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Diagnosis of Psoriasis and Eczema Using Deep Features Based on Transfer Learning with Different Domains

Fatemeh Mosallanejad[1], Hassan Masoumi [2*], Mehdi Taghizadeh [3], Mohammad Mehdi Ghanbarian [4]
[1]Department of Biomedical Engineering, Kazerun Branch, Islamic Azad University, Kazerun, Iran.
f.mosalanejad@iau.ir
[2]Department of Biomedical Engineering, Kazerun Branch, Islamic Azad University, Kazerun, Iran.
Ha.masoumi@iau.ac.ir
[3]Department of Electrical Engineering, Kazerun Branch, Islamic Azad University, Kazerun, Iran.
Mehdi.taghizadeh@iau.ac.ir
[4] Department of Electrical Engineering, Kazerun Branch, Islamic Azad University, Kazerun, Iran.
mm.ghanbarian@iau.ac.ir

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Abstract: Misdiagnosis of skin diseases is a common occurrence worldwide. Psoriasis is a skin disease that has many similarities with other diseases, and its wrong diagnosis causes many problems in the treatment process. Misdiagnosis of this disease increases the length of treatment. The small number of medical images and dermatological databases makes examination and diagnosis difficult, so diagnosis using different images is very useful. Diagnostic methods using deep features based on transfer learning have received much attention in medical imaging today. This method reduces the dependency on matched data. Deep learning methods have been able to show their ability to recognize images well. Therefore, in this article, two data sets with different domains have been investigated using deep features based on transfer learning. In this research, the data of the first database was used for the training data and the data of the second database was used for the test, and this work was also set to the test mode for other data. In this article, by using convolutional neural network without manual intervention, deep features have been extracted and then three groups of diseases have been diagnosed. Accuracy results were calculated by 10-fold cross-validation method and reached 99.68% accuracy. This study shows that the proposed method differentiates skin diseases with acceptable accuracy.

Keywords: Convulsive neural network (CNN), Transitional learning, Psoriasis and eczema skin disease, Deep learning.

1. INTRODUCTION

Human skin is the largest organ in the body. The skin mass is between six and nine pounds and is estimated at about two square meters of surface. The inner part of the body is separated by the skin.

The skin also protects against fungal infections, bacteria, allergies, and viruses and controls body temperature. Many people have skin conditions that are affected by bacteria or viruses. Many people neglect their skin health and take care of it. There are several types of skin diseases such as eczema, alopecia, ringworm, and psoriasis.

There are about 3,000 disorders in the world of dermatology. This large number of diseases includes many groups that etiologically include a wide range of diversity: from genetic disorders to infectious diseases, diseases caused by exposure to environmental factors, and many diseases that, although not fatal.

Most skin diseases are multifactorial. In general, it can be said that there are various reasons for the relationship between skin and psyche that a skin disease can initially cause psychological problems due to the unpleasant appearance that it causes in a person. On the other hand, some psychological problems can be Skin manifestations such as dysmorphophobia, in the other case, the two can manifest as a systemic underlying disease such as luposarithomatosis. Each person's personality is a determining factor that overshadows all human behaviors and

*Corresponding Author Email: *Ha.masoumi@iau.ac.ir*)

tendencies, due to maladaptive traits and characteristics, can cause some psychological and even physical problems and disorders.

2. RELATED WORKS

Skin disease is one of the most common diseases among people all over the world. There are different types of skin diseases such as basal cell carcinoma (BCC), melanoma, intraepithelial carcinoma and squamous cell carcinoma (SCC) [1].

Psoriasis is a common skin disease and affects about one to three percent of the world's population [2]. This disease has a genetic background and the disease is affected by some environmental factors such as stress in general it can be said that this disease is dependent on the genetics of the environment [3]. Medications, hormonal and metabolic agents of sunlight. Studies in the UK show that men and women with the disease die on average 3.9 and 4.9 years earlier, respectively [4].

Often only experienced physicians can achieve accurate diagnosis with these visual methods [5]. Histopathological examination of a suspicious lesion is the gold standard for diagnosing skin disease. Several examples of clinical pictures of common skin diseases are shown in Figure 1.

Figure 1. Examples of skin diseases

Therefore, the development of an effective method that can automatically differentiate skin diseases will be useful as a primary screening tool. Distinguishing a skin condition from dermoscopic images may be inaccurate or unrepeatable because it depends on the experience of dermatologists. In practice, the diagnostic accuracy of melanoma from dermoscopic images by an inexperienced specialist is in the range of 0:75 to 0:84 [5]. One of the limitations of the diagnosis made by human specialists is that it is highly dependent on subjective judgment and varies greatly between different specialists. In contrast, a computer-aided diagnostic (CAD) system is more targeted. Using manual features, traditional CAD systems for skin disease classification can achieve excellent performance in some skin disease diagnostic tasks [6]. This is because manual features are not suitable for the universal diagnosis of skin disease. On the one hand, manual features are usually extracted specifically for a limited variety of skin conditions. They can hardly adapt to other types of skin diseases. On the other hand, due to the variety of skin diseases, man-made features can not be effective for any skin disease [6]. Valid public features can be one of the solutions to this problem that eliminates the need for feature engineering and automatically extracts effective features [7]. Many methods have been proposed for this in the last few years [8]. However, most of them focused on dermoscopic or histopathological image processing tasks and mainly on the diagnosis of mitosis and cancer markers [9]. Recently, deep learning methods have received a lot of attention and have achieved excellent performance in various tasks such as image classification [10], image segmentation [11], object recognition [12], and so on. Various studies [13] have shown that deep learning techniques are able to surpass humans in many computer vision tasks. One of the success factors of deep learning is its ability to learn. Semantic features are automatically extracted from large data sets and used for classification and recognition [14]. In particular, much work has been done on the use of deep learning methods in the diagnosis of skin diseases [15]. In [16], for example, he proposed a global skin disease classification system based on a pre-trained convolutional neural network (CNN). The accuracy of the top classification was 80%, which was significantly better than the performance of human specialists. Deep neural networks (DNNs) can cope with large changes in the image of skin diseases by learning effective features with multiple layers. Despite these technological advances, the lack of large amounts of labeled clinical data has limited the widespread use of in-depth learning in the diagnosis of skin diseases.

Over the past decade, many research papers, dissertations, and books have been published on the diagnosis of skin diseases [18]. In particular, there are several survey articles that provide good reviews of the methods used to diagnose skin diseases [19]. However, some of them mainly focused on traditional machine learning methods and mentioned deep learning methods with only a small part of the whole content [20]. As it turns out, in-depth learning develops rapidly with the numerous articles that are published each year. Therefore, it is necessary to include the latest works to analyze the trends in this field. In addition, previous surveys [21] discussed only specific skin diseases (such as melanoma) or specific diagnostic tasks (e.g., classification of skin lesions), while other diseases (e.g., non-melanoma diseases) or tasks (e.g., skin lesions) were discussed. And skin diseases such as eczema and psoriasis are less common. A number of comparative studies of skin color pixel classification have been reported to diagnose skin diseases. [22] They compared the skin. Gaussian mixed models were compared in a series of 110 images of 30 people from Asia and the Caucasus [24].

Classification of skin lesions into "benign" or "malignant" classes is a task supervised using learning [25]. Machine learning can be divided into many sub-areas. In particular, deep learning is a branch of machine learning and has developed rapidly over the past few years. Previously, designing a machine learning algorithm required domain information or human engineering to extract identifying features that could be used for pattern recognition. However, a deep learning model consisting of multiple layers can directly convert raw input data into the display needed for pattern recognition without much human intervention. Layers in a deep learning architecture are arranged sequentially and consist of a large number of nonlinear, predefined operations so that the output of one layer enters the next layer to form more complex and abstract representations. In this way, the deep learning architecture is able to learn complex functions. People have witnessed the massive development of deep learning algorithms and their widespread applications in various tasks such as object classification, machine translation, and speech recognition. In particular, health and medical care benefit greatly from the prevalence of deep learning due to the large volume of medical data [29].

Three major factors have contributed to the success of deep learning to solve the complex problems of modern society, including:

1- Availability of massive training data. With the ubiquitous digitization of information in the recent world, large volumes of data are available to the public to teach complex models of deep learning.

2- Availability of powerful computing resources. Teaching complex deep-learning models with big data requires a lot of computing power. Only the availability of powerful computing resources, in particular the improvement of GPU performance and the development of methods for using GPUs for computing, have recently met such requirements.

3- Availability of deep learning frameworks. People in various research communities are increasingly willing to share their source code on public platforms. Easy access to the implementation of deep learning algorithms has accelerated the speed of detecting practical tasks day by day.

3. MATERIALS METHOD

In this study, two datasets including skin disease, psoriasis, and eczema were used.

3.1. THE FIRST DATABASE

The freely available DermNet NZ online database is used [28] and launched in 1996 by a team of dermatologists from New Zealand. It has become a world-renowned source of information on skin diseases. In this study, 100 eczema data and 100 psoriasis data were used.

Figure 2. Skin disease. (A) Psoriasis (b) Eczema.

3.2. THE SECONDE DATABASE

Hormozgan Hospital dermatologist data that have been labeled under the supervision of a dermatologist has been used. These data include 50 patients with psoriasis and 50 eczema data. These data are imaged from the skin disease site after diagnosis by a specialist doctor.

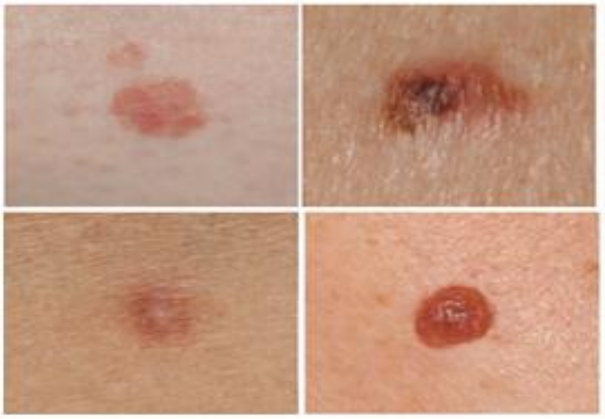

Figure 3. Skin disease. (A) Psoriasis (b) Eczema.

3.3. Deep image features

Feature extraction from images is a very useful and sensitive task to identify and classify and the better this feature extraction is done, the better the detection and separation. Here, a convolution neural network with ResNet, GoogleNet and AlexNet architectures is used to extract deep features from images.

3.4. AlexNet Architecture

Neural network architectures are pre-trained networks that have the ability to distinguish 1000 classes. The typical AlexNet network has 8 layers, the first five layers being convolutional and the last three layers fully connected. Figure 4 shows the general structure of the AlexNet network. In this research, an Alexnet neural network with three fully connected layers has been used.

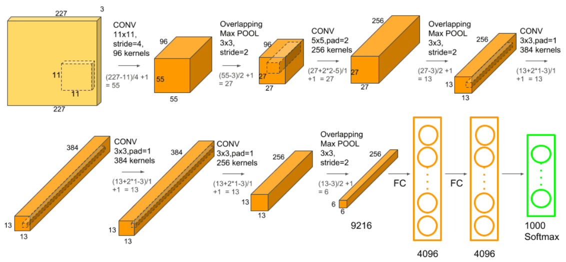

Figure 4. AlexNet convolution neural network image

3.5. ResNet architecture

In fact, the ResNet architecture introduced no shortcuts and introduced a gateway shortcut network. Thus, ResNet can be considered as a special case of deep networking. You can see the ResNet network in Figure 5.

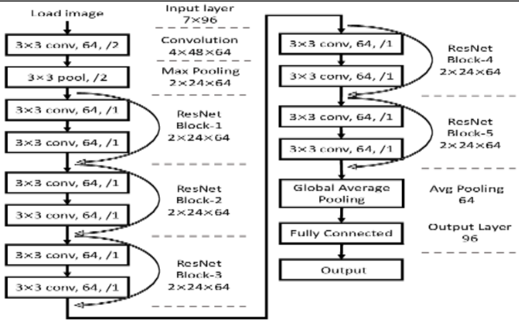

Figure 5. ResNet convolution neural network image

3.6. GoogleNet Architecture

Google Net was suggested by Google Research (in collaboration with various universities) in a 2014 research paper entitled "Going Deeper with Convolutions." This architecture won the ILSVRC 2014 Image Classification Challenge. There was a significant reduction in error rates compared to previous winners AlexNet (ILSVRC 2012 winner) and ZF-Net (ILSVRC 2013 winner) and a significantly lower error rate than VGG (2014 runner-up). This architecture uses techniques such as 1 * 1 convolution in the middle of the architecture and the integration of the global average. The GoogLeNet architecture is very different from previous architectures. It uses a variety of methods such as 1x1 convolution and global average integration, which allows it to create a deeper architecture. The overall architecture is 22 layers deep. The architecture is designed to have computational performance in mind. The idea behind this is that architecture can be implemented on individual devices even with limited computing resources. The architecture also includes two auxiliary classification layers that are connected to the output of the Inception (4a) and Inception (4d) layers. You can see the Google Net architecture in Figure 6.

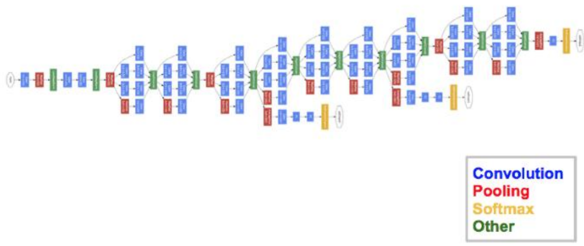

Figure 6. GoogleNet convolution neural network image

3.7. Transfer learning

In this research, 4 stages and 3 architectures have been studied, which are as follows. Step 1: Training and test data The first database images are used. Step 2: Training and test data The images of the second database are used. Step 3: The first database images are used for training and the second database images are used for testing. Step 4: The second database images are used for training and the first database images are used for testing. All these 4 modes are used for 3 neural network architectures, which are shown in Figure 7.

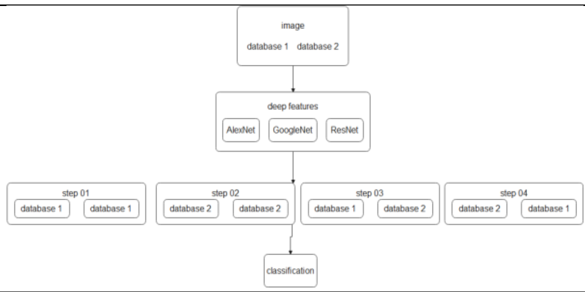

Figure 7. Flowchart of our methods

4. RESULTS

In this paper, the confusion matrix is used for accuracy and sensitivity results. Equations 1 and 2 according to the confusion matrix have been used to calculate the accuracy and sensitivity.

Equation 1

Accuracy = (TP + TN) / (TP + TN + FP + FN)	(1)

Equation 2

Sensitivity = (TP) /(TP + FN)	(2)

Table 1 shows the results of the accuracy and sensitivity of the classifiers in the first step.

TABLE 1. Results of the first stage classifier types

Classifier	**acc**	**sens**
AlexNet	98.69	97.87
GoogleNet	94.23	93.65
ResNet	99.68	99.45

Table 2 shows the results of the accuracy and sensitivity of the classifiers in the second step.

TABLE 2. Results of the second stage classifier types

Classifier	**acc**	**sens**
AlexNet	97.23	97.15
GoogleNet	90.32	89.72
ResNet	99.12	99.27

Table 3 shows the results of the accuracy and sensitivity of the classifiers in the third step.

TABLE 3. Results of the third stage classifier types

Classifier	**acc**	**sens**
AlexNet	94.35	92.63
GoogleNet	86.38	82.71
ResNet	98.71	97.32

Table 4 shows the accuracy and sensitivity of the classifiers in the third step.

TABLE 4. Results of the fourth stage classifier types

Classifier	**acc**	**sens**
AlexNet	93.85	91.93
GoogleNet	85.83	83.73
ResNet	98.12	97.81

5. DISCUSSION

The deep learning method is a very new and efficient method of diagnosis and classification without manual intervention. This makes the detection process completely automated and systematic. Transitional learning is a method that reduces dependence on databases and also reduces the need for specific data, and this can be used to distinguish a complication and disease from disease-related signals and images.

Tables 1 to 4 show the classification results of different methods, in Table 1 shows 99.68 accuracy, which is a very reliable and suitable result for the diagnosis of skin diseases. Table 5 shows the different results and algorithms in the different datasets used.

TABLE 5. Results of other articles

Acc	Classifier	diagnostic	Ref
82.9	CNN	psoriasis	[29]
77.87	PSE-Net CNN	psoriasis	[30]
99.68	CNN (ResNet)	Eczema & psoriasis	My method

As you can see in Table 5, the accuracy of the proposed classifier is higher than other classifiers and is selected as the preferred classifier. The main purpose of this study is to provide a fully automated method without hand intervention based on deep feature learning and using the transfer learning method to diagnose psoriasis from a similar disease. In this project, deep features are extracted from the images without manual intervention. This reduces the need for humans and does not require images to be examined by humans.

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