IJCRT.ORG ISSN : 2320-2882

INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Skin Cancer Classification At The Dermatologist Level Using Handcrafted Deep Neural Networks

[1]Ms.D.R.Maheswari, [2]Mr.S.Malaiarasan

[1]Student of M.E, [2]Assistant Professor

[1]Department of CSE, Francis Xavier Engineering College, Tirunelveli, Tamilnadu, India

[2]Department of CSE, Francis Xavier Engineering College, Tirunelveli, Tamilnadu, India

Abstract: One of the most common malignancies in the world is Skin Cancer. The features of the illness can only be evaluated by a clinical assessment of skin lesions, but this process might take a long time and can be interpreted in many ways. Machine Learning and Deep Learning techniques have been developed to assist dermatologists in making an early and accurate diagnosis of Skin Cancer, which is critical for increasing patient survival rates. In this study, we give a comprehensive literature review of recent studies that have used deep learning to categorize skin lesions, with the goal of giving researchers who are just getting started in this field a good place to begin their investigations. The papers that thoroughly and clearly defined the methods used and presented the findings obtained were chosen after an extensive search of many internet databases using inclusion/exclusion criteria. Sixty-eight studies were chosen for further study, the vast majority of which use Deep Learning methods, in particular Artificial Neural Networks, for skin cancer detection and classification. Given the encouraging findings too far, it seems likely that these methods will be incorporated into clinical practice in the not-too-distant future. . The deep learning architectures such as Deep Convolutional Neural Networks are developed to utilize the Convolutional Neural Network. It is demonstrated that accuracy of deep learning model is improved to 98.8% from 92.3% of Convolutional Neural Network model.

Index Terms **- Skin Cancer, Skin lesions, Machine Learning, Deep Learning, Artificial Neural Networks, Deep Convolutional Neural Networks.**

I. INTRODUCTION

The most prevalent malignant disease in the body is skin cancer. The unchecked and abnormal development of skin cells is the primary cause of this malignancy. In the nucleus of skin cells, ultraviolet radiation from sunshine and tanning lamps alters the genetic code. Skin cells start to develop quickly and unchecked if the body's immune system is unable to repair the damage. This first manifests as rapidly expanding moles with bleeding, tumors, or wounds that do not heal, which if left untreated can spread to other places (metastasis). The skin is the major tissue of the human body that covers the complete body and its thickness differs significantly over all parts of the body[1], [2]. The skin shields against thermal and mechanical harms. It also defends us against bacteria and the elements, and the presence of intercellular lipids prevents moisture loss [3], [4]. Skin cancer sufferers must have early detection and regular diagnosisin order to survive. Computer Based Diagnosis is basically clinical decision support system that assists clinicians in the understanding of medical images. Its primary goal is to increase the diagnosis accuracy and consistency of dermatologist by decreasing the false negative rate due to observational oversight, intra-observer and inter-observer variation. Most of the time two types of broad methodologies are deployed in CBD systems. The first stage is to get the position of the lesions. The next stage is to classify the type of image patterns. Usually, the computer based diagnosis system includes three basic components. The foremost is the image processing and analysis system that supports to enhance and extract the lesions by selection of the primary candidates of the lesions and apprehensive patterns [7], [8]. The second is the segmentation of image features for example the size, color, texture, shape and contrast of the pigments selected in the first step. It is essential to identify distinctive features that can discriminate consistently between a lesion and other usual anatomical structures. The last stage is feature processing and classification which classifies between abnormal and normal patterns or identify skin lesion class, based on the features acquired in the second stage [9], [10].

1.1 Deep Learning With Medical Image Processing

We have more than 2000 algorithms in Machine Learning and Deep Learning ,In this paper we are using Deep Convolutional Neural Network and Artificial Neural Network. Machine Learning performs the needed task automatically by using their trained data to make predictions and decisions. They are used in a wide variety of applications. It is a part of Artificial Intelligence. Deep learning is a subset of Machine Learning based on Artificial Neural Network. In Image Processing the system processes our input image using some efficient algorithms in order to produce an enhanced and extracted image as the output. Medical Image Processing encompasses the use of 3D image datasets of the human body, obtained from CT scan or MRI scan to guide the medical interventions such as surgical planning or for some research purposes.

II. Related Work

In the field of medical image classification, CNNs have already been used extensively and so forth. To established a very deep CNN and a collection of learning frameworks with minimal training data, they obtain a dermatologist-level diagnosis of more than 120 thousand photographs. A pre-trained CNN technique have been used by dermatologists for dermoscopic melanoma recognition and comparison. The skin cancer classification process can be determined under uncertainty by using sophisticated methodology like Belief Rule Based Expert Systems (BRBES) in an integrated framework. The lesion boundary segmentation is vital to locate the lesion accurately in dermoscopic images and lesion diagnosis of different skin lesion types. In this work, we propose the fully automated deep learning ensemble methods to achieve high sensitivity and high specificity in lesion boundary segmentation. The system heavily relies on the processing unit for removing image occlusions and the data generation unit, based on generative adversarial networks, for populating scarce lesion classes, or equivalently creating virtual patients with pre-defined types of lesions. Two sets of training samples (positive and negative sample pairs) are input into the feature extraction module to Lightweight CNN recognition model. The contours of the pectoral muscle boundary in the blocks often reveal specific patterns in terms of geometric location and topological features MFTL employs several feature extractors and classifiers for each view of skin images, leveraging view-information according to their contributions to skin lesion classification. Multi-View Filtered Transfer Learning is a kind of skin lesion classification technique that can learn various type of information from different image views.

III. Overview Of Proposed Image Classification For Skin Cancer

This Paper presents the first systematic review of the state-of-the-art research on classifying skin lesions with Deep Neural Network. The main objective of this paper is to classify the type of skin cancer from the input image and to predict the maturity level of skin cancer with the help of Deep Neural Network algorithms. The accuracy predicted matches the dataset so that earlier detection of skin effect is analyzed periodically. Skin lesion separation and classification is done using a Deep pre-trained DCNN model for dimensional reduction. The image is first augmented using various image processing techniques in order to make it suitable for analysis and skin cancer detection. Multiple features from the images are extracted as used as base points .The following figure 1 shows the overall flow of proposed system architecture.

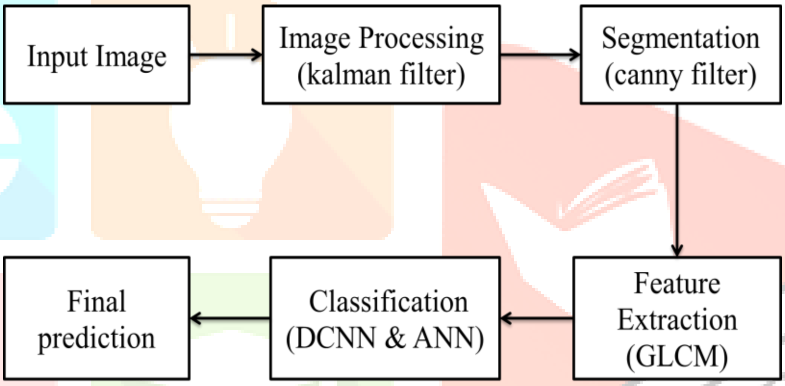

Figure 1 : Proposed System Architecture

3.1 Image Preprocessing

Initially the image is processed through the kalman filter to indicate the pixel as well as the neighboring pixel to predict the accuracy of the lesion image. The lesion image is marked with a ruler so that how the infection spreads in a small part of the skin. Input image contains more number of noises and it is too blur. So we are using Kalman filter to remove unwanted noise from the input image. Here genetic algorithm also used to generate high quality solutions to optimization and search problems. They are especially used to solve complex optimization problems.

3.2 Image Segmentation

The processed image is given to segmentation phase. In this phase we are using Canny filter to segment the particular affected part from the cancer affected image. Region Base Segmentation is also done to detect the edge and boundary of skin lesion image. It looks for similarities between adjacent pixels such as brightness, color and texture.

3.3 Feature Extraction

The segmented image is then given as input to feature extraction. Here we are using Gray Level Co-occurrence Matrix at different kernel sizes is used as input to classification algorithms. It takes the input parameters as shape, height, width, texture of the image. And then it identifies the diameter, area, radius, perimeter, compactness and brightness of the image.

3.4 Image Classification

In this module the classification is done with the help of Deep Convolutional Neural Networks and Artificial Neural Networks to classify the type and the maturity level of skin cancer from the given cancer affected input image. Using these types of optimization approaches we can classify the skin cancer as 7 types ie.,

- Melanocytic nevi
- Melanoma
- Benign keratosis-like lesions
- Basal cell carcinoma
- Actinic keratoses
- Vascular lesions
- Dermatofibroma

Deep Convolutional Neural Network which is developed in this work, optimizes both sections of the feature selection and classification phases.

3.5 Input Dataset

This work has achieved admirable classification accuracy on the International Skin Imaging Collaboration (ISIC) image dataset. It becomes a leading repository for researchers in Machine Learning for medical image analysis especially in the field of skin cancer detection. The ISIC dataset is then used to test the final constructed model, and its results have been confirmed using a number of recent techniques to demonstrate the method's increased effectiveness. Totally there are 10,015 images, from that 8012 images are trained and 2003 images are tested. The following table shows the total number of trained and tested images.

Table 1: Number of Trained and Tested Images

INPUT IMAGES	NO.OF IMAGES
Total Images	10,015
Trained Images	8012
Tested Images	2003

IV. Results And Discussions

The experiment produces the classification of skin cancer of given input images. Initially the input is given as csv(comma separated value) file. After all training, testing and modeling have been done with the csv file, the input is given as image file. CSV file only contains text values, this text file that has a specific format which allows data to be in a table structured format. This format contains a single line where a comma separates each database. Here csv file is applied for training and testing phases. 8012 images are allocated for training and 2003 images are allocated for testing. After training, modeling phase is done. In each and every step, Loss and Accuracy is calculated for the model. The following figure shows an increased amount of accuracy for the model.

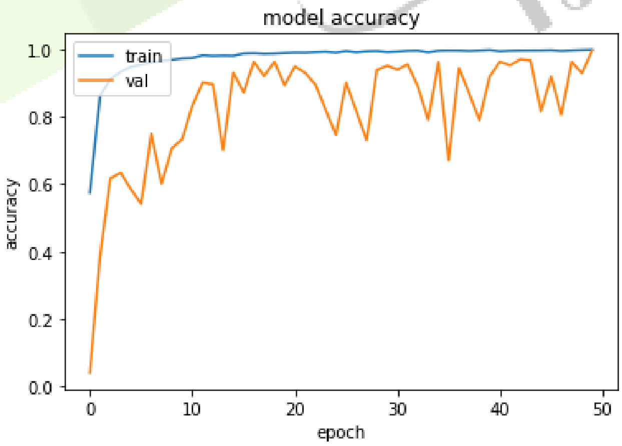

Chart 1: Accuracy function for the model

Here the training is done with the help of ReLu and softmax layers. ReLu denotes Rectified Linear Unit, it performs on multi layer neural network and does not activate all the neurons at the same time. Softmax function is to test the readability of the model as loss function, cross function and entropy function in order to maximize the performance of neural network. The following figure shows the small amount of loss for the model.

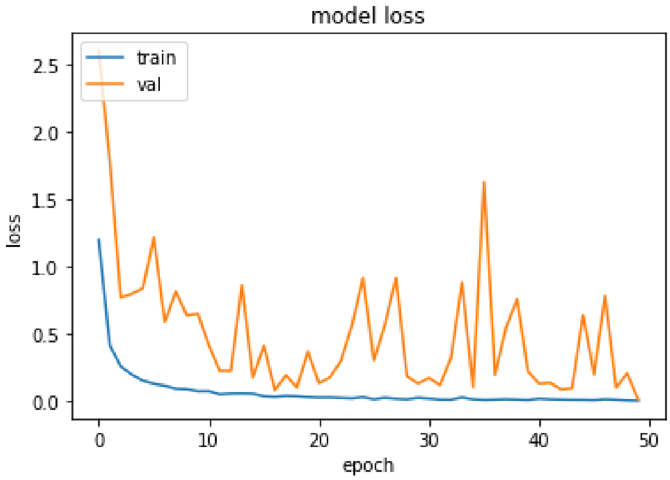

Chart 2: Loss function for the model

Thus modeling procedure provides more number of accuracy and small amount of loss. Also confusion matrix have been generated for predicted and actual values. Generally confusion matrix calculates the amount of True Positive , True Negative, False Positive, False Negative. Here 7*7 confusion matrix have been generated for the model.

Figure 2 : Confusion matrix for predicted and actual values

Dense package is used that deeply connected with its previous layer which is most commonly used in Artificial Neural Network. It classify the image based on the output layer. Arrays with their class names are defined to classify the type of skin cancer. Each and every label denote particular type of skin cancer. After all training, modeling and testing phases have been done ,it classifies the type of skin cancer for our given input image. Finally this paper reached 98.8% accuracy when compared to other literature papers.

V. CONCLUSION

Throughout the process, a new Deep Convolutional Neural Network and Artificial Neural Network based approach has been suggested to classify the type and the maturity level of skin cancer using an efficient solution based multiple classifiers for melanoma detection from lesion images. Skin cancer of any form when detected in an early stage is preferably curable. This proves that this model developed using tensor flow, can be further modified and developed for use by oncologists for particularly facial cancer detection. The results obtained were satisfactory with accuracy 98.8%. With high performance, based on Artificial Intelligence for the detection of melanomas in images. With the correct feature extraction, selection and classification ,we can identify the malignant instances. Utilizing these types of optimization approaches, we can solve these issues optimally.

VI. ACKNOWLEDGMENT

Financial support obtained from the All India Council for Technical Education (AICTE) under Research Promotion Scheme (RPS), Sanction order no: F.No 8.9/RIFD/RPS/Policy- 1/2017-18 coordinated by Anna University Recognized Research Centre, Department of Computer Science and Engineering, Francis Xavier Engineering College, Vannarpettai, Tirunelveli 627003, Tamilnadu, India.

REFERENCES

[1] D. Didona, G. Paolino, U. Bottoni, and C. Cantisani, ''Non melanoma skin cancer pathogenesis overview,'' Biomedicines, vol. 6, no. 1, p. 6, Jan. 2018.

[2] T. J. Brinker, A. Hekler, J. S. Utikal, N. Grabe, D. Schadendorf, J. Klode,Berking, T. Steeb, A. H. Enk, and C. von Kalle, ''Skin cancer classifi- cation using convolutional neural networks: Systematic review,'' J. Med. Internet Res., vol. 20, no. 10, Oct. 2018, Art. no. e11936.

[3] P. Tschandl, C. Rinner, Z. Apalla, G. Argenziano, N. Codella, A. Halpern, M. Janda, A. Lallas, C. Longo, J. Malvehy, J. Paoli, S. Puig, C. Rosendahl, H. Peter Soyer, I. Zalaudek, and H. Kittle, ''Human–computer col- laboration for skin cancer recognition,'' Nature Med. vol. 26, no. 8, pp. 1229–1234, 2020.

[4] B. C. Baumann, K. M. MacArthur, J. D. Brewer, W. M. Mendenhall, C. A. Barker, J. R. Etzkorn, N. J. Jellinek, J. F. Scott, H. A. Gay, J. C. Baumann, F. A. Manian, P. M. Devlin, J. M. Michalski, N. Y. Lee, W. L. Thorstad, L. D. Wilson, C. A. Perez, and C. J. Miller, ''Management of primary skin cancer during a pandemic: Multidisciplinary recommen- dations,'' Cancer, vol. 126, no. 17, pp. 3900–3906, Sep. 2020.

[5] A. Esteva, B. Kuprel, R. A. Novoa, J. Ko, S. M. Swetter et al., "Dermatologist-level classification of skin cancer with deep neural networks," Nature, vol. 542, no. 7639, pp. 115–118, 2017

[6] R. L. Siegel, K. D. Miller and A. Jemal, "Cancer statistics 2020," A Cancer Journal for Clinicians, vol. 70, no. 1, pp. 7–30, 2020.

[7] M. A. Kassem, K. M. Hosny, R. Damaševičius, and M. M. Eltoukhy, ''Machine learning and deep learning methods for skin lesion classification and diagnosis: A systematic review,'' Diagnostics, vol. 11, no. 8, p. 1390, Jul. 2021.

[8] O. O. Abayomi-Alli, R. Damaševičius, S. Misra, R. Maskeliunas, and A. Abayomi-Alli, ''Malignant skin melanoma detection using image aug- mentation by oversampling in nonlinear lower-dimensional embedding manifold,'' TURKISH J. Electr. Eng. Comput. Sci., vol. 29, nos. SI–1, pp. 2600–2614, Oct. 2021.

[9] T. C. Pham, V. D. Hoang, C. T. Tran, M. S. K. Luu, D. A. Mai, A. Doucet, and C. M. Luong, ''Improving binary skin cancer classification based on best model selection method combined with optimizing full connected lay- ers of deep CNN,'' in Proc. Int. Conf. Multimedia Anal. Pattern Recognit. (MAPR), Oct. 2020, pp. 1–6.

[10] N. Hameed, A. Ruskin, K. Abu Hassan, and M. A. Hossain, ''A com- prehensive survey on image-based computer aided diagnosis systems for skin cancer,'' in Proc. 10th Int. Conf. Softw., Knowl., Inf. Manage. Appl. (SKIMA), 2016, pp. 205–214.

[11] B. Mohamad, A. M. Zain, N. Erne and N. Bazin, "Coot search algorithm for optimization problems | a literaturereview and its applications," Applied Artificial Intelligence, vol. 28, no. 5, pp. 419–448, 2014.

[12] L. Chen, L. Chen and L. Chen, "Dimension-by-dimension enhanced Coot search algorithm for global optimization," Soft Computing, vol. 23, no. 21, pp. 11297–11312, 2019.

[13] .M. Al-masni, M. Al-antari, M. Choi, S. Han and T. S. Kim, "Skin lesion segmentation in dermoscopy Images via deep full resolution convolutional networks," Computer Methods and Programs in Biomedicine, vol. 162, no. 1, pp. 221–231, 2018.

[14] S. Kumari and S. Pushkar, "Coot search based hybrid models for improving the accuracy of software effort estimation," Microsystem Technologies, vol. 24, no. 12, pp. 4767–4774, 2018.

[15] M. Capó, A. Pérez and A. Lozano, "An Efficient approximation to the K-means clustering for massive data,"Knowledge Based System, vol. 117, no. 1, pp. 56–69, 2017.

[16] O. Ronneberger, P. Fischer and T. Brox, "U-net: convolutional networks for biomedical image segmentation," in Int. Conf. on Medical Image Computing and Computer-Assisted Intervention, USA, Springer, vol. 28, pp. 234–241, 2015.

[17] W. Sun, X. Chen, X. R. Zhang, G. Z. Dai and P. S. Chang, "A multi-feature learning model with enhanced localattention for vehicle re-identification," Computers, Materials & Continua, vol. 69, no. 3, pp. 3549–3560, 2021.

[18] W. Sun, G. C. Zhang, X. R. Zhang, X. Zhang and N. N. Ge, "Fine-grained vehicle type classification using lightweight convolutional neural network with feature optimization and joint learning strategy," Multimedia Tools and Applications, vol. 80, no. 20, pp. 30803–30816, 2021.

[19] D. P. Mahato, "On scheduling transaction in grid computing using Coot search-ant colony optimization considering load," Cluster Computing, vol. 23, no. 2, pp. 1483–1504, 2019.

[20] C. Zhang, G. Zeng, H. Wang and X. Tu, "Hierarchical resource scheduling method using improved Coot search algorithm for internet of things," Peer-to-Peer Networking and Applications, vol. 12, no. 99, pp. 1606–1614, 2019.

[21] H. Tran-ngoc, S. Khatir, G. De Roeck, T. Bui-tien and M. A. Wahab, "An Efficient artificial neural network for damage detection in bridges and beam-like structures by improving training parameters using Coot search algorithm," Engineering Structures, vol. 199, no. 433, pp. 109637, 2019.

[22] Y. Yading, M. Chao and L. Yeh-Chi, "Automatic skin lesion segmentation using deep fully convolutional networks with jaccard distance," IEEE Transaction on Medical Imaging, vol. 36, no. 9, pp. 1876–1886, 2017.

[23] T. J. Brinker, A. Hekler, A. H. Enk, J. Klode and T. Letz, "Deep Learning outperformed 136 of 157 dermatologists in a head-to-head dermoscopic melanoma image classification task," European Journal of Cancer, vol. 113, no.10151, pp. 47–54, 2019.

[24] X. Yang and S. Deb, Coot search via levy flights. In: World Congress on Nature & Biologically Inspired Computing.Coimbatore, India: IEEE, pp. 210–214, 2009.

[25] A. Euijoon, K. Jinman, B. Lei, K. Ashnil, L. Changyang et al., "Saliency-based lesion segmentation via background detection in dermoscopic images," IEEE Journal of Biomedical And Health Informatics, vol. 21, no. 6, pp. 1685–1693, 2017.