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An Expert Smart Scalp Inspection System Using Deep Learning

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With the advent of the "beauty economic era", in which people are paying more attention to beauty and health, the health of the scalp is being increasingly valued. However, current scalp care services are limited by problems such as they are not automatic and objective, and the results are not significant, which make them unacceptable to the public. Because of these reasons, in this study, we focus on the obstacles that hairdressers face and propose an expert inspection system that is suitable for determining scalp problems by utilizing deep learning, cloud computing techniques, and an embedded system. Dandruff is the most common scalp problem. In this work, we propose a convolutional neural network (CNN)-based method to analyze the severity of dandruff and evaluate the health of the scalp. The convolutional block attention module (CBAM) is adopted to improve the feature extraction performance of the CNN model. The depth separable convolution (DSC) and spinal fully connected (FC) are applied in this work to reduce the number of model parameters. Aside from offering a more effective smart scalp inspection process, this method also enables hairdressers and customers to track their scalp problems easily. In the future, we expect to reduce the stress of hairdressers and enhance customers' trust on scalp care services by using the smart health inspection offered by this system. Last but not the least, it has been shown that the method proposed in this research can achieve an accuracy of 85.03%, which is higher than those achieved by recently proposed methods.

1. Introduction

Along with economic and technological progress, the demand for quality of life is no longer limited to food, clothes, housing, transportation, and entertainment. People also pay more attention to beauty and health, which leads to the new emerging industry of "beauty economy," and this has caused the fashion and beauty service industry to thrive as well. According to the latest information obtained by the focus on internet's news & data (FIND) team of the Institute for Information Industry (III), there are about 30665 domestic hairdressing, beauty, and

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bodybuilding shops in Taiwan, and their annual revenue can be up to NTD$ 37.9 billion. Among these shops, there are approximately 21915 hairdressing stores and their annual revenue is up to NTD$ 24.8 billion, which makes up 60% of the revenue of the whole beauty and fashion industry in Taiwan. However, the increasing market scale has also brought a new operation mode to this moderately competitive market. To enhance brand competitiveness and improve customers experience with respect to scalp health, hairdressing shops nowadays are not only restricted to hairdressing services such as washing, cutting, dyeing, hair care, and perming; some shops have been thinking of collaborating with hospitals and launching scalp care services.(1)

To deal with patients' scalp problems, these hairdressing shops have aided customers to find hairdressing products that are suitable for them by hiring dermatologists or licensed professional scalp therapists to determine the health condition of customers' scalps and offer a series of treatments for different scalp problems.

Recently, because of dietary changes, environmental contamination, poor lifestyle, and stress, almost every person nowadays has scalp problems, as shown in Fig. 1. Common scalp problems include seborrheic dermatitis, folliculitis, dry seborrhea, hair loss, oily seborrhea, allergy, and hyperkeratosis, and among those problems, at least 30% belong to serious scalp patients who have apprehensions about hair loss.(2) Although hair and scalp disorders do not usually cause serious physical discomfort, they may lead to psychological effects. In modern times, hair is not only for keeping warm and protecting one's head, but it also has a crucial effect on outward appearance. Serious hair problems may affect self-confidence and lead to social barriers. Moreover, in some situations, changes in one's scalp may be a sign of some serious physical illness; hence, physiotherapy services that mainly focus on healing the scalp have become an imperative trend.

The physiotherapy services currently offered by hairdressing shops can be divided into three stages. The first stage is collecting scalp samples from different areas, and dermatologists or professional scalp therapists use scaling microscopes to obtain images of different scalp areas and show those scalp images on a computer screen or a tablet. During this process, dermatologists

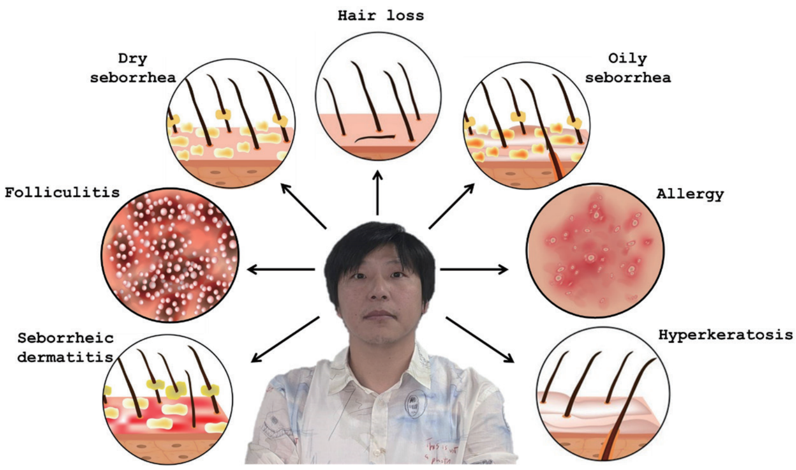

Fig. 1. (Color online) Common scalp problems.

or professional scalp therapists will also comment on the condition of each part of the patient's scalp and let the patient understand his or her scalp problems. The second stage is scalp health analysis; the above-mentioned professionals will manually analyze each part of the scalp to determine the current health condition of the patient's scalp. The third and last stage involves scalp therapy and tracking; scalp therapists will introduce a customized therapy to the customer along with a suitable shampoo and related skincare to improve the customer's scalp problems. Although this is an operation mode with unlimited business opportunities, there are many nonscientific objective problems, which result in some customers not willing to pay extra for related services. There are three main reasons for this, as follows.

(1) Subjective diagnosis and treatment method: Although professional doctors and scalp therapists have gone through professional training, when it comes to determining the health score for a patient's scalp, scores vary owing to personal subjective cognitive or mental conditions. For example, feature misjudgement caused by shadows in the environment, subjective cognitive differences regarding the assessment standard, and mental fatigue due to long-term observation all lead to the imprecise judgement of a patient's current scalp health condition by these professionals.

(2) High professional personal cost: Different from ordinary hairdressing services offered by hairdressers, scalp therapists must observe the client's scalp using a 200-fold high-magnification microscope to analyze the client's scalp health condition. To acquire this skill, people must go through education and training for at least half a year.[3] Given the high cost of training a new employee and the frequent personnel turnover in this business, the company will have to keep investing in manpower and spending for high training fees.

(3) Nonsignificant treatment effect: During the scalp health analysis stage, scalp therapists will subjectively comment on the problems in different scalp areas shown on the monitor, and since there is no objective and scientific data analysis for the client's reference, during the course of treatment, some customers cannot feel a significant difference when looking at the treated scalp areas, which often leads to some cognitive dispute, causing trouble for both the company and the customer.

From the above-mentioned problems, we can observe that the current scalp therapy services are restricted by issues such as "not objective, not automated, not significant," which makes it difficult to promote related businesses. Hence, how to improve the service quality through the use of technology has become an urgent, unavoidable, and crucial topic. As a matter of fact, in this paper, we focus on the need for scalp care services offered by hairdressers, which starts from scalp health inspection by scalp therapists, then combining with computer vision (CV) techniques and the concepts of artificial intelligence of things (AIoT) to build an expert inspection system for smart scalp (IE3S).

2. Related Work

Recently, along with the rise of health consciousness, people have started to sense the importance of scalp problems, and researchers have conducted related research on scalp problems in succession. Elewski[4] was the first person to analyze scalp problems caused by different factors, including tinea capitis and seborrheic dermatitis caused by superficial mycoses, pediculosis capitis caused by pesticide contamination, and psoriasis as an inflammatory disease. All the above-mentioned problems have similar manifestations such as dandruff, inflammation, hair loss, and itching, which result in difficulties when recognizing the cause of the problem during therapy. Thus, with the use of a microscope, a way of recognizing the features of various illnesses and an appropriate therapy method are described. Continuing with the previous research, Grimalt[5] used videodermoscopy to analyze the common features of scalp problems, and aside from analyzing the causes of the problems, he also reanalyzed the common features of scalp problems shown in videodermoscopy and formulated the corresponding treatment strategies. In addition to recognizing the features of illnesses and conducting related research on treatment strategies, Kim *et al.*[6] also utilized microscope image analysis to assess the condition of hair and scalp, and used a manual statistical method to define the severity criterion. Ross *et al.*[7] utilized videodermoscopy to observe scalp problems, and through high-magnification resolution, clinical features can be clearly visible to the naked eyes, which proved the feasibility of recognizing hair problems by videodermoscopy. It is observable from the research carried out by these predecessors that most scalp illness features can be determined visually, and with the support of high-magnification videodermoscopy, medical personnel can distinguish scalp illnesses from various image characteristics and treat them properly. However, such a manual diagnosis method often leads to different extents of errors due to long-term diagnosis fatigue and subjective consciousness. Hence, some scientists are gradually focusing on studying subjects related to scalp problems and hoping to support medical personnel through scientific ways of analyzing and distinguishing these scalp problems to improve medical service quality and diminish the diagnosis pressure of medical personnel.

Traditionally, the severity of scalp problems is determined by scanning and analyzing eight scalp sectors, as shown in Fig. 2, to determine the current health condition of a person's scalp.

Among them, dandruff is the main scalp lesion caused by scalp illness. With respect to dandruff problems, adherent scalp flaking score (ASFS) is a vital index when assessing dandruff, which represents the severity of dandruff.[8] In the scalp assessment, doctors will first

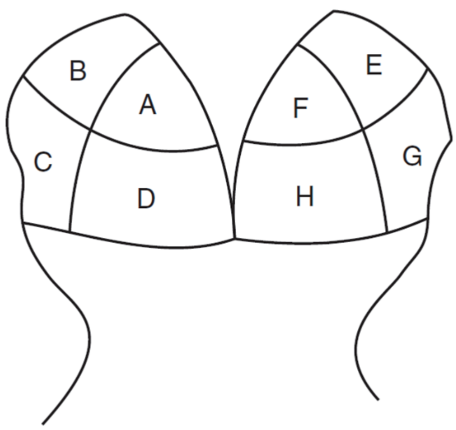

Fig. 2. Schematic diagram of eight scalp scanning sectors.[8]

divide the scalp into eight parts and then evenly separate the subject's hair until the scalp can be observed clearly. In the meantime, doctors will utilize a digital microscope or videodermoscopy to extract scalp images of the eight parts and then use a fixed 0 to 10 (at intervals of 2 units at a time) classification standard to assess the severity of each part, as shown in Fig. 3. The six fixed classification standards are defined as follows:

(1) 0 points: no dandruff;
(2) 2 points: finely divided dandruff (small-extent desquamation, small pieces);
(3) 4 points: flakelike dandruff (small-extent desquamation, flaky);
(4) 6 points: bulky dandruff (medium-extent desquamation, bulky);
(5) 8 points: lumpy dandruff (medium-extent desquamation, lumpy);
(6) 10 points: cloddy dandruff (high-extent desquamation, cloddy).

By adding up the scores for all the eight parts, doctors will obtain the ultimate assessment result.

In this research, on the basis of the severity index of two main scalp lesions, we propose a scalp health inspection algorithm based on CV and deep learning (DL) through the attention module to enhance the detailed information of scalp lesions and using the spinal FC[9] structure to diminish the gradient loss problem and lower the excessive classification computation to resolve the insufficiency of traditional scalp analysis and reach the goal of automated scalp health inspection.

3. Proposed Method

This work has gone through detailed literature exploration and analysis, analyzing a method to improve and enhance past techniques used in multiple research, and lastly combining cloud computing techniques on a Raspberry Pi-embedded platform. The research direction can be separated into three parts: (1) scalp image collection, (2) scalp lesion classification model architecture, and (3) cloud computing techniques.

3.1 Scalp image collection

We adopted a high-magnification USB mobile digital microscope under a realistic therapy service environment, as shown in Fig. 4. We collected around 6000 images of scalps with problems, which were labeled the ground truth by doctors.

(a) (b) (c) (d) (e) (f)

Fig. 3. (Color online) Schematic diagram of dandruff classification standard: (a) 0 points, (b) 2 points, (c) 4 points, (d) 6 points, (e) 8 points, and (f) 10 points.

Fig. 4. (Color online) Mobile digital microscope.

3.2 Scalp lesion classification model architecture

We have referenced the classic model DenseNet[10] in this research, where the proposed classification model architecture is shown in Fig. 5. For scalp lesion classification, most scalp lesion images have much background noise, and the features are extremely tiny, which made some classic natural imaging models unable to effectively extract scalp lesions and which led to an unstable detection effect for the model. To resolve this problem effectively, we added attention mechanisms into the model, namely, the convolutional block attention module (CBAM),[11] as shown in Fig. 6. CBAM is composed of two attention mechanisms, where channel attention mainly enables the model to focus on meaningful features, which can effectively separate tiny lesions and those with small differences. We adopted two ways to extract feature information, including the use of the global average pooling and max pooling layers, which obtains channel attention features through two lesions passing through one sigmoid activation function as shown in Eq. (1) and multiplied by the original feature. On the other hand, space attention enables the model to be more aware of regional features on the feature image, which made it easier for the model to extract the features it needs. Through CBAM, the model's expression ability is enhanced for features of interest and is more focused on lesion areas that need handling. Another point worth noting is that in order to effectively diminish unnecessary computations and deep model gradient loss problems of fully connected (FC) layers, we have changed the FC and classification layers to spinal FC layers, as shown in Fig. 7, and we can not only avoid unnecessary neural connection but also minimize the problem of the model, which is not effectively caused by model gradient loss.

$$F^a = \frac{e^{F^i}}{e^{F^i} + 1} \tag{1}$$

Here, F and F^a represent the input and attention features, respectively.

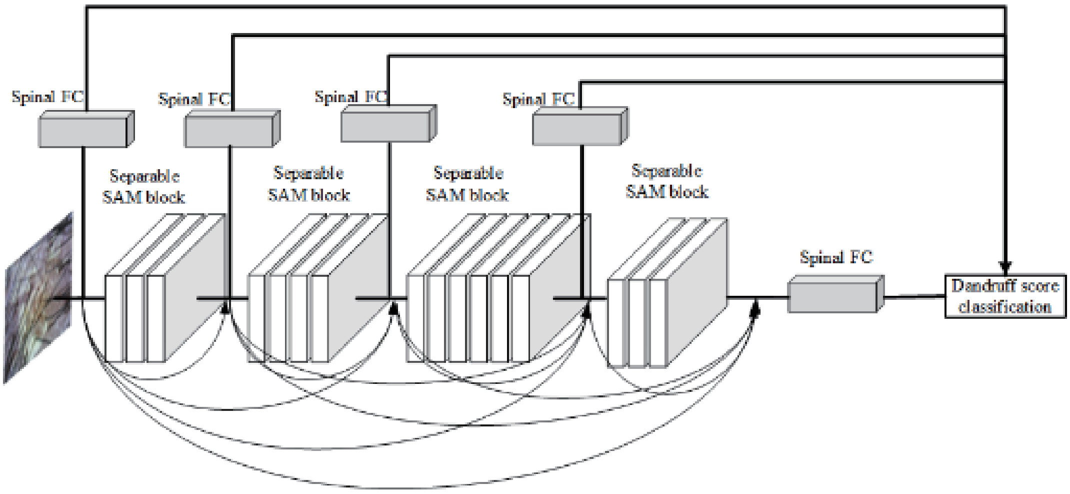

Fig. 5. (Color online) Proposed scalp lesion severity classification model.

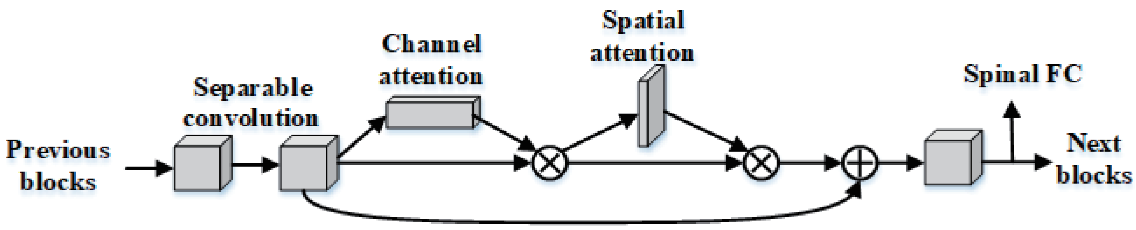

Fig. 6. CBAM module.

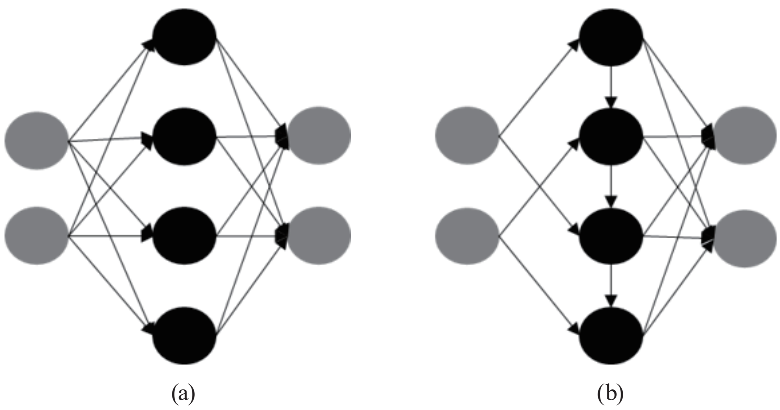

Fig. 7. Comparison of structure between traditional and spinal hidden layers: (a) traditional FC and (b) spinal FC.

3.3 Cloud computing techniques

Aside from the first and foremost accuracy for analyzing scalp problems, human–computer interaction reaction time is also one of the factors when considering whether to use the inspection system. Although the accuracy can be enhanced through the proposed deep learning model mentioned earlier, it will result in higher computation complexity. Hence, we imported cloud computing techniques to diminish a possible situation where the reaction time is very long. Distributed computing and the concept of virtualization have been highly valued recently, whereas cloud computing is a new application of distributed computing by means of the Internet to automatically dismantle a large computing procedure to countless smaller subprocedures, then hand over data to a gigantic system built by multiple servers through searching and computing analysis; after that, it will send the processed result back to the user. As a matter of fact, distributed computing is dividing a large working area into small parts and handing them over to multiple computers to do the computation, and then all the results are collected. Currently, the cloud operators on the market include Amazon web service, Microsoft Azure, and Google cloud platform. Aside from efficiency and price, security is also one important factor to consider. Many cloud providers provide abundant rules, technologies, and control options to strengthen the integral security condition and assist in protecting information, applications, and basic structures from violation caused by potential threats. On the basis of the above-mentioned considerations, we built its fundamentals on the cloud computing platform provided by human–computer interaction and imaging systems lab (HIS-LAB) from Taiwan University of Science and Technology, the efficiency of which is equivalent to that of a Microsoft Azure Nc6 virtual machine, and we can connect local and cloud computers through a secure shell (SSH). Through this cloud computing technique, the high price for building hardware equipment can be reduced and the maintenance fee can be eliminated, while we will still be able to access user information and achieve powerful cloud computing ability.

4. Experimental Results and Comparison

The system architecture diagram of this research is shown in Fig. 8. To validate the feasibility of this research, we adopted a USB mobile digital microscope to capture scalp images and input the images into Raspberry Pi. Consequently, we uploaded them to the lab's cloud server to process the information and algorithm, and then resent the analysis result back to Raspberry Pi, where it will show the current patient's scalp condition based on the resent information, which includes instant scalp area score, average scalp score, and scalp health condition assessment

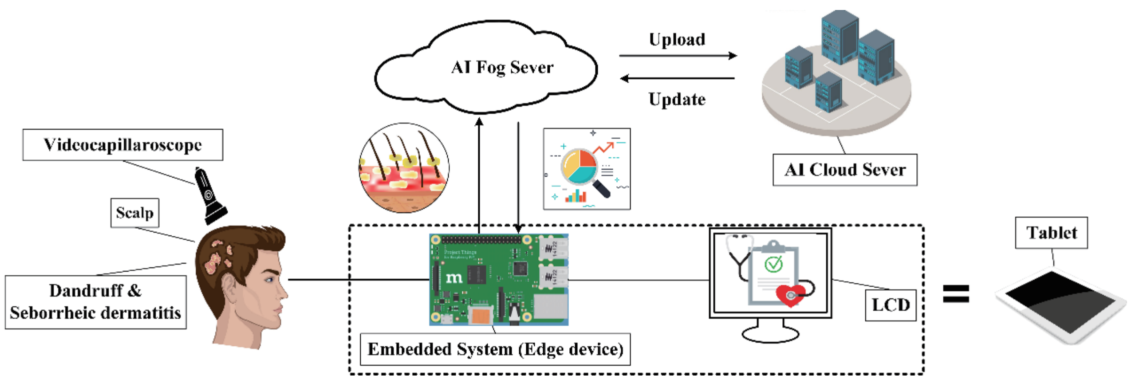

Fig. 8. (Color online) System architecture diagram.

Table 1
Raspberry Pi system specification sheet.

CPU	ARM Cortex-A53 1.4 GHz
Operation system	Raspbian Stretch
Memory	1 GB LPDDR2
Programming languages	C++, Python

Table 2
Cloud server specification sheet.

CPU	Intel® Core™ i7-10700 2.90 GHz
GPU	GeForce RTX 2080 Ti
Operation system	Windows 10
Memory	32 GB DDR4

Table 3
Comparison of scalp problem classification methods.

Method	Accuracy (%)	Inference time (s)
Wang *et al*.[12]	62.81	0.066
DenseNet[10]	79.24	4.563
ResNeSt-101[13]	79.91	0.047
EfficientNet B7[14]	83.29	0.152
NFNet-F4[15]	84.17	0.458
This work	85.03	0.378

results. The embedded system and cloud server specifications are shown in Tables 1 and 2, respectively.

Accuracy is a vital index for scalp inspection, where a higher score means that the classification is more accurate and the system is more stable. We reached the most optimal parameters by continuously training and testing the learning model, and Table 3 shows a comparison of the accuracy and inference time of each method. Although Refs. 12–14 show a fast inference time, the performance of our model is higher than those of others. Accordingly, we have achieved high accuracy and rapid real-time response.

5. Conclusions

We proposed a new smart scalp inspection system. In addition to using CBAM and spinal FC to enhance and improve the classification of scalp lesion problems, we have also combined cloud computing and AIoT design architecture to let the model be applied more in realistic circumstances. Compared with those described recently in the literature, the method proposed in this research can achieve higher classification performance, reaching an accuracy of 85.03% with its cloud service. In the future, we will establish a more complete assessment system of scalp health by extending our model to a multilabel task for other scalp symptoms and their severities.

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