Systematic Investigation on Deep Learning Network in Skin Cancer Diagnosis

Sihan Bian[a]
Department of Information Security, Shanghai Jiao Tong University, Shanghai, China

Keywords: Machine Learning, Deep Learning, Skin Cancer.

Abstract: Skin cancer is raising global concern in healthcare. Researchers are looking into the application of deep learning networks in skin cancer diagnosis, which is full of potential in saving labour and time. This paper summarizes the framework of machine learning algorithms in skin cancer detection, and reviews several recent studies on deep learning of skin cancer diagnosis. The approaches from these studies fall into three primary categories: classification, segmentation, and the creation of supplementary data. Techniques like Grad-CAM are integrated with Explainable Artificial Intelligence for the classification of skin lesions, offering insights by emphasizing critical regions. Additionally, the paper touches on the constraints and hurdles associated with employing deep learning for diagnosing skin cancer, noting common problems such as a lack of data diversity and concerns over privacy protection. The influence of parameters on model efficacy and the limited scope of interpretable models to explanations based on individual samples are highlighted. Furthermore, it's pointed out that deep learning models have not been sufficiently tested in clinical settings. In conclusion, the paper summarizes the methods evaluated and underscores that deep learning frameworks require further exploration and enhancements before they can be reliably used in clinical settings without direct oversight from medical professionals.

1 INTRODUCTION

Skin Cancer is a remarkable health issue due to its growing incidence rate. According to the cancer statistics in the United States, 6 cases per 100,000 and year at the beginning of the 1970s were diagnosed, while there were 18 cases per 100,000 inhabitants and year at the beginning of 2000 (Garbe et al., 2009). According to the World Health Organization's tumor classification, there are up to 60 types of malignant tumors of skin cancer, among which the malignant melanoma (MM) has the strongest lethality, and the Basal cell carcinoma (BCC) has the greatest commonality (Garbe et al., 2009). The main causes of skin cancer are Ultraviolet radiation and genetic factors. With human life expectancy rising, the average age of melanoma incidence increases. Economic burdens are also growing in healthcare of the skin cancer intervention.

Prompt diagnosis of skin cancer is crucial for potential patients because the death rate of malignant skin cancer soars with the fast development and spread of tumors, as well as the difficulty of medical treatment. Traditional diagnosis of skin cancer under clinical settings includes dermoscopy, blood tests, biopsy, and histopathological examination. However, the manual examination by dermatologists can cost time and potential misdiagnosis may occur. Due to this reason, researchers have looked into deep learning as a kind of auxiliary diagnosis due to their excellent prediction performance.

Convolutional Neural Network (CNN) is a deep learning technique widely used in the recognition of visual features and the classification of images, demonstrating excellent performance in many tasks including medical image analysis, autonomous driving, face recognition etc. (Coşkun et al., 2017; Li et al., 2019; Qiu et al., 2022). In recent years, studies on the diagnosis of skin cancer using convolutional neural network have emerged and most models perform as well as specialists in classifying the sign of skin cancer (Haggenmüller et al., 2021). Researchers are improving the classification models so as to prepare them for clinical use. For example,

[a] https://orcid.org/0009-0001-5726-3309

Bian, S.
Systematic Investigation on Deep Learning Network in Skin Cancer Diagnosis.
DOI: 10.5220/0012953200004508

In *Proceedings of the 1st International Conference on Engineering Management, Information Technology and Intelligence (EMITI 2024)*, pages 469-473
ISBN: 978-989-758-713-9

FixCaps V2 is an advanced method based on FixCaps, a capsule network and has good generalization and stability in skin cancer diagnosis (Lan et al., 2022). PRU-Net, on the other hand, is a new algorithm for skin cancer segmentation through the strengthened dissemination and reuse of image information (Li et al., 2023). Moreover, the explainable artificial intelligence (XAI) model can interpret its diagnosis and includes an interface for experts to participate in, which enables the further advancement of the model (Mridha, Krishna et al., 2023). The aim of this study is to present an overall review of the recent study on the application of CNN in skin cancer diagnosis.

The paper is structured as follows: The first part is the introduction to the use of deep learning on skin cancer classification. Second, the methods of several recent studies will be reviewed. Third, the limitations, challenges and future prospects of these methods will be discussed. Finally, conclusions of the review on convolutional neural network in cancer diagnosis will be presented.

2 METHOD

2.1 The Framework of Machine Learning-Based Algorithms in Skin Cancer Detection

Figure 1 presents the framework of machine learning-based algorithms in skin cancer detection.

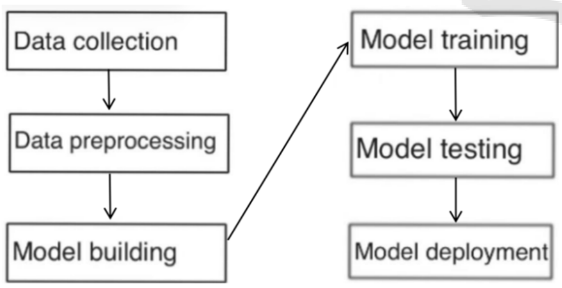

Figure 1: Framework of machine learning-based algorithms in skin cancer detection (Picture credit: Original).

Data Collection: Sufficient data is crucial for deep learning models to make accurate predictions and diagnoses for medical image analysis applications. The datasets of the skin cancer images were built through the following sources:

Kaggle, the well-known scientific community website contains a dataset called HAM10000 which provides 10015 images of dermoscopy. All the sizes of these images are regularized into 600 × 450, sampled from 7728 patients.

The existing dataset from the International Skin Imaging Collaboration, which contains 25, 94 images and 12970 labeled images of great qualification. These data are collected under clinical circumstances and are labeled and noted by specialists.

Dermnet is a community website containing over 20, 000 dermatology images and they have gone through the censor of consultant dermatologists.

Data Preprocessing: Data preprocessing is introduced into the process of deep learning. Preprocessing includes normalization and augmentation so as to improve the quality of the data and enhance the generalization ability of the model.

Model Building: Appropriate learning model such as Convolutional Neural Network (CNN), Support Vector Machine (SVM), or Decision Tree are selected in consideration of the size of image sizes and the availability of computational resources. This step includes the adjustment and improvement of existing training models in order to avoid defects such as the insufficient feature utilization caused by ignoring inter-layer feature interaction or overfitting in convolutional neural networks caused by imbalanced dataset categories.

Model Training: Optimization algorithms such as Stochastic Gradient Descent are applied to the training of model. Researchers adjust the hyperparameters of the model to improve its performance.

Model Testing: The trained model should undergo the comparison of deep learning outcomes and the real results provided by specialists. Here are the evaluation metrics of the model performance: accuracy, precision, recall, and F1-score.

Model Deployment: For real-time clinical use, the trained model should be transformed into an executable format, such as saving the model parameters as files.

2.2 Classification

2.2.1 Convolutional Neural Network

Convolutional neural network (CNN) is a deep learning technique widely used in the recognition of visual features and the classification of images. CNN has flexible structure including convolutional layer, pooling layer, normalization layer and fully connected layer. CNN models extract features through hierarchical abstraction: Networks from lower levels can extract basic texture and color information (points, lines, blocks) which is applied to various object recognition tasks. On the other hand, networks of higher levels can interpret these features in an abstract way. Pooling layers decrease the sizes of input neurons. Images of skin lesions are extracted by CNN and obtained features are classified into several groups of different diseases (Dorj, Ulzii-Orshikh et al., 2018; Wang, 2018).

2.2.2 XAI-Based Skin Lesion Classification System

Mridha et al. proposed an Explainable Artificial Intelligence (XAI)-based skin lesion system incorporating Grad-CAM and Grad-CAM++. This model can be used as an auxiliary tool for early-stage skin cancer diagnosis and provides the explanation for the model's decisions.

Grad-CAM is implemented as follows: First, compute the gradient about feature maps of the convolutional layers. Second, compute the alphas through averaging gradients. Third, calculate the final Grad-CAM heatmap.

Grad-CAM explains its classification on skin lesions by highlighting the most significant parts of the input images that decide the outcome. Grad-CAM++ improves its performance by using guided backpropagation to produce a more detailed heatmap.

2.2.3 FixCaps V2

FixCaps V2 proposed by Lan et al. is a CapsNets-based skin diagnosis algorithm that inherits the features of CapsNets that "outputs are the clustering of inputs" and maintains its capsule architecture. FixCaps V2 solves the size issue of high-resolution images through feature-aware networks without stacking large amounts of convolutional or capsule layers. (Lan et al., 2022; Cai, 2023)

What's more, FixCaps also has improvements on CapsNets such as the larger receptive field. This is achieved by ultilizing large kernel convolution exceeding 9×9. With larger kernel, more image information is received by the network. FixCaps V2 also applies convolutional block attention model (CBAM) so as to make itself more concentrated on the object and reduce the loss of spatial information due to convolution and pooling.

2.3 Segmentation

2.3.1 PRU-Net

Li et al. proposed a new skin cancer segmentation model called PRU-Net. It is a combination of dense link modules and pyramid-type void convolutional modules, plus the residual module (Li, 2023).

First, PRU-Net adopts U-Net and Densely Connected Convolutional Network (DenseNet) as the segmentation model to enhance the propagation and reuse of global information. Secondly, channel attention mechanism is added to improve the segmentation accuracy of edge images. After that, the residual modules in ResNet and the dilated pyramid pooling module are introduced to enhance the segmentation performance of the model.

U-Net combines shallow feature information and deep semantic information to provide accurate segmentation for data images. PRU-Net not only shares the same advantages as U-Net, but also solves the defects of U-Net such as the segmentation blur caused by low contrast between image feature regions and background regions.

2.4 Supplementary Data Generation

2.4.1 Self-Attention StyleGAN

Generate adversarial networks are used in image enhancement of the datasets in deep learning. (Zhao, Chen et al, 2022). designed a framework combining self-attention SA-styleGAN with SE-ResNeXt-50. The "style" in StyleGAN borrows from style transfer and enables highly controllable image generation in an unsupervised manner. For further improvement, SA-StyleGAN abandons the use of mixup regularization. Single latent code is used in SA-StyleGAN in order to effectively eliminate image distortion and blur, providing high-quality sample images for classifiers. The number of noise modules is also reduced to eliminate unnecessary noise in generated data.

3 DISCUSSION

Although significant progresses have been achieved, there still are some limitations and challenges in terms of the use of deep learning in skin cancer diagnosis.

First, the datasets of the studies reviewed are similar and have insufficient sample variety. 4 out of 8 studies use HAM10000 to train models so these models may have similar bias over dermoscopic images. For example, 67% of the HAM10000 is made up of samples of melanocytic nevi dermatoscopy so models trained by it are likely to be less accurate diagnosing from other skin lesions. To address this problem, researchers might unite medical experts integrate a large amount of legal public dermatological datasets available online, or utilize deep learning algorithms for legal information mining and analysis (Xia et al., 2017). That will aid in the creation of a more accurate and comprehensive skin lesion image recognition and diagnostic system.

Another issue is about the parameters of these models. When the dataset is explicitly different from the original dataset of a pre-trained model, the initial parameters of the network do not well express the primary features of the new dataset (Wang, 2018). This limits the flexibility of a single model's application on diagnosing skin cancers of prominent differences. Furthermore, different random seeds may have huge impacts on the iteration results of a model. Different architectures have varying adaptation degrees to pseudo-random numbers. The cause of this phenomenon is still waiting to be studied (Cai, 2023).

Third, when it comes to the interpretability of deep learning models, the related study points out that their current model has only achieved success in giving out single-sample explanations (Mridha, Krishna et al., 2023). The stage of applying their explanation approach to several samples and combining them is still waiting for research, which is crucial for complicated lesion analysis in clinic use. In addition, as Mridha proposed in his paper, current evidence is not enough to relate the observed relevance of feature dimensions to the real score. Therefore, multiple measures for evaluating explanations should be explored.

The fourth challenge is the issue of privacy. Medical information is confidential so any research involving personal health data may raise data privacy controversies. Although datasets from International Skin Imaging Collaboration or HAM10000 have removed all personal identity information and are all anonymized, there are still risks to data security and privacy protection. Other datasets from medical institutions may not be free to access, but these datasets also undergo risks of privacy thefts due to the fierce competition of the medical industry. What's more, deep learning networks are able to memorize training datasets. If the network is subjected to malicious attacks, it may lead to the leakage of private user data (Tian, 2020).

The fifth main challenge is the practicability of deep learning methods. Since the deep learning models are trained and tested under artificial circumstances, their performance under real circumstances is rarely measured. Therefore, the diagnosis by deep learning networks must be under the supervision of human specialists. In addition, some advanced deep learning approaches can also be considered for further improving the performance (Li et al., 2024; Sun et al., 2020; Wu et al., 2024).

4 CONCLUSIONS

This paper has reviewed 8 current studies on deep learning in the area of skin cancer diagnosis. Deep learning technique is time-and-labour-saving in analyzing the images of skin lesions if trained through prompt algorithms and fed by balanced datasets of lesion images in various conditions.

Most recent studies on this topic concentrate on the classification of images, using convolutional neural network or improved capsule networks like FixCaps V2. Some explored auxiliary methods for the diagnosis such as image segmentation by PRU-Net or supplement data generation by Self-Attention StyleGAN. In addition, XAI-based classification system provides explanations for the decisions of the deep learning model.

To satisfy the need of the medical industry, further studies may explore the integration of these methods so as to address the insufficiency of data and provide well-segmented data. Deep learning models may also be ported to mobile devices to ensure early awareness of people on their skin lesions.

REFERENCES

Cai, S. B. 2023. Research on skin cancer assisted diagnosis method based on FixCaps [Doctoral dissertation, Chongqing Jiaotong University].

Coşkun, M., Uçar, A., Yildirim, Ö., & Demir, Y. 2017. Face recognition based on convolutional neural network. In 2017 international conference on modern electrical and energy systems (MEES) (pp. 376-379). IEEE.

Dorj, U. O., et al. 2018. The skin cancer classification using deep convolutional neural network. Multimedia tools and applications, 77(8), 9909-9924.

Garbe, C., MD, & Leiter, U., MD. 2009. Melanoma epidemiology and trends. Clinics in dermatology, 27(1), 3-9.

Haggenmüller, S., et al. 2021. Skin cancer classification via convolutional neural networks: systematic review of studies involving human experts. European Journal of Cancer, 156, 202-216.

Lan, Z., et al. 2022. FixCaps: An Improved Capsules Network for Diagnosis of Skin Cancer. IEEE Access, 10, 76261-76267.

Li, M., He, J., Jiang, G., & Wang, H. 2024. DDN-SLAM: Real-time Dense Dynamic Neural Implicit SLAM with Joint Semantic Encoding. arXiv preprint arXiv:2401.01545.

Li, P., Chen, X., & Shen, S. 2019. Stereo r-cnn based 3d object detection for autonomous driving. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (pp. 7644-7652).

Li, Y. L., Tian, J., Chen, D. X., Deng, Y., Zeng, W. X., & Zeng, Y. Q. 2023. Research on skin cancer segmentation method based on PRU-Net. Computer Knowledge and Technology, 19(24), 9-13.

Mridha, K., et al. 2023. An interpretable skin cancer classification using optimized convolutional neural network for a smart healthcare system. IEEE Access, 11, 1.

Qiu, Y., Wang, J., Jin, Z., Chen, H., Zhang, M., & Guo, L. 2022. Pose-guided matching based on deep learning for assessing quality of action on rehabilitation training. Biomedical Signal Processing and Control, 72, 103323.

Sun, G., Zhan, T., Owusu, B.G., Daniel, A.M., Liu, G., & Jiang, W. 2020. Revised reinforcement learning based on anchor graph hashing for autonomous cell activation in cloud-RANs. Future Generation Computer Systems, 104, 60-73.

Tian, X. T. 2020. Research on privacy protection technology of training data in deep learning [Doctoral dissertation, Harbin Engineering University].

Wang, L. 2018. Machine learning based skin disease image classification [Doctoral dissertation, Zhejiang University].

Wu, Y., Jin, Z., Shi, C., Liang, P., & Zhan, T. 2024. Research on the Application of Deep Learning-based BERT Model in Sentiment Analysis. arXiv preprint arXiv:2403.08217.

Xia, Y., Zhang, L., Meng, L., et al. 2017. Exploring web images to enhance skin disease analysis under a computer vision framework. IEEE Transactions on Cybernetics, 48(11), 3080-3091.

Zhao, C., Shuai, R. J., Ma, L., Liu, W. J., & Wu, M. L. 2022. Generation and classification of skin cancer images based on self-attention StyleGAN. Computer Engineering and Applications, 58(18), 111-121.