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Skin Cancer Detection Using Convolutional Neural Network

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ABSTRACT

Skin cancer is an alarming disease for mankind. The necessity of early diagnosis of the skin cancer have been increased because of the rapid growth rate of Melanoma skin cancer, itś 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% and the training accuracy of 93.7% have been achieved after applying the publicly available data set.

CCS CONCEPTS

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

KEYWORDS

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

1 INTRODUCTION

According to the WHOś statistics, the number of people will affected by the skin cancer will rise upto almost 13.1 millions by 2030 [12] [7]. Skin cancer is a condition in which there is an abnormal growth of melanocytic cells in the skin. Malignant melanoma class of skin cancer is generally caused from the pigment-containing cells known as melanocytes. Melanoma is found among non-Hispanic white males and females, and results in approximately 75% of deaths associated with skin cancer [2]. According to the world cancer report, the primitive reason of melanoma is ultra violate light exposure in those people who have low level of skin pigment. The UV ray can be from the sun or any other sources and approximately 25% of malignant can be from moles [11]. Neural Network algorithm is utilized to detect the benign and malignant. This framework is based on learning the images that are captured with dermatoscopic device to find out whether it is benign or malignant [13]. Convolutional Neural Network (CNN) is a type of neural network which is used in signal and image processing. Convolutional Neural Network [3] is also used in Recommender System [14]. CNN is chosen because it gives high accuracy in image processing. CNN has four working standards. The primary layer fills in as input layer where dermatologists give every one of the information they obtained. The input layer at that point forms the information and send it to the next layers which is then send to the pooling layer. The pooling layer pools the information structure by performing max pool or min pool. The pooling layer sends that information for smoothing to straighten layer which changes over the information to one dimensional vector. At that point the information gets into the thick layer to get changed over to the class they want which is for the situation benign or malignant [1]. This paper represents a automatic skin cancer detection approach based on convolutional neural network to classify the cancer images into either malignant or benign melanoma.

2 MOTIVATION

Skin cancer is an alerning issue and it must be detected as early as possible. The diagnostic is a manual process that is time consuming as well as expensive. But, todayś world science has become advanced by using machine learning and it can be helpful in many ways. Hence, machine learning can make easy for detecting cancerous cells and that is why machine learning specially convolutional neural network is used to detect cancerous cell more quickly, and efficiently.

3 BACKGROUND AND RELATED WORKS

The diagnosis of the skin cancer is done by dermatologist where they can access the images of cancer patients and analyze the result whether the patient has cancerous cells or not. Because of having cancerous cells, dermatologist suggest it as malignant melanoma

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and benign on vice versa. The issue with this framework is, it sets aside a lot of time to process a ton of patients and furthermore it takes a great deal of labor to expand the rate of recognition which makes the cost go up. The developing computerized system can automate this skin cancer detection process that will assist the dermatologists, and makes their works easier and faster. Different methods or techniques have been developed for years to make the skin cancer diagnosis. A closed elastic curve technique along with intensity threshold method is proposed in [5] to detect the skin lesion boundary accurately. Robert Amelard et al. in paper [10] have suggested an illumination correction and feature extraction framework based on high level intuitive feature implemented on skin images. Authors in [4] have proposed an artificial neural network approach with Back-propagation neural network (BNN) and Auto-associative neural network. Ramteke et al. [6] have proposed a method dependent on ABCD standard to recognize skin malignant growth. At this method 'E' is not implemented in ABCD rule which is performance increasing method. In [9], the authors have proposed a system which recognizes dangerous melanoma skin malignant growth by removing special highlights through 2D wavelet change. At that 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%.

4 OUR METHODOLOGY

At present, to check skin malignancy of a patient, he needs to experience singular screening by a dermatologist so as to recognize whether they have skin disease or not. This framework helps dermatologist to process various cases a lot quicker than expected. There are a number of symptomatic checklist have been established. ABCDE is one of the checklists [11], such as - Asymmetry(A) - One portion of the affected cell that has turned into a tumor does not coordinate the other half. Wattage for this factor is 1.3. Border(B)- The edges/the fringe of the tainted cells wind up battered, scored, obscured. For this corresponding factor, the wattage is 0.1. Color(C)- Shade isn't uniform. Shades of tan or dark colored spots on skin and dark are available. Dashes of red, white and blue add to the repulsive appearance. The wattage for this factor is 0.5. Diameter(D)- The cell width ends up more noteworthy than 6mm and over. Evolution(E)- Previously mentioned changes or advancements show Malignant Melanoma.

4.1 Proposed Method

The labeled images "benign" and "malignant" were used in this system. The images labeled as "other and unknown" were not used since the images in those groups could not be diagnosed. Images were put into dataset relying upon their analysis mark which has been extracted from the metadata of the pictures. The dataset has been organized in to two classes one containing all the dangerous dermoscopic pictures and other containing favorable dermoscopic pictures. The images from ISIC dermoscopic archive have been chosen randomly for the experimental section. In our proposed system, there exist three layers. First layer is the input layer where the data sets are trained on. Input layer collects data that are delivering and adding some weight with it that goes to hidden layers. The neurons of hidden layer separate the features from the data to find out a pattern. The pattern is then used as basis to output layers that selects to appropriate classes. Finally, binary classification are used which appropriately select class 1 and class 0. For our case, class 0 means no harmful cells are present and class 1 means having malignant cancerous cells. How our system are implemented using convolutional neural network are depicted in figure 1.

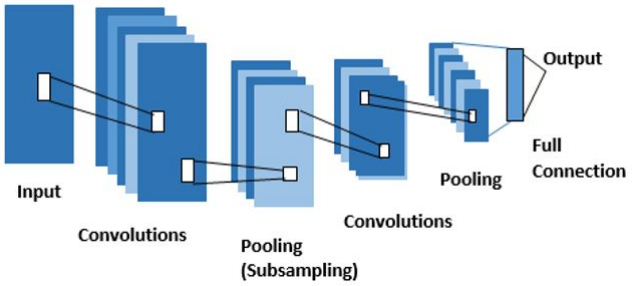

Figure 1. Convolutional neural network with its multiple layers.

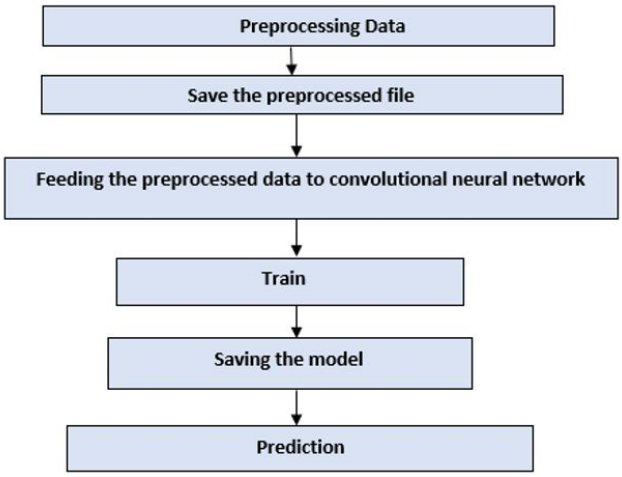

Figure 2. Flow chart for the system using convolutional neural network.

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 that are needed for system.
- `Step2`: The system takes a training image as input and saves the images into the system.
- `Step3`: The system uses convolutional neural network and finds out the prediction.

- Step4: Training with the convolutional neural network that are generated in step 3.
- Step5: Save the model into the system for prediction of the test data.
- Step5: Evaluate the result with the standard evaluation metrics like accuracy, precision, recall, and f1 score.

The description of the six steps are written in follows-

4.3.1 Step 1 : Preprocessing data. In compute vision, one of the main obstacles is the huge size of the images. The input data can be very big. The input feature dimension can be 14700 is the inputted images is is 70×70×3. Suppose the image size is 1024×1024×3 then the feature size will be huge for computation to pass it to a deep neural network specially convolutional neural network (depending on the number of hidden units). There are three channel of images. The three channels are RGB (Red, Green, Blue). Because of the lack of computational capacity, we need to attempt to characterize a solitary channel when we read the picture. Another issue is the span of the picture. The data set containing the pictures that is exceptionally huge in width and height. The width of the picture is 1022 and the height of the picture is 767 which is extremely substantial to process and needs considerably more computational capacity to register several pictures which is very time consuming and wastage of memory. Along these lines, we need to resize the information pictures so our machine can process the pictures with less memory and graphical computational power. To tackle these two problems while reading the images, it will be defined such a way that only one color channel remains. For our cases, gray scale images are generated from original images that is easier for CPU to process.

4.3.2 Step 2 : Save the preprocessed file. Each of the preprocessed images are saved in the record along with their classes. From the dataset, benign and malignant images are taken for further processing. We have to discard the images that do not have any class label. Finally, the recorded images are used to feed to a convolutional Neural Network.

4.3.3 Step 3 : 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

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 examples $5{\times}1{+}0{+}2{\times}{-}1{+}3{\times}1{+}5{\times}0{+}8{\times}{-}1{+}2{\times}1{+}5{\times}0{+}6{\times}{-}1 = -6$. 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 as figure 6.

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

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

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 4. 4×4 **image after applying** 3×3 **filter to** 6×6 **image.**

- Input: $x \times x$
- Filter size: $y \times y$
- Output: $(x - y + 1) \times (x - y + 1)$

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: $x \times x$
- Padding: p
- Filter size: $y \times y$
- Output: $(x + 2p - y + 1) \times (x + 2p - y + 1)$

To reduce the image size stride is an important and useful feature in CNN. For example, convoluting the image via choosing a stride of 2 will take both vertical and horizontal directions separately. The dimensions for stride s can be stated as:

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

So after adding the bias the equation will look like 1. Then it is passed to the rectified linear unit activation function 2. Here b_i is the biased terms. x_i is the input image and w_i is the filter.

$$z_i += b_i + x_i \times w_i \tag{1}$$

$$Relu(z_i) = max(0, z_i) \tag{2}$$

Pooling Layers: To reduce the image size and increase the computation 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.

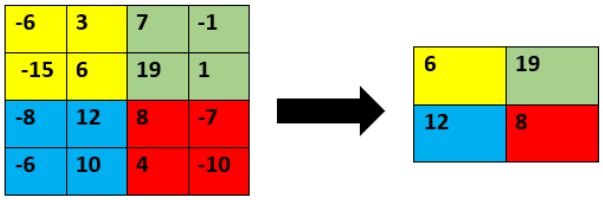

Figure 6. Result after applying max pooling.

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

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.

$$Output = \frac{Z_i}{\sum_{i=1}^{n} (Z_{i,k})} \tag{3}$$

4.3.4 Step 4 : Train. We have to train our model up to 200 times. Every times 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.

4.3.5 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.

4.3.6 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 score measures.

5 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.

$$Recall = \frac{TruePositive}{Positive} \tag{4}$$

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

$$specificity = \frac{TrueNegative}{negative} \tag{5}$$

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

$$Precision = \frac{TruePositive}{TruePositive + FalsePositive} \tag{6}$$

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

$$F_{Measures} = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{7}$$

6 RESULT AND DISCUSSION

Here, precision, recall, specificity, f1 score and accuracy are determined.

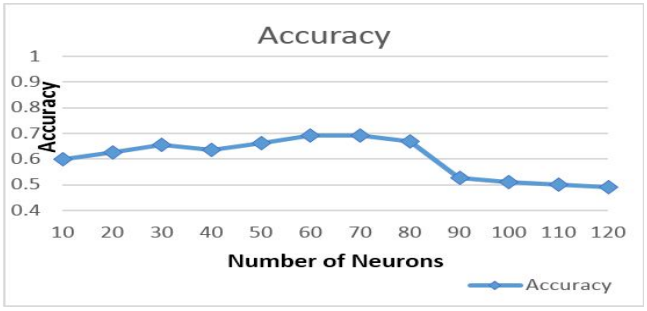

Figure 7. Neurons vs accuracy.

In figures 7-10, accuracy, Loss function and mean squared error of the proposed model are given. In figure 7 the number of iterations of neurons and accuracy are shown. If the iterations are increased, the accuracy is also increased. But, after 80 iterations, the accuracy is decreased because the added neurons are contributed to the system negatively. Loss vs iteration has been shown in figure 8. The loss is reduced with the increase of the iteration. Again, in figure 12, accuracy graph is shown. With the increase of iteration, the accuracy is increased. The next graph, figure 13 is about mean

Figure 8. iteration vs loss.

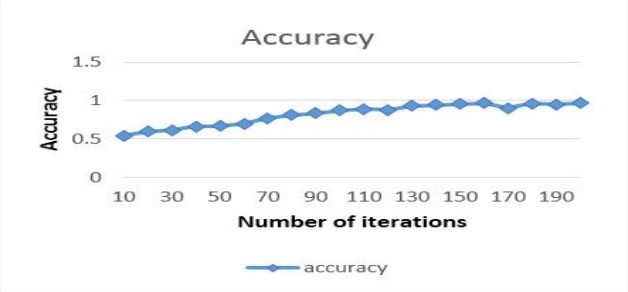

Figure 9. iteration vs accuracy.

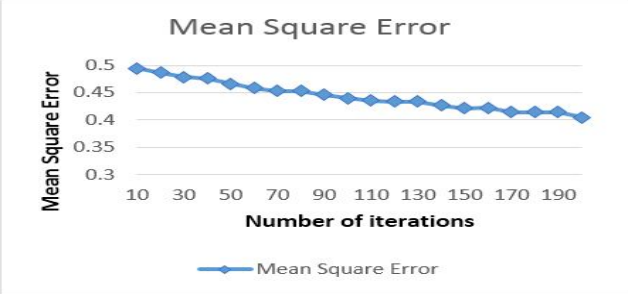

Figure 10. iteration vs mse.

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.

7 CONCLUSION

In this paper, a Convolutional Neural Networks based approach have been proposed for melanoma classification. A system is developed that can help patients and doctors to be able to detect or identify skin cancer classes whether it is benign or malignant. From the experimental and evaluation section, it can be said the model can be considered as a benchmark for skin cancer detection by assisting healthcare professionals. By taking some random images any doctor can identify the accurate results but in traditional approach too much time are taken to detect the cases correctly.

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