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Research Progress of Computer Models for Melanoma Diagnosis Assisted by Hyperspectral Imaging and Deep Learning Technologies at Home and Abroad

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Abstract:

Malignant melanoma is often diagnosed at an advanced stage, with a high mortality rate. In recent years, there has been a gradual increase in research on computer models for hyperspectral imaging-assisted medical diagnosis. This article reviews the research progress of computer models for melanoma diagnosis assisted by hyperspectral imaging and deep learning techniques at home and abroad.

Keywords:

Melanoma
Hyperspectral imaging technology
Deep learning

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1. Background

Malignant melanoma (MM) originates from melanocytes located between basal cells of the epidermal mucosal epithelial tissue, commonly found in skin but also occurring in mucous membranes and internal organs. The annual growth rate of melanoma incidence is 3% to 5% [1], and malignant melanoma ranks third among skin malignancies. Apart from early surgical removal, malignant melanoma lacks specific treatment and has a poor prognosis. Therefore, early diagnosis and treatment of malignant melanoma are extremely crucial. The sooner the diagnosis and treatment of melanoma begin, the better it is for prolonging patient survival and effectively reducing mortality. Most skin melanomas develop from melanocytic nevi, with 84% originating from benign nevi [2]. In clinical diagnosis, the "ABCDEF" rule is primarily used to monitor and assess the early malignant transformation of melanocytic nevi, standing for Asymmetry, Border irregularity, Color variation, Diameter greater than 6 millimeters, Elevation, and Funny look. Although simple, this rule has a high misdiagnosis rate, and its accuracy cannot be guaranteed. Biopsy is the gold standard for diagnosis, often combined with visual observation and histopathological examination. Conventional biopsy observes stained pathological samples under a microscope, limiting observation to two-dimensional spatial features of the image. Morphological features of the pathological sample tissue are difficult to observe, and the process is time-consuming and costly. Variations in staining procedures and operational differences can lead to variations in prepared pathological samples, and there are no auxiliary tools to provide a more detailed quantitative analysis of stained samples. Therefore, relying solely on visual diagnosis and conventional biopsy cannot effectively improve diagnostic accuracy and efficiency. Additionally, a biopsy is an invasive procedure that can cause discomfort to patients.

2. Introduction to hyperspectral imaging technology

With the advancement of computer technology, algorithms for detecting and classifying skin lesions have increased. Computer-aided diagnosis systems based on traditional RGB images for skin lesion detection and classification seem to have reached their performance limits. However, hyperspectral imaging, as an emerging technology, may improve system performance. Hyperspectral imaging technology offers several advantages, including a wide spectral range, high resolution, and the ability to record both spatial and spectral information of materials. It can explore spectral regions beyond human visual capabilities, making it a valuable research tool [1]. Scholars worldwide have conducted numerous studies on hyperspectral imaging technology. For instance, Li *et al.* [3] proposed a development framework for a generalized composite kernel machine for hyperspectral image classification, which demonstrates state-of-the-art classification performance in complex analysis scenarios. Wei *et al.* [4] presented an algorithm based on matrix decomposition for feature extraction from hyperspectral data. In recent years, hyperspectral images have attracted increasing research interest from basic science and clinical researchers due to their ability to provide auxiliary diagnostic and prognostic information for clinical applications [4]. Akbari *et al.* [5] collected hyperspectral images of pig arteries and veins and classified them using a support vector machine classifier. This system can also assist surgeons in locating vessels and determining their abnormality. Furthermore, Akbari *et al.* [6] acquired hyperspectral images of prostate cancer pathology slides from a hyperspectral imaging system. They extracted and evaluated spectral features in cancerous and normal tissues, classified the hyperspectral data using least squares support vector machines, and employed spatial resolution methods to highlight differences in reflectance properties between cancer and normal tissues, enhancing cancer detection. These findings suggest that hyperspectral imaging technology can serve as an emerging non-invasive, quantitative auxiliary medical detection technique with promising development potential in the field of medical disease diagnosis.

3. Hyperspectral imaging technology aids melanoma diagnosis

Early detection and accurate excision of primary lesions in malignant melanoma are crucial for preventing melanoma and reducing deaths associated with it. Automated screening systems for early melanoma detection based on hyperspectral imaging technology have undergone considerable research and development. Classification algorithms are designed to automatically categorize melanoma and other skin types based on the spectral characteristics of different tissues. Nagaoka *et al.* [7] proposed a melanoma discrimination index at the molecular level of skin pigment based on hyperspectral data, obtained spectral information change characteristics of skin lesions, and utilized these features to develop a hyperspectral melanoma screening system capable of distinguishing melanoma from other pigmented skin, with a sensitivity and specificity of 90% and 84%, respectively. Tsapras *et al.* [8] combined a hyperspectral camera system with spectral classification algorithms to classify dysplastic nevi and melanomas. Additionally, they collected hyperspectral images of normal tissue and melanoma, used the Spectral Angle Mapper algorithm with spectra collected from normal skin areas as reference spectra, and compared them to spectra obtained from diseased tissues to construct an animal melanoma diagnostic model. The sensitivity and specificity of both were 77%. Zherdeva *et al.* [9] proposed an *in vivo* hyperspectral skin tumor analysis system to classify melanoma and other cancer types, with a sensitivity and specificity of 63% and 72%, respectively. Hyperspectral imaging technology can also be combined with microscopic imaging techniques to analyze hyperspectral images with integrated spectra at the microscopic level. Wang *et al.* [2] utilized laser confocal scanning microscope images, extracted melanoma textures based on wavelet transformation, and employed the Classification and Regression Tree (CART) algorithm to classify melanoma and benign nevi, improving the accuracy of early melanoma diagnosis and reducing the misdiagnosis rate of benign nevi. Ornberg *et al.* [10] used a hyperspectral microscopic imaging system for high-throughput color image analysis of tissue sections, providing richer dimensional information for the analysis of pathological tissue sections.

4. Application of deep learning in assisting melanoma diagnosis

4.1. Deep learning

In recent years, deep learning, as a subset of machine learning, has developed rapidly. Unlike traditional machine learning, which requires manual feature extraction and consideration of domain expertise, deep learning can automatically extract features. Deep learning is a computational model composed of multiple processing layers that automatically learns data representations by converting input information into multiple levels of abstraction with simple but nonlinear modules [11]. Through these transformations, deep learning models automatically learn a very complex function, enabling them to automatically extract image features and perform intelligent image analysis.

4.2. Deep learning-assisted melanoma diagnosis models

With the development of artificial intelligence, deep learning is increasingly used in the analysis of medical images. Some studies have applied deep learning methods to melanoma identification. Tognetti *et al.* [12] collected 979 dermoscopic images of atypical melanocytic skin diseases, clinical data, and related omics data. They established a deep convolutional neural network model to classify atypical melanocytic skin diseases with an accuracy of 90.3%, effectively supporting dermatologists in accurately identifying atypical nevi and early-stage melanomas. Hekler *et al.* [13] used a convolutional neural network model to classify histopathological melanoma images, achieving an average sensitivity, specificity, and precision of 76%, 60%, and 68%, respectively. In comparison, 11 pathologists classified atypical melanocytic skin diseases with an average sensitivity, specificity, and precision of 51.8%, 66.5%, and 59.2%, respectively. They believed that their convolutional neural network model was superior to the 11 histopathologists in classifying histopathological melanoma images, indicating that artificial intelligence can assist doctors in diagnosing melanoma. Seeja and Suresh [14] used a U-Net-based convolutional neural network to automatically segment skin tumors and classify melanoma and benign lesion images using a support vector machine classifier with an accuracy of 85.19%. They believed that the U-Net segmentation algorithm is the best method for segmenting medical images in a deep learning environment, which helps improve classification performance. Esteva *et al.* [15] used a pre-trained architecture consisting of GoogLeNet and Inception V3 and performed transfer learning on the model. In diagnosing melanoma, the average performance of dermatologists was lower than the ROC curve of their deep learning model, and only one dermatologist performed better than the model's ROC curve. This indicates that in this study, the deep learning model based on convolutional neural networks had higher accuracy than dermatologists.

4.3. Melanoma diagnosis model based on hyperspectral imaging technology and deep learning

With the development of hyperspectral imaging and deep learning technology, the two have been combined and applied to assist in the diagnosis of melanoma. Räsänen *et al.* [16] performed hyperspectral imaging and pathological examination on 26 cases of pigmented lesions (10 cases of pigmented basal cell carcinoma, 12 cases of *in-situ* melanoma, and 4 cases of invasive melanoma). Then, they used a convolutional neural network classifier to identify pigmented basal cell carcinoma and melanoma based on hyperspectral images. The system had a sensitivity of 100% (95% confidence interval: 81%~100%), a specificity of 90% (95% confidence interval: 60%~98%), and a positive predictive value of 94% (95% confidence interval: 73%~99%). This indicates that the convolutional neural network classifier can distinguish between melanoma and pigmented basal cell carcinoma in hyperspectral images. Hirano *et al.* [17] used a hyperspectral imager to obtain hyperspectral data containing information about wavelength and location. They pre-trained a deep learning model called GoogLeNet using ImageNet and used a network layer called "Mini Network" to convert hyperspectral data with 84 channels into 3-channel data, which was then input into the GoogLeNet model. They trained and evaluated the deep learning model using 619 lesions (including 278 melanoma lesions and 341 non-melanoma lesions). The sensitivity, specificity, and accuracy of the model were 69.1%, 75.7%, and 72.7%, respectively.

5. Discussion

This article reviewed the application of hyperspectral imaging technology, deep learning in melanoma, and the combination of hyperspectral imaging and deep learning technology for assisted diagnosis of melanoma. However, there are some disadvantages to using hyperspectral technology to assist in the diagnosis of melanoma, such as data redundancy, extracting useful information from large amounts of data, and difficulties in data calibration, correction, compression, dimensionality reduction, and analysis. Currently, many scholars are still studying hyperspectral image data processing methods. Additionally, there is still a lack of large, high-quality hyperspectral skin lesion dataset images [18]. Future research should focus on developing large databases for the target population, which should include case data, skin images, omics data, and diagnosis results of melanoma patients. This will enable the training of more targeted algorithm models, ensure the reliability of the algorithm models, and improve the accuracy and generalizability of the algorithm for assisting in the diagnosis of melanoma. It is also necessary to expand current classification methods, build and improve various deep learning models, use all spatiotemporal information from hyperspectral images, and apply hyperspectral imaging technology to more biomedical and clinical fields.

Disclosure statement

The authors declare no conflict of interest.

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