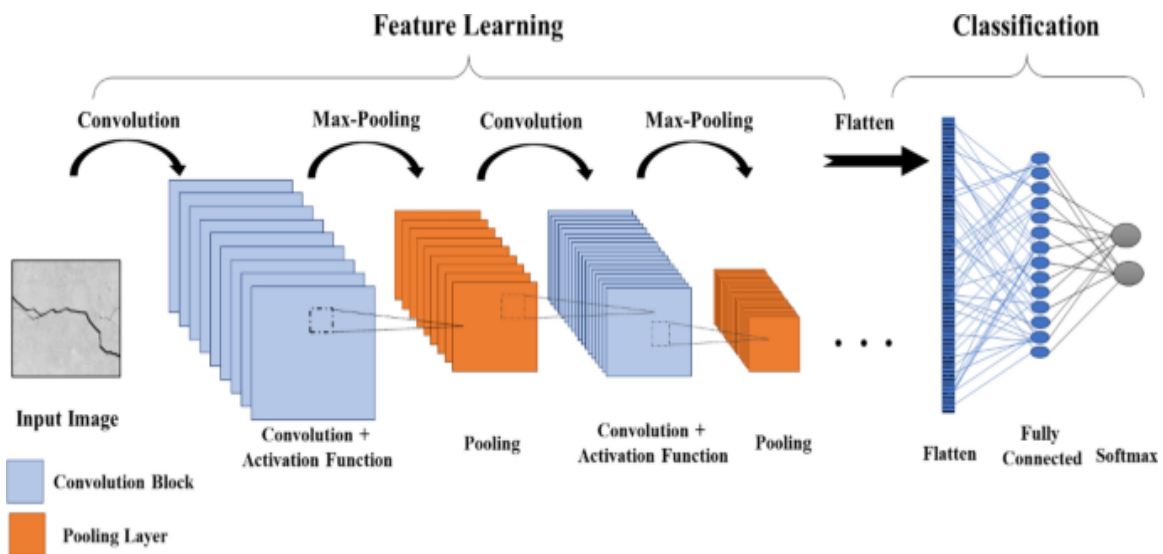


Figure 4: Architecture of Convolutional Neural Network [11]

3.4.1 Convolutional Layer

As mentioned in the footnote, complex layers play an important role in the operation of CNNs. Class limits depend on the use of the training kernel. These kernels are usually small, but depend on the overall size of the input. This layer transforms each band in the spatial dimension of the input data to provide an accurate 2D current map while the data overwrites the group layer. As the input data iterates, the kernel completes the computation of cost-specific scalar artifacts. When a feature is seen instead of a virtual spatial feature, the community perceives the core as a "flame", which can be collectively referred to as activation. Each kernel has the same activation graph, the purpose of which is to determine the complexity of forming the set of output sizes of the convolutional layer. Composite classes also have the ability to extend the output, greatly reducing the complexity of the prototype. It runs through three hyper parameters: strength, stride, and zero cushioning.

The intensity of the output lengths distributed across the convolutional layer can be set practically with a large number of neurons for the layer at the same input location.

We are also ready to symbolize the steps as we ask how to lay out open fields by setting the intensity in the spatial dimension of the input. For example, if you set your stride to 1, you can assume in this case actively activated reaction training with a huge number of

activations. Also finding steps in the direction of higher quotas will reduce the amount of overlap combined with producing smaller spatial dimension outputs.

In addition to the powerful way to further control the dimension of the output dimension, zero padding is taken into account because of the easy way to pad the input boundary. These methods help to control the spatial dimension of the convolutional layer output. The following equation is used for this calculation:

$$\frac{(V-R)+2Z}{S+1} \quad (1)$$

Here, V is an abbreviation of e, and input the length of the number including height \times width \times depth, R and Z indicate comfortable training length, and the quantity 0 is entered separately. S stands for pitch. If the planned final result of this equation is not equal to an integer value, the step was previously fixed incorrectly because the neuron could no longer recover error-free from the pre-sorted input.

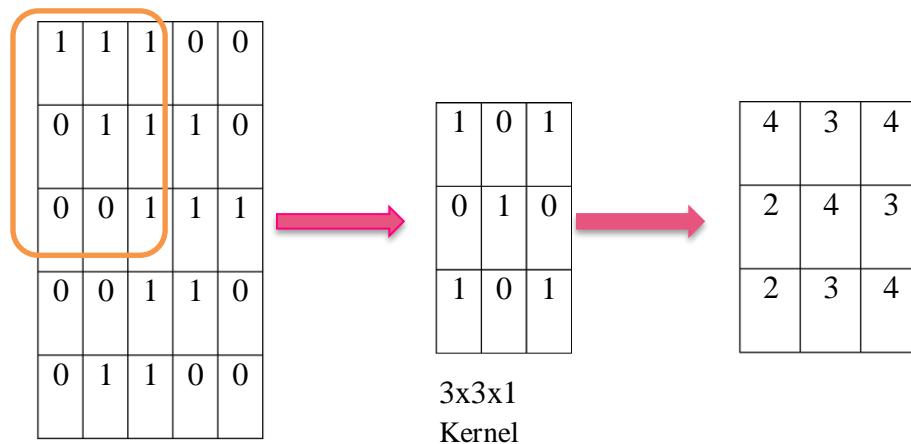


Figure 5: A 5x5x1 image convolved with a 3x3x1 kernel to become a 3x3x1 convolved feature.

3.5 Gaussian Noise

Gaussian noise is a time from the idea of symbolic processing to represent a form of symbolic noise that has the same characteristic density function as a conventional distribution (also known as a Gaussian distribution). In other words, the values the noise can take are Gaussian. The opportunity density function p of a Gaussian random variable z is defined as-

$$p_G(Z) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(z-\mu)^2}{2\sigma^2}} \quad (2)$$

Spatial filters can be used to minimize Gaussian noise when processing virtual images, but when smoothing images can also blur edges and image information due to the undesirable end result. The scale is small because it also responds to locked overshoot frequencies. Common spatial filtering strategies for de noising include mean filtering (convolution), median filtering, and Gaussian smoothing.

3.6 Transfer Learning

Communication is often a tool for gathering information about an approach that uses established, archaic, and continuous know-how to solve a problem, and is reused as the first method to solve a problem another topic. The deeply integrated neural community mode can take days or weeks to train on very large disk sets. One way to reduce this system is to reuse version weights in pre-trained mods that have been improved on popular and creative test cases that are lo ved on laptops like regular tasks. Image Clear image. You can download the top notch actor mod to use right away, or switch to the new version on laptops with imagination and projection problems.

3.6.1 VGG16

There are VGG modes: VGG-16 and VGG-19. In this study, VGG-sixteen was used to classify the dataset. Specifically, VGG-sixteen consists of three parts: a convolutional layer, a merged layer, and a fully associative layer. Convolution Layer: This layer applies filters to extract features from the image. The most important parameters are scale and kernel peak. Full Layer: Its function is to reduce the distance to reduce the parameters and computational scope within the network. Fully Connected: A fully connected connection is absolutely connected to the previous layer, as in a simple neural network. This figure shows the structure of the model.

3.6.2 Resnet50

ResNet-50 is a 50 layer cumulative neural community (48 convolutional layers and 1 MaxPool layer and 1 intermediate group). Residual Neural Network (ResNet) is an Aggregated Neural Network (ANN) that bureaucratizes communities by superimposing redundant blocks on top of each other. Over one million pre-selected photos are available for download from the ImageNet database. Pre-qualified communities can categorize photos into thousands of items, including keyboards, mice, pencils, and various animals. Community-created images measure 224 x 224.

3.6.3 InceptionV3

Inception v3 is a complex and deep neural community capable of classifying irrelevant label images from the Image Net dataset. The only v3 model released in 2015 has only 42 instructions and has a lower error rate than its predecessor. Let's see if various optimizations improve the V3 model well. Key fixes in Inception V3 style:

- a) Divide it into several small loops.
- b) Spatial multiplication in odd convolutions
- c) the usefulness of auxiliary classifiers
- d) reducing effective communities

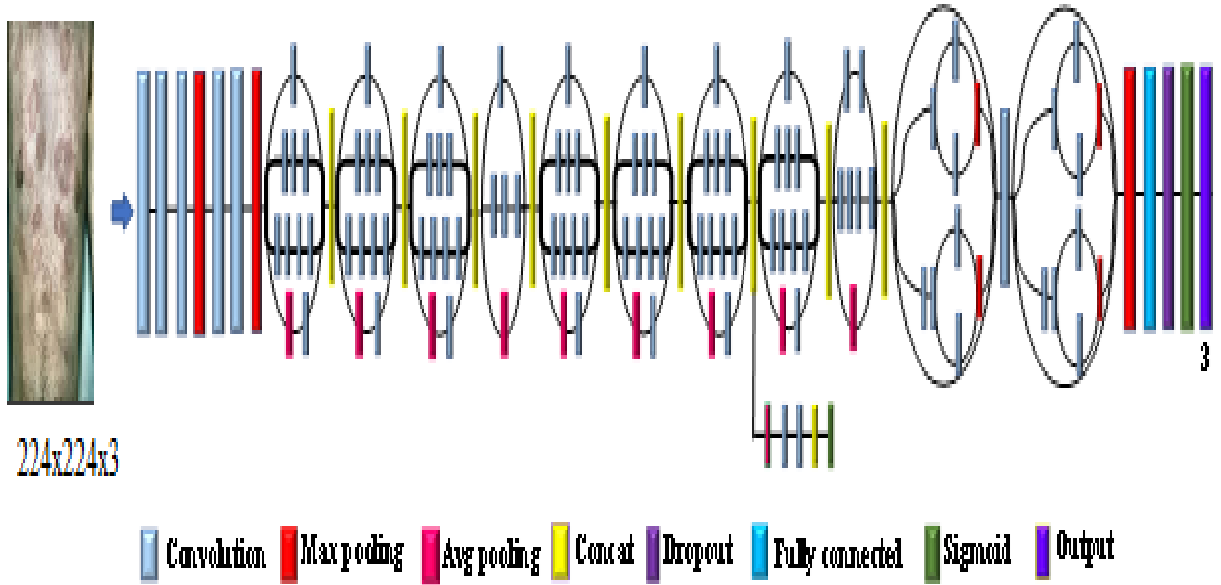


Figure 6: Schematic Representation of InceptionV3 [11]

3.7 Training and Testing

Initially, the entire dataset is distributed among elements that include training in addition to dataset validation. This data set partitioning method is performed randomly, the training set contains about 10,000 pixels, of which 80% is used for version training and the last 20% is used for version validation. And the test part used 7500 new pixels to evaluate the overall performance of the version where each image consists of 2500 pixels. The same tests are performed on both raw and noisy pixels.

All models were validated using the switching study method with cross-expression entropy applied due to loss characteristics as in equation (1). The voting price is fixed at 0.001,

$$L_{CE} = - \sum_{i=1}^n t_i \log(p_i) \quad (3)$$

We use the Adam optimizer where SoftMax is used as the activation property for all architectures shown in equation (2).

$$f_i(\overrightarrow{a}) = \frac{e^{a_i}}{\sum_k e^{a_k}} \quad (4)$$

The whole working process of the experiment is given in figure 1.

All experiments were performed on a processor with a 32/64-bit Windows operating system, Intel Core i5-7200U processor, at least 4 GB RAM and 1 TB hard drive using the Python programming language in a Jupyter notebook or Google Colaboratory environment.

CHAPTER 4

Experimental Results and Discussion

4.1 Results and Discussion

Several powerful CNN architectures through a transfer learning approach were evaluated in this experiment for the classification of melanoma skin cancer. Though the experiment was initially completed utilizing raw images but the outcomes were not acceptable at all. Then we applied Gaussian Noise in the dataset but again outcome were not acceptable. After that, the raw images were traded with contrast-enhanced images which prompt an incredible outcome.

Vgg16, Resnet50, and InceptionV3 are some of the prevailing CNN architectures used in this experiment. Among all these CNN architectures came out with the best accuracy of 97.00% while using raw images where InceptionV3, Resnet50 and Vgg16.

The confusion matrix is used to evaluate the viability of infinite patterns (Table I). True Positives, Bad Tests, False Positives, and False Bads were found in the misclassification table. The diagonal role inner values of the confusion matrix evaluate the accuracy of model predictions. Accuracy, sensitivity, recall, precision, and F1 scores were mainly calculated based on the misclassification table using the following formulas (3-6):

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (5)$$

$$\text{Precision} = \frac{TP}{TP + FP} \quad (6)$$

$$\text{Recall} = \frac{TP}{TP + FN} \quad (7)$$

$$\text{F1 Score} = 2 \times \frac{\text{precision} \times \text{recall}}{\text{precision} + \text{recall}} \quad (8)$$

Raw pix and pix with higher contrast are provided for Wallpaper II and Wallpaper III respectively. Taking into account each unlabeled pixel and preferred contrast, the values of all overall performance matrices include Accuracy, Sensitivity, Recall, and Accuracy, and an F1 rating is calculated for a deeper understanding of the architecture. It is very clear that in Desktop II, VGG16 achieved better end results than mitigations of other CNN architectures using raw images. In contrast, on Desktop III, we determined that InceptionV3 achieved excellent fidelity in most of the various relaxed CNN architectures using high-contrast pixels.

TABLE I. CONFUSION MATRIX OF CNN ARCHITECTURES USING CONTRAST-ENHANCED IMAGE







Architectures	Predicted 	<i>Benign</i>	<i>Malignant</i>
	Actual 		
VGG16	<i>Benign</i>	54	101
	<i>Malignant</i>	40	4565
	Predicted 	<i>Benign</i>	<i>Malignant</i>
	Actual 		
InceptionV3	<i>Benign</i>	0	155
	<i>Malignant</i>	0	4605
	Predicted 	<i>Benign</i>	<i>Malignant</i>
	Actual 		
Resnet50	<i>Benign</i>	25	130
	<i>Malignant</i>	1	4604

TABLE II. PERFORMANCE MATRICES OF CNN ARCHITECTURES USING CONTRAST-ENHANCED IMAGE

Architectures	Accuracy (avg)	Precision (avg)	Recall (avg)	F-1score (avg)
InceptionV3	97	95	98	97
Resnet50	92	94	97	96
VGG16	90	92	97	94

CHAPTER 5

Conclusion and Future Work

5.1 Conclusion

Various CNN architectures such as InceptionV3, Resnet50 and VGG16 have been applied to this proposed method to achieve high accuracy in discriminating benign and malignant diseases due to the amount of nutrients. excess nutrition. Some special image properties have been extracted to reduce the amount of redundant data in the data set. Then the CLAHE (contrast enhancement) method is used to improve the control accuracy. As a result, InceptionV3 performed well with an accuracy of 97% when evaluated using VGG16 and Resnet50.

5.2 Future Work

Larger, more dynamic and specific models can be developed to improve the accuracy of pore and skin identification systems for most cancers. In addition, after a period of time, a mobile phone widget is created that selects the most cancer cases, and the popular program records the most cancer cases for breeders. This software contributes very well to the sensitive topics of most cancer cultures and protects people from dangerous exposure.

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