xIlkogretim Online - Elementary Education Online,2021; Vol 20 (Issue 1): pp.3061-3066
http://ilkogretim-online.org
doi: 10.17051/ilkonline.2021.01.343

Comparative Analysis on Skin Cancer diagnosis using Deep Learning Neural Networks

M. Mohan Babu, Research Scholar, Department of Electronics and Communication Engineering, SRM Institute of Science and Technology, Kattankulathur, Tamil Nadu, India
P. Radhika, Department of Electronics and Communication Engineering, SRM Institute of Science and Technology, Kattankulathur-603203, Kanchipuram, Tamilnadu, India
P. Sudheer, Associate Professor, Department of Electronics and Communication Engineering, SITAMS, Chittoor, Andhra Pradesh, India.

Abstract- The skin can be considered as the largest part in the human being .Majorly skin cancer can be classified into two types like melanocytic nature and non melanocytic nature. Among these two melanocytic is more dangerous due to spreading nature under epidermis and sub-cutaneous layers. The dermoscopic methods are time consuming process in early prediction of melanocytic lesions. There are many deep learning neural network algorithms were employed for early prediction of skin cancer. During the prediction of the skin condition different factors are considered like artifacts, hair, color and noise .In skin cancer diagnosis, pre-processing steps and augmentation techniques were employed. The mostly used algorithm is deep convolutional neural network (DCNN).This paper proposes intelligent hybrid deep learning algorithms (IHDLA) for improving the prediction accuracy.

Keywords: Deep learning neural networks, Skin Cancer, Augmentation, Accuracy

I. INTRODUCTION

Diagnosis of Skin cancer was increasing significantly over the past decade [1]. From 2009 to 2020 the diagnosis of skin cancer rate is about 60 to 70 %.Cancers in skin was in irregular form of skin cells which multiplies with speed because of DNA or genetic disorders [2]. Ultraviolet radiation which is coming from sun makes exposure to cause the irregularities [3]. Biopsies and physical assessment were used by dermatologists to analyze skin problems which are called conventional method. For this few samples from skin has been taken and it is send to the laboratory for assessment purpose. The ultimate diagnosis of a skin cancer will took more than one week. For the time being approximately more than 10000 people in USA were examined every day for skin cancer .Conventional method rate in early hours were detected for skin cancer is about 98%.Regrettably the recognition with late process was diminishes noticeably up to 23% [4]. More than two people for every hour were died because of affected melanoma diseases was projected as 7230 members in 2019.Moreover between 15 to 39 age group 55% of men and more than this the women with same age group was likely died with melanoma [5]. In medical image segmentation deep learning has achieve important breakthroughs like brain tumor segmentation, retinal vessel segmentation etc to [6]. Skin cancer is a challenging work due to hair, reflection and oil bubbles artifacts [7]. Other critical challenge of medical issue was trained partially with available data and the augmentation practices produce high number of related images by varying the features in original image [8]. The skin diseases are broadly classified as two types like growing and non-growing cells [9]. With the source of these leision the genetic fault in pigment cells which are known as melanocytes were derived. The melanoma cell can develop from zero stage to fourth stage without correcting management [10] the severity of leisions which can be divided into benign and malignant. The growing cell structure is shown in Figure 1a. The growing nevus (NV) image is shown in Figure 1b. [11] The growing carcinoma cell design is shown in Figure 1c. Actinic Keratosis is usually white structure less areas show in Figure 1d[12].The moderate growing keratosis shown in Figure 1e [13]. Dermato fibroma is a growing type of cell shown in Figure 1f [14]. The most effected cell structure shown in Figure 1g. The dot structure cell is shown in Figure 1h [15].

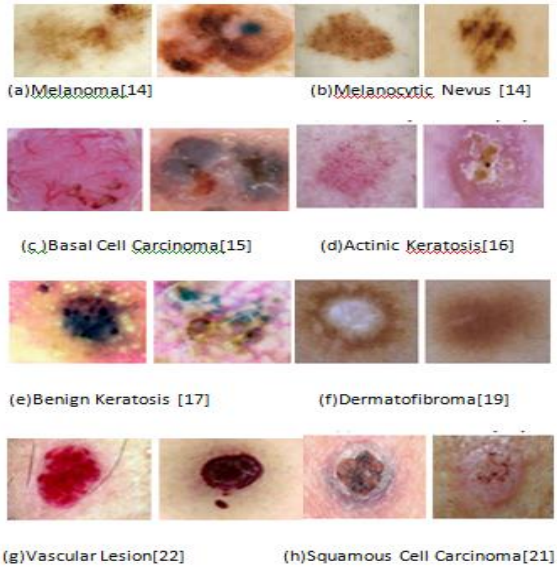

Figure 1. Skin Lesion Categories [1]

II. ALGORITHMS AND ARCHITECTURES FOR SKIN CANCER DETECTION

Substantial development in research for the growth of skin cancer predictions using a variety of advanced deep learning methods in the recent century [16], the deep Convolution Algorithm is used mostly in skin lesions because of less training parameters. Bayes man Optimization Algorithm [1], [22] used to accomplish searching speed. Tryan Adityas team proposed an usual augmentation policy to increase the dataset [17]. In this need not to train the model at all time when new augmentation is used [18]. By using this work low convergent rate is obtained because of stochastically tuned weights, which has been rarely obtained using low augmentation. The authors of [23] performed analysis on hill-climbing approach along with network morphism operations to explore search space. The network preserving transformations had taken benefit from formerly trained networks by using the weights again from the before trained process which leads to important computational cost reduction [19]. This scheme has a constraint of less efficiency because of searching based on substantiation accuracy. Authors proposed [24] whale optimization for optimizing the efficiency results from CNN. They used Dermi Quest and Derm IS data sets for training the model. Authors applied [25] non dermoscopic images. Because of limited training information these algorithms results in dramatic losses in accuracy. The authors of [26] performed research on intelligent area region of Interest based system for recognition and distinguish of melanoma by means of transfer learning method .Advanced k-mean techniques are used to pull out ROI from given images. This process uses entire image for classification. Because of DermIS and DermQuest the dataset and some sample images for training purpose.The authors of [27] used light weight model with extraordinary features and its classification principle.This method obtains more accuracy with less quantity of obtained parameters.The authors of [28] used the completely automatic deep learning methods .It has a merit of towering with high prediction rate and most suitable method in lesion process. The authors of [29] discussed saliency appraisal and the choice of most discriminated CNN features collection in deep. In this, lesion dissimilarity is being improved with used Gaussian technique is needed for preprocessing, addition and segmentation. The authors of [30] planned Multi Stage completely Convolution Networks and New Parallel incorporation Method. This technique was achieved precise segmentation by adding the crucial characteristics of the skin lesions. The proposed method is capable of doing skin lesions without utilizing any preprocessing techniques [20]. Performance Evaluation Metrics are used for the assessment of algorithms for given datasets. The results were assessed by number of algorithms applied. In the described parameters four were very important to predict true positives and negatives when observation is not belonging to a class [21]. False positives and false negatives were occurs when the prediction that an observation does belongs to a class when in reality, not in reality respectively. The metrics which were useful to evaluate the performance are described below [1] [31].

Precision indicates the ability of the trained model to predict the exact true positive or negative in the given datasets.

Precision= $\frac{TP}{TP+FN}$ (1)

Recall is defined as the number of obtained similar predictions from the total obtained predictions.

Recall =$\frac{TP}{TP+FN}$ (2)

Sensitivity is described as the ratio of change in output to the change in input.

Sensitivity = $\frac{TP}{TP+FN}$ (3)

Specificity indicates the variation of negative predictions to the total predictions for the given datasets.

Specificity = $\frac{TN}{TN+FP}$ (4)

Accuracy can be defined as the amount variation of exact predictions to the total given predictions for the given datasets.

Accuracy= $\frac{TP+TN}{TP+TN+FP+FN}$ (5)

The same model characteristics from the total models for the given datasets can describe using Jacard Index.

Jaccard Index= $\frac{2*TP}{2*TP+FP+FN}$ (6)

$J(A,B)=\frac{|A\cap B|}{|A\cup B|} = \frac{|A\cap B|}{|A|+|B|-|A\cup B|}$ (7)

Where $J(A, B)$ is Jaccard Index $0 \leq J(A,B) \leq 1$ (8)

1. Jaccard distance indicates the dissimilarity between the given datasets.

$d_j\ (A, B)$= 1- J(A,B) = $\frac{|A\cup B|-|A\cap B|}{|A\cup B|}$ (9)

Where $d_J\ (A, B)$ is the Jaccard distance $0 \leq dj(A,B) \leq 1$ (10)

Dice coefficient is defined by

Dice coefficient S = $\frac{2+J}{1+J}$ (11)

Dice coefficient S= $\frac{2*TP}{2*TP+FP+FN}$ (12)

The sensitivity and Specificity are most significant factors in describing the performance of the model [3]. F1 Scores the recall as very significant from a medical point of view, and it doesn't want the model to classify each and every sample as positive one. F1 score can control the precision and recall.

F1 score can be defined as

F1 score = 2*$\frac{Precision*Recall}{dPrecision+Recall}$ (13)

III. PERFORMANCE ANALYSIS

Algorithms and Techniques which was used in a variety of datasets is the challenge for intelligent Skin cancer detection. The different algorithms which has been improved and applied for skin cancer detection and the past is appreciatable. Now in this section it is captured the relevance of few algorithms. Performance evaluation of algorithms was depicted in Table 1.The authors applied Bayesian Optimization algorithm [1]for enhanced skin condition prediction. The performance results are compared with the International Skin Image Classification (ISIC) 2019.This work proposes auto augmentation technique for reducing the training time for the given model. This work achieves an average accuracy of eight types skin lesions is 95%,sensitivity of 65% and with average Area Under Curve(AUC) is 0.91.The authors of [23] applied hill-climbing strategy along with network morphism operations to discover the search breathing space. The network defend transformations took advantage of formerly trained networks by using the weights again from the preceding training, which leads to significant computational cost reduction for skin cancer classification which is achieved an usual accuracy of 77% and 0.843 AUC. The applied network altogether was improved in terms of performance for used techniques. The drawback for the work is that Search based on justification accuracy get worse the efficiency of the architecture search process. The authors of [24] approved the optimized efficiency and the result of convolution neural network (CNN).The used Datasets for this work was DermQuest and DermIS. Proposed superior algorithm and its performance were compared to the other algorithms like genetic algorithm etc are. In this paper the two datasets like DermQuest and DermIS are discussed .The authors were applied [25] Predict-Evaluate-Correct K-fold algorithm and a new technique called SCIDOG are urbanized precisely to detect lesion in non- dermoscopic images. This particular technique achieved an accuracy of 91% and Mathews Correlation Coefficient is 0.83.Authors of [26] were applied Region of Interest based system for recognize and distinguish melanoma by using transfer learning method. ROI's were extracted from images by using

enhanced k-mean technique .The authors of [27] were used Lightweight recognition model with discriminated features which is based on principle of categorization were utilized. Authors from [28] were applied fully automated deep learning assembly methods. This work achieved an accuracy of 93.8%, Dice of 0.907, Jacard Index of 0.839, Sensitivity of 93.2% and a specificity of 92.9%.Authors from [29] were applied selection of deep CNN features and the lesion was enhanced by using Gaussian technique. In this work the accuracy 97.74% for PH2 were achieved for ISBI 2016, 97% ISBI 2017 dataset respectively The authors [30]were utilized Multi Stage with fully Convolution Networks and New Parallel Integration Method. This work achieved an accuracy of 94.24%, Dice of 90.66%, Jacard Index of 83.99, and Sensitivity of 94.89% and a specificity of 93.98%.

IV. CONCLUSION

Significant and in-depth investigation on survey of present state-of-art methods which is used for the performance prediction of skin cancer, for that the different datasets and its utilizing with an effective utilization are achieved successfully. Among those some important algorithms were discussed clearly and compared with its performance in the presence of dermoscopic images. The evaluation criteria with its metrics were also clearly depicted. Finally inference also drawn from the successful analysis made and the best performing algorithms were observed. From those observations it is concluded that the utilization of deep learning neural network had recorded satisfaction results in terms of performing analysis with dermoscopic images. The recorded results in all aspects most especially in the prediction of skin cancer had given useful improvement and in future the most effective utilization of such algorithms may be useful to detect skin cancer with further more accuracy.

Table1: Performance estimation for the various deep learning algorithms

Techniques	**Accuracy in percentage**	**Dice Coefficient**	**Area Under Curve**	**Jaccard Index**	**Sensitivity in percentage**	**Specificity in percentage**
Bayesian Optimization	95%	-	0.91	-	65%	-
hill-climbing with network morphism	77%	-	0.843	-	-	-
PECK and Synthesis with Convergence	91%	-	-	-	-	-
An improved k-mean algorithm	97.9%	-	-	-	-	-
Fine grained classification principle	94.08%	-	-	-	89.93%	97.98
The fully automated deep learning ensemble methods	93.8%	0.907	-	0.839	93.2%	92.9%
Deep Convolutional Neural Network	97.74%	-	-	-	-	-
Fully Convolutional Networks and A New Parallel Integration Method	94.24%	90.66	-	83.99%	94.89%	93.98%

REFERENCES

1. Tryan Aditya Putra et al, Enhanced Skin Condition Prediction Through Machine Learning Using Dynamic Training and Testing Augmentation, IEEE Access VOLUME 8, 2020, Digital Object Identifier 10.1109/ACCESS.2020.2976045
2. Cancer Facts Figures 2019. https://www.cancer.org/content/dam/cancer-org/research/cancer-facts-and-statistics/annual-cancer-facts-and-figures/2019/ cancer-facts-and-figures-2019.pdf.
3. D. M. Parkin, D. Mesher, and P. Sasieni, ''13. Cancers attributable to solar (ultraviolet) radiation exposure in the UK in 2010,'' Brit. J. Cancer, vol. 105, no. S2, pp. S66–S69, Dec. 2011
4. R. Z. Conic, C. I. Cabrera, A. A. Khorana, and B. R. Gastman, ''Determi- nation of the impact of melanoma surgical timing on survival using the national cancer database,'' J. Amer. Acad. Dermatology, vol. 78, no. 1, pp. 40–46, Jan. 2018.,
5. D. E. Fisher and A. C. Geller, ''Disproportionate burden of melanoma mortality in young US men,'' JAMA Dermatology, vol. 149, no. 8, p. 903, Aug. 2013.
6. N. Ibtehaz and M. Sohel Rahman, ''MultiResUNet : Rethinking the U-Net architecture for multimodal biomedical image segmentation,'' 2019, arXiv:1902.04049. [Online].Available: http://arxiv.org/abs/1902.04049
7. J. Jian, F. Xiong, W. Xia, R. Zhang, J. Gu, X. Wu, X. Meng, and X. Gao, ''Fully convolutional networks (FCNs)-based segmentation method for colorectal tumors on T2-weighted magnetic resonance images,'' Australas. Phys. Eng. Sci. Med., vol. 41, no. 2, pp. 393–401, Apr. 2018
8. L. Bi, J. Kim, E. Ahn, A. Kumar, M. Fulham, and D. Feng, ''Dermoscopic image segmentation via multistage fully convolutional networks,'' IEEE Trans. Biomed. Eng., vol. 64, no. 9, pp. 2065–2074, Sep. 2017, doi: 10.1109/TBME.2017.2712771.
9. A. A. Adeyinka and S. Viriri, ''Skin lesion images segmentation: A survey of the state-of-the-art,'' in Proc. 6th Int. Conf. Mining Intell. Knowl. Explor. (MIKE), Cluj-Napoca, Romania, Dec. 2018, pp. 321–330, doi: 10.1007/978-3-030-05918-7_29.
10. N.C.F. Codella et al , ''Skin lesion analysis toward melanoma detection, April 2018.
11. S. Lim, I. Kim, T. Kim, C. Kim, and S. Kim, ''Fast autoaugment,'' in Proc. Adv. Neural Inf. Process. Syst. (NeurIPS), 2019, pp. 6662–6672.
12. C. Szegedy, W. Liu, Y. Jia, P. Sermanet, S. Reed, D. Anguelov, D. Erhan,V. Vanhoucke, and A. Rabinovich, ''Going deeper with convolutions,'' in Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR), Boston, MA, USA, Jun. 2015, pp. 1–9, doi: 10.1109/CVPR.2015.7298594.
13. K. He, X. Zhang, S. Ren, and J. Sun, ''Deep residual learning for image recognition,'' in Proc. IEEE Conf. Comput. Vis. Pattern Recog- nit. (CVPR), Las Vegas, NV, USA, Jun. 2016, pp. 770–778, doi: 10. 1109/CVPR.2016.90.
14. C. Rosendahl, A. Cameron, I. Mccoll, and D. Wilkinson, ''Dermatoscopy in routine practice:'Chaos and clues,'' Austral. Family Physician, vol. 41, p. 482, Jul. 2012.
15. A. Lallas, Z. Apalla, G. Argenziano, C. Longo, E. Moscarella,F. Specchio, M. Raucci, and I. Zalaudek, ''The dermoscopic universe of basal cell carcinoma,'' Dermatol. Practical Conceptual, vol. 4, pp. 11–24, Jul. 2014.
16. I.Zalaudek, J. Giacomel, K. Schmid, S. Bondino, C. Rosendahl,S. Cavicchini, A. Tourlaki, S. Gasparini, P. Bourne, J. Keir, H. Kittler,L. Eibenschutz, C. Catricalà, and G. Argenziano, ''Dermatoscopy of facial actinic keratosis, intraepidermal carcinoma, and invasive squamous cell carcinoma: A progression model,'' J. Amer. Acad. Dermatol., vol. 66, no. 4, pp. 589–597, Apr. 2012.
17. H. P. Soyer, G. Argenziano, R. Hofmann-Wellenhof, and R. H. Johr, Eds., Seborrheic Keratosis Including Lichen Planus-Like Keratosis. Berlin, Germany: Springer, 2007, pp. 313–328.
18. R. P. Braun, ''Dermoscopy of pigmented seborrheic keratosis: A morpho- logical study,'' Arch. Dermatol., vol. 138, no. 12, p. 1556, Dec. 2002.
19. P. Zaballos, S. Puig, A. Llambrich, and J. Malvehy, ''Dermoscopy of der- matofibromas: A prospective morphological study of 412 cases,'' Arch. Dermatol., vol. 144, no. 1, pp. 75–83, Jan. 2008.
20. P.Tschandl, C. Rosendahl, and H. Kittler, ''The HAM10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions,''2018,arXiv:1803.10417.[Online]. Available: http://arxiv.org/abs/1803.10417
21. C. Rosendahl, A. Cameron, G. Argenziano, I. Zalaudek, P. Tschandl, and H. Kittler, ''Dermoscopy of squamous cell carcinoma and keratoacan- thoma,'' Arch. Dermatol.,vol.148,no.12,pp.1386–1392,Dec.2012,doi:10.1001/archdermatol.2012. 2974.
22. P. Zaballos, M. Carulla, F. Ozdemir, I. Zalaudek, J. Bañuls, A. Llambrich, S. Puig, G. Argenziano, and J. Malvehy, ''Dermoscopy of pyogenic granuloma: A morphological study,'' Brit. J. Dermatol., vol. 163, pp. 1229–1237, Dec. 2010.

23. Arkadiusz kwasigroch , micha. Grochowski , and agnieszka miko.ajczyk, “Neural Architecture Search for Skin Lesion Classification”, IEEE Access,2020
24. Ni Zhanga et al , Skin cancer diagnosis based on optimized convolutional neural network, Elsevier,2020.
25. Benjamin Alexander et al,” Deep Learning From Limited Training Data Novel Segmentation and Ensemble Algorithms Applied to Automatic Melanoma Diagnosis”, IEEE Access,2020.
26. Rehan ashraf, Sitara afzal , et al,”Region-of-Interest Based Transfer Learning Assisted Framework for Skin Cancer Detection”, IEEE 2020.
27. lisheng wei, kun ding, et al, “Automatic Skin Cancer Detection in Dermoscopy Images based on Ensemble Lightweight Deep Learning Network” ,IEEE2020
28. Manu Goyal , amanda oakley , et al, “Skin Lesion Segmentation in Dermoscopic Images With Ensemble Deep Learning Methods”,IEEE,2020.
29. M. Attique Khan,et al, “An integrated framework of skin lesion detection and recognition through saliency method and optimal deep neural network features Selection”, Springer 2019.
30. Lei Bi, Jinman Kim*, et al,”Dermoscopic Image Segmentation via Multi-Stage Fully Convolutional Networks”,IEEE 2017.
31. Adegun Adekanmi, et al, “Skin Lesion Images Segmentation: A Survey of the State-of-the-Art”, Springer Nature Switzerland 2018. https://doi.org/10.1007/978-3-030-05918-7_29.