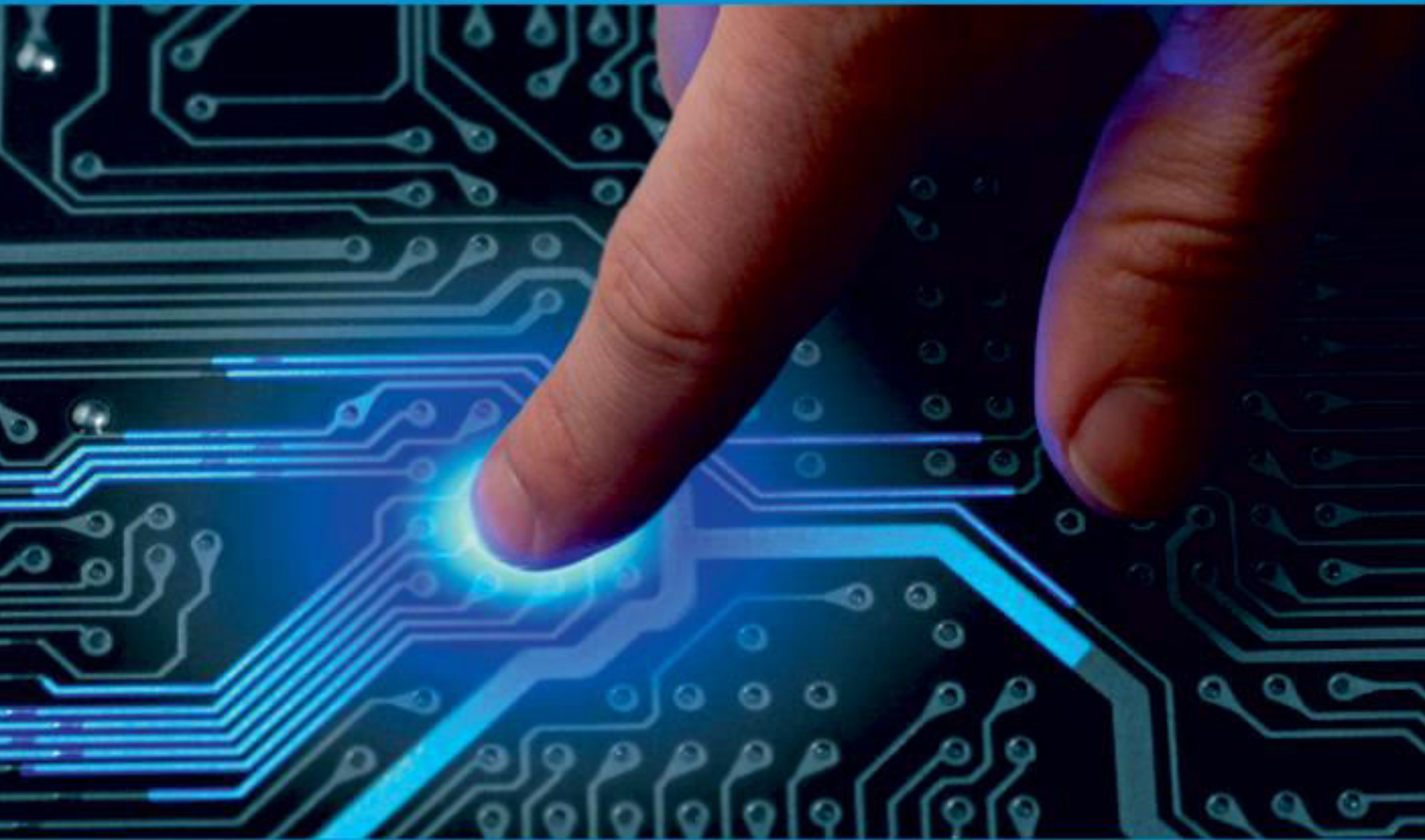
IJIRCCE

e-ISSN: 2320-9801 | p-ISSN: 2320-9798



INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

Volume 10, Issue 5, May 2022

INTERNATIONAL STANDARD SERIAL NUMBER INDIA

Impact Factor: 8.165

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.165 |

|| Volume 10, Issue 5, May 2022 ||

| DOI: 10.15680/IJIRCCE.2022.1005056|

Skin Cancer Detection Using Deep Learning

Prof. Prateeksha Chouksey[1], Samiksha Raghamwar[2], Pratiksha Chavan[3], Sapna More[4], Nikita Wadekar[5]

Professor, Dept. of CSE, GSMCOE Engineering College, Pune, India[1]

UG Student, Dept. of CSE, GSMCOE Engineering College, Pune, India[2,3,4,5]

ABSTRACT: Melanoma is the most common of all skin cancers and its incidence has reached epidemic proportions. It is important to distinguish between benign and malignant melanoma as soon as possible to increase the chance of recovery. Advances in computer technology, especially machine learning and computer vision, make it possible to classify diseases based on their image. Diagnosis by imaging is advantageous because it can be performed easier, cheaper, faster, and without attack than with a biopsy. The use of a standard reading machine and a computer-assisted visual approach makes its phase-functioning more sensitive to the result of the separation of the skin lesion and the features selected for the separation process. The latest developments of an in-depth learning algorithm, such as CNN (Convolutional Neural Network), make it possible to classify images without going through the process of image classification and manual features and provide high performance with sufficient training data. Therefore, in this study we propose a convolutional neural network (CNN) to classify melanoma images into a dangerous and dangerous category. The proposed network architecture consists of several sets of convolutional layers and layers of mass integration, followed by an exit layer and a fully integrated layer. From the test results in 352 test images, the proposed network provides 84.76% accuracy, sensitivity, and clarity, and 78.71%. The efficiency of a hopefully built model can be improved for the actual use of that I can help a specialist diagnose and treat better.

I.INTRODUCTION

Melanoma is a very serious skin cancer [1] and is now the most common type of cancer in white people. Its incidence has reached epidemic proportions [2]. Melanoma can be treated surgically if it is detected early (metastasis) in other organs [3]. However, in severe cases when malignant melanoma has spread to other organs, it is difficult to treat and therefore a higher mortality rate [4]. It is important to distinguish between benign and malignant melanoma as soon as possible to increase the chance of recovery. A biopsy of a doctor or dermatologist is usually needed to differentiate between malignant and malignant melanoma. However, advances in computational technology, especially machine learning and computer vision, make it easier to distinguish diseases based on their image. Diagnosis by imaging is advantageous because it can be performed easier, cheaper, faster, and without attack than with a biopsy. Brinker, et al. (2019) compared performance between dermatologists with varying degrees of experience with a computer program that uses the Convolutional Neural Network (CNN) algorithm to make melanoma image classification more dangerous and risky.

II. METHODOLOGY

An image set of melanoma image was obtained from the ISICA archive [9]. The train set contains 1,440 images of benign melanoma and 1,197 photographs of malignant melanoma. The test set contains 360 images of benign melanoma and 300 images of malignant.

Fig.1.Examples of benig nmelanoma

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.165 |

|| Volume 10, Issue 5, May 2022 ||

| DOI: 10.15680/IJIRCCE.2022.1005056|

Fig.2.Examples of them alignant melanoma

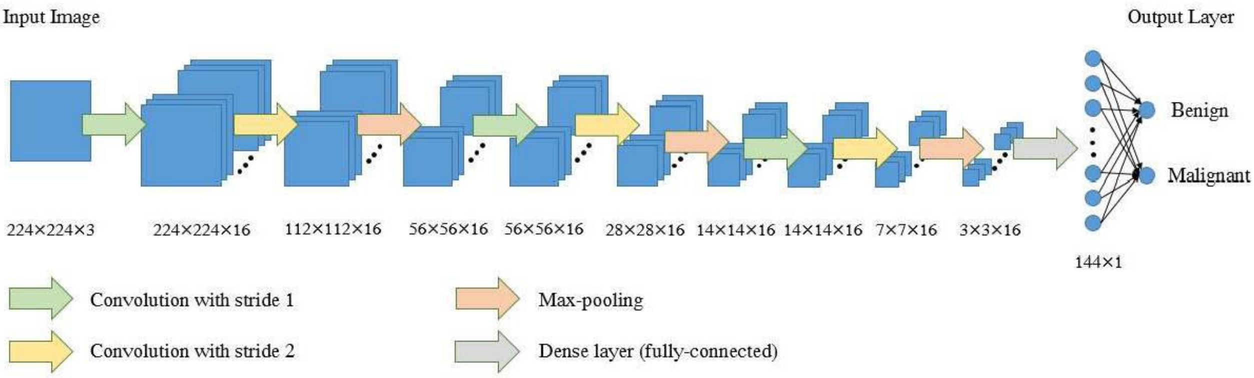


Fig.3.Architecture of the proposed deep CNN

an example of malignant and malignant melanoma images can be seen in Fig. 1 and Fig. 2, respectively. Images are in RGB color mode (red, green, blue) in size pixels. According to Indraswari, et al. (2017), benign melanoma has a very small size, normal shape, and light color while malignant melanoma has a large size, abnormal shape, and dark color [8]. To differentiate melanoma images, we suggested using the deep convolutional neural network (CNN) method. CNN is a development of a neural network algorithm that can be used for image classification. Similar to a typical neural network, CNN studies a given train set pattern to separate test classes set using forward and backward broadcasts. In the feed transfer process, the network attempts to predict the input image phase by using the process of duplicating with a few filters or kernels the original value is set as a random number. The guessing result is then compared with the actual label or category (basic fact) to calculate the network error number. By using an error number, back distribution is done to improve the number of filters in the network. This forward and forward transmission is repeated until the maximum number of times (period) is reached or until the error number does not change (merge).

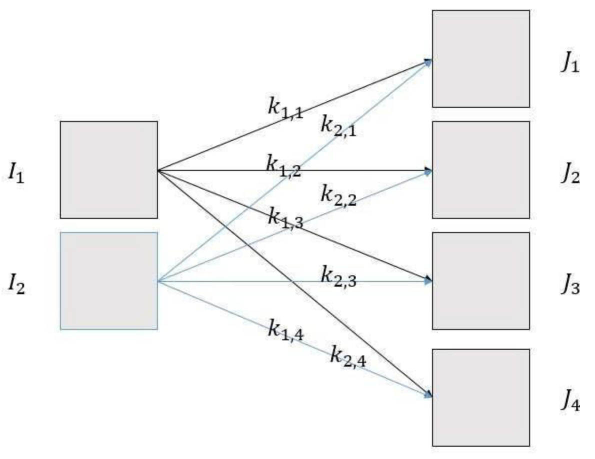
The proposed CNN structure is shown in Fig. 3. Network processes or layers represent the arrows in Fig. 3, while the shape of the square represents the input or output image of each layer. The number below each square in Figure 3 indicates the size of the image. For example, the number after the first green arrow means that the first rotation process using stride = 1 results in a wide image = 224 pixels, length = 224 pixels, and channel = 16. -combining layers, followed by a fully integrated layer. The main layers of the network are described below. In this study, data were entered into the network in small groups containing 16 images each. The development algorithm used in the training process.

A. Admans Optimizer because the method is able to reach the convergence condition quickly. "224 × 224 × 16 "

B. Convolutional Layer

In the convolutional layer, several image convolution processes (or filtering) by using filter with specified size are done to the each channel of the input image. The results of filtering on each input channel are then summed to produce an output channel (feature map) of the convolution process. The illustration of convolutional layer is shown in Fig. 4. Let the input image of the convolutional layer consists of 2 channel (I_i; {1,2}) and we set the output channel (the number of channel of the output image) as 4 (J_j; $j = \{1,2,3,4\}$). This convolutional layer will use the total of 8 convolution filters $k_{i,j}$. Equation (1) is used to produce the output channel J_j, where is the symbol of convolution process and *N* is the number of input channel. $J_j = \sum_{i=1}^{N} I_i * k_{i,j}$(1)

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.165 |
|| Volume 10, Issue 5, May 2022 ||
| DOI: 10.15680/IJIRCCE.2022.1005056|



In the convolutional layer, there are a few parameters that needed to be determined first. Those parameters are: 1) convolution filter size, 2) step, and 3) output channel value. In the proposed network, the size of all convolution filters is pixels and the output channel number is 16. Larger filter size can capture more information in an image than smaller filter size. However, larger filter size means calculation costs and longer training time .

The stride parameter determines the number of pixel shifts on the image to insert in the convolution process. In the proposed network, a few convolutional layers use 1 as a step and one as a 2. If 2 is used as a step, the output image size wi ll be half the size of the input image. $f(x) = \max(0, x) (2)$

Each layer of convolution is followed by an activation function. The output image of the convolution layer is then opened using the ReLU function (modified line units). The ReLU function converts the input value x from the effect of the convolution layer to the output value f (x) using (2) . ReLU work increases network size and speeds up the training process .

C. *Max-pooling Layer*

In the proposed network, the max merging process with a pixel window size is also done to compress the image and capture important features. The multiplication process divides the input image into parts of a certain size (window), and in each window only 1 pixel with the highest value (size) will be taken to take the output image. With the merging process, the image size will be smaller so the required computational costs will be lower. In addition, this process also creates a constant network rotation, because the selected pixel location in the first window is not taken. A maximum number of pixels is selected in the merging process because it is the most dominant value in the window.

D. *Fully-connected Layer*

The fully integrated layer is the last layer on CNN before the output layer. The front layer output which is a set of 2-dimensional (2D) images flat into 1D nodes. For example, if the output of the previous layer is a 16 pixel image with a pixel size, then a fully integrated layer will have notes.

The network output layer uses one hot code and combines two locations because the database contains only 2 categories (dangerous or bad). In Fig. 3, The upper node in the output layer is kept in the correct

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.165 |

|| Volume 10, Issue 5, May 2022 ||

| DOI: 10.15680/IJIRCCE.2022.1005056|

phase while the lower node in the output layer is kept in the critical section. In a single hot code, the data category is determined by which node has the highest value. If the input image has an actual category (basic truth) as dangerous, the target value of the output layer will be [0 1], whereas if the input image has an actual category (basic truth) as correct, the target value of [1] 0] .

$$\text{Error: } -\frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{K}\left(\widehat{y_k^{(i)}}\log(\,y_k^{(i)})\right)$$

III.EXPERIMENTAL STATUS

The study was conducted using the Python programming language and the Tensorflow library. Specification of the machine where the network was used by GPU NVIDIA GeForce GTX 860M, RAM 2 x 8GB 2400 MHz DDR4. Tests were performed on 2624 images on the train set and 352 images on the test set. We also do a few tests using the k-fold interval method to separate the train from the test data but the results are not very different from using a fixed train with test data. Therefore, we prefer not to use the verification method so that the calculation costs are not increased. In this study, two experiments were performed to determine the amount of time the training process was performed and to evaluate the use of layers that stopped flowing from network construction. Network performance is measured using accuracy, sensitivity, and clear values calculated using a confusion matrix. The confusion matrix is shown in Fig. 5 where TP claims true, FN is false, FP is false, and TN is true.

		Malignant	**Benign**
Ground Truth	**Malignant**	TP	FN
	Benign	FP	TN

IV. MODULE

Pre-processing Pre-processing is a common term for images with a very low level of output both input and output are dynamic images. The purpose of pre-processing is to improve image data that suppresses unwanted distortions or enhances other image features that are important for further processing.

Extrasion Feature The component is part of the process of reducing size, in which, the original set of raw data is separated and downgraded into control groups. So if you want to process it will be easy.

Classification Classification is a supervised (machine-readable) learning method, in which the algorithm reads the data input given to it and uses this learning to distinguish new ones

V.CONCLUSION

In this project, completely different stages of image process were applied to the skin nodes. From these various image process techniques, a nonlinear filter can give effective sound. From these various image processing techniques, a nonlinear filter will provide effective sound. Splits made with a watershed-based algorithm based on the mark, provides a different area of image. GLCM is used to extract different aspects of an image and which takes less time to produce the result. These effects are transmitted through the CNN Classifier, which classifies nodules as dangerous or dangerous. The CNN category provides 92.5 percent accuracy.

International Journal of Innovative Research in Computer and Communication Engineering

| e-ISSN: 2320-9801, p-ISSN: 2320-9798| www.ijircce.com | |Impact Factor: 8.165 |

|| Volume 10, Issue 5, May 2022 ||

| DOI: 10.15680/IJIRCCE.2022.1005056|

REFERENCES

[1] J Abdul Jaleel, Sibi Salim, Aswin.R.B, "Computer Aid Detection 01 Skin Cancer", International Conference on Regional, Energy and Computer Technology, 2013. International Research Journal of Engineering and Technology (IRJET) -ISSN: 2395 -0056 Volume: 04 Released: 04 | Apr -2017 www.irjet.net p-ISSN: 2395-0072 © 2017, IRJET | Impact Factor Value: 5.181 | ISO 9001: 2008 Certified Journal | Page 2881

[2] C.Nageswara Rao, S.Sreehari Sastry and K.B.Mahalakshmi "Co-Occurrence Matrix and Its Mathematical Matters How to Identify the Mesogens Transformation Phase", International Journal of New Engineering and Technology Research, Vol. 2, Issued 9, September 2013.

[3] Santosh Achakanalli & G. Sadashivappa, "Statistical Analysis of Skin Cancer Image -Study Story", International Journal of Electronics and Communication Engineering (JECE), Vol. 3, Issued 3, May 2014.

[4] "Digital image processing" by jayaraman. Page 244,254-247,270-273. (gray level, medium filter).

[5] Kawsar Ahmed, TasnubaJesmin, "Early Prevention and Disease Prevention of Skin Cancer Using Data Mining", International Journal of Com puter Applications, Volume 62- No.4, January 2

[7] M.Chaithanya Krishna, S.Ranganayakulu, "Skin Cancer Detection and Exclusion With Clustering Technique", International Journal of New Research in Computer and Communication Engineering, Vol. 4, Issued March 3, 2013.

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING