Skin Cancer Detection Using Convolutional Neural Network

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Abstract- ***Skin cancer is a deadly disease in humans. The need to diagnose skin cancer early has increased due to the rapid growth rate of melanoma skin cancer, high treatment costs, and mortality rates. These cancer cells are detected by hand and take time to heal in most cases. This paper has proposed a practical skin cancer screening program using image processing and machine learning. The characteristics of the affected skin cells are removed after the separation of dermoscopic images using the feature removal method. An in-depth approach based on learning convolutional neural network classifier is used for classification of extracellular features. 89.5% accuracy and 93.7% training accuracy were achieved after using a publicly available data set.***

CCS CONCEPTS

- ***Information systems → Information extraction;***
- ***Computing methodologies → Neural networks; Feature selection.***

Indexed Terms- Machine Learning; Convolution Neural Network; Information Search and Retrieval; Melanoma; Feature Extraction

I. INTRODUCTION

According to WHOś figures, the number of people diagnosed with skin cancer will rise to about 13.1 million by 2030 [12] [7]. Skin cancer is a condition in which there is an abnormal growth of melanocytic cells in the skin. The malignant stage of skin cancer is usually caused by pigmented cells called melanocytes. Melanoma is found among non-Hispanic white men and women, and leads to about 75% of skin cancer-related deaths [2]. According to the World Cancer Report, the oldest cause of the problem is light exposure in people with low skin color. UV radiation can come from the sun or any other source and about 25 percent of malignants are from moles [11]. The Neural Network algorithm is used to detect risk and harm. This framework is based on reading images taken with a dermato-scopic device to determine if it is true is neither fair nor cruel [13]. Convolutional Neural Network (CNN) is a type of neural network used to process signal and image. Convolutional Neural Network [3] is also used in the Recommender System [14]. CNN is preferred because it provides high accuracy in image processing. CNN has four performance standards. The main layer fills in as a layout layer where dermatologists give all the information they have received. The input layer for that point creates information and sends it to the next layer which is then sent to the integration layer. The integration layer includes a knowledge structure by making a max pool or min pool. The integration layer sends that information smoothly to direct the layer that switches over the information to a single larger vector. Then the information goes into a dense layer to be converted into the desired class which is either bad or bad [1]. This paper represents an automated method of diagnosing skin cancer based on the convolutional neural network to classify cancer images into malignant or malignant melanoma.

II. MOTIVATION

Skin cancer is a warning sign and should be diagnosed early. Diagnosis is a time-consuming and expensive manual procedure. However, modern world science has greatly improved with the use of machine learning and can be useful in many ways. Therefore, machine learning can make it easier to find cancer cells which is why machine learning using the convolutional neural network very quickly and effectively.

III. BACKGROUND AND RELATED WORKS

A skin cancer diagnosis is made by a dermatologist where they are able to obtain pictures of cancer patients and analyze the effect on whether a patient has cancer cells or not. Because of having cancer cells, a

dermatologist classifies it as malignant melanoma and benign on the contrary. The problem with this framework is that it sets aside a lot of time to process a ton of patients and moreover it takes a lot of work to increase the level of recognition which makes the costs go up. An advanced computer program can automate the process of skin cancer screening that will help dermatologists, and make their tasks easier and faster. Different methods or techniques have been developed over the years to diagnose skin cancer. The closed curve method and the stiffness method are proposed to [5] determine the boundary of the skin lesion accurately. Robert Amelard et al. in paper [10] they suggested light adjustment and a feature extraction framework based on the high-quality element used on skin images. The authors in [4] proposed a neural network with a Back-propagation neural network (BNN) and an Auto-associative neural network. Ramteke et al. [6] proposed an ABCD-based approach to detect malignant skin growth. In this case 'E' is not used in ABCD law which is a means of increasing efficiency. In [9], the authors proposed a system that detects dangerous growth of melanoma skin by removing special highlights by 2D wave transformation. At that time point, the resultant picture is given as contribution to fake neural system classifier. Be that as it may, the impediment of the procedure is it can distinguish results up to exactness dimension of 84%.

IV. OUR METHODOLOGY

Currently, in order to diagnose a patient's skin damage, they need to be examined by a dermatologist to determine if they have a skin disease or not. This framework helps the dermatologist to process various cases much faster than expected. There is a number of symbolic checklists already established. ABCDE is another experimental series [11], such as - Asymmetry (A) - One part of the affected cell that turned into a tumor does not cover another part. Wattage for this feature is 1.3. Border (B) - The edges / edges of the dirty cells turn into a beat, earn points, hidden. In this corresponding factor, the thermal energy is 0.1. Color (C) - Shade does not match. Darker or darker skin tones are available. The red, white and blue dyes add to the disgusting look. The wattage of this feature is 0.5. Width (D) - The diameter of the cell remains significantly higher than 6mm and above. Evolution (E) - Predicted changes or developments indicate Malignant Melanoma.

4.1 Proposed Method

Images labeled "benign" and "evil" are used in this program. Images labeled "other and anonymous" were not used as images in those groups were not found. Images are included in the database based on their analytical mark extracted from the image metadata. The database is organized into two classes, one containing all the dangerous dermoscopic images and the other containing positive dermoscopic images. Images from the dermoscopic ISIC archive are randomly selected from the test phase. In our proposed system, there are three stages. The first layer is the input layer on which the data sets are trained. Input layer collects data that brings and adds a certain amount of weight to hidden layers.

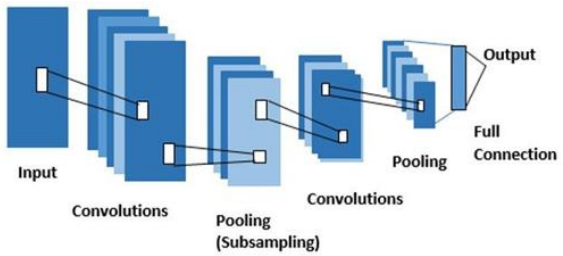

Figure 1. Convolutional neural network with its multiple layers.

The neurons of the encrypted layer separate features in the data to find the pattern. The pattern is then used as a basis for extracting layers that select the appropriate classes. Finally, two distinctive categories are selectively selected for phase 1 and phase 0. For us, category 0 means that no harmful cells exist and class 1 means having dangerous cancer cells. How our system is operated using the convolutional neural network is shown in Figure 1.

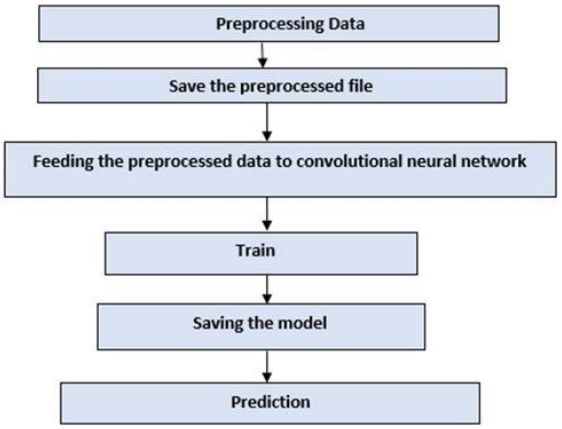

Figure 2. Flow chart for the system using convolutional neu- ral network.

4.2 Flow Chart

The following flow chart is used in this system:

4.3 Steps of the system

The following steps are used to detect whether the given dermoscopic image has cancer or not-

- Step1: Initializing all the images and all the parameters thatare needed for system.
- Step2: The system takes a training image as input and savesthe images into the system.
- Step3: The system uses convolutional neural network andfinds out the prediction.
- Step4: Training with the convolutional neural network thatare generated in step 3.
- Step5: Save the model into the system for prediction of thetest data.
- Step5: Evaluate the result with the standard evaluation metrics like accuracy, precision, recall, and f1 score.

The description of the six steps is written in follows-

4.3.1 Step 1:

Data processing. From a computer perspective, one of the biggest obstacles is the size of the images. Input data can be very large. The size of the input element is about 14700 installed images 70 70 3. Suppose the image size is 1024 1024 3 the size of the feature will be large enough to be integrated to transfer to a deep neural network specifically a neural convolutional network (depending on the number of hidden units) . There are three photo channels. The three channels are RGB (Red, Green, Blue). Due to the lack of computational capacity, we need to try to show the channel alone when reading the image. Another problem is the length of the image. A set of data containing the largest images in width and height. The image size is 1022 and the image length is 767 which is too large to process and requires a lot of integration power to register a few time-consuming and memory-consuming images. In line with these lines, we need to increase the image size of the information so that our machine can process images with minimal memory and click-through capabilities. To deal with these two issues while reading pictures, will be explained in such a way that there is only one color channel left. In our case, gray scale images are produced in real images that are easy for the CPU to process.

4.3.2 Step 2:

Save the processed file. Each pre-processed image is stored in a record along with their classes. In the database, bad and bad images are taken for further processing. We should discard images that do not have a class label. Finally, the recorded images are used to feed the Neural Neural Network.

4.3.3 Step 3:

Feeding pre-processed data on the convolutional neural network (CNN). Three types of layers exist in the convolutional Neural Network. That is given in the next section-

- Transformation layer
- Bonding layer
- Fully connected layer

Convolution Layer: Using exmaple, our program is described here. Suppose we have a picture of 6 6 scales (i.e. only one channel) as figure 3. Also, We have a 3 3 filter.

First, 3 3 matrix are taken from the 6 6 image and accumulate a filter through it. As a result, the total product output of these values is equal to the first 4 4 output, for example 5 1 + 0 + 2 1 + 3 1 + 5 0 + 8 1 + 2 1 + 5 0+ 6 1 = 6.

The second part of the 4 4 output is also calculated by the amount of smart product by removing the filter one unit to the right. Similarly, the whole image was combined to produce a 4 × 4 output as an image 6.

Generally, it can be described as a combination of input x × x with y × y filter will result in (x - y + 1) × (x - y + 1):

Figure 3. 6 × 6 image with 3 × 3 filter.

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

Figure 3. 6 × 6 image with 3 × 3 filter.

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

Figure 4. 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)

The biggest downside to convolution performance is the size of the image. Compared to the center pixel and image, corner pixels are used several times to overcome information loss. It is done by finishing the image by adding an extra border (i.e. adding one pixel around the edges) making the input size an 8 × 8 matrix (instead of a 6 × 6 matrix). Now, an 8 × 8 input conversion with a 3 × 3 matrix filter will result in a real 6 × 6 matrix image size that can be completed by:

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

Reducing image size is an important and useful feature for CNN. For example, merging an image by selecting 2 lines will take direct and horizontal directions separately. Stride s estimates can be stated as follows:

- Input: x × x
- Packing: p
- Step: z
- Filter size: y × y
- Output: [(x + 2p - y) / z + 1] × [(x + 2p - y) / z + 1]

So after adding bias the number will look like 1. Then we are transferred to the modified function of the activation unit unit 2**.** Here bi is biased condition. Xi is an input image and wi filter.

zi + = bi + xi × wi (1)

Relu (zi) = plural (0, zi) (2)

Pooling Layers: To reduce the image size and increase the com-putation speed, pooling layers are typically used. Consider a 4 4 matrix as shown below:

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

Figure 5. Images for pooling layer.

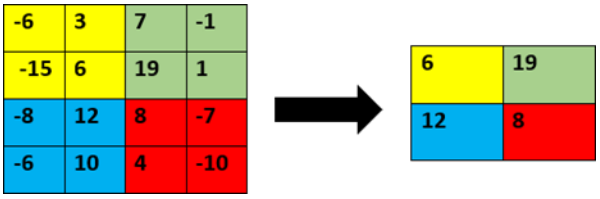

Figure 6. Result after applying max pooling.

For every consecutive 2 × 2 block, the maximum number were taken and 2-unit size of both filter and stride were applied. If theinput of the pooling layer is $x_h \times x_w \times x_c$, the output will be $[\{(x_h - y \quad z + x_w \; y \; z + x_c \; 1\}x]$

Then, we again apply convolutions and pulling for extract morecomplex 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.

$$Output = \frac{z_i}{n\left(\underset{z}{\quad} i,k\right)} \text{ i=1} \qquad (3)$$

V. EXPERIMENTAL SETUP

5.1 Data Set

Approximately 23907 images are collected from ISIC Archive [8]. These images are used to predict cancer.

5.2 Metrics

To assess the model, accuracy, recall, precision, specificity and f1 score are utilized to determine the performance of proposed model. Here, Recall is what number of threatening cases can distinguish out of complete given dangerous cases.

$$Recall = \frac{TruePositive}{Positive} \quad (4)$$

Specificity is what number of benign cases can recognize out ofcomplete given favorable cases.

$$specificity = \frac{TrueNegative}{negative} \quad (5)$$

Precision is what number of threatening cases model could fore- see effectively out the all-out cases it anticipated as harmful.

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive} \quad (6)$$

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

$$F\,m \qquad easures = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad (7)$$

VI. RESULT AND DISCUSSION

Here, precision, recall, specificity, f1 score and accuracy are deter-mined.

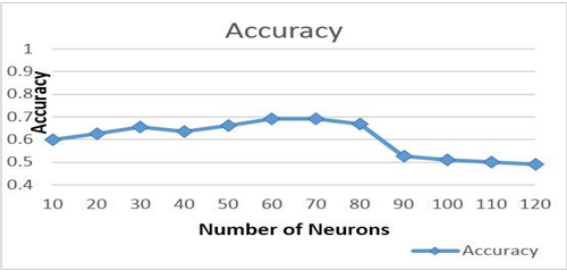

Figure 7. Neurons vs accuracy.

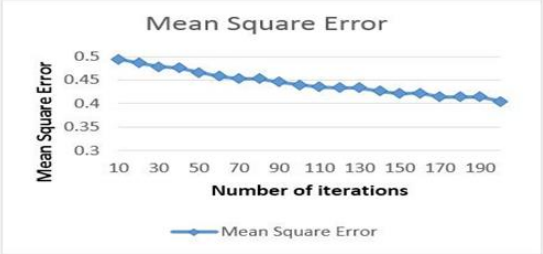

Figure 8. iteration vs loss.

6.1.1 Step 4:

Train. We have to train our model up to 200 times. Every time the loss of the system decreases to a certain level. While training epochs is approximately 180, then we didn't notice any significant amount of change in loss. So, we have to stop our iteration at 200.

6.1.2 Step 5:

Saving the model. Model is saved for further testing purposes. The model is then used to predict the images that might contain malignant or benign images.

6.1.3 Step 6:

Prediction. We have to predict the images using the final output layer. After the prediction of the testing images, we evaluate

our system with the accuracy, precision, recall and f1 scoremeasures. In Figures 7-10, the accuracy, Loss function and the square root error of the proposed model are given. In Figure 7 the number of repetition of neurons and accuracy is shown. As the frequency increases, the accuracy also increases. But, after 80 repetitions, accuracy decreases because more neurons are donated to the malignant system. Loss compared to repetition is shown in the figure

6.1.48. Loss is reduced by increasing frequency. Also, in Figure 12, an accuracy graph is displayed. With increasing repetition, accuracy increases.

Figure 8. iteration vs loss.

Table 1. Showing the result of recall, precision and F1 Score

Parameter	Result
Recall	0.84
Precision	0.8325
F1 Score	0.8325

squared error vs iteration. Here, with the increase of iteration number the mean squared error are reduced. Using the ISIC archive date we have found the recall, precision, f1 score as given in table 1.

CONCLUSION

In this paper, a method based on Convolutional Neural Networks for melanoma classification is proposed. A program is being developed that can help patients and doctors to diagnose or treat certain types of skin cancer. From the testing and evaluation phase, it can be said that the model can be considered as a sign of skin cancer diagnosis by assisting health care professionals. By taking random photos any doctor can see the exact results but in the normal way it takes a lot of time to get the cases right.

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