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A Web-Based Skin Disease Detection System: Medilab-Plus

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Abstract

Skin diseases are reported to be the most common disease in humans among all age groups and a major cause of illness in sub-Saharan Africa. However, diagnosis and treatment of skin disease are seen to be difficult, due to the orthodox approaches used by many medical centers globally. In recent times, artificial intelligence has been applied to enhance computer vision applications to permit easy detection of patterns in images. Notwithstanding this breakthrough in technology, the dermatological process in Ghana is yet to be automated, making the diagnosis of skin disease difficult and time-consuming. The current study sought to develop a web-based skin disease detection system (Medilab-Plus), which allows an online user to detect skin diseases in human and to make available, advises or possible medical actions in a precise short period. A convolutional neural network classifier built upon a Tensor flow framework for classifying a user-uploaded image as Eczema, Impetigo or Melanoma. Experimental results of the proposed system exhibit disease identification accuracy of 88% for Atopic dermatitis, 85% for Acne vulgaris and 84.7% for Scabies.

Keywords: Skin disease identification; Expert-system; Convolutional neural network; Tensor flow; Atopic dermatitis; Acne vulgaris; Scabies

Introduction

The skin plays a huge part of our physical appearance, and it is the biggest organ of the human body, with its weight between six and nine pounds and surface area is about two square yards. The inner part of the body is separated by skin from the outer environment. The skin provides protection against fungal infection, bacteria, allergy, viruses and controls temperature of the body [1] situations that changes the texture of the skin, or damage the skin can produce symptoms like swelling, burning, redness and itching. Antipathies, genetic structure, irritants, and particular diseases and immune system associated complications can produce hives, dermatitis and other skin problems. Many of the skin diseases, such as acne, alopecia, ringworm, eczema also affect your look. Skin can also produce many types of cancers [1,2]. Skin diseases are very common these days, some of them are simple and easy to recover from; others are very harmful and might be incurable; therefore, extensive care must be given to this important organ in our body.

Skin disease diagnosis is seen to be complex, particularly when two or more diseases portray same or similar symptoms, hence requires a dermatologist with wide experience of skin diseases [3]. However, the development in technology and machine learning has changed all aspects of our day-to-day life, including the medical field [4-6]. Many medical systems have been developed with the help of artificial intelligence (AI) and technological advancement to help both medical doctors and patients in diverse ways, starting from Out Patient Department (OPD), consultation to operating theater or operating room (OR).

The rate of growth in skin disease is increasing for past few decades, and many of these diseases are very dangerous, particularly if not treated in early stages. A survey by Hogewoning et al. revealed that the total frequency of pupils with some skin disease was 34.6% and 42.0% in two Ghanaian studies, out of 4,839 pupils surveyed. Again, out of 529 participants surveyed, 700 discrete skin diagnoses were made [3]. The early detection of skin disease is paramount to its spreading.

The introduction of artificial intelligence into the health industries has brought tremendous improvement in the diagnoses of skin disease and other illness [7]. However, in Ghana most dermatologists still uses a variety of manual visual clues such as color, scaling and arrangement of the lesions, the body site distribution among others. Nevertheless, when these individual components are analyzed separately, the recognition of the disease can be quite complex, thus requiring high level of experience. Human diagnosis is based on a subjective judgment of the dermatologist so it is hardly reproducible, unlike computer aided diagnostic systems, which are more realistic and reliable.

To reduce diagnosis time and provide quick health service, some researchers in recent years proposed skin disease detection system with the ability of detecting skin disease like impetigo, eczema, melanoma and acne using machine learning [8-10]. On the other hand, these skin diseases are not prevalent in Ghana [3].

Furthermore, Ghana currently has only one dermatology-training center at the Korle Bu Teaching Hospital (KBTH), with only four (4) dermatologists three (3) on full-time and one (1) part-time, and three (3) trainees. In reality the total number of dermatologists serving the whole people of Ghana is lesser than 25 [3]. On an average, a patient with skin disease spent not less than two hours in a medical center.

Finally, with a population 30,030,189 as of May 2019 [11], it implies that every dermatologist in Ghana is to 1,201,207.56 patients.

To reduce the aforementioned issues, the current study seeks to develop a smart web-based skin-disease detection system (Medilab-Plus) for faster and reliable early detection of Atopic dermatitis, Acne vulgaris and Scabies, using the convolutional neural network (CNN).

The development of this system will offer foreknowledge, quick and faster diagnosis system to users through the internet. Again, this system will serve as the first skin diseases system built and tested with sample data from Ghana.

The remaining section of this study is categorized as follows: Section 2 present review of common skin diseases in Ghana, the application of machine learning in diagnosing system and related studies. Section 3, covers the methods and tools for the study and used evaluation metrics. Section 4 presents the outcome and discussion of the study. Finally, section 5 concludes the study and the direction for future studies.

Literature Review

This section gives a brief discusses common skin-disease in Ghana, the application of machine learning in diagnosing system and related studies.

Common skin diseases in Ghana

There are numerous types of skin diseases identified in Ghana. Table 1 shows the top 10 of these diseases and their prevalence among male and females presented (Rosenbaum et al., 2017).

Table 1: Top 10 diagnoses overall and by gender.

Overall (N=700)	N (%)	Males (N=302)	N (%)	Females (N=396)	N (%)
Atopic dermatitis	59 (8.4)	Atopic dermatitis	24 (7.9)	Atopic dermatitis	35 (8.8)
Acne vulgaris	37 (5.3)	Scabies	17 (5.6)	Pityriasis rosea	21 (5.3)
Scabies	36 (5.1)	Warts	17 (5.6)	Lichen planus	21 (5.3)
Irritant contact dermatitis	33 (4.7)	Acne vulgaris	16 (5.3)	Acne vulgaris	20 (5.1)
Lichen planus	26 (3.7)	Irritant contact dermatitis	14 (4.6)	Scabies	19 (4.8)
Seborrhoeic dermatitis	25 (3.6)	Seborrhoeic dermatitis	11 (3.6)	Irritant contact dermatitis	19 (4.8)
Warts	23 (3.3)	Tinea pedis	10 (3.3)	Vitiligo	14 (3.5)
Vitiligo	22 (3.1)	Pityriasis versicolor	9 (3.0)	Papular urticaria	13 (3.3)
Pityriasis versicolor	17 (2.4)	Chronic urticaria	9 (3.0)	Seborrhoeic dermatitis	13 (3.3)

Skin disease diagnosis

Readily visible alterations of the skin surface have been recognized since the dawn of history, with some being treated, and some not. In developing countries, overcrowding and poor hygiene is responsible for spreading of skin diseases. One of the earliest known sources documenting skin ailments is the Ebers Papyrus, a medical document from ancient Egypt dating to around 1500 BC. It describes various skin diseases, including ulcers, rashes, and tumors, and prescribes surgery and ointments to treat the ailments [12]. There are two ways of detecting or diagnosing skin disease.

The first method is the traditional method, also known as the orthodox method in which skin diseases are detected based on special color space. Due to mixing of chrominance and luminance data, RGB is not a good choice for detection. Although it avoids this problem, its actual detection effect is still unstable and susceptible to some environmental influences [13,14]. The specific positioning of the affected area is necessary to detect the type of skin disease.

The second method is technological method, with the emergence of machine learning, diagnosing of skin disease has become easy for most dermatologists. Computer Vision, Machine Learning and Artificial Intelligence are the approach introduce on clinically evaluated histopathological attributes to accurately identify the disease. In the first stage, the image of the skin disease is subject to various kinds of pre-processing techniques followed by feature extraction. The second stage involves the use of machine-learning algorithms to identify diseases based on the histopathological attributes observed on analyzing of the skin.

Computer vision is an interdisciplinary field that deals with how computers can be made to gain high-level understanding from digital images or videos. From the perspective of engineering, it seeks to automate tasks that the human visual system can do. Sub-domains of computer vision includes scene reconstruction, event detection, video tracking, object recognition, object pose estimation, learning, indexing, motion estimation, and image restoration [1,6].

Machine learning

Machine learning (ML) is a subset of artificial intelligence that uses statistical and computational tools to offer human like abilities to computers [15,16]. Thus, ML offers automation and enhancement of the learning process of computers based on their experiences without being actually programmed (no human assistance) [17]. ML Techniques can be grouped into three main categories, namely; supervised, unsupervised and reinforcement learning [18,19]. Machine learning algorithms such as decision trees (DT), artificial neural network (ANN) support vector machines (SVM), Naïve Bayes and Adoboost has been applied in diverse disease-diagnosis system [1,8,20]. Figure 1 shows a comparison of accuracy between some machine learning algorithms in disease detection over the period of 2009 to 2015.

Related works

A skin disease diagnosis system was proposed, where a user uploads an image of the affected area of the skin into an online system and receive a medical treatment or an advise in a very short-time period. An empirical result of their system offered an accuracy of 95% for Impetigo, 85% for Eczema and 85% for Melanoma.

An Android app for the diagnosis of melanoma skin disease was proposed in [21].

The accuracy level of the skin vision app was 81%. Users of the app take an image of the disease spot with a phone camera and upload it into the app and a verdict is given within 30 seconds as low, medium or high risk. A Melanoma skin cancer detection model was proposed in [10], using support vector machine.

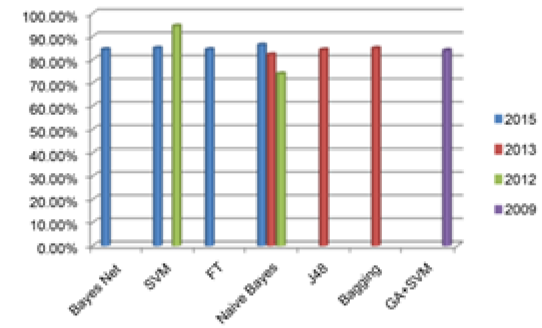

Figure 1: Accuracy of machine learning algorithms in disease detection (source: [10]).

Table 2 shows a summary of related studies. Most previous studies were based on the classification of Melanoma and Eczema [8,10]. Only a few studies [9] were carried out on acne detection, however, these diseases are not prevalent in Ghana as From Table 2 it is evident that, there is a need for a system that can detect these prevalent skin diseases discussed in section 2.1, to help facilitate the diagnosis process by dermatologists in Ghana's health sector.

Table 2: Compilation of related methods.

Reference	Approach	Disease	Programming language	Machine language algorithm	Country
(Amarathunga et al., 2015)	Web-based	Eczema, melanoma, Impetigo	Note stated	Not stated	Not stated
(SkinVision, 2011)	Mobile App (IOS)	Skin cancer	Python, java and swift	k-nearest network algorithm	United Kingdom
(Lubax, 2015) (Poornima and Shailaja, 2017)	Mobile App Not stated	Melanoma Melanoma, Eczema		k-nearest network Support Vector Machine	Holland India
(Edrees, 2017)	Android app	Melanoma, eczema, acne	Matlab, Java	K-means clustering algorithm	
Medilab-plus	Web-based	Atopic dermatitis Acne vulgaris and Scabies.	Python	Convolutional neural network	Ghana

Methodology

This section discussed the methods and materials for the implementation of the proposed skin-disease diagnosis system. Figure 2 shows the workflow diagram of the proposed classification model. The workflow diagram is divided into three (3); the first discusses the data collection, the second phase deals with the preprocessing of images and learning of the model, and third part involves the classification task and performance measure. The obtained images are passed through image enhance techniques and required feature are extracted afterwards. The extracted features are subdivided into three sets, thus train, test and validation datasets as shown in Figure 2.

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Dataset and data preprocessing

Three diseases, namely: atopic dermatitis, acne vulgaris and scabies based on their prevalence among the Ghanaian population as discussed in section 2.1 were selected for this study. The sample data (images) used for this study were collected from four (4) medical centers in the Sunyani Municipality, Ghana within a period of 30 days. Two hundred and fifty images were used for the current study. Data preprocessing contributes a lot to the accuracy of discussed in section Common skin diseases in Ghana.

Machine learning model. The obtained dataset was preprocessed through data cleaning techniques such as smoothing, aggregation normalization, and attribute construction. Table 3 shows the distribution of the collected dataset for this study.

Table 3: Dataset size.

Skin Diseases	Data sample	Percentage
Atopic dermatitis	102	40.16%
Acne vulgaris	87	34.25%
Scabies	65	25.59%
	254	100%

Image preprocessing: Image processing as explain in literature is the technique of detection and exploring the various images out there and providing the desired output within the type of images or diverse elaborate report [22]. The acquired images were firstly preprocessing to enhance the image quality and to improve the accuracy of the proposed model for better generalization. Features such as hairs and pigments, which are typically regarded as noisy, were filtered off in order to facilitate the separation of the lesion area from the surrounding skin.

Image segmentation: the preprocess images were segmented into disjoint regions that are homogeneous with respect to a chosen property such as luminance, color, and texture. At this stage, the goal was to simplify and/or change the representation of an image into something that is more meaningful and easier to analyze.

Feature extraction: feature selection is an essential part of machine learning, since the performance of a machine learning model is greatly dependent on this phase [23,24]. The dataset was finally passed through this phase to select the features for the predictive model. For clinical purposes, it is arguable that parsimony is a desirable feature of a good predictive model.

Convolutional Neural Network (CNN)

The Convolutional Neural Networks are deep artificial neural networks used primarily for classifying images. CNN cluster images by similarity and perform object recognition within scenes. CNN are applied in identifying faces, individuals, street signs, tumors, platypuses and many other aspects of visual data [10]. CNN algorithm proposed [25] was adopted for the current study. Figure 3 shows the operational steps of CNN. The CNN reduces the input image into a form which easier to process. The first convolutional layer (CL) then moves to the max-pooling layer (PL) stage second convolutional stage until the fully connected neural network is obtained. The combination of the CL and PL forms the ith CNN.

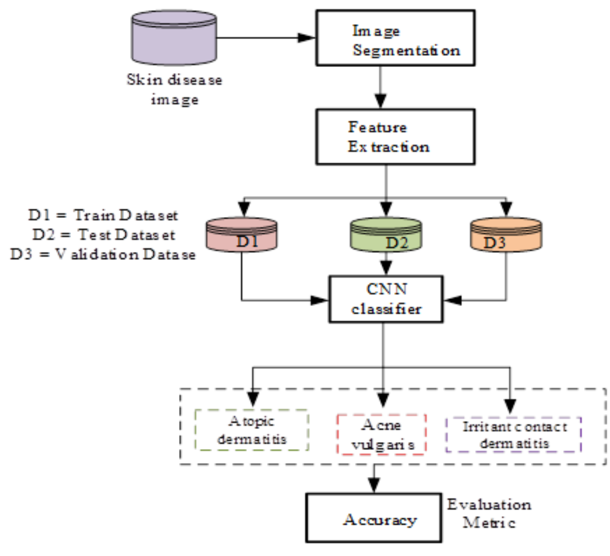

Figure 2: Workflow of proposed system.

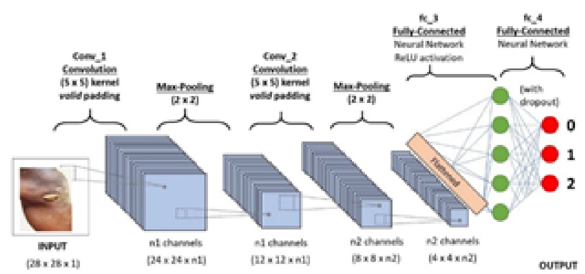

Figure 3: Proposed CNN operation.

Evaluation metrics

The performance of the proposed model was measured using the accuracy metric as defined by equation (3.1).

$$\text{Accuracy } (\%) = \frac{\text{TP+TF}}{\text{TP+FP + FF + TF}} \times 100 - (3.1)$$

Where, TP=Number of correctly predicted Positive, TF=Number of correctly predicted False, FP=Number of incorrectly predicted Positive and FF=Number of incorrectly predicted False.

Results and Discussion

This section presents the experimental setup, the obtained results and its discussion.

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Experimental setup

An experiment of the proposed skin-disease detection system was carried out in order to estimate its performance. An Intel core i3 @ 3.0 GHz with 8 GB RAM laptop was used. The proposed skin-disease detection system was implemented with Tensorflow library and Python. Figure 4 shows the interface of the proposed system, where a user follows two simple steps to identify and skin disease. The user firstly clicks on the load file button to select an image of a skin disease, then clicks on the upload image button to load the image into the system for onwards processing. The system processes the image and classify the image as melanoma or basal cell carcinoma, or squamous cell carcinoma based on the pattern extracted, as shown in Figure 4.

Figure 4: Interface of proposed system for skin disease detection.

Results

The final clean dataset was partitioned into three (3) subset, 75% for training, 15% for testing and 10% for validation of the proposed model. Figure 5 shows the accuracy score during the training phase. It is revealed that the proposed model obtained a training accuracy 89%. Figure 6 shows the graph loss rate. The loss rate declined as the accuracy increased. The results revealed an average testing accuracy measure of 88% for atopic dermatitis, 85% for acne vulgaris and 84.7% for scabies as shown in Figure 7. The prediction time was 0.0010 seconds. This compared with human diagnosis is many times faster.

Discussion

The current study aimed at developing a web-based skin disease detection system to help specialist and the ordinary Ghanaian detect the three (3) most common skin diseases in Ghana. The findings of this study clearly show that the proposed system offers better accuracy and faster prediction time for skin disease diagnosis as compared with the human performance rate. The developed predictive app exhibited disease identification accuracy of 88% for Atopic dermatitis, 85% for Acne vulgaris and 84.7% for Scabies, with prediction time of less than minutes. The results revealed that, technology could greatly influence the medical sector of Ghana. Few errors within 12% – 15.3% were measured; however, as compared to human errors the proposed system is more accurate.

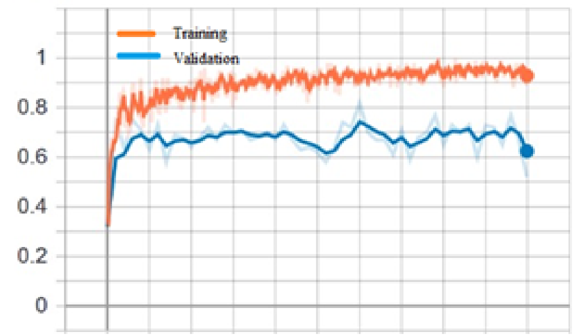

Figure 5: Accuracy of training.

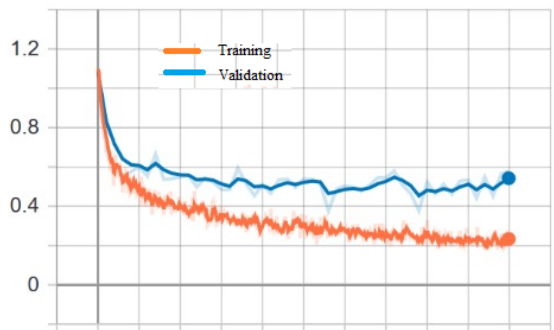

Figure 6: Loss rate.

The difference in accuracy level by the model over Atopic dermatitis, Acne vulgaris and Scabies can be attributed to the difference in data size and the difference in the quality of obtained images. This confirms that prediction is affected by the data size and its quality.

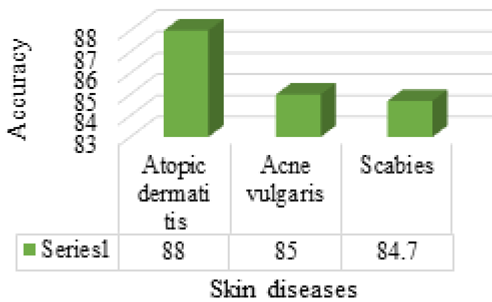

Figure 7: Accuracy measure of predictive model.

The proposed system is capable of diagnosing these three well-known diseases with the shortest possible time of (0.0001 seconds). This implies that any dermatologist, who decides to implement this study, can attend to not less than 1,440 patients a day.

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Conclusion

Based on the obtained results it can be established that convolutional neural networks are effective for extracting features from raw image data for skin disease detection. The implementation of the proposed system on a pilot based by the Ghana health service can avoid the need of manual detection of skin disease and reduce the treatment and diagnosis time. It is hoped that this study helps to catalyze the further development of artificial intelligence in dermatology service in Ghana. On the other hand, the data size for the study was limited due to the difficulty in obtaining sample data from some medical centers. Finally, we wish to say that medilab-plus are not a final diagnostic tool, as such, we advise users to consult their health professionals.

Direction for Future Research

Our future work will focus on the enhancement of the proposed model to incorporate more disease detection and enable batch upload of images.

Competing Interests

The authors declare that they have no competing interests.

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