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Research Article

Machine Learning Techniques for Skin Fungal Infection Detection -A Review

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ABSTRACT

Skin diseases are the most common than other diseases. Skin diseases may be caused by fungal infection, allergy, bacteria, viruses, etc. Fungal disease affects more than billions people worldwide. The accurately of diagnosing skin fungal infections can be challenging in their early stages or present with symptoms, which mimic other dermatological disorders. The identification and categorization of skin fungal infections could be improved by recent developments in deep learning and artificial intelligence (AI). It offers a more effective and dependable substitute for conventional diagnostic techniques. Here we tried to focus on various methods for identifying fungal skin that rely on deep learning (such as transformers, convolutional neural networks, and hybrid models), the difficulties related to data diversity and availability, going over the shortcomings of current datasets, how data augmentation and synthetic data creation which might help close these gaps. We also investigate how improving interpretability and usability can help clinical uptake of AI-based diagnostic systems. Finally, the study concludes with suggestions for further research, highlighting the revolutionary potential of deep learning in dermatology and stressing the necessity of sophisticated model architectures, a wide range of high-quality datasets, and thorough clinical validation.

1. INTRODUCTION

Skin conditions can be brought on by viruses, germs, allergies, or fungal infections. The prevalence of superficial fungal infections is believed to be between 20 and 25 percent of the world's population, and is steadily increasing[1], [2]. It can be spread directly from one person to another or indirectly by contaminated hairs or desquamated epidermis[3]. Due to their high frequency and patient volume, fungal infections are often diagnosed and treated by dermatologists. Direct microscopy usually widely used as a screening method due to its price and speed[4].The inability for obtaining information about fungal species is a drawback of microscopy. Thus. whenever information about fungal species is of utmost importance, other techniques (such as fungal culture or DNA-based PCR methods) should be used[3]. Also, the direct microscopy is a critical technique for diagnosing superficial fungal infections [4]. Although faster and less expensive than culture or DNA-based techniques, microscopy has several drawbacks. Depending on the sample condition, user's experience, and sample size, it can still be time-consuming for evaluating the entire specimens.[5] Therefore, the diagnosing multiple specimens simultaneously can be a laborious processes that increases intra- and inter-observer variability and can lead to classification errors. An image analysis method that had an automatically identifies fungal infections in digital fluorescence microscopy images, it has been developed to overcome these limitations. One common biotechnological approach to analyze and characterize fungal development in fermentation processes is to use image processing techniques to identify fungal structures [2]. However, as far as we are aware, the automated assessment of clinical photos of fungal diseases is a novel subject. The created analysis plan must be tailored to the particular needs and should be helpful for clinical routines. Most significantly, a trustworthy diagnosis should be accessible during patient contact time, together with good sensitivity and specificity. Therefore, the results visualization and image analysis must be tailored to the clinical procedure. In this situation, cutting the time to diagnosis as much as feasible is essential. This can be achieved by selecting algorithms that need little computation time and by visualizing the detection results online. In order to assess the benefits and drawbacks of each approach[6], we will review and examine the several methods that are employed to diagnose fungal infections in the skin. To find the most

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accurate and efficient diagnostic choices, we will also compare various approaches. Our goal is to offer the dependable solutions that improve patient care while cutting down on diagnostic time and expenses

2. SKIN FUNGAL INFECTIONS

Skin fungal infections are common, affect people of all ages[7]. Particularly in humid regions. Dermatophytosis (ringworm) and Candidiasis are important forms[6]. While candidiasis, which is frequently associated with compromised immunity or diabetes, affects moist skin areas, dermatophytosis, which is caused by dermatophytes, appears as red, scaly patches and extreme contagious. Immunocompromised people may be susceptible to less common illnesses (like aspergillosis), which could make treatment more difficult.[8] the following figure show some types of fungal skin.

(a) Dermatophytosis

(b) Candidiasis

Fig. 1. Some types of Skin Fungal Infections[7]

3. DIAGNOSTIC CHALLENGES

Diagnosing fungal diseases on the skin accurately is crucial yet difficult for a number of reasons. Visual evaluations become more difficult because illnesses visually mimic other disorders, such as eczema. Traditional techniques like fungal biopsy, culture, and microscopy have drawbacks like subjectivity, long culture times, and invasiveness[8]. Additionally, the differences between irregularities and populations in sample collection impact the trustworthiness of diagnostics. These difficulties highlight the requirement for sophisticated diagnostic equipment. AI and deep learning, both present promising non-invasive ways to enhance patient outcomes by increasing diagnostic accuracy, speed, and consistency[7], [8].

4. DEEP LEARNING TECHNIQUES FOR FUNGAL DETECTION

In contrast, conventional methods have a variety of models and methodologies , which demonstrated potential in identifying cutaneous fungal infections the good in developments in deep learning is offering more precise and easily accessible diagnostic choices[2]. Careful consideration of imaging methods, data preprocessing, and model architecture are necessary to create efficient deep learning models for this use. These crucial elements are covered in this section.

4.1. Image Acquisition and Preprocessing

it is necessary for the deep learning-based accurate diagnosis of cutaneous fungal infections for high-quality[2]; its important in all image recognition to get good results. The confocal microscopy offers high-resolution views of skin layers, which it helps diagnose deeper infections, while the dermoscopy provides a detailed images of skin lesions, capturing patterns that help differentiate fungal infections[9]. To improve model performance, preprocessing techniques(such picture augmentation, noise reduction, normalization, and segmentation) are crucial. By focusing on contaminated regions, eliminating extraneous parts, ensuring consistency across sources, and increasing dataset variety, these procedures improve diagnostic accuracy[10].

4.2. Deep Learning Models:

In fungal infection identification, there are several deep learning architectures have been investigated; each has special qualities that are appropriate for various facets of medical image analysis. Among the important model kinds are:

a) Convolutional Neural Networks (CNNs) are Effective preprocessing methods and high-quality imagery, that necessary for the deep learning-based accurate diagnosis of cutaneous fungal infections.[11]. It is used to analyze medical photographs to detect fungal diseases on human skin by extraction of information including texture and color changes. This is frequently accomplished via fine-tuning pre-trained models such as ResNet and VGG, which increase accuracy even when data is scarce. The ability of CNNs to differentiate fungal infections from other illnesses, is comparable to dermatologists, facilitating quick diagnosis. For economical detection, they are included with cloud-based and mobile solutions. Despite ongoing issues with generalizability and dataset availability, CNN technological advancements continue to increase their efficacy in fungus identification. [6]

b) Transformers and Attentions Mechanisms: In contrast to CNNs types, it may identify long-range relationships in data, which has led to their recent success in medical imaging. Transformers provide a comprehensive image of the infection area by evaluating the significance of different visual sections using attention mechanisms (such as Vision Transformers), These models extract the global context by segmenting images into patches and processing them as sequences. When fungal infections are dispersed or asymmetrical, this may help[12].

c) Hybrid Models: CNNs for local feature extraction and transformers for large context, both of them are used in hybrid models, which improve the identification of fungal infections named (CNN-Transformer Hybrids). These models are perfect for a variety of infection presentations, such as dispersed fungal patches, because they combine the global context of transformers with the fine-grained detail-capturing capabilities of CNNs[13]. Other types of hybird Models are CNN-RNN; these models are beneficial for longitudinal research and in situations where temporal data is available, such as the course of an infection over time. By combining several architectural strengths, hybrid models provide a flexible framework that increases the accuracy of identifying complicated or unusual fungal illnesses[14].

5. SUMMARIZED AND LITERATURE REVIEW

In recent years, Deep learning has shown a lot of potential in the medical imaging industry, particularly in the detection of fungal skin infections. The literature review that follows gives a summary of recent research in this field, including deep learning algorithms, datasets, limitations and contributions for each method as shown in table 1.

TABLE I. SUMMARY OF RECENT STUDIES ON DEEP LEARNING FOR SKIN FUNGAL INFECTION DETECTION

Studies	An algorithm	Data set	limitation	Contributions
Smith et al. [15]	MeFunX (Meta-learning with CNNs + XGBoost)	DeFungi [16] and real-world data	Limited number of clinical mycologists, high costs, time-consuming procedures	Achieved 92.49% accuracy for early fungal infection detection in microscopic images
Johnson et al.[17]	ResNet-50 for feature extraction, SVM for classification	1000-3000 images of fungi	Sensitive to dataset variability, lower accuracy on datasets >2000 images	Accurate detection of fungal infections like Candidiasis and Tinea
Lee et al. [18]	CNN with transfer learning and data augmentation	Microscopic images of fungi	-	Achieved up to 97.19% accuracy in fungal detection
Tanaka et al. [19]	Transformer with Convolutional Tokenizer and attention mechanisms	Fluorescent images	Limited clinical data for some fungi, complexity of traditional CNNs	High accuracy in identifying fungal infections, from 84.38% to 97.19%
Abdurrahim et al. [20]	Custom deep neural network, VGG16	Microscopic images (81 fungi, 235 ceratine)	Manual inspection is time-consuming and has lower accuracy	High accuracy (99.84%) in onychomycosis detection
Md. Sazzadul Islam Prottasha [21]	Five CNN architectures, best: Inception ResNet v2	Eczema and Psoriasis datasets	-	Achieved maximum validation accuracy of 97.1%
Hasan M et al. [22]	InceptionV3 with fully connected layers	Skin fungi image set	-	Reduced manual identification costs
Han S et al. [23]	Ensemble model (ResNet-152 and VGG-19)	Multiple datasets from different universities	Non-standardized images, varying quality	Outperformed dermatologists in onychomycosis diagnosis accuracy
Mayya V. et al. [24]	CNN	Fungal mycelium and mycelium-free images	-	High recognition speed and accuracy for fungal keratitis
Tahir M. et al.[25]	CNN with optical sensor system	Novel fungus dataset (40,800 images)	-	Created a large, labeled fungus spore dataset with 94.8% detection accuracy
Lv J et al.[26]	CNN	Images of Chaetomium and Aspergillus fungi	Detection quality reliant on image processing	Achieved 98.03% accuracy in automatic fungal detection
Essalat M et al. [27]	ResNet	2088 IVCM images for training, 535 for testing	Decreased accuracy on diabetic patient images	Validated model for fungal keratitis diagnosis

Vayadande K[28]	SVM, CNN, RNN, GANs	University of São Paulo Skin Disease Database	Strengths and limitations of each algorithm discussed	Analyzed effectiveness for skin disease identification, including fungal infections
Jain A et al. [29]	CNN for image analysis, \SVM for clinical features	Skin disease datasets	Testing and safety evaluations needed	Efficient Tinea Corporis detection with hybrid model
Kumar R. et al. [30]	Weightless model in PyTorch	23 skin disease images	Limited to few disease classes, decreased efficiency on larger sets	Achieved 96.37% training and 87.75% test accuracy
Choi et al. [31]	CNN with VGG-16 for feature extraction	Medical images (various skin diseases)	-	Demonstrated CNNs' effectiveness in skin disease detection
Ahalya R et al.[32]	LeNet CNN architecture	Nine skin diseases dataset	-	Achieved 95% accuracy in classifying nine skin diseases
Nigat T. et al.[2]	CNN	407 images (four fungal diseases) from Ethiopia	Limited focus on tinea pedis and corporis	Achieved 93.3% accuracy in fungal disease classification
Martin et al.[33]	RESNET-50	Skin disease images	High cost of dermatologists and equipment	Effective skin disease diagnosis with neural networks
Kashyap N. et al. [34]	Multiclass CNN with AlexNet and VGG19	Images of Five skin illnesses	Challenges in accurate identification and costly tests	Accurate categorization of skin diseases, including fungal infections
Annie G. S et al.[35]	RCNN and SVM	Eye photos from COVID-19 patients	Limited effectiveness in advanced diagnostics	Achieved 81.65% accuracy for mucormycosis detection
Yilmaz A. et al. [36]	VGG16 and InceptionV3	160 images (onychomycosis) and 297 images (normal)	Variable diagnostic accuracy among clinicians	Deep learning outperformed dermatologists in fungal detection
Nourin.N.[37]	ANN with GLCM and HOG	Images of skin diseases	-	Achieved 93.5% accuracy with GLCM features
Kumar Y. al. [38]	Fine-tuned VGG16	Five skin disease classes	Costly, time-consuming for dermatologists	Improved classification accuracy with transfer learning
P.Sri Lakshmi [39]	CNN	Images of black fungus symptoms	Sample size variation by disease category	Effective prediction of black fungus infection probabilities
Ahammed Met al. [40]	Decision Tree, SVM, KNN	ISIC 2019, HAM10000	Manual diagnosis is time-consuming	Improved diagnosis speed with automated lesion detection

8. RECOMMENDATIONS

To improve the effectivity and reliability of deep learning models for the detection of cutaneous fungal infections, several key strategies are proposed to address data quality, model architecture, and clinical integration.

1. Enhance dataset quality and diversity: By creating diverse, high-quality datasets is crucial for reliable model performance. While data-sharing frameworks and synthetic data generation (such as GANs) might help overcome data scarcity, working with clinics across regions can increase dataset inclusiveness.

2 Apply Advanced data Augmentation technique: The model (generalization and adaptation) in clinical situations can be improved by domain-specific methods, like masking and context-specific augmentations , that mimic real-world variability (such as texture variations).

3 Optimize architecture model selection: Real-time applications in clinical settings are supported by hybrid architectures, that increase accuracy and efficiency (such as CNNs with transformers, lightweight models, and Efficient-Net).

4 Enhance diagnostic interpretability and usability : When displaying model decision areas, explainable AI (XAI) techniques like heatmaps help clinicians gain trust, while feedback loops and user-friendly interfaces support clinical usability and ongoing the development of model .

9. CONCLUSION

Using AI, especially deep learning, to identify fungal diseases on the skin has the potential to revolutionize medical treatment. Deep learning models provide a promising means of improving the accuracy, speed and accessibility of fungal infection diagnosis due to their ability to interpret complex visual patternsBy automating t he detection process, AI may assist dermatologists in making faster and more accurate diagnoses, especially in places with limited access to specialized medical care. However, significant hurdles remain, particularly regarding data diversity, model interpretability, and integration into clinical settings. To ensure from that, AI tools are reliable and trustworthy by healthcare professionals, future research should prioritize developing diverse, high-quality datasets, enhancing model transparency, and conducting extensive clinical validation. Furthermore, improving clinical usability and acceptance will require creating interpretable models and user-friendly interfaces. Thus, the application of deep learning models to dermatology has the potential to transform the detection of fungal infections, and thereby improve patient care and outcomes across healthcare systems worldwide, as long as these models continue to evolve and advance. For more realizing the impact of AI, in this critical area of healthcare, clinicians, academics, and policymakers must continue to collaborate

Conflicts of Interest

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