Automated AI Skin Medical Analysis using Deep Learning

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ABSTRACT

Skin medical lesions are various abnormalities on the skin that appear on a patient due to many different reasons. These can be due to the exposure of skin to harmful UV rays or they can be mere birthmarks or an uncontrolled growth in the skintissue, defined as cancer. Not all skin lesions are cancerous and therefore it is important to identify them at an early stagewhich can potentially improve the survival rate in case the pigment on skin turns out to be cancerous. The proposed system helps the user to identify if the spots on the skin are cancerous or benign by using their mobile devices. The model was trained on HAM10000 ("Human Against Machine with 10000 training images") dataset using convolutional neural network. The dataset comprised of seven different classes of skin lesions and augmentation was used to increase the number of images in the dataset. Due to limited number of images in the dataset, to achieve better results, the model was trained using transfer learning with MobileNet adapted for mobile use. The model was then integrated into the android application which could be used to detect whether the skin lesion is cancerous or benign using the camera of the mobile device. The proposed system can be used to detect if the spotson skin.

Keywords:
Deeplearning,python,CNN,Opencv,Tensorflow,keras,Skin analysis.Lesions etc.

INTRODUCTION:

Skin Cancer is uncontrolled growth of cellsin the body. The incidence of both melanoma and other skin cancer has been increasing over the past decades [1]. The cure rate can be reached up to 90%, where doctors can save patients' lives if the lesion is detected in the primary stage. In general, visual examination of skin cancer is difficult and can lead to mis identification of lesions, as there are similarities between the different types of skin lesions. There are different types of skin lesions like Actinic keratoses, Basal Cell Carcinoma, Benign Keratosis, Dermatofibroma, Melanocytic Nevi, Vascular lesions, Melanoma. Melanoma is considered more serious type of skin cancer than the others since it has a tendency to spread to other parts of the body and if not treated at an early stage may even lead to the death of the patient. On the other hand, melanocytic nevi are the skin lesions which are not always cancerous. They are also commonly called as birth mark or moles. It is important to classify whether the skin lesion is cancerous or benign so that the patient can undergo appropriate treatment. If skin cancers are discovered early, it could usually be cured with medicinal drugs, strategies achieved within the office by way of a dermatologist, or a simple surgical procedure. The main objective of this project is to provide an application which can be used to detect and classify the skin lesions as cancerous or benign which will help the patient to identify cancerous lesions at an early stage and seek medical treatment.Dermoscopy, which is one of the noninvasive skin imaging techniques, has become a key method in the diagnosis of melanoma. Dermoscopy is the method that magnifies the region of interest (ROI) optically and takes digital pictures of the ROI. Misdiagnosis or underdiagnosis of melanoma is the main reason for skin cancer-related fatalities . The cause of these errors is usually due to the complexity of the subsurface structures and the subjectivity of visual interpretations. Hence, there is a need for computerized image understanding tools to help physicians or primary care assistants to minimize the diagnostic errors.The problems addressed in this thesis how to eliminate the subjectivity on visual interpretation of dermoscopy images for border irregularity/abruptness; ii) how to improve the performance of feature extraction algorithms by providing more accurate skin lesion segmentations; and iii) how to reduce the number of false-negative diagnosis. Images used in this thesis are obtained from the International Skin Imaging Collaborations Archive. image classification between malignant and benign tumour, using histopathology images. Resnet50 architecture has been trained on new dataset for feature extraction, and fully connected layers have been fine-tuned for achieving highest training, validation and test accuracies. The result illustrated state-of-the-art performance of the proposed model with highest training, validation and test accuracies as 99.70%, 99.24% and 99.24%, respectively.On the other hand, skin disease diagnosis is seen to be complicated, mainly when two or more diseases portray same or similar symptoms, hence requires a dermatologist with vast experience of skin diseases [2,4]. Nevertheless, the development in technology and machine learning have changed all aspects of one's day- to-day life, including the medical field [5,6]. Many therapeutic systems have been developed with the help of artificial intelligence (AI) and technological advancement to help both doctors and patients in diverse ways, starting from Out Patient Department (OPD), consultation to the operating theatre or operating room (OR). Thus, 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 use a variety of manual visual clues such as colour, scaling, and arrangement of the lesions, the body site distribution, among others. Nonetheless, when these individual components are analysed separately, the recognition ofthe disease can be quite complex, thus requiring a 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 to detect 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, as indicated in [4].Furthermore,Ghana currently has only one dermatology-training centre at the Korle Bu TeachingHospital (KBTH), with only four (4) dermatologists three.Skin Cancer is uncontrolled growth of cells in the body. Theincidence of both melanoma and other skin cancer has beenincreasing over the past decades [1]. The cure rate can be reached up to 90%, where doctors can save patients' lives ifthe lesion is detected in the primaryReadily visible changes of the skin surface have been recognised since the genesis of history, with some treatable, and some not. In developing countries, overcrowding and poor hygiene are responsible for spreading of skin diseases. One of the known initiallysources detailing skin diseases is the Ebers Papyrus, a medical paper from antique Egypt dating to around 1500 BC. It offers descriptions of the various skin diseases, including ulcers, rashes, and tumours, and prescribes surgery and ointments to treat the ailments [12]. There are two ways of detecting or diagnosing skin diseaseThe first method is the traditional method, also knownas the conventional method in which skin diseases are detected based on unique colour space. Due to the mixing of chrominance and luminance data, RGB is not the right 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.clinical events, such as severe sepsis, unexpected cardiac arrest, ICU admission or mortality [9], and tend to select one or more end-point measures of clinicaldeterioration.Such events incur high costs of prolonged hospital stays, litigation, staff time, impact on patients and staff, and broader economic consequences [10].Our system leverages the benefits of machine learning, structured knowledge representation, and logic-based inference in a novel fashion. We demonstrate on real world data that it is capable of providing robust, intelligent decision support, despite the complexity of medical relationships and the inter dependencies inherent in medical decisions.

II.LITERATURE SURVEY:

Skin cancer is one of the most common type of skin disorder which is chiefly diagnosed visually with scientific screening observed by dermoscopic evaluation, histopathological evaluation, and a biopsy. Diagnostic accuracy is strongly related to the professional experience of the doctor. Without additional technical support, dermatologists have an accuracy rate of 65% -80% in the diagnosis of melanoma. The model proposed in this paper uses convolutional neural networks that classifies skin lesion into benign or malignantlesion based on novel regularizer technique [2].

An approach for classification of melanoma skin cancer using Convolutional Neural Network is performed in [3]. The application makes use of Convolutional Neural Network method and LeNet-5 architecture for classification and the percentage of accuracy achieved was 93% in training and 100% in testing. The variety of education information used of 176 snap shots and 100 epochs. The application was created using Python programming language and Keraslibrary as Tensorflow back-end.

This paper proposed the use of image processing techniques for the detection of Melanoma Skin Cancer [4]. The skin lesion image is taken as input and then by applying various image processing techniques, the proposed system checks for the various Melanoma parameters like Asymmetry, Border, Colour, Diameter,(ABCD) etc. by texture, size and shape analysis for image segmentation and feature stages and the image is then classified as normal skin or melanoma cancer lesion.as the conventional method in which skin diseases are detected based on unique colour space. Due to the mixingof chrominance and luminance data, RGB is not the right 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 the technological method, with the emergence of machine learning, diagnosing of skin disease has become easy for most dermatologists. Computer Vision (CV), Machine-Learning, and Artificial Intelligence are the approach introduce on clinically evaluated histopathological attributes to identify the condition accurately. Firstly, the image is pre-processed, followed by feature extraction. The second stage involvesthe use of machine-learning algorithms to classify conditions based on the histopathological attributesobserved on the analysing of the skin.A CV is an interdisciplinary field that concerns with how computers can be made to gain a high-level understanding from digital images and videos. From the engineering perspective, it seeks to automate tasks that the human visual system can do.

III.PROPOSED METHODLOGY:

The methodology of the proposed system is described in thissection. The system design for the proposed model has been divided into two parts: Building the model and Integrating the model into android application.

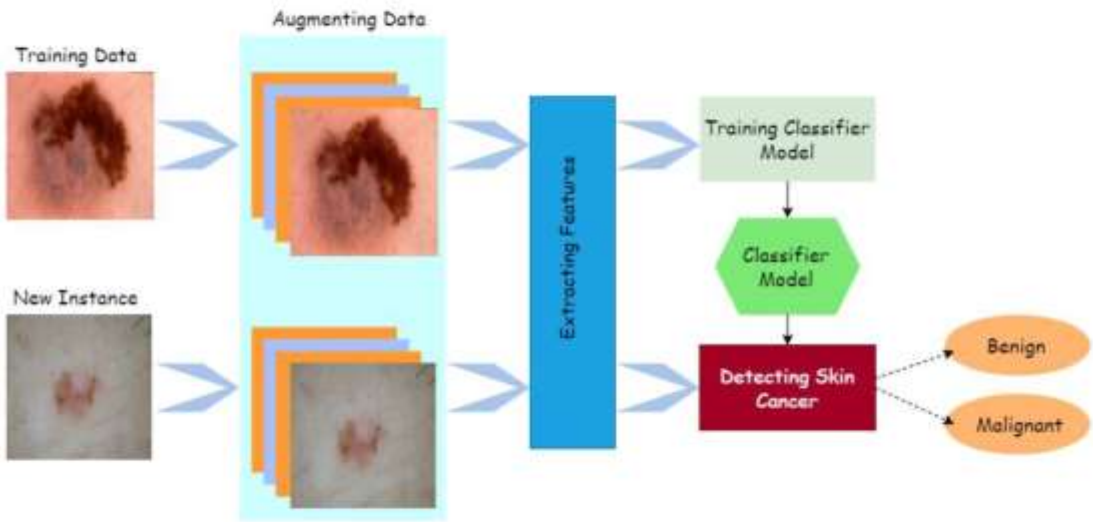


Figure 1:Pipeline Methodlogy

3.1.Dataset:

The Skin Cancer MNIST: HAM10000 dataset consists of 10015 dermatoscopic images. These images were collected from two different sites, the Department of Dermatology at the Medical University of Vienna, Austria, and the skin cancer practice of Cliff Rosendahl in Queensland, Australia. The dataset includes pigmented lesions from different populations and it has images belonging to seven classes of skin lesions. Polarized and non-polarized dermatoscopy devices were used to take the images for the dataset. The dataset includes representative examples of pigmented skin lesions that are practically relevant and most of the lesions encountered during clinical practice fall into one of the seven diagnostic categories that are present in the dataset. The dataset also contains images of the same lesion taken at different magnifications or angles. The dataset also contains image of same lesion taken at different angles or magnifications. The seven classes of skin lesions included in the dataset are Actinic keratoses, Basal Cell Carcinoma, Benign Keratosis, Dermatofibroma, Melanocytic Nevi, Vascular lesions and Melanoma [5].

3.2.Convolutional Neural Network(CNN)

Convolutional Neural Networks (CNN) are made up of neurons having learnable weights and biases. Convolutional Networks consists of three-layer types: CONV, POOL and Fully Connected. The RELU activation function as a layer is also used which applies elementwise non-linearity. Inputs are received by each neuron which performs a dot product and optimally follows it with a non-linearity. The convolution layer is the central element of a convolutional network that performs most of the heavy computationalwork. Down sampling the spatial dimensions of the input isdone by the pool layers. The image dataset is trained using CNN to obtain the model which can be then used to classify the skin lesions [6].

3.3.Pre processing:

Pre-processing is the technique that transforms the raw data into a format that is required by the system. The available data may contain duplicate and empty fields and also may be inconsistent. The duplicate images are removed from the dataset and the images are separated into seven folders named according to their skin lesion classes. The images are also resized and split into testing and training datasets. Using data pre-processing the dataset is made consistent foruse. The training dataset will be used to train the data model to identify the skin cancer and the model will be tested using the testing data and the accuracy of the model is determinedafter the model has been trained.

3.4.Image Augmentation

Augmentation is the process which is used to increase the number of images in the dataset. Increased number of images in the dataset improve the performance of the system. There are different methods available such as Mirroring, Random cropping, Rotation and colour shifting forthe augmentation of the images, out of which Random Cropping can be used for augmentation process

Figure 2:Image augmentation

3.5..Building the model

The model is trained using the training dataset. Labelled images are used to train the model which is also known as supervised learning. The model is then tested using the testing data and the accuracy of the model is determined.StepwiseProcedureof Proposed Methodology.

[1] Step 1: - Collection, pre-processing and augmentation ofthe dataset

[2] Step 2: - Splitting the dataset into testing and trainingimages

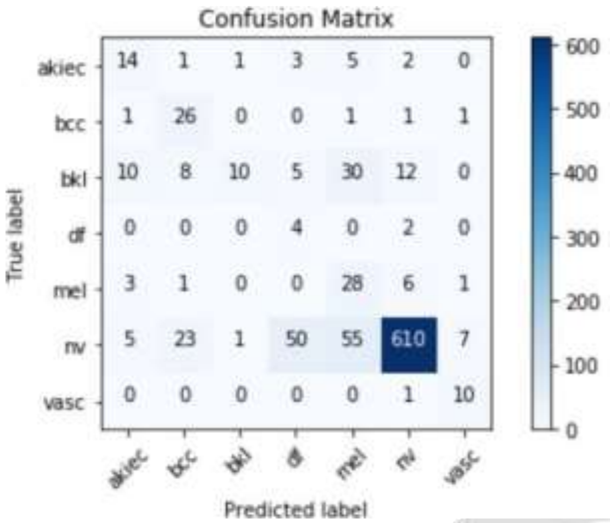
[3] Step 3: - Building the model using the training dataset

[4] Step 4: Testing the dataset using test images

[5] Step 5: - Conversion of the model into TensorFlow Lite foruse in android application

IV.RESULTS

The confusion matrix is used to visualize performance of the model on the test data. The confusion matrix shows the number of testing images that it was able to classify accurately. Here it can be seen that the model shows a greater amount of accuracy in classifying melanocytic nevi.This shows that the model will be able to classify non- cancerous pigments more accurately.



	precision	recall	f1-score	support
akiec	0.42	0.54	0.47	26
bcc	0.44	0.87	0.58	30
bkl	0.83	0.13	0.23	75
df	0.06	0.67	0.12	6
mel	0.24	0.72	0.35	39
nv	0.96	0.81	0.88	751
vasc	0.53	0.91	0.67	11
accuracy			0.75	938
macro avg	0.50	0.66	0.47	938
weighted avg	0.88	0.75	0.78	938

Figure 3:Confusion matrix and Report

Direction for Future research:

Future work will focus on techniques to enhance the accuracy of the classification proposed system by using hybrid machine-learning algorithms and also enable batchupload of images to multiple images to be upload at the same time for faster processing.

Competing interests:

The authors of the current study declare that they have no competing interests.

VI.References:

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