1. Multiclass Skin Lesion Classification Using a Novel Lightweight Deep Learning Framework for Smart Healthcare

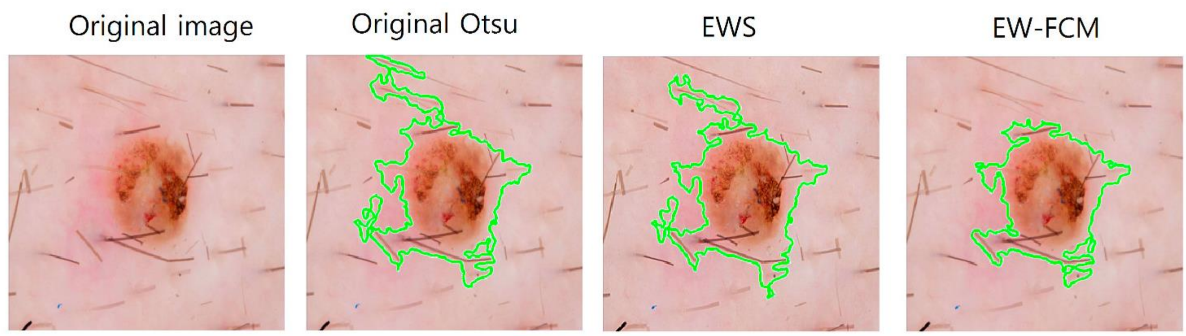
AUTHORS: Long Hoang , Suk-Hwan Lee, Eung-Joo Lee and Ki-Ryong Kwon

Abstract: Skin lesion classification has recently attracted significant attention. Regularly, physicians take much time to analyze the skin lesions because of the high similarity between these skin lesions. An automated classification system using deep learning can assist physicians in detecting the skin lesion type and enhance the patient's health. The skin lesion classification has become a hot research area with the evolution of deep learning architecture. In this study, we propose a novel method using a new segmentation approach and wide-ShuffleNet for skin lesion classification. First, we calculate the entropy-based weighting and first-order cumulative moment (EW-FCM) of the skin image. These values are used to separate the lesion from the background. Then, we input the segmentation result into a new deep learning structure wide-ShuffleNet and determine the skin lesion type. We evaluated the proposed method on two large datasets: HAM10000 and ISIC2019. Based on our numerical results, EW-FCM and wide-ShuffleNet achieve more accuracy than state-ofthe-art approaches. Additionally, the proposed method is superior lightweight and suitable with a small system like a mobile healthcare system.

Skin lesions, which are irregular skin changes compared to the neighboring tissue, can evolve into skin cancer, one of the most dangerous cancers. There are two main types of skin cancer: nonmelanoma and melanoma. Melanoma lesions are responsible for the significant increase in mortality and morbidity in recent years; they are the most destructive and dangerous among various lesion types . If the physicians detect the lesions earlier, they can increase the curing rate to 90% . Moreover, visual inspection for skin cancer is complex because of high similarity among different skin lesion types (e.g., nonmelanoma and melanoma), leading to misdiagnosis. A solution for healthcare systems and image inspection is using the automatic classification of lesion pictures by machine learning (ML).
Presently, 132,000 melanoma skin lesion cases and approximately three million nonmelanoma skin lesion cases occur yearly in the world. Furthermore, 60,000 people died due to prolonged sun exposure (12,000 nonmelanoma and 48,000 melanoma), according to the World Health Organization. Approximately 80% of skin cancer mortalities occur with melanoma lesions . Besides long sun exposure, a record of sunburn has been linked to the development of skin cancer, especially melanoma. In the beginning grades, patient survival rates can be improved if melanoma is identified correctly . To handle the interobservation differences, technicians are guided to recognize melanoma manually. Consequently, an automatic classification system can enhance the precision and efficiency of the early discovery of this cancer type.

Melanoma is similar to benign moles in their early stages of development; thus, it is not easy to distinguish malignant and benign (even for qualified dermatologists). Several methods have been proposed to solve these problems, including handcrafted and artificial intelligence (AI) approaches.
First, low-level properties, such as border, color, and visual texture features. were used to separate melanoma and nonmelanoma lesions . Celebi et al. used shape, color, and texture features, but experiences with huge observed intraclass similarity led to low results. Segmentation is another approach to drop unwanted features and background, as presented in . Tommasi et al. used a binary mask to segment the images and a support vector machine (SVM) to classify the segmented images. The segmentation process in calculates the thresholding values using Gabor filter masks, which yields poor outcomes.
The second approach is AI, an area with numerous possible utilizations, such as mining, ecology, urban planning. AI is subdivided into ML and deep learning (DL) . ML builds algorithms to identify data and obtain predictions . DL can study related features of images and extract the features with various architectures. Additionally, DL is highly efficient for big data investigation . One of the DL prototypes is a convolutional neural network (CNN), which has presented an excellent performance in video and images processing with the development of graphics processing unit (GPU) computing systems. CNN is a powerful mechanism for bioimage examination based on a

recent study . Hence, it allows the high potential in melanoma classification .
Moreover, CNN ensemble approaches have shown success for this classification task .
Skin cancer is extremely common, and early detection is crucial. Although computeraided diagnostic tools have been extensively studied, they still lack clinical practice.
ML (and particularly DL) models have demonstrated great promise in skin lesion classification tasks; however, some challenges limit their adoption: data availability for some lesion categories and the requirement of trained professionals handling equipment (e.g., dermatoscopy to collect and annotate the data). Thus, developing powerful but efficient models that can run in decentralized devices (e.g., smartphones) is critical.
Conventional DL methods require high parameters and are not suitable for a portable system. Therefore, creating a framework for a mobile system is a challenging task. Unlike previous methods, we propose a novel approach for skin lesion classification that uses low parameters while keeping high accuracy. The proposed method is appropriate for a portable system like a mobile healthcare system. Our framework combines a novel segmentation technique and a new wide-ShuffleNet to classify skin lesions. The proposed segmentation method increases the segmentation accuracy compared with previous methods and helps the network detect the skin lesion object better boost the classification process.
The contributions of this study are as follows:
_ We propose a novel method to segment the skin image using the entropy-based weighting (EW) and first-order cumulative moment (FCM) of the skin image.
_ A two-dimensional wide-ShuffleNet network is applied to classify the segmented image after applying EW-FCM. To the best of our knowledge, EW-FCM and wide-ShuffleNet are novel approaches.
_ Based on our numerical results on HAM10000 and ISIC2019 datasets, the proposed framework is more efficient and accurate than state-of-the-art methods.
The remainder of the paper is organized as follows. We explore the related works in Section 2. In Section 3, we present the proposed method. Section 4 presents the numerical results and analysis. Finally, Section 5 presents the conclusion and future studies.



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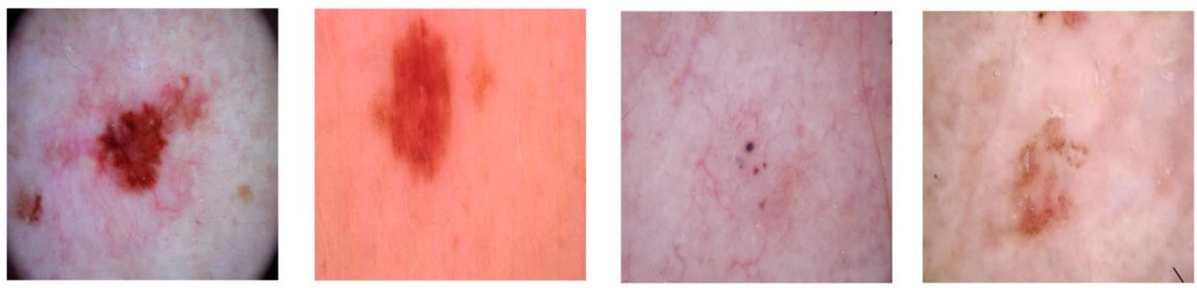

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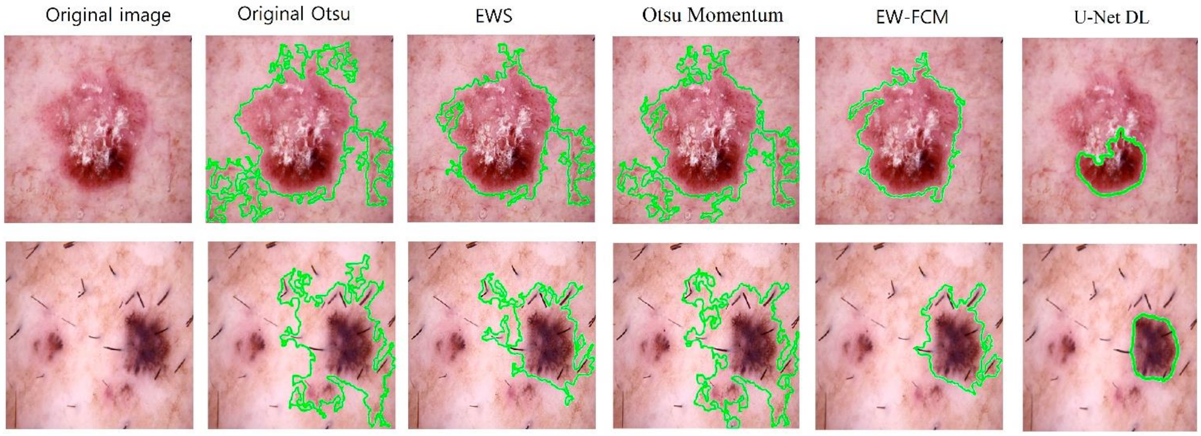

5. Conclusions

Skin cancer is one of the most dangerous diseases in humans. The automated classification of skin lesions using DL will save time for physicians and increase the curing rate. Typical DL frameworks require high parameters and cannot work on the mobile system. Hence, developing the lightweight DL framework for skin lesion classification is essential. In this paper, we propose a novel method for skin lesion classification. Our lightweight method improves the limitation of evaluating a small number of skin lesion images in the past. The numerical results show that the proposed framework is more efficient and accurate than the 20 other approaches (see Table 3). The proposed method reduces the number of the parameters to approximately 79 times that of another method (VGG19) while maintaining higher accuracy. Additionally, the proposed method achieves higher accuracy than other non-segmentation and non-DL segmentation methods and the approximate results at the level of the DL segmentation methods while reducing the complexity of the DL segmentation methods. Our framework does not require ground truth for image segmentation, whereas DL segmentation methods cannot work without ground truth. Thus, the proposed method decreases the effort of the dermatologists to manually outline the ground truth pixel-wise segmentation. We create an accurate and efficient framework by combining the new EW-FCM segmentation technique and wide-ShuffleNet.

We will compare the proposed framework with more networks in future work. Another future direction for research and development is to integrate the proposed method into real-world problems like the mobile healthcare system.

2. AI analysis of a combination of skin lesion images with demographic and clinical data

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Study design and workflow

Patient inclusion and exclusion criteria and overallworkflow until AI data analysis, are illustrated in Supplementary. At the first visit, patients presentingskin lesions were examined and those diagnosed with“leprosy-like lesions” (macule, plaques or nodules) were eligible to enroll. These patients received information on the research, completed the informed consent as well as general health and demographic information along with potential symptoms. Photography was taken and then skin biopsies and slit skin smears from ear lobes were used to confirm (or exclude) leprosy diagnosis. Leprosy diagnosis was defined only after the results of histology and Ziehl-Neelsen staining of slit skin smears for the detection of leprosy tissue morphological features or Mycobacterium leprae, respectively. qPCR was only performed when equivocal results in histological analysis were found.2 Final diagnosis was only established at the third visit (up to 30 days after visit two), as laboratory results would then be available and enable the dermatologists to communicate the diagnosis and initiate the appropriate treatment. Leprosydiagnosis followed the WHO operational classification and the Ridley and Jopling6 (Supplementary Figs. 2 and 3). Confirmed leprosy patients were treated with MDT,according to the national guidelines of the Ministry of Health and WHO.Patients’ socio-demographic data were recorded in the standard local health information system, including a tag (name and register number) to identify study patients. Skin lesion images were stored in a computer exclusively used for the study and on a backup device,and labeled with the VGG image annotator.12 Image assessments followed minimal requirements of theInternational Skin Imaging Collaboration (ISIC) including background color, lighting, field of view, focus/depth of field, resolution, scale, and color calibration.Details on the step-by-step process for image capture, and storage are described in Supplementary .Overall, up to three images were taken from each skinlesion: a panoramic photo to identify the body partwhere the lesion was situated, a close-up photo and another picture from the edge of the lesion, including surrounding normal skin.

A model will only work well when additional data from new patients from multiple geographical backgrounds are used to continue to train and improve it. This is possible when further data collection follows a similar protocol to that used for the model’s training, enhanced by digital data collection tools to prevent manual errors. Model transferability in different populations must be considered. In 2018, Han et al. trained their skin lesion model on an Asian population and tested iton a European population. This resulted in an accuracy of 55.7% over the 10-classes of Dermfit, which was significantly lower than that of other models trained and tested over Dermfit (81%). Such a decrease in the accuracy can be attributed to the differences in skin manifestations across populations or the lack oftransferability in learned features across datasets, due to image acquisition protocols. For that reason, it will be paramount to train the AI4leprosy model in multiple, diverse populations.

3. SKIN DISEASE DETECTION USING COMPUTER VISION AND MACHINE LEARNING TECHNIQUE

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ABSTRACT

Skin types of diseases are most common among the globe, as people get skin disease due to inheritance, environmental factors. In many cases people ignore the impact of skin disease at the early stage. In the existing system, the skin disease are identified using biopsy process which is analyzed and medicinal prescribed manually by the physicians. To overcome this manual inspection and provide promising results in short period of time, we propose a hybrid approach combining computer vision and machine learning techniques. For this the input images would be microscopic images i.e histopathological from which features like color, shape and texture are extracted and given to convolutional neural network (CNN) for classification and disease identification. Our objective of the project is to detect the type of skin disease easily with accuracy and recommend the best and global medical suggestions.

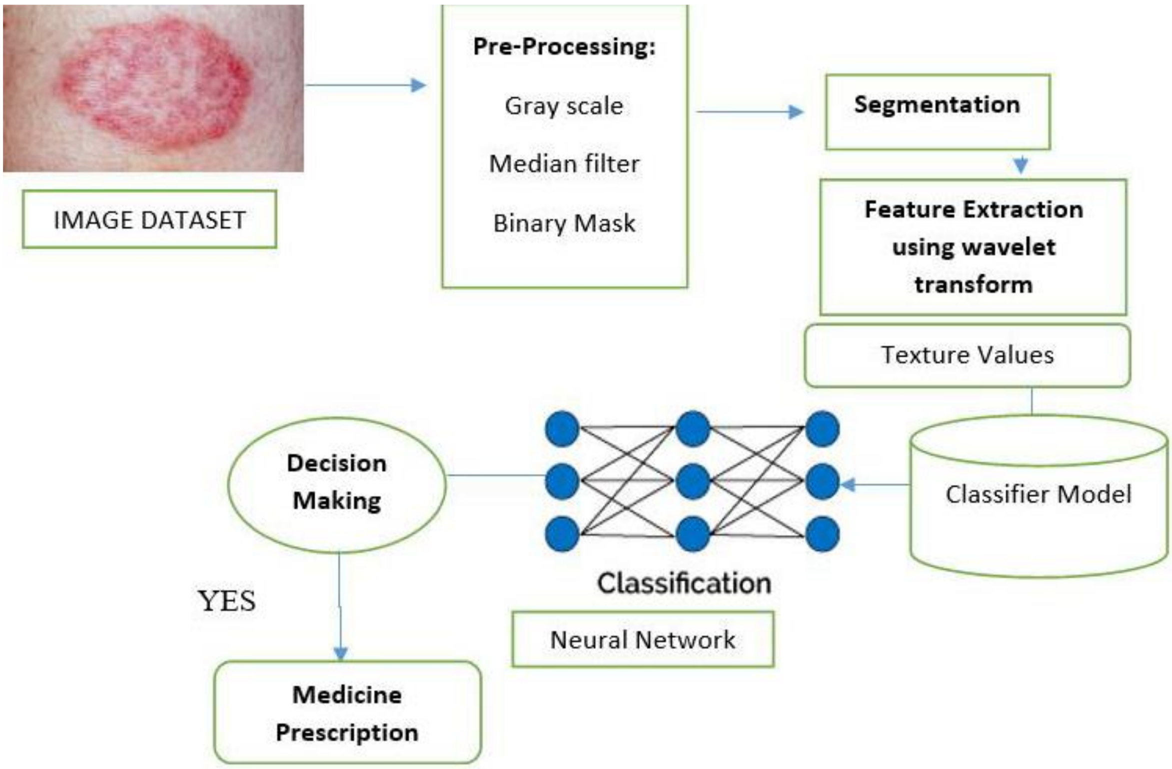
This paper proposes a skin disease detection method based on image processing and machine learning techniques. The patient provides an image of the infected area of the skin as an input to the prototype. Image processing techniques are performed on this image and feature values are extracted and the classifier model predicts the disease. The proposed system is highly beneficial in rural areas where access to dermatologists are limited. For this proposed system, we use Pycharm based python script for experimental results.

INTRODUCTION

Skin disease is one of the most common and difficult disease for diagnosis because of its lack of awareness and ignorance. In many developing countries also people consult dermatologist for skin disease and prevention measures. The people are uncertain of the medicinal prescriptions provided by the dermatologist and there is no justification in the current system. Importance of skin disease without ignoring at the early stage is very important as skin plays a major role in protecting the human body against fungal and harmful bacterial infections. Many people get skin disease through their inheritance, job, lack of nutrition, regular habitats, exposed to chemicals etc. Environmental factors also influence the existence of skin disease like climate, summer season, winter season. Thus identifying skin disease and diagnosis at the early stage is very crucial.

Thus to provide feasible and efficient system and due to the emergence of smart phones, image processing based disease analysis is more demandful as this could provide promising results in less time. Utilization of camera technique, the people can provide the input and integration of

image processing and machine learning techniques the respective skin disease is identified and diagnosis is recommended. The input analysis are performed using two staged approach to address this problem. The first approach is the image processing technique and second approach is the machine learning technique to train the model. This trained model is kept on training to predict different types of skin diseases. As the characteristics and features of different skin disease are different, the machine algorithm needs to be trained for efficient prediction [1].
Skin disease are mostly ignored and provided less importance at the early stages. Some ignorance among people might lead to skin cancer. In existing approach, the increased skin disease are identified at the later stage using biopsy only. The inspection is performed manually by considering many histopathological features. Thus this process is performed manually which can lead to human errors and takes 1-2 days for providing the biopsy results. Also the physician find it difficult to identify the type of skin disease and the stage of disease at the analysis stage. Thus making the medicine prescription difficult. This concern can be addressed by usage of machine learning and deep learning techniques by analyzing the microscope image. This proposed machine learning based approach can be an effective tool to identify the clinical data and provide the results in a short period of time. This approach can provide a promising results by combining computer vision and machine learning techniques [2].
The identification of skin disease from the microscope images are provided to image processing model. Pre-processing, feature extraction are performed in the image processing stage. In the image processing model, color, texture and share of the features are extracted and analyzed. Then processed to the classifier model. This classifier model predicts whether its normal, benign and malignant skin type of diseases



CONCLUSION

The proposed system is able to detect the skin disease with promising results combining computer vision and machine learning techniques. It can be used to help people from all over the world and can be used in doing some productive work. The tools used are free to use and are available for the user, hence, the system can be deployed free of cost. The application developed is light-weight and can be used in machines with low system specifications. It has also a simple user interface for the convenience of the user. The image processing and machine learning algorithms were successfully implemented.

4.Skin Disease Classification from Image - A Survey

Abstract— Skin diseases are one of the most common types of health illnesses faced by the people for ages. The identification of skin disease mostly relies on the expertise of the doctors and skin biopsy results, which is a time-consuming process. An automated computer-based system for skin disease identification and classification through images is needed to improve the diagnostic accuracy as well as to handle the scarcity of human experts. Classification of skin disease from an image is a crucial task and highly depends on the features of the diseases considered in order to classify it correctly. Many skin diseases have highly similar visual characteristics, which add more challenges to the selection of useful features from the image. The accurate analysis of such diseases from the image would improve the diagnosis, accelerates the diagnostic time and leads to better and cost-effective treatment for patients. This paper presents the survey of different methods and techniques for skin disease classification namely; traditional or handcrafted feature-based as well as deep learning-based techniques.

Clinical and Dermoscopic Images

A clinical image is said to be the image of the patient's affected body part - such as an injury, skin lesion or it can be diagnostic image. The image is captured with normal or digital camera. This type of image may have different lightening, resolution and different angle depend on the type of camera used for capturing the image.



This paper is focused on various techniques for classification of skin diseases. Automating the process of skin disease identification and classification can be very helpful and takes less time for diagnosis as well. This paper presents the survey of traditional or feature extraction based and CNN based approach for skin disease classification. From the study it is concluded that for traditional approach the feature selection process is time consuming also selection of relevant feature is very important. Whereas, the deep learning algorithm CNN learns the features automatically and efficiently, for feature extraction CNN selects the filters intelligently as compared with manual ones. The pre-trained models like Inception v3, resnet, VGG16, VGG19, Alexnet etc are trained on very large dataset with millions of general images and can be used with transfer learning or fine tuning. However, the pre-trained model has to be trained from scratch if it is not being trained with skin disease images before. Also, the CNN needs quite big dataset for training so it can learn effectively as compare to the traditional way of skin disease classifications.

5.AI-based localization and classification of skin disease with erythema

Computer-aided diagnosis (CAD) is a computer-based system that is used in the medical imaging field to aid healthcare workers in their diagnoses
CAD has become a mainstream tool in several medical fields such as mammography and colonography
However, in dermatology, although skin disease is a common disease, one in which early detection and classification is crucial for the successful treatment and recovery of patients, dermatologists

perform most noninvasive screening tests only with the naked eye. This may result in avoidable diagnostic inaccuracies as a result of human error, as the detection of the disease can be easily overlooked. Furthermore, classification of a disease is difficult due to the strong similarities between common skin disease symptoms. Therefore, it would be beneficial to exploit the strengths of CAD using artificial intelligence techniques, in order to improve the accuracy of dermatology diagnosis. This paper shows that CAD may be a viable option in the field of dermatology using state-of-the-art deep learning models.

The segmentation and classification of skin diseases has been gaining attention in the field of artificial intelligence because of its promising results. Two of the more prominent approaches for skin disease segmentation and classification are clustering algorithms and support vector machines (SVMs). Clustering algorithms generally have the advantage of being flexible, easy to implement, with the ability to generalize features that have a similar statistical variance. Trabelsi et al. experimented with various clustering algorithms, such as fuzzy c-means, improved fuzzy c-means, and K-means, achieving approximately 83% true positive rates in segmenting a skin disease. Rajab et al. implemented an ISODATA clustering algorithm to find the optimal threshold for the segmentation of skin lesions. An inherent disadvantage of clustering a skin disease is its lack of robustness against noise. Clustering algorithms rely on the identification of a centroid that can generalize a cluster of data. Noisy data, or the presence of outliers, can significantly degrade the performance of these algorithms. Therefore, with noisy datasets, caused by images with different types of lighting, non-clustering algorithms may be preferred; however, Keke et al. implemented an improved version of the fuzzy clustering algorithm using the RGB, HSV, and LAB color spaces to create a model that is more robust to noisy data. SVMs have gained attention for their effectiveness in high-dimensional data and their capability to decipher.

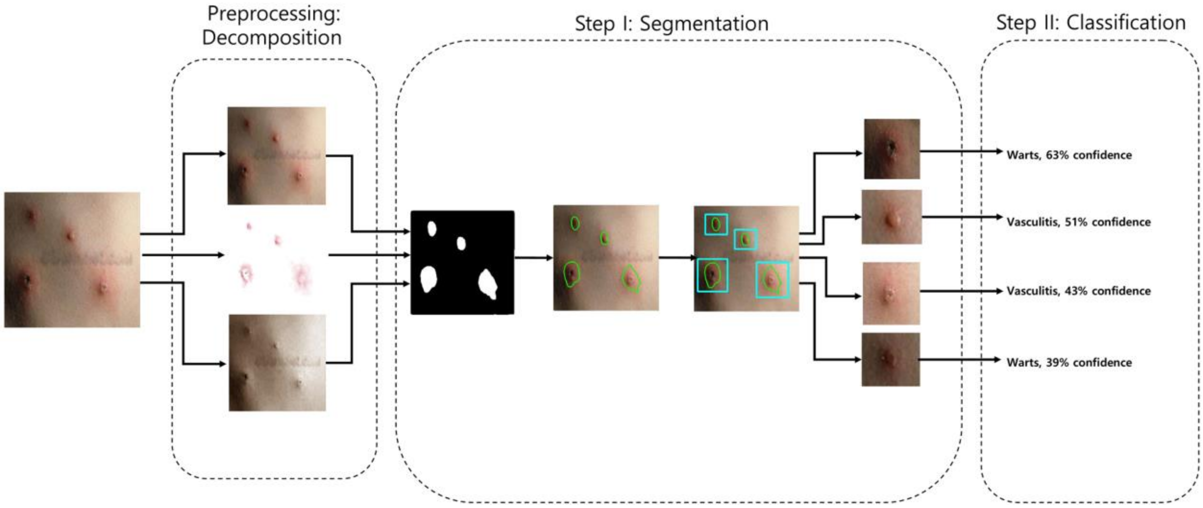
Results and discussion

Figure shows the schematic flow of our study. We started with the original image. We preprocessed this image by decomposing it into its hemoglobin and melanin constituents. These images were then input to the U-Net to generate the segmented output. We drew contours around each cluster and used a convex hull algorithm to draw rectangles around these clusters and crop them as individual images. These cropped images were used as input to the EfficientNet, which generated a prediction along with the confidence rate.

Table shows the results of the test data for segmentation on our Dermnet dataset. The K-means clustering algorithm showed sub-optimal performance, owing to its limitations with noisy data. The SVM method showed a significant improvement in performance, that was attributed to the advantages of using SVMs to extract information from decomposition, rather than clustering algorithms. Even without the extra information, the U-Net trained without decomposition outperformed the previous two methods in terms of sensitivity. The U-Net model was also trained with decomposition and showed the highest sensitivity rate.

In our results, we focused on the sensitivity metric because our objective was to assess the viability of using CAD with skin images. Although our U-Net model was not as good as the SVM model in terms of the specificity rate, it showed the best sensitivity rate, thus satisfying the objective of our study. In addition, we included the Dice coefficient and Hausdorff distance to demonstrate the performance of our methods with greater transparency. Our method showed clear improvements considering these alternative metrics. A major contributing factor to the underperformance of other methods is that performance of the SVM algorithm deteriorated when the images contained differences in lighting and shade. The K-means clustering method was also affected by the lighting and shade in the images. As our data had a significant mix of shade and lighting, the CNN was able to generalize the data better by learning to use the context of the image.

In any classification problem, it is important to set the baseline performance. We set our baseline to be the accuracy rate of the data without segmentation. The original image was input into the EfficientNet without going through the U-Net to determine the baseline accuracy rate. We compared this to the accuracy rate of the model trained to classify segmented images. Figure 2 shows the accuracy rates for the classification of our Dermnet dataset. We observed similar accuracy in the baseline model with and without contextual segmentation. The performance did not decrease when compared with the baseline. Thus, as we gained knowledge of the location of the disease without degrading the performance, we may say that the classification model was successfully implemented.



Conclusion

We have shown that even without a large dataset and high-quality images, it is possible to achieve sufficient accuracy rates. In addition, we have shown that current state-of-the-art CNN models can outperform models created by previous research, through proper data preprocessing, self-supervised learning, transfer learning, and special CNN architecture techniques. Furthermore, with accurate segmentation, we gain knowledge of the location of the disease, which is useful in the preprocessing of data used in classification, as it allows the CNN model to focus on the area of interest. Lastly, unlike previous studies, our method provides a solution to classify multiple diseases within a single image. With higher quality and a larger quantity of data, it will be viable to use state-of-the-art models to enable the use of CAD in the field of dermatology.

6. Skin Disease Detection using Machine Learning

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- Dr. Swapna Borde

— Dermatology is the branch of bioscience that's involved with diagnosing and treatment of skin based mostly disorders. The immense spectrum of dermatologic disorders varies geographically and additionally seasonally because of temperature, humidness and alternative environmental factors. Human skin is one amongst the foremost unpredictable and tough terrains to mechanically synthesize and analyse because of its quality of unevenness, tone, presence of hair and alternative mitigating options. Though, many researches are conducted to find and model human skin victimisation (PC Vision techniques), only a few have targeted the medical paradigm of the matter. Due to lack of medical facilities available in the remote areas, patients usually ignore early symptoms which may worsen the situation as time progresses. Hence, there is a rising need for automatic skin disease detection system with high accuracy. Thus, we develop a multiclass deep learning model to differentiate between Healthy Skin Vs Skin suffering from a Disease and Classification of Skin Diseases into its main classes like MelanocyticNevi, Melanoma, Benign keratosis-like lesions, Basal cell Carcinoma, ActinicKeratoses, Vascular lesion and Dermatofibroma. We have used Deep Learning to train our model, Deep Learning is a part of Machine Learning in which unlike Machine Learning it uses large dataset and hence the number of classifiers is reduced substantially. The machine learns itself and divide the data provided into the levels of prediction and in a very short period of time gives the accurate results, thereby promoting and supporting development of Dermatology. The algorithm that we have used is Convolutional Neural Network (CNN) as it is one of the most preferred algorithm for image classification.

Artificial Intelligence is taking over automation in all fields of application even within the healthcare field. In the past years these diseases have been a matter of concern due to the sudden arrival and the complexities which has increased life risks. These Skin abnormalities are very infectious and the require to be treated at earlier stages to avoid it from spreading. The majority of diseases is caused by unprotected exposure to excessive Ultraviolet Radiation(UR). Among all, benign type is considered to be less dangerous than malignant melanoma and can be cured with proper treatment, whereas the deadliest form of skin lesion is malignant Melanoma. The survey results indicate that the back and lower extremity, trunk and upper extremity are heavily compromised regions of skin cancer. There are large instances of patients with age ranging from 30 to 60. Also, MelanocyticNevi, Carcinoma and Dermatofibroma are not prevalent below the age of 20years.

EXISTING TECHNOLOGY

Artifical Neural Network(ANN). An artificial neuron network (ANN) is a statistical nonlinear predictive modelling method which is used to learn the complex relationships between input and output. The structure of ANN is inspired by the biological pattern of our brain neuron [2]. An ANN has three types of computation node. ANNs learn computation at each node through back-propagation. There are two sorts of data set trained and untrained data set which produces the accuracy by employing a supervised and unsupervised learning approach with different sort of neural network architectures like feed forward, back propagation method which uses the info set at a special manner. Using Artificial Neural Network, accuracy obtained in various researches is 80% which isn’t optimum [2]. Also, ANNs require processors with parallel processing power. ANN produces a probing solution it does not give a clue as to why and how it takes place which reduces trust in the network

LITERATURE

Skin diseases are the 4th common cause of skin burden worldwide. Robust and Automated system have been developed to lessen this burden and to help the patients to conduct the early assessment of the skin lesion. Mostly this system available in the literature only provide skin cancer classification. Treatments for skin are more effective and less disfiguring when found early and it is a challenging research due to similar characteristics of skin diseases. In this project we attempt to detect skin diseases .A novel system is presented in this research work for the diagnosis of the most common skin lesions (Melanocytic nevi, Melanoma, Benign keratosis-like lesions, Basal cell carcinoma, Actinic keratoses, Vascular lesion, Dermatofibroma). The proposed approach is based on the pre-processing, Deep learning algorithm, training the model , validation and classification phase. Experiments were performed on 10010 images and 93% accuracy is achieved for seven-class classification using Convolution Neural Networks (CNN) with the Keras Application API.

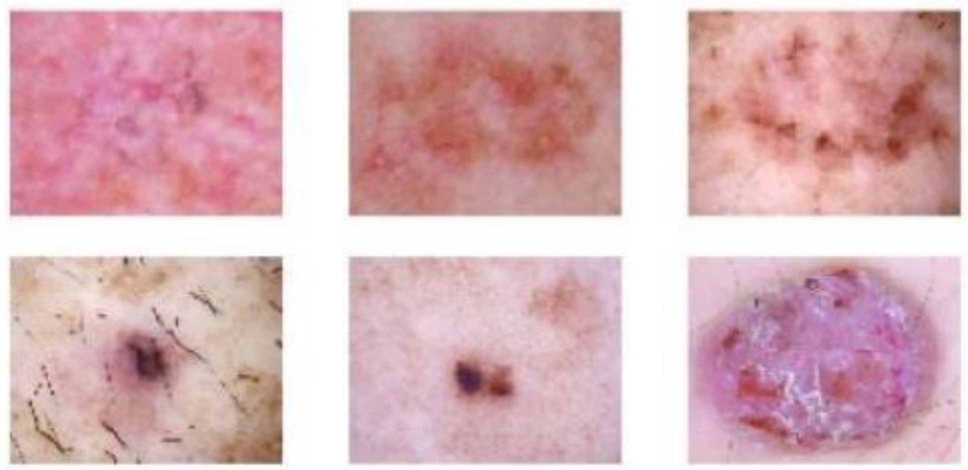

Fig. 1. Sample Data

CONCLUSION:

Skin Diseases are ranked fourth most common cause of human illness, but many still do not consult doctors. We presented a robust and automated method for the diagnosis of dermatological diseases. Treatments for skin are more effective and less disfiguring when found early. We should point out that it is to replace doctors because no machine can yet replace the human input on analysis and intuition. Researches in European Society of Medical Oncology have shown for the first time that form of AI or ML is better than experienced dermatologists. In this a brief description of the system and the implementation methodology is presented.

7. Automated Skin Disease Identification using Deep Learning Algorithm

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- P Muthu

Dermatological disorders are one of the most widespread diseases in the world. Despite being common its diagnosis is extremely difficult because of its complexities of skin tone, color, presence of hair. This paper provides an approach to use various computer vision based techniques (deep learning) to automatically predict the various kinds of skin diseases. The system uses three publicly available image recognition architectures namely InceptionV3, InceptionResnetV2, MobileNet with modifications for skin disease application and successfully predicts the skin disease based on maximum voting from the three networks. These models are pretrained to recognize images upto 1000 classes like panda, parrot etc. The architectures are published by image recognition giants for public usage for various applications. The system consists of three phases- The feature extraction phase, the training phase and the testing / validation phase. The system makes use of deep learning technology to train itself with the various skin images. The main objective of this system is to achieve maximum accuracy of skin disease prediction

The Dermatology remains the most uncertain and complicated branch of science because of it complicacy in the procedures involved in diagnosis of diseases related to hair, skin, nails. The variation in these diseases can be seen because of many environmental, geographical factor variations. Human skin is considered the most uncertain and troublesome terrains due to the existence of hair, its deviations in tone and other mitigating factors. The skin disease diagnosis includes series of pathological laboratory tests for the identification of the correct disease. For the past ten years these diseases have been the matter of concern as their sudden arrival and their complexities have increased the life risks1 . These Skin abnormalities are very infectious and need to be treated at earlier stages to avoid it from spreading. Total wellbeing including physical and mental health is also affected adversely. Many of these skin abnormalities are very fatal particularly if not treated at an initial stage. Human mindset tends to presume that most skin abnormalities are not as fatal as described thereby applying their own curing methods. However if these remedies are not apt for that selective skin problem then it makes it even worse. The available diagnosis procedure consists of long laboratory procedures but this paper proposes a system which will enable users to predict the skin disease using computer vision.

Fig. 1. Training Data Set

Fig. 2. Testing Data Set

Methodology Development of a widespread plan to test the special features and general functionality on a range of platform combination is firstly initiated by the test process. The procedures used are strictly quality controlled. The method involves use of pre-trained image recognizers with modifications to identify skin images. The process verifies that the application is bug free and it meets the requirements stated in the requirements document of system10. The following are the considerations used to develop the framework from developing the testing methodologies. Module design are:-

1) Feature extraction module.

2) Training module.

3) Validation/ Testing phase

RESULTS AND DISCUSSIONS

This study projects a method that uses techniques related to computer vision to distinguish different kinds of dermatological skin abnormalities. We have employed various types of Deep learning algorithms (Inception_ v3, MobileNet, Resnet, xception) for feature extraction and learning algorithm (preferably Random forest or Logistic Regression) for training and testing purpose. Using the state of the art architecture considerably increases the efficiency up to 88 percentage. And further more by using ensemble features mapping, combing the models trained using Inception V3, MobileNet, Resnet, Xception a voting based model will be ensembled and thereby increasing the efficiency13. For enhanced performance and selecting the optimum architecture for the application, we have used logistic regression technique. In this method, the divide mode is set to 90% for the training of the data, 10% for the validating/testing of the data. To characterize the efficiency of a classification model (or “classifier”) on a set of test data for which the true values, a table of confusion matrix is used.

CONCLUSION

In this work a model for prediction of skin diseases is done using deep learning algorithms. It is found that by using the ensembling features and deep learning we can achieve a higher accuracy rate and also we can go for the prediction of many more diseases than with any other previous models done before. As the previous models done in this field of application were able to report a maximum of six skin diseases with a maximum accuracy level of 75%. By implementing deep learning algorithm we are able to predict as many as 20 diseases with a higher accuracy level of 88%. This proves that deep learning algorithms have a huge potential in the real world skin disease diagnosis. If even a better system with high end system hardware and software with a very large dataset is used the accuracy can be increased considerably and the model can be used for clinical experimentation as it does have any invasive measures. Future work can be extended to make this model a standard procedure for preliminary skin disease diagnosis method as it will reduce the treatment and diagnosis time.

8. Skin Disease prediction

AUTHORS:

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- Mr. O.V.Gaware
- Mr. S.R.Maurya

This method is mobile based and hence very accessible even in remote areas and it is completely noninvasive to patient's skin. The patient provides an image of the infected area of the skin as an input to the prototype. Image processing techniques are performed on this image and the detected disease is displayed at the output. The proposed system is highly beneficial in rural areas where access to dermatologists is limited.

One of the medical areas which needs mobile health technology is skin analysis to identify diseases. Around 24% of the population in England and Wales (12.9 million people) visited their general practitioner with a skin problem in 2006, with the most common reasons being skin infection and eczema (WHO). One of the most preventable types of cancer is the skin cancer and the best ways to keep the skin healthy and cancer free is checking and examining skin once a month for suspicious moles or spots .This exam is a visual and clinical skin exam, it costs more than Rs.5000 and it needs hospital scan which is difficult for disabled people. In our paper, we propose a low cost Smartphone based intelligent scheme that allows people for regular skin examinations. We use a Smartphone camera and an intelligent learning algorithm to scan skin images.

MOTIVATION OF THE PROJECT

Skin disease is the most common disease in the world. The diagnosis of the skin disease requires a high level of expertise and accuracy for dermatologist, so computer aided skin disease diagnosis model is proposed to provide more objective and reliable solution. Many researches were done to help detect skin diseases like skin cancer and tumor skin. But the accurate recognition of the disease is extremely challenging due to the following reasons: low contrast between lesions and skin, visual similarity between Disease and non-Disease area, etc. This paper aims to detect skin disease from the skin image and to analyze this image by applying filter to remove noise or unwanted things, convert the image to grey to help in the processing and get the useful information. This help to give evidence for any type of skin disease and illustrate emergency orientation. Analysis result of this study can support doctor to help in initial diagnoses and to know the type of disease. That is compatible with skin and to avoid side effects.

LITERATURE SURVEY

Several researchers have proposed image processing-based techniques to detect the type of skin diseases. Here we briefly review some of the techniques as reported in the literature. In, a system is proposed for the dissection of skin diseases using color images without the need for doctor intervention. The system consists of two stages, the first the detection of the infected skin by uses color image processing techniques, k-means clustering and color gradient techniques to identify the diseased skin and the second the classification of the disease type using artificial neural networks. The system was tested on six types of skin diseases with average accuracy of first stage 95.99% and the second stage 94.016%. In the method of extraction of image features is the first step in detection of skin diseases. In this method, the greater number of features extracted from the image, better the accuracy of system. The author of applied the method to nine types of skin diseases with accuracy up to 90%. Melanoma is type of skin cancer that can cause death, if not diagnose and treat in the early stages. The author of focused on the study of various segmentation techniques that could be applied to detect melanoma using image processing. Segmentation process is described that falls on the infected spot boundaries to extract more features. The work of proposed the development of a Melanoma diagnosis tool for dark skin using specialized algorithm databases including images from a variety of Melanoma resources. Similarly, discussed classification of skin diseases such as Melanoma, Basal cell carcinoma (BCC), Nevus and Seborrheic keratosis (SK) by using the technique support vector machine (SVM). It yields the best accuracy from a range of other techniques. On the other hand, the spread of chronic skin diseases in different regions may lead to severe consequences.

.PROBLEM DEFINITION AND SCOPE

The patient provides an image of the infected area of the skin as an input to the prototype. Image processing techniques are performed on this image and the detected disease is displayed at the output B. Goal and Objectives: Our objective of the project is to detect the type of skin disease easily with accuracy and recommend the best. First stage of the image the skin disease is subject to various kinds of pre-processing techniques followed by feature extraction. Then the second stage involves it uses the Machine learning algorithms to identify diseases based on the analyzing and observance of the skin. The proposed system is highly beneficial in rural areas where access to dermatologists is limited. For this proposed system, we use Pycharm based python script for experimental results. Statement of scope Skin is the largest organ in human body, which is important to cover human bone, and to protect human from any harm, fight the bacteria and other kind of diseases, and may have numerous potential abnormalities. Several factors may affect the skin directly or indirectly and cause diseases which can be treated with specific medicine and others require doctor's consultation. This paper will help people to know what are the required procedures for treatment of skin disease by analyzing the image and extract useful information that help to show the infected skin area and classification of image based on the kind of skin disease D. Software context Python will be used for development which is free of cost for development. Pycharm community version is free for development. We use DJango MVC Framework for development E. Methodologies of problem solving and efficiency is- sues Waterfall approach was first SDLC Model to be used widely in Software Engineering to ensure success of the project. In "The Waterfall" approach, the whole process of software development is divided into separate phases. In this Waterfall model, typically, the outcome of one phase acts as the input for the next phase sequentially.

3. ARCHITECTURAL DESIGN

Purpose and Scope of Document The purpose of SRS and what it covers is to be stated Overview of responsibilities of Developer. What all activities carried out by developer? B. Usage scenario This section provides various usage scenarios for the system to be developed. - User profiles The profiles of all user categories are described here. (Actors and their Description) - Use-cases All use-cases for the software are presented. Description of all main Use cases using use case template is to be providedC. Data model and description - Data Description Data objects that will be managed/manipulated by the software are described inthis section. The database entities or files or data structures required to be described. For data objects details can be given as below - Data objects and Relationships Data objects and their major attributes and relationships among data objects are de- scribed using an ERD- like form. D. Functional model and description A description of each major software function, along with data flow (structured analysis) or class hierarchy (Analysis Class diagram with class description for object oriented system) is presented.

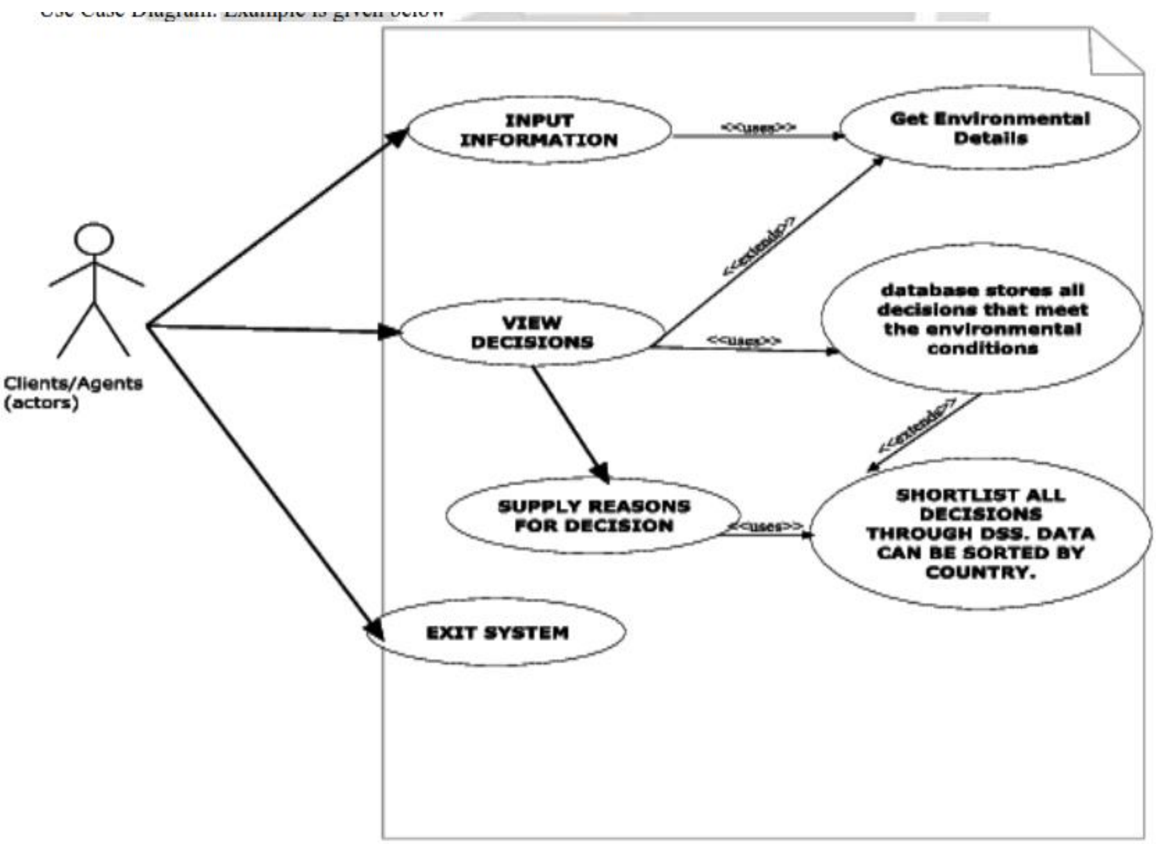

Fig.3.1 .Use case diagram

CONCLUSION

In this work a model for prediction of skin diseases is done using deep learning algorithms. It is found that by using the ensembling features and deep learning we can achieve a higher accuracy rate and also we can go for the prediction of many more diseases than with any other previous models done before. As the previous models done in this field of application were able to report a maximum of six skin diseases with a maximum accuracy level of 75%. By implementing deep learning algorithm we are able to predict as many as 20 diseases with a higher accuracy level of 88%. This proves that deep learning algorithms have a huge potential in the real world skin disease diagnosis. If even a better system with high end system hardware and software with a very large dataset is used the accuracy can be increased considerably and the model can be used for clinical experimentation as it does have any invasive measures. Future work can be extended to make this model a standard procedure for preliminary skin disease diagnosis method as it will reduce the treatment and diagnosis time.

9.A Deep Learning Based Framework for Diagnosing Multiple Skin Diseases in a Clinical Environment

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Numerous studies have attempted to apply artificial intelligence (AI) in the dermatological field, mainly on the classification and segmentation of various dermatoses. However, researches under real clinical settings are scarce. This study was aimed to construct a novel framework based on deep learning trained by a dataset that represented the real clinical environment in a tertiary class hospital in China, for better adaptation of the AI application in clinical practice among Asian patients.

Dermatology is a branch of clinical medicine of which the diagnosis and treatment monitor greatly rely on the morphology of various cutaneous lesions. The traditional diagnostic process of dermatoses is thus based on the integration of patients' medical history, clinical manifestation, dermoscopic images and sometimes histopathological evaluation by the dermatologists. pre-trained networks worked better than training from scratch. Numerous researches based on AI using dermoscopic and non-dermoscopic images have attempted to apply this technology in the dermatological field, including segmentation and classification of melanocytic tumors, keratinocyte tumors, ulcers, psoriasis and other inflammatory dermatoses

MATERIALS AND METHODS

Ethical Approval We conducted this research according to the ethical tenets of the Declaration of Helsinki. And this study was approved by the Medical Ethics Committee of Peking Union Medical College Hospital (NO. JS-2003). Informed written consents were obtained from all the included adult patients or the guardians of juvenile patients. Datasets Our dataset was collected and formed from the imaging database of the Department of Dermatology, Peking Union Medical College Hospital in China from October 2016 to April 2020. All the included patients were Asian with Fitzpatrick skin type III or IV, and their dermoscopic images were consecutively acquired using a digital dermoscopy system (MoleMax HD 1.0 dermoscope, Digital Image Systems, Vienna, Austria) by the same technician to ensure the quality and standardization of the images. Generally, multiple dermoscopic images were captured of a single lesion in different angles or in subsequent followup presentations. The annotation process was performed by 2 dermatologists with more than 5-years experience according to the patients' medical history, clinical manifestations and dermoscopic features independently.

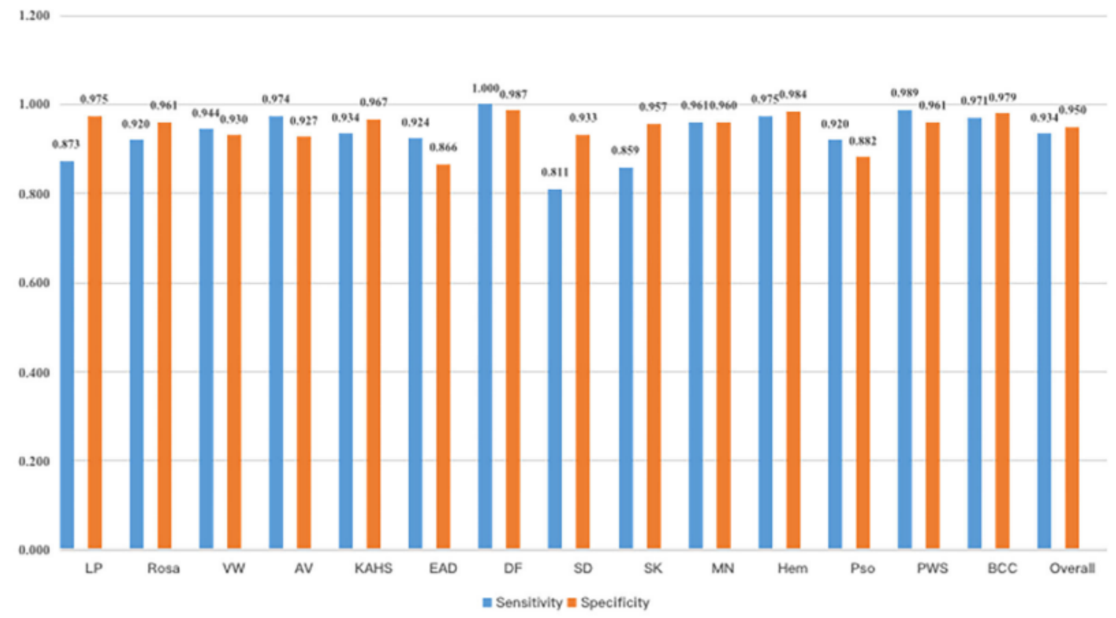

FIGURE 4 | Sensitivity and specificity of our model. As a result, our model had an overall sensitivity of 93.38 ± 0.08% and specificity 94.85 ± 0.05%.

CONCLUSIONS

The proposed framework retrained by the dataset that represented the real clinical environment in our department could accurately classify most common dermatoses that we encountered during outpatient practice including infectious and inflammatory dermatoses, benign and malignant cutaneous tumors.

10. Classification of Skin Disease Using Deep Learning Neural Networks with MobileNet V2 and LSTM

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Deep learning models are efficient in learning the features that assist in understanding complex patterns precisely. This study proposed a computerized process of classifying skin disease through deep learning based MobileNet V2 and Long Short Term Memory (LSTM). The MobileNet V2 model proved to be efficient with a better accuracy that can work on lightweight computational devices. The proposed model is efficient in maintaining stateful information for precise predictions. A grey-level co-occurrence matrix is used for assessing the progress of diseased growth. The performance has been compared against other state-of-the-art models such as Fine-Tuned Neural Networks (FTNN), Convolutional Neural Network (CNN), Very Deep Convolutional Networks for Large-Scale Image Recognition developed by Visual Geometry Group (VGG), and convolutional neural network architecture that expanded with few changes. The HAM10000 dataset is used and the proposed method has outperformed other methods with more than 85% accuracy. Its robustness in recognizing the affected region much faster with almost 2× lesser computations than the conventional MobileNet model results in minimal computational efforts. Furthermore, a mobile application is designed for instant and proper action. It helps the patient and dermatologists identify the type of disease from the affected region's image at the initial stage of the skin disease. These findings suggest that the proposed system can help general practitioners efficiently and effectively diagnose skin conditions, thereby reducing further complications and morbidity.

Methodology:

In this section, integrating the LSTM with the MobileNet V2 is explained with an architecture diagram. MobileNet V2 is used in classifying the type of skin disease, and LSTM is used to enhance the performance of the model by maintaining the state information of the features that it comes across in the previous generation of the image classification. 3.1. MobileNet Architecture Model for Image Classification As opposed to MobileNet V2 [63], MobileNet [4] is a CNN-based model that is extensively used to classify images. The main advantage of using the MobileNet architecture is that the model needs comparatively less computational effort than the conventional CNN model that makes it suitable for working over mobile devices and the computers that work over lower computational capabilities [64–66]. The MobileNet model is a simplified structure that incorporates a convolution layer that can be used in distinguishing the detail that relies on two manageable features that switch among the parameter's accuracy and latency effectively. The MobileNet model is advantageous in reducing the network size [67]. MobileNet [68] architecture is equally efficient with a minimum number of features, such as Palmprint Recognition [17]. The architecture of MobileNet is depth-wise [69]. The fundamental structure is based on different abstraction layers, a component of different convolutions that appear to be the quantized configuration that assesses a regular problem complexity in-depth. The complexity of 1×1 is called point-wise complexity. Platforms to make in-depth are designed to have abstraction layers with structures in-depth and point through a standard, rectified linear unit (ReLU). The resolution multiplier variable ω is added to minimize the dimensionality of the input image and each layer's internal representation with the same variable. The feature vector map of size $Fm \times Fm$ and the filter is of size $Fs \times Fs$ the input variable is denoted by p, and the output variable is recognized as q. For the core abstract layers of the architecture, the overall computation efforts are represented by the variable ce and may be assessed through the following Equation (1):

$$ce = Fs \cdot Fs \cdot \omega \cdot \alpha Fm \cdot \alpha Fm + \omega \cdot \rho \cdot \alpha Fm \cdot \alpha Fm \text{----} \quad (1)$$

The multiplier value is context-specific, and for the experimental analysis in skin disease classification, the value of multiplier ω is considered to be in the range 1 to n. The value of the variable resolution multiplier identified by α is deemed to be 1. The computational efforts are recognized through the variable coste can be assessed through Equation (2) stated below:

$$coste = Fs \cdot Fs \cdot \omega \cdot \rho \cdot Fm \cdot Fm \text{------------------------} \quad (2)$$

The proposed model incorporates the depth-wise, and point-wise convolutions are bounded by the depletion variable identified by the variable d that is approximated through the Equation (3) stated below:

$$d = Fs \cdot Fs \cdot \omega \cdot \alpha Fm \cdot \alpha Fm + \omega \cdot \rho \cdot \alpha Fm \cdot \alpha Fm \; Fs \cdot Fs \cdot \omega \cdot \rho \cdot Fm \cdot Fm \text{------ } (3)$$

Design Model:

The MobileNet V2 architecture comprises the residual layer with a stride of 1 and the downsizing layer with a stride of 2 alongside the ReLu component. The architecture of the same is represented in Figure 1. Both residual and downsizing layer encompass 3 sub-layers each. • The 1 × 1 convolution with the ReLu6 is the first layer. • Depth-Wise Convolution is the second layer in the architecture. The Depth-Wise layer adds a single convolutional layer that performs a lightweight filtering process. • 1 × 1 convolution layer without non-linearity is the third layer in the proposed architecture. In the third layer, the ReLu6 component is used in the output domain. • ReLu6 is used to ensure the robustness used in low-precision situations and improvise the randomness of the model. • All the layers have the same quantity of output channels within that overall sequence. • The filter of size 3 × 3 is common for contemporary architecture models, and dropout and batch normalization are used during the training phase. • There is a residual component to support the gradient flow across the network through batch processing and ReLu6 as the activation component.

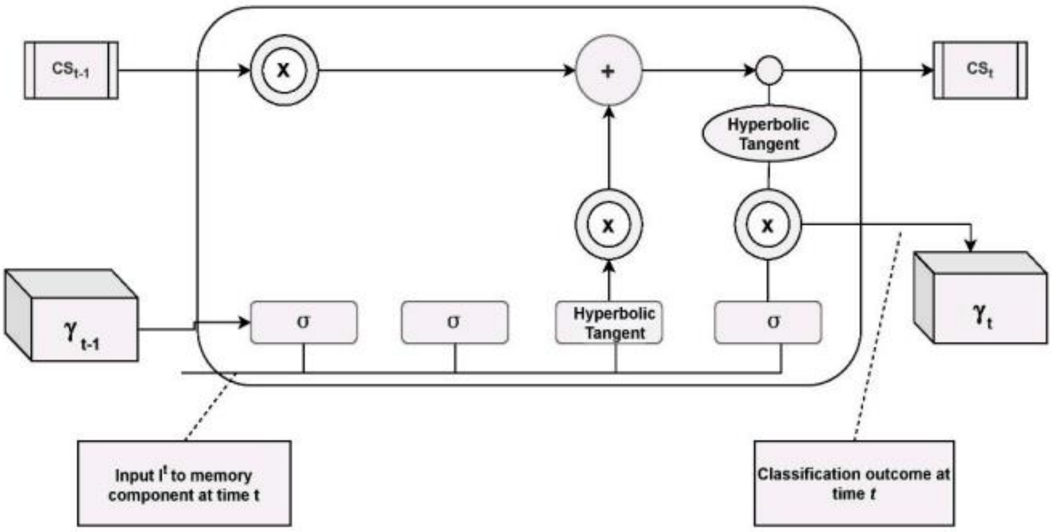

Figure 2. Architecture of LSTM component.

Performance Evaluation of Proposed Model:

The experiment is carried out on the dataset discussed in Section 3. The proposed model's results on implementation and the statistical analysis through various performance evolution metrics that include, but are not limited to, accuracy measures determine how many times the proposed MobileNet V2 model with the LSTM model is successfully classifying the skin disease. To make a reasonable contrast among various approaches concerning the implementation configurations, the authors decided to standardize pivotal parameters throughout all the studies. Table 2 represents the parameters that are considered in the implementation of the proposed model.

CONCLUSIONS:

In this section, the results of the proposed model are discussed in detail. The proposed MobileNet V2 with LSTM performance is evaluated through the hyperparameters like training and validation loss measures that determine the proposed model's capabilities. The proposed model's learning rate at various training levels is discussed in the current section. The performance evaluation with other existing approaches in terms of Sensitivity, Specificity, Accuracy, Jaccard Similarity Index (JSI), and Mathew Coefficient Correlation (MCC) are presented. The proposed model's computational time is evaluated as a part of performance evaluation and compared against the existing approaches on performing the classification over similar data.