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Application of Artificial Intelligence in Skin Cancer Diagnosis: Convolutional Neural Network-Based Methods

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Abstract:

Skin cancer, a common malignant tumor, poses a significant global health burden, with traditional diagnosis methods relying primarily on visual observation, which often lack accuracy and consistency. In recent years, Artificial Intelligence (AI), particularly deep learning, has made notable advancements in medical imaging diagnosis, exemplified by systems such as Google's LYNA and various AI-based skin cancer classification models. This paper reviews skin cancer diagnosis using Convolutional Neural Networks (CNNs) in recent two years, covering baseline CNNs e.g., VGG16, MobileNet, attention-based CNNs e.g., Graph Attention Network (GAT)+SENet, Convolutional Block Attention Module (CBAM), and hybrid models e.g., CNN-Transformer, Convolutional Neural Network-Recurrent Neural Network (CNN-RNN). These methods enhance accuracy via transfer learning, attention mechanisms, and hybrid architectures. Challenges include model interpretability (black-box nature), generalization across diverse populations, and data privacy. Future directions point toward the development of white-box models, standardized evaluation benchmarks for generalization, and the adoption of federated learning frameworks to enable privacy-preserving collaborative model training. This review aims to provide a comprehensive overview to advance the field.

Keywords: Skin cancer; convolutional neural network; deep learning.

1. Introduction

Skin cancer is a malignant tumor originating from the epidermal or accessory cells of the skin, and is one of the most common types of cancer worldwide, posing a significant public health burden. The main pathogenic culprit is exposure to ultraviolet radiation. In clinical practice, skin cancer is mainly divided into three categories: basal cell carcinoma, squamous cell carcinoma and melanoma. Traditionally,

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clinical doctors use visual observation and palpation to evaluate the characteristics of skin lesions, such as shape, color, boundary, texture and size, for the diagnosis of skin cancer. Although this method is convenient, its accuracy is not high. In this situation, introducing some more advanced technologies of this kind is necessary. Artificial Intelligence (AI) technology can assist in diagnosis, improving the efficiency and accuracy of the entire process, which can be considered.

In the last decade, AI has achieved a remarkable leap from theoretical exploration to industrial transformation through the development of deep learning. Innovations in architecture, such as the evolution of Convolutional Neural Networks (CNNs) and breakthroughs in sequence modeling, have rapidly expanded their application areas. The image classification and object detection technology of computer vision has rapidly reached and surpassed the human level. Therefore, the application of artificial intelligence in medical imaging diagnosis assistance is becoming increasingly widespread in medicine. In early screening for lung cancer, Google AI's LYNA uses a 3D convolutional neural network to analyze lung CT scans and automatically detect tiny nodules [1]. By identifying metastatic breast cancer in pathological sections, the recognition accuracy is as high as 99%. Its accuracy in diagnosing stroke is as high as 98%. In contrast, doctors have an average accuracy rate of only 85%. This is a golden time window for rescuing patients.

In the field of diagnosing skin cancer, skin cancer convolutional neural network classification is also playing an increasingly important role. Saleh developed an optimized skin cancer classification framework that combines CNN, Grey Wolf Optimizer (GWO), and Multi Criteria Decision Method (MCDM) to select the best classification scheme from multiple models [2]. The combination of AlexNet+GWO1+Wide Neural Network (WNN) is the best. Its accuracy is 94.5%, sensitivity is 90%, and specificity is 96%. This framework can be integrated into Computer-aided Diagnosis (CAD) systems to assist doctors in quickly and accurately identifying skin cancer. Houssein proposed a novel Deep Convolutional Neural Network (DCNN) to address the issue of class imbalance in skin cancer classification and improve diagnostic accuracy [3]. Its high accuracy of 98.5% is much higher than 87.2% of other transfer learning models such as VGG16. He addressed the issue of imbalance by verifying the effectiveness of random oversampling in skin cancer image classification.

The rest of this paper is organized as follows. Firstly, in Section 2, this review will provide an overview of the research and methods on skin cancer convolutional neural network classification in the past two years. Then, in Section 3, this review will discuss the advantages and disadvantages of each method (challenges limitations and future prospects). Finally, Section 4 summarizes the whole paper.

2. Method

2.1 Baseline CNN

2.1.1 VGG16/VGG19

Faghihi et al. used the VGG16/VGG19 model to identify skin cancer types [4]. They pioneered weight fusion transfer learning. By combining the ImageNet weights of VGG16/VGG19 with the AlexNet layer weights through cross architecture fusion, the feature expression ability is enhanced. And through targeted freezing: freezing the first three layers instead of the traditional final layer, preserving the edge sensitive features of the skin mirror image.

2.1.2 MobileNet

In the Chaturvedi et al.'s article, they used MobileNet, a lightweight CNN model, to identify seven categories of skin cancer [5]. They first proposed the MobileNet skin cancer 7 classification. They also optimized the deployment for mobile devices, with only 4.2 million model parameters, far less than VGG16's approximately 138 million, greatly improving inference speed.

2.2 Attention-based CNN

Attention based Convolutional Neural Networks (CNNs) improve model performance by introducing attention modules that enable the network to dynamically focus on more important feature regions or channels in input data.

2.2.1 GAT and SENet

Graph Attention Network (GAT) cleverly introduces attention mechanisms into the processing of graph structured data, addressing some limitations of traditional graph convolutional networks. Squeeze-and-Excitation Network (SENet) proposed a lightweight but highly effective channel attention mechanism that can significantly improve the performance of CNN. Yang et al. combined GATwith SEnet together [6]. The model uses GAT for feature extraction. By using a shared attention mechanism to calculate the attention coefficients between nodes, and normalizing them with softmax, the features of neighboring nodes are weighted and aggregated, and the node representations are updated.

The model uses SENet for feature enhancement. Compressing spatial dimensions through Squeeze operation, learning channel importance weights through Excitation operation, and achieving feature recalibration through

Scale operation to enhance key features. Through this model, the recognition accuracy reached 98.5%.

2.2.2 CBAM

Convolutional Block Attention Module (CBAM) is a lightweight, plug and play hybrid attention module designed to capture key information in both channel and spatial dimensions, significantly enhancing the feature representation capability of CNNs. According to Lan et al.'s paper [7], the CBAM attention module is applied in the Feature Perception Network. Channel attention (CAM) is used to learn cross channel semantic information and enhance discriminative features. Spatial attention (SAM) is used to compensate for the loss of spatial information caused by pooling. This model achieves an accurate rate of 99.37% in the diagnosis of skin cancer.

2.3 Hybrid CNN

Hybrid CNN is a model design paradigm that combines traditional CNN with other deep learning architectures such as Transformer, RNN, GNN, or attention mechanisms. Its core goal is to combine the advantages of different architectures to make up for the limitations of a single model, so as to improve performance, efficiency or generalization ability on complex tasks.

2.3.1 CNN-Transformer

CNN Transformer combines two powerful but fundamentally different techniques, Convolutional Neural Networks and Transformers. Simultaneously modeling local details and global context to obtain richer and more robust feature representations. It has stronger representational power. Zareen et al. first applied the deep fusion of Transformer and CNN to skin cancer diagnosis [8], with Transformer's multi head self-attention mechanism capturing global spatial dependencies such as the overall morphology of lesions. CNN local priors extract local texture features through convolutional layers. The local feature extraction capability of CNN is integrated with the global context modeling capability of Transformer. Through this integration, the model can effectively extract fine-grained local features from input data while capturing long-range spatial dependencies, enabling it to achieve more comprehensive and robust feature representation in complex tasks.

2.3.2 CNN-RNN

The advantages of convolutional neural networks and recurrent neural networks are integrated within CNN-RNN. It has the following advantages: firstly, it combines spatial and time/sequence modeling: CNN efficiently extracts spatial features of input, while RNN effectively models the dynamic changes or dependencies of these features in the time or sequence dimension. Secondly, it is suitable for handling complex input-output relationships: it is perfectly suited for tasks where the input is spatial data, and the output is sequential data. Sakib et al. extract spatial features such as texture and shape using the ResNet-50 backbone CNN module, and outputs feature maps [9]. They use RNN modules to receive feature maps as sequence inputs and model temporal dependencies. Their innovation lies in the pioneering CNN-RNN hybrid architecture. Double module collaborative optimization through end-to-end training to avoid feature separation.

3. Discussion

3.1 Challenges and Limitations

3.1.1 Interpretability

Although significant progress has been made in this field, the models mentioned above may still face challenges in terms of interpretability. In clinical medicine, interpretability is a very important rule. Reyes et al. introduced that most models are black box methods [10]. Only by analyzing the input-output relationship, can the model explain the key features of specific predictions. Local interpretable model independent interpretation (LIME) is achieved by perturbing the input image and fitting a linear model. Doctors need to explain the cause and condition of the illness. AI lacks the process of analysis. In this case, doctors can only tell patients what illness they have, but cannot provide a diagnosis process. This will cause patients to lose trust in the doctor's diagnosis. What's more, the lack of interpretability makes it difficult for hospitals to correct model errors. Although the analysis accuracy of AI models is high, it has not reached 100%. This makes it impossible for hospitals to fully trust AI models.

3.1.2 Generalization

Generalization is also a challenge. Generalization refers to the adaptability and effectiveness of a model to different clinical scenarios and diverse patient populations. Factors such as age, gender, race, and complications make the same type of skin cancer present differently in different patients. For example, a Chinese hospital has trained its own model for diagnosing skin cancer. The dataset for this model is mostly from patients of the yellow race. Training such a model requires a significant amount of time and financial cost. However, if an American hospital wants to use this model to diagnose skin cancer patients in the United States, they cannot directly use this model. They need to spend a lot of cost training the model again because their patients are mostly white and black.

3.1.3 Privacy

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In the information age, people place greater emphasis on the privacy of personal information. Privacy is not only about personal identity information, but also about pathological information. Moreover, centralized data storage increases the risk of hacker attacks. According to Edidin's article, more than 30 million health data breaches in the United States in 2023. This seriously violates the privacy rights of citizens [11].

3.2 Future Prospects

3.2.1 Algorithm bottom layer

In order to make the information output by AI interpretable, it can be addressed from a technical architecture perspective. Prioritizing the white box model can visualize the analysis process of the model. It is possible to combine deep learning with rule engines by designing hybrid models. For example, in the diagnosis of skin cancer, CNN is used to analyze images, and the results are verified through a rule library to ensure compliance with clinical guidelines. Moreover, global interpretation tools such as partial dependency graphs can be applied. These tools can demonstrate the overall dependency relationship between features and predicted results. These methods enhance the interpretability of the model, making it more trustworthy.

3.2.2 Generalization criteria

To make a high-cost skin cancer diagnostic model widely applicable, establishing medical specific generalization standards is an effective solution. Multi-dimensional test set design can increase dataset diversity. Cross regional and cross-national medical alliances can share data and jointly design models that meet the conditions. Meanwhile, the model needs to be validated with the participation of clinical experts. Goetz et al. proposed a method called selective deployment. Exclude abnormal data through data filtering [12]. Or identify high-risk predictions through model uncertainty estimation and switch to manual diagnosis. In the skin cancer diagnosis model, data that is abnormal from the dataset will be identified. This increases the accuracy of the model.

3.2.3 Federated learning

Federated learning is characterized as a distributed machine learning framework. Its core goal is to achieve collaborative modeling among multiple parties without sharing raw data. It can provide data privacy protection. The original data is kept locally to avoid the risk of transmission leakage. Hospitals can participate in AI model training without sharing patient images, which complies with privacy regulations. Horizontal Federated Learning is well-suited for models where data share the same structure but differ in samples. This is in line with the model of skin cancer diagnosis. This provides a solution to the problem of model generalization. According to Li et al.'s article, the technology of using horizontal federated learning to aggregate hospital models has been applied in the multi center lung cancer screening project in China [13]. This reveals the application prospects of this technology in medicine.

4. Conclusion

This article explores how artificial intelligence, especially convolutional neural networks, is being used to detect skin cancer. It discusses different approaches like standard CNNs such as VGG16, VGG19, and MobileNet; attention-focused models like GAT combined with SENet, and CBAM; and hybrid systems. The paper emphasizes techniques like transfer learning and how features are extracted for better accuracy. However, there are still challenges, such as the difficulty in understanding how these black-box models make decisions, their limited effectiveness across diverse patient groups, and concerns about data privacy. Looking ahead, the focus is on creating more transparent, white-box models, setting broader standards for how well these models generalize by sharing data across multiple centers, and using federated learning. This way, patient privacy can be protected while still enabling collaborative efforts to improve these diagnostic tools.

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