Skin Cancer Detection using Machine Learning

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ABSTRACT Skin is an extra ordinary human structure. There are various types of skin cancer. And people are unaware about it. There are large number of skin diseases and some of them are most common. Due to lack of medical facilities available In remote areas, patients usually ignore it. The diagnose of this skin cancer also take the longer time. Melanoma skin cancer detection at an early stage is crucial for an efficient treatment. Recently, it is well known that, the most dangerous form of skin cancer among the other types of skin cancer is melanoma because it's much more likely to spread to other parts of the body if not diagnosed and treated early. The non- invasive medical computer vision or medical image processing plays increasingly significant role in clinical diagnosis of different diseases. Such techniques provide an automatic image analysis tool for an accurate and fast evaluation of the lesion. The steps involved in this study are collecting Dermoscopy image database, preprocessing, segmentation using thresholding, statistical feature extraction using Gray Level Co-occurrence Matrix (GLCM), Asymmetry, Border, Color, Diameter, (ABCD) etc., feature selection using Principal component analysis (PCA), calculating total Dermoscopy Score and then classification using Convocation neural network (CNN After using the publicly accessible data set, an accuracy of 89.5 percent and a training accuracy of 93.7 percent were reached..

INDEX TERMS *Melanoma, Feature Extraction, Machine Learning, Convolution Neural Network, Skin Lesion, Non-Melanoma.*

I. INTRODUCTION

In the past decades, a great deal of research work has been devoted to the development of systems that could improve radiologists accuracy in detecting skin nodules. Despite the great efforts, the problem is still open. In this paper, we present a fully automated system processing digital poster anterior (PA) chest radiographs, that starts by producing an accurate segmentation of the skin field area.

The segmented lung area includes even those parts of the lungs hidden behind the heart, the spine, and the diaphragm, which are usually excluded from the methods presented in the literature. This decision is motivated by the fact that lung nodules may be found also in these areas. The segmented area is processed with a simple multi scale method that enhances the visibility of the nodules, and an extraction scheme is then applied to select potential nodules. To reduce the high number of false positives extracted, cost- sensitive Convolutional neural networks (CNNs) are trained to recognize the true nodules. Different learning experiments were performed on two different data sets, created by means. In the recent 3 decades Melanoma incidence rates have been increasingly high, though most people diagnosed with skin cancer have higher chances to cure, Melanoma survival rates are lower than non- Melanoma skin cancer. Melanoma skin cancer (MSC) can occur on any skin surface, and its incidence has continued to rise over the past two decades in many regions of the world. In men, it's often found on the skin on the head, on the neck, or between the shoulders and the hips while, in women, it's often found on the skin on the lower legs or between the shoulders and the hips. It's rare in people with dark skin and when it does develop in people with dark skin. Because of melanoma's high fatality rate, skin cancer is commonly divided into two types: melanoma and non-melanoma algorithm was then tested on new skin lesion photos. Melanoma is a type of skin cancer that starts in the melanocytes. Melanocytes are epidermal skin cells that create melanin, the dark pigment that gives skin its colour. Melanin also serves as a natural sunscreen, protecting the skin's deeper layers from UV damage. Melanoma accounts for 5% of skin malignancies in the United States, but it is responsible for 75% of skin cancer mortality. A dermatologist's ability to diagnose skin cancer from a dermoscopy image of a skin lesion is limited . A biopsy and pathology investigation may be required to diagnose cancer in some circumstances. Previous research has established computer-based systems for detecting skin cancer from photographs of skin lesions. These models were previously based on traditional machine learning techniques that required segmentation of the lesion from the surrounding skin in the image, followed by extraction of valuable information from the lesion area. The shape, texture, and colour of the lesion are examples of these characteristics. Finally, to detect cancer, the features are given into a classifier. This strategy, on the other hand, is inconvenient because defining and extracting traits that would be effective in identifying cancer is challenging.

Deep learning has emerged as a potent technique for feature learning, because to recent breakthroughs in software and hardware technology. Feature engineering, or the process of a human expert defining and extracting features, is a time-consuming and tedious task. Deep learning eliminates the need for feature engineering by learning and extracting meaningful features from raw data automatically. Many fields, particularly computer vision, have been transformed by deep learning.

Deep learning has recently shown considerable promise in biomedical engineering. Deep learning has been used to identify skin cancer in multiple research since 2016.

A deep learning convolutional neural network (CNN) model built with 125000 clinical pictures of skin lesions was used in a study done by Stanford University researchers in 2017.

This study shows that deep learning is effective at detecting skin cancer. However, the study's database is not open to the public, preventing other researchers from developing models for future improvements. Tschandl et al. published HAM10000 in 2018, which is public dataset of 10,000 dermoscopy images collected from Austrian and Australian patients. photos in this dataset contain around 8000 benign lesions and the rest are malignant lesions. Pathology, expert consensus, and confocal microscopy were used to corroborate the ground truth for this dataset. A deep learning algorithm is suggested in this article to determine the malignancy of skin lesion photos from the

II. LITERATURE SURVEY

Melanoma is a type of skin cancer that causes a malignant tumour to form on the skin. Dermatological pictures are used to detect skin cancer. Skin cancer was detected using machine learning based on a high-performance image, and the detection rate was high (Srividhya, Sujatha, Ponmagal, Durgadevi, Madheshwaran, et al., 2020). However, by extracting more characteristics, the model's accuracy can be improved, and the sensitivity can be raised. The author presented a system that uses image processing processes to improve skin cancer diagnosis accuracy (Hoshyar, Al-Jumaily, & Hoshyar, 2014). They were unable to describe a precise model that can effectively identify cancer.

In another work, the author proposed an architecture-driven model for skin cancer diagnosis that used a DL algorithm. Because DL based on model-driven architecture can be developed so quickly, the model can anticipate the outcome almost instantly. It had a greater detection rate for skin cancer (Kadampur & Al Riyaee, 2020). However, in order to improve the medical profession, the methodology requires real-time interface with medical images.The author proposed CNN-based skin cancer diagnosis in (Hasan, Barman, Islam, & Reza, 2019), where the feature is retrieved from dermoscopic pictures utilising feature extracting algorithms. During the testing phase, they achieved an accuracy of detection of 89.5 percent.

In this paper, a 3D reconstruction algorithm is proposed using 2D images, where the detection of 3D image shape and RGB are performed.

1. The images are pre-processed and converted into binary images of 0 s and 1 s. Adaptive snake algorithm is used for segmentation purpose. Along with all the features a 3D depth estimation parameter is also used to increase the efficiency of classification. Early detection of melanoma at its premature stage is the best way to decrease the effect of the disease.

2. This paper discusses the one of the approaches that uses MVSM classifier. Five different skin lesion types such as actinic keratosis, Squamous Cell Cancer, Basal Cell Cancer, Seborrhoeic Verruca, Nevocytic nevus are grouped and considered by the proposed system. GLCM is used to extract color and texture features such as contrast, gradient, homogeneity. K-means clustering is used for the purpose of segmentation. The tumor area was calculated forall the five types of images.

The classification and segmentation results are shown using a GUI. Melanoma is the most common type of skin cancer.

3. This paper proposes an idea to classify the melanoma using shearlet transform coefficients and naïve Bayes classifier. The dataset is decomposed using shearlet transform with the predefined number of (50, 75 and 100) shearlet coefficients. Then to the naïve bayes classifier, the required coefficients are applied. The accuracy achieved at 3rd level of classification using 100 coefficients of shearlet transform. Dermoscopy is the major technique used to detect skin cancer. The Dermoscopic images must be very clear and there should be an expert dermatologist to deal the issues related to diseases. But, this is a time consuming process.

4. This paper presents a ground idea of an annotation tool which can upgrade the manual segmentation methods, by building a ground truth database for the automation of segmentation and classification processes, developed under the guidance of dermatologists. The main functionalities of this tool are: image uploading and displaying, manual segmentation, boundary reshaping, region labelling, a posteriori boundary edition, multi-user ground truth annotation and segmentation comparison, and storage of the segmented images. From all the above functionalities, it is more advantageous for boundary reshaping and free hand drawing

5. Thus, this paper proposes an idea to use grey images instead of color profile for texture analysis. GLCM is used for the feature extraction whereas SVM is used as a classifier to classify the various types of skin cancer However, the detection accuracy was insufficient and needs to be improved. Furthermore, there was overfitting between the testing and training phases, which was a flaw in that study. The author suggested a lesion indexing network (LIN) based on DL to identify and classify skin cancer in (Li & Shen, 2018). By extracting more features, they were able to achieve good results . However, in order to improve the results even further, segmentation performance needs to improve. There are several challenges in detecting skin cancer due to differences in image kinds and sources. The variability in human skin tone makes skin cancer detection more difficult and complex. These difficulties are depicted in Fig. 1, and the most visible features of skin lesions photographs are detailed below:

The main challenges in skin cancer are the various sizes and shapes of the pictures, which make reliable identification impossible. Pre-processing is necessary for accurate analysis in this case. A few unused signals that were not initially part of an image but can interfere with a good result will be compromised. All of these noise and artefacts should be removed during the pre-processing phases.

In some cases, low contrast from nearby tissues adds to the difficulty of accurately analysing skin cancer. Color illumination creates challenges due to aspects such as colour texture, light beams, and reflections. Some moles on the human body may never form cancer cells, but they make it difficult to effectively diagnose skin cancer from malignant photos.

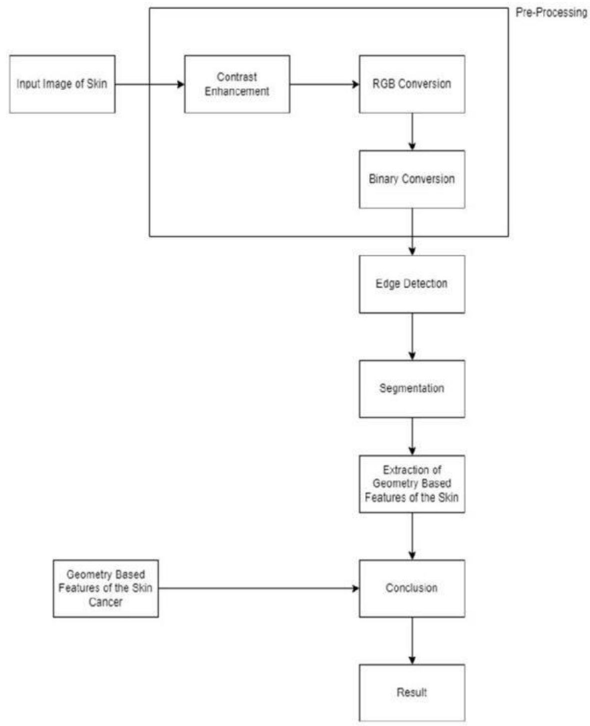
III. METHODOLOGY

Our dataset consists of a collection of various skin cancer photos. To use deep learning techniques, you'll need a lot of data to get a solid result. The collecting of skin cancer photographs, on the other hand, is quite important. Furthermore, thelack of training data is one of the major difficulties when using DL algorithms.To address these issues, we used the HAM10000 dataset, which contains 10015 dermoscopy images collected from Australian and Austrian patients. In this collection, there are 6705 benign photos, 1113 malignant images, and 2197 images with undetermined lesions. Pathology, master agreement, or confocal microscopy were used to confirm the ground truth for this dataset. The HAM10000 data used in our work are meticulously crafted from biopsy-proven melanocytic tumours that are classified as malignant or benign.

A. Proposed Approach

This method employed the tagged images "benign" and "malignant." Because the photos in the "other and unknown" groups could not be diagnosed, they were not used. Images were included to the dataset based on their analysis mark, which was derived from the photographs' information. The dataset has been divided into two categories: one for harmful dermoscopic images and another for positive dermoscopic images. For the experimental portion, photos from the ISIC dermoscopic archive were picked at random. There are three layers in our proposed system. The input layer is the first layer, which is where the data sets are trained. The input layer collects data and adds some weight to it before sending it to hidden levels.

To detect a pattern, the neurons in the hidden layer separate the characteristics from the data. After that, the pattern is utilized to create output layers that select relevant classes. Finally, binary classification is utilized to identify appropriate classes 1 and 0. In our situation, class 0 denotes the absence of hazardous cells, whereas class 1 denotes the presence of malignant cancerous cells. The implementation of our system utilizing convolutional neural networks is shown.



B. The System Steps

The steps below are used to determine whether a dermoscopic image has cancer or not:

•Step-1: Initialize all of the photos and settings required by the system.

•Step-2: The system receives a training image as input and saves the images.

•Step-3: The system determines the prediction using a convolutional neural network.

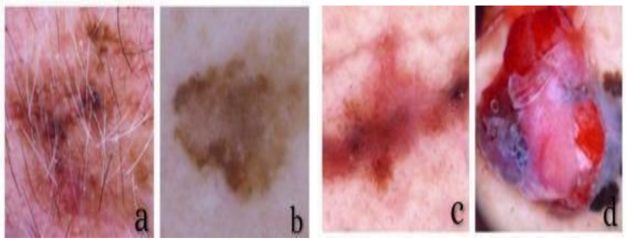
•Step-4: Train using the convolutional neural network created in step-3.

•Step-5: Save the model into the system for test data prediction.

•Step 6: Assess the outcome using common assessment criteria like as precision, recall, and f1 score.

Preprocessing data

One of the most significant challenges in computational vision is the enormous size of the images. The data intake can be quite large. When the inputted photos are 70703, the input feature dimension can be 14700. If the image size is 102410243, the feature size for calculation to transmit it to a deep neural network, particularly a convolutional neural network, will be enormous (depending on the number of hidden units). There are three image channels.

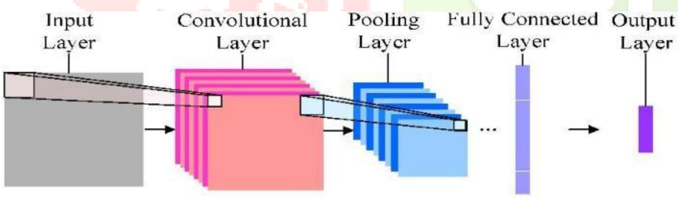


RGB has three channels (Red, Green, Blue). We must attempt to define a single channel when reading the picture due to a lack of processing resources. Another issue is the image's length. The data set contains photos with unusually large widths and heights. The picture's width is 1022 pixels and its height is 767 pixels, making it extraordinarily large to analyse and necessitating significantly greater computer capability to register many images, which takes a long time and wastes memory. In this vein, we must resize the information pictures so that our machine can process them with less memory and computing power. To address these two issues during image reading, it will be defined in such a way that only one colour channel remains. Gray scale images are generated from original photographs in our situation since they are easier for the CPU to process.

Save the preprocessed file

Each of the preprocessed photos, together with their classifications, is preserved in the record. For further processing, benign and malignant photos are selected from the dataset. The photos that do not have a class label must be discarded. Finally, the recorded images are fed into a convolutional Neural Network for processing

Feeding the preprocessed data to convolutional neural network (CNN).



Three types of layers are present in a convolutional Neural Network.

That are given in following part-

•Convolution layer

•Pooling layer

•Fully connected layer

Prediction

Using the final output layer, we must anticipate the images. We evaluate our system using the accuracy, precision, recall, and f1 score measures after we forecast the testing images.

IV. PERFORMANCE METRICS AND EXPERIMENT

A. Convolution Layer

By using an exmaple, our system are described here. Suppose we have a 6 × 6 gray-scale image (i.e. only one channel) as figure 3. Again, We have 3 × 3 filter. Firstly, 3 × 3 matrix were taken from the 6 × 6 image and accumulate the filter with it. As a result, the sum of the element-wise product of these values equals to the first element of 4×4 output, for examples5×1+0+2×−1+3×1+5×0+8×−1+2×1+5×0+6×−1= −6. The second element of 4 × 4 output were calculated again by the sum of the element-wise product via shifting the filter one unit at the right. Similarly, the entire image were convoluted to produce a 4 × 4 output.

In general, it can be stated as convolving an input of x × x with a y × y filter will results in (x − y + 1) × (x − y + 1):

5	3	2	1	7	4
3	5	8	9	1	3
2	5	6	0	1	4
1	6	7	1	0	2
6	2	4	0	8	2
2	5	4	2	3	9

1	0	-1
1	0	-1
1	0	-1

Fig : 6 × 6 image with 3 × 3 filter.

-6	3	7	-1
-15	6	19	1
-8	12	8	-7
-6	10	4	-10

Fig : 4 × 4 image after applying 3 × 3 filter to 6 × 6 image.

- Input: x × x
- Filter size: y × y
- Output: (x − y + 1) × (x − y + 1)

One major disadvantage of the convolution operation is the shrinkage of the size of the image. Compare to the pixel at the center of an image, the pixels at the corner are utilized only a few number of times to overcome the information loss. It has been done by padding the image by adding an extra border (i.e. adding one pixel all around the edges) which makes the input of size an 8 × 8 matrix (instead of a 6 × 6 matrix). Now, convolution of 8 × 8 input with a filter of size 3 × 3 matrix will result the original image of a size of 6 × 6 matrix which can be generalized as:

- Input: x × x
- Padding: p
- Filter size: y × y
- Output: (x + 2p − y + 1) × (x + 2p − y + 1)

CNN has a tool that allows you to minimise the image size significantly. Convoluting the image with a stride of 2 will, for example, capture both vertical and horizontal directions individually.

The dimensions for stride s can be stated as:

- Input: x × x
- Padding: p
- Stride: z
- Filter size: y × y
- Output: [(x + 2p − y)/z + 1] × [(x + 2p − y)/z + 1]

Pooling Layers

To reduce the image size and increase the computation speed, pooling layers are typically used. Consider a 4 × 4 matrixas shown below:

-6	3	7	-1
-15	6	19	1
-8	12	8	-7
-6	10	4	-10

For every consecutive 2 × 2 block, the maximum number were taken and 2 unit size of both filter and stride were applied. If the input of the pooling layer is xh ×xw ×xc , the output will be [{(xh − y)/z + 1} × {xw − y)/z + 1} × xc]. Then, We again apply convolutions and pulling for extract more complex features. The features are flatten to a single layer so that we can feed the model to a fully connected neural network. Then after applying the softmax as shown in equation 3, the desired result that is benign or malignant is found.

Output = Zi Ín i=1 (Zi,k)..

Metrics:

- True Positives (TP): An incident in which the expected yield matched the actual yield.
- True Negatives (TN): When we predicted a false result and the actual result was also false
- False Positives (FP): This is when we expect something to be true but it turns out to be false.
- False Negatives (FN): This is when we expect something to be false but it turns out to be true.

To evaluate the model, accuracy, recall, precision, specificity, and the f1 score are used to quantify its performance. Recall is the number of threatening cases that can be distinguished from a set of all dangerous cases. Recall = True Positive / Positive Specificity is what number of benign cases can recognize out of complete given favorable cases.

Specificity = True Negative / Negative

The number of potentially dangerous situations that the model could effectively predict out of the total number of cases it predicted as harmful is known as precision.

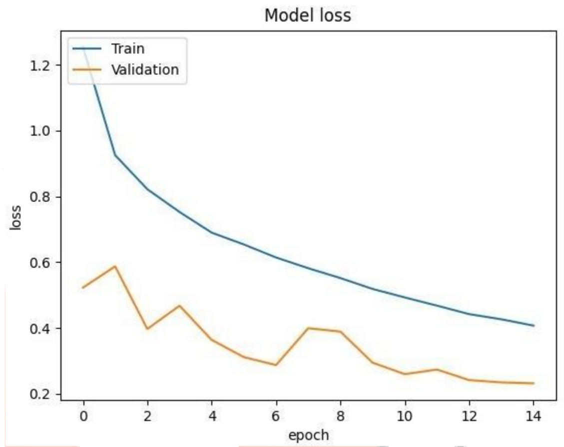
Precision = True Positive / True Positive + False Positive

F1-score is a consolidation of precision and recall to admit the fundamental concept on how this system works.

FMeasures = 2 × Precision × Recall / Precision + Recall

V.RESULT

The primary goal of our proposed model is to classify benign and malignant skin lesions from a extracted dataset. The results come from the total number of photos acquired following the data reduction stage (http://www.isic-archive.com). depicts some benign and cancerous appearances..



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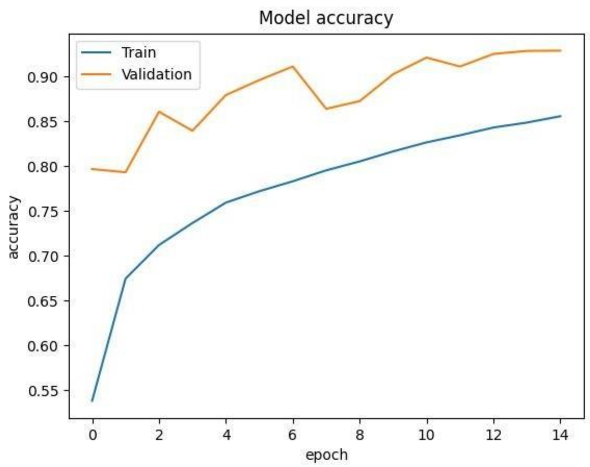
In this work, we tested our suggested model in two ways: one with 70% of training photos, and the other with 80% of training images, which showed the best accuracy



VI. CONCLUSION

A Convolutional Neural Networks-based technique for melanoma classification is proposed in this research. A technique is being created to assist patients and doctors in detecting and identifying skin cancer classifications, whether benign or malignant. The model can be considered a benchmark for skin cancer identification by supporting healthcare practitioners, according to the experimental and assessment part. Any doctor may identify accurate findings by obtaining few random photos, but the usual approach takes far too long to recognize instances correctly.

Detection of skin cancer is a very important step to reduce death rates, and the development of skin cancer. From these different image processing techniques, the fuzzy filter will provide the efficient de noising. Segmentation done by marker based watershed algorithm, gives various region of image. GLCM is used to extract the different features of image and which takes less time for generating the result. This results are passed through CNN Classifier, which classifies the nodules as benign or malignant.

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