Image Recognition of Pigmented Skin Diseases Based on Deep Learning

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Abstract: One of the most common skin conditions is pigmentary skin disease. It is also challenging to differentiate between the lesions of various pigmentary skin diseases with the unaided eye due to their striking similarity. The paper wishes to investigate whether deep learning image recognition can resolve this issue because deep learning technology has advanced significantly in recent years and has shown promise in a number of domains. In order to help the investigation, the paper modified the weights of three pigmented skin illnesses that have similar clinical features to help two deep learning models that paper used to identify to gain higher accuracy. The findings demonstrate that deep learning can effectively identify many forms of pigmented skin illnesses and is very helpful in the recognition of skin diseases. In subsequent research, the paper will attempt to use deep learning to determine the lesion's stage, which will be extremely beneficial for diagnosing pigmented skin conditions.

1 INTRODUCTION

The rapid evolution of computer vision and deep learning technologies has brought significant advancements to medical image analysis, particularly in the detection and evaluation of pigmented skin diseases. Pigmented skin conditions, which are characterized by abnormalities in skin pigmentation, represent a common category of dermatological disorders. (Cai, 2023) The early detection and precise staging of these conditions are critical for effective clinical intervention and prognosis assessment. Traditionally, the diagnosis of skin lesions has relied heavily on the expertise of dermatologists, because it is challenging to recognize and categorize skin lesions due to the wide range of pigmented skin lesions, the high degree of resemblance between distinct classes, and the significant differences within the same class. (Chen, 2014) This conventional approach, while valuable, is often subjective and can suffer from variability in diagnostic accuracy due to differences in clinical experience and judgment.

In recent years, the integration of deep learning techniques, particularly Convolutional Neural Networks (CNNs), has introduced a transformative shift in the analysis of medical images. CNNs have demonstrated exceptional performance in tasks related to image classification and object detection, surpassing traditional methods in accuracy and efficiency (Chu, 2024). These advancements present promising solutions for the automatic identification and staging of pigmented skin lesions, offering potential improvements in diagnostic consistency and operational efficiency.

This paper explores the application of deep learning technologies to the recognition and staging of pigmented skin lesions. The paper will examine the current state of deep learning models used in skin lesion image analysis, highlighting their applications, the challenges they face, and their future prospects. The discussion will focus on several key areas: the mainstream deep learning methods employed, including various CNN architectures; the processes involved in constructing and processing datasets; and the strategies for training and optimizing models. Furthermore, the paper will consider the practical implications of these technologies, evaluating how they can be integrated into clinical practice to enhance diagnostic capabilities and improve patient outcomes.

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By providing a thorough examination of these aspects, this paper aims to offer insights into the current advancements in deep learning for skin lesion analysis and to outline the potential for future developments in this rapidly evolving field.

2 PIGMENTED SKIN LESION DETECTION

Pigmented skin lesions (PSLs), a common type of skin problem, are known to show more skin coloring, mostly happening because melanocytes start to multiply more. Proper detection and labeling of these lesions are important as they come in both harmless types, like melanocytic nevi (or just nevus), and harmful ones like melanoma. Especially melanoma, a very serious kind of skin cancer, is usually the cause of many deaths related to skin cancer. It becomes quite important to detect PSLs early on and categorize them correctly for better treatment options and improved health results for patients.

2.1 Types of hyperpigmented lesions

Pigmented skin lesions can mainly be broken down into either benign or malignant forms. The usual examples include the most common ones.

Melanocytic nevus: It is where melanocytes gather in a benign way, showing up as dark spots on the skin. Most of the time, they do not cause harm, but there can be rare occasions where they turn into melanoma.

Melanoma: A very dangerous type of skin cancer that comes from melanocytes. Melanoma has a high level of aggression, spreading to other body parts quickly, so detecting it early is very important. (Han, 2018)

Sunspot: often referred to as liver spot or even senile spot, it is mostly considered as a harmless pigmented area that is the result of prolonged exposure to the sun. These spots do not develop into cancer, though sometimes they can be mistaken for dangerous lesions of a malignant kind.

Seborrheic keratosis: This is identified as a non-cancerous growth that is wart-like in its appearance, which can form on different parts of the body. Though these growths pose no harm, their visual similarity to melanomas creates certain issues during diagnosis.

Abnormal nevus: A kind of nevus that has irregular characteristics and may suggest early signs of melanoma, and regular check-ups become necessary to watch for possible changes in these skin areas.

2.2 Limitations of traditional recognition methods

The common ways of identifying pigmented lesions on skin mainly depend on doctors visually inspecting, sometimes with help from dermoscopy, which is a tool used to magnify the skin surface for better viewing without causing harm. (Niu, 2024) Even though these approaches can work well, they still face certain limits and are not always fully sufficient.

Subjectivity: The evaluation of visuals is very subjective, depending much on the experience and expertise of dermatologists, which introduces variations and inconsistencies in diagnoses made.

Limited accuracy: Even with dermoscopy being used, some lesions remain difficult to tell apart, particularly when they are in early development or show unusual characteristics, adding to the difficulty in making precise distinctions.

Time being consumed: Examining several lesions manually, particularly when a patient has many pigmented spots, takes much time and can be not practical in certain clinical environments due to how long it might take to complete.

Variability among observers: Different dermatologists might see one lesion in various ways, which creates inconsistency in diagnoses and advice for treatments provided across different patients and practitioners.

2.3 Image Classification Methods Through Deep Learning

The traditional methods have limitations that deeplearning methods aim to overcome, especially by using CNNS more and more for the purpose of classifying skin lesions with pigments.

2.3.1 Convolutional Neural Network (CNN) Basic Idea

CNNS represent a kind of deep learning models designed to handle structured grid-like data, for example, images. A CNN typically consists of several layers, which might include convolutional layers, pooling layers, and layers that are fully connected.

Convolutional layers: In these layers, convolution operations get applied to the input, with filters detecting various local patterns like edges or shapes, possibly textures. What results from this is a feature map, which highlights such patterns but does so without strict detail. (Dong, 2017)

Pooling layer: Pooling reduces the size of the feature map by summarizing certain features present in regions, which has the function of lowering computational complexity and also reducing overfitting risks, although the exact effect is not always completely clear.

Fully connected layers: Each neuron in one layer gets connected with every neuron that belongs to the next layer, allowing predictions to be formed based on features coming from the convolutional and pooling layers, though these predictions can be influenced by many factors at the same time, some of which could change.

2.3.2 Common Deep Learning models

There have been many different deep learning models that have managed to be applied for the classification of skin lesions that are pigmented, which shows the versatility of these models in handling tasks related to this field.

ResNet: ResNet brings up the idea of residual learning, which makes networks able to go much deeper by reducing issues with vanishing gradients. It has been said to perform better in tasks like image classification, including images from medical fields, showing better results.

EfficientNet: EfficientNet represents a group of models that, through scaling dimensions like depth, width, and resolution in a structured manner, improves performance. These models manage to reach higher accuracy levels while using fewer parameters than what is commonly seen in older models. The approach provides better results not just by increasing one aspect, but by adjusting several dimensions together. Compared to more traditional models, which may not consider such structured scaling, EfficientNet shows advantages in both efficiency and accuracy, making it stand apart. (Petra, 2024) However, exact improvements can vary depending on implementation.

3 EXPERIMENTAL PRINCIPLE

3.1 Experimental procedure

As shown in Figure 1. Images and the associated labels (melanoma, chromatoma, seborrheic keratosis) make up the training set. The paper applies a Softmax loss function and modify the weights according to the mistake.

The images are routed to the convolutional, pooling, fully connected (FC), and Softmax output layers of ResNet101.

The model's performance is verified using the images and labels that make up the verification set. Images pass through the ResNet101 layers in a manner akin to that of training.

Following the output's progression through the ResNet101 layers, a test set is used to optimize and validate it. To increase classification accuracy, the optimization model modifies the parameters in response to the output.

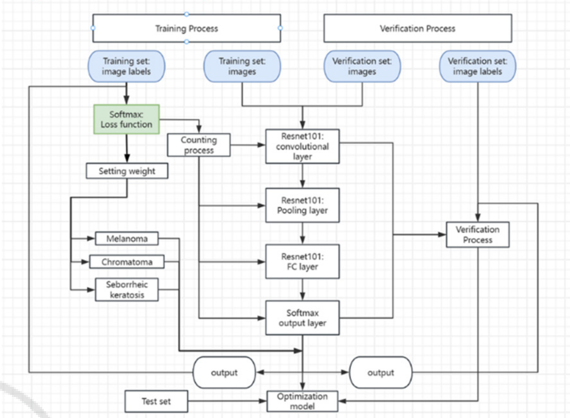

Figure 1: Flow chart of Deep learning
(Photo/Picture credit : Original)

3.2 The Role of Deep Learning in Stage Detection

Deep learning models are becoming more significant in how pigmented skin lesions are automatically detected and staged, helping with:

3.2.1 Feature Extraction and Discrimination

CNNs, which are used in many cases, can find and get important features out of dermoscopic images. These features, which are helpful in separating the stages of melanoma, do not only include how the lesion looks, but also other patterns that might exist, though these patterns may not be easily noticed by human observers. (Wang, 2024) These patterns can sometimes be less obvious and need more attention to be seen clearly.

3.2.2 Semantic and Instance Segmentation

Deep learning techniques, such as the more advanced ones including semantic segmentation and also instance segmentation, give the possibility of a clearer outline of lesion boundaries, as well as finding different areas inside a lesion that might match up with various pathological traits. Semantic segmentation is used to assign a label to each pixel in the image, which can help with recognizing certain areas like tumor tissue in contrast with healthy parts. But instance segmentation goes even further to separate different objects or lesions found in one image, though they might still fall under the same general category.

3.3 Current Research and Applications

Recent research shows that deep learning models have possibilities in automatically classifying and staging pigmented skin lesions. For instance, some researchers have created CNN-based models, which can sometimes reach accuracy levels close to or even higher than experienced dermatologists when it comes to detecting melanoma. Additionally, models that were trained on big annotated datasets, such as the ISIC dataset (International Skin Imaging Collaboration), are now used to automate the staging process for melanoma. (Niu, 2024) This offers a useful tool to help clinicians with decisions when making diagnoses.

4 EXPERIMENT AND RESULT

4.1 Construction and Choosing of Datasets

The deep learning model's effectiveness when it comes to detecting and staging pigmented skin lesions relies a lot on the type of dataset and how varied it is, especially for training purposes. Important points to think about include:
Data Collection: High-resolution images must be gathered from different groups of people and medical settings. These images are needed for creating reliable models. The images should cover different phases of illness and show both frequent and unusual types of lesions, which is important to ensure the data is comprehensive enough for the purpose of training.
Annotation: It is necessary to annotate datasets with accuracy. Usually, experts like dermatologists are responsible for labeling images, and they mark them with details like lesion categories, disease stages, and important clinical attributes. In some situations, the annotations may even provide pixel-wise labeling for tasks related to segmentation.

The data set used in this study was HAM10000 skin image dataset on hyperai(shows on Figure 2), which collected 10000 skin lesions images from different populations. The cases included several representative types of hyperpigmented lesions, mainly melanoma, nevus and seborrheic keratosis.

HyperAI (hyper.ai) artificial intelligence and high performance computing community aims to help developers and enthusiasts of data science and artificial intelligence industry learn, understand and practical by providing multiple services such as accelerated download of data sets, online tutorial demonstrations, in-depth interpretation of papers, and integration of top conference calendar.

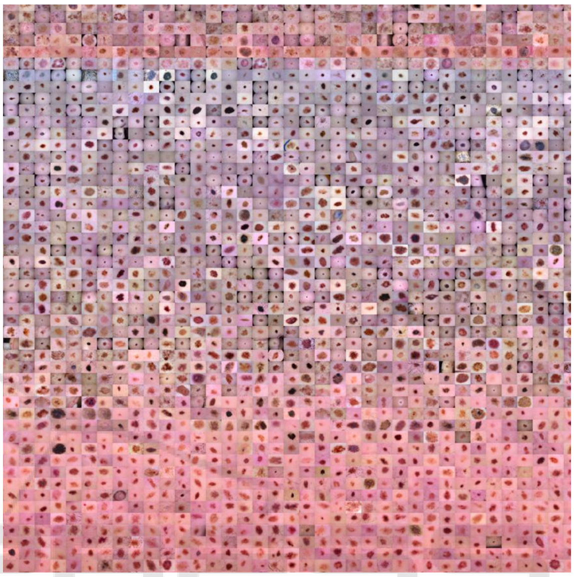

Figure 2: Dataset from Hyperai(Photo/Picture credit : Original)

4.2 Model Training and Performance Evaluation

It is very important to do model training and performance evaluation correctly if you want deep learning models to be used in clinical practice.

4.2.1 Choosing and Preparing the Training data

After removing the unidentifiable bad graphs in the dataset, the paper divided the dataset into three independent datasets that did not cross each other to ensure the generalization ability of the model on unknown data. There were 6000 images in the training set, 1800 images in the validation set, and 450 images in the test set.

The distribution of three types of tumor images on the three datasets is shown in table 1.

Table 1: Dataset distribution

Dataset	Melan-oma	Chrom-atoma	Seborrh-eic keratosi-s	Total
Training set	1800	2400	1800	6000
Verificati-on set	540	720	540	1800
Test set	145	180	135	450

4.2.2 Model Evaluation Metrics

Metrics commonly used for evaluating how models perform include:

Accuracy: It is the ratio of correct predictions compared to the total number of predictions that the model has made overall.

Sensitivity (Recall): This measures how well the model can find positive instances, like when it identifies malignant lesions correctly.

Precision: Precision is a metric that is used in statistical classification and information retrieval that represents the proportion of correctly extracted samples to total extracted samples. (Tian. 2024) Recall, which is the ratio of the number of extracted samples to the total number of samples, is a related idea.

F1 Score: Precision and recall come together to make a harmonic mean, and that gives a measure which balances how the model performs on both sides, providing an understanding of overall performance.

4.3 Experimental result

During the training phase, the model's prediction performance was assessed in real time using the validation set, which allowed for parameter adjustments and overall model optimization. The final model for predicting the test set data was determined by using the training result from the round that had the highest accuracy of the validation set. There were 100 training epochs in this model.

ResNet101 was used as the training model in this experiment in order to confirm the experiment's efficacy. By establishing category weights, the efficacy of deep learning in recognizing photos of pigmented skin diseases was assessed. This experiment is trained on a Tesla V100S-PCI-32GB GPU and is based on the Aliyun computing platform to guarantee experiment efficiency.

It can be seen from Figure 3 that the accuracy of diagnosing pigmentary skin illnesses improved to 65% after many training sessions, indicating that deep learning is a viable method for doing so. The figure 4 compares the particular recognition results of each category when the two training procedures are used with this model.

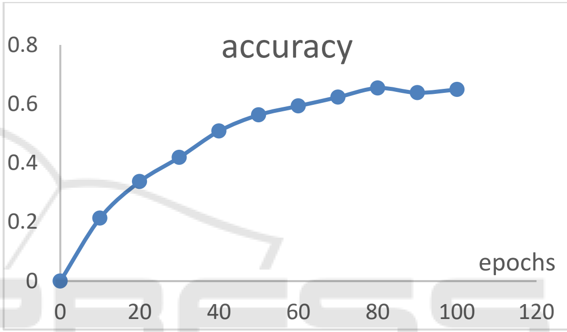

Figure 3: Curve of average accuracy(Photo/Picture credit : Original)

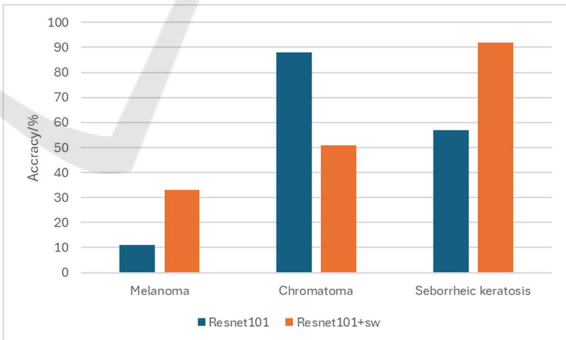

Figure 4: Accuracy of 3 kinds of skin diseases (Photo/Picture credit : Original)

Deep learning had generally good accuracy in identifying chromopoma and seborrheic keratosis, but less desirable results when it came to melanoma.

5 CONCLUSION

One of the most crucial responsibilities in dermatology is the diagnosis of pigmented skin diseases, which has a big influence on patient outcomes. While useful, traditional diagnostic techniques have drawbacks that deep-learning models might be able to solve. These models are able to correctly classify partly pigmented lesions through the use of sophisticated techniques including segmentation algorithms and CNN. Many obstacles still need to be overcome, particularly in the areas of data heterogeneity, model applicability, and distinguishing between different kinds of pigmented dermatoses. It will be up to continued study and creative problem-solving to resolve these obstacles before deep learning in dermatology can realize its full potential.

The paper employed two distinct deep learning models to identify three common pigmented skin illnesses from images. By varying the weights of the models, the paper was able to increase the recognition accuracy. The encouraging outcomes demonstrated that deep learning may be used to diagnose skin illnesses, with up to 80% accuracy being able to distinguish between chromoblastoma and seborrheic keratosis. The paper will attempt to use deep learning to distinguish between various phases of pigmented skin lesions and to increase the accuracy of diagnosing skin disorders like melanoma, which are challenging to diagnose.

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