Detection and Visualization of Neglected Tropical Skin Diseases using EfficientNet and Grad-CAM

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***Abstract*— Early skin disease detection is crucial for both effective treatment and the prevention of spreading to others. Neglected Tropical Skin Diseases (skin-NTDs) primarily affect low-income and developing countries, receiving inadequate attention and resources in comparison to other health issues. In this study, an automated system has been developed for detecting five skin-NTDs, capable of recognizing the diseases from raw lesion images without requiring any pre-processing. A dataset was created in the initial phase of the study since no publicly available benchmarks are available. The EfficientNet family of pre-trained models was utilized to train the classifier, and the EfficientNet-B3 was selected based on the experimental results. Additionally, the proposed work has developed a Grad-CAM based visualization technique to identify the most influential regions within images for the classification of specific diseases. The proposed model exhibited an overall classification accuracy of 91.53% on the test data. The proposed work will offer benefits to frontline medical staff and local residents in low-income countries.**

Keywords—EfficientNet, Grad-CAM, Neglected Tropical Skin Diseases

I. Introduction

The human skin serves several essential functions that are vital for a person's overall health and well-being, such as protecting the body from external threats, maintaining a constant body temperature, playing a major role in the body's immune system, and allowing us to perceive touch, temperature, and pain through numerous sensory receptors. Human skin is easily affected by a wide range of diseases due to its exposure to the environment, and its complex structure. Although skin diseases are highly-noticeable with the naked eye by observing the changes in the skin's texture, colour, or appearance, recognizing the disease at its early stage is a very challenging task. Early skin disease detection is crucial for both effective treatment and the prevention of spreading to others. Although dermatologists are certainly adept at identifying skin diseases in their early stages, there exists a pressing need for computer-based automated systems [1-3] capable of detecting and recognizing these conditions at an early stage in order to provide support for all individuals.

Neglected Tropical Skin Diseases [4, 5], known as skin-NTDs, are a group of skin-related illnesses that primarily affect populations in tropical and subtropical regions of the world, particularly in low-income and developing countries. These diseases are often overlooked and receive insufficient attention and resources compared to other health issues; therefore, they are referred to as 'neglected'. The skin-NTDs have highly visible skin manifestations, making them significant contributors to disability, stigma, and the worsening of poverty. Researchers found that almost 1.8 billion people are affected by skin-NTDs all over the world [6, 7]. The World Health Organization (WHO) has listed five diseases as major skin-NTDs [5]: Cutaneous Leishmaniasis, Buruli ulcer, Leprosy, Mycetoma, and Scabies. Among these

Fig. 1. Skin lesions images of the Neglected Tropical Skin Diseases. First row: Cutaneous Leishmaniasis, Buruli ulcer, and Leprosy. Second row: Mycetoma and Scabies. Images are taken from [11].

skin-NTDs, Cutaneous Leishmaniasis, Leprosy, and Scabies are still present in Sri Lanka. The skin lesion images of these five skin-NTDs are shown in Fig. 1 and their symptoms and causative agents are described in Table I.

The Neglected Tropical Skin Diseases are detected by dermatologists through various methods. In most situations, they are identified through visual examinations based on the characteristics of the skin. Microscopic examinations are then conducted in laboratories. In some countries, advanced diagnostic methods like histopathology are employed; however, these methods can be expensive and require specialized expertise [6].

TABLE I: DETAILS OF SKIN-NTDS USED IN THIS STUDY

Disease	**Causative agent**	**Symptoms on the Skin**
Cutaneous Leishmaniasis	Leishmania protozoa	Rounded or flat lumps with an ulcerating centre Red and readily bleed ulcer's base Elevated ulcer margins
Buruli ulcer	Mycobacterium ulcerans	Lumps that later become large ulcers with yellowish surfaces and a crimson moist base underneath
Leprosy	Mycobacterium leprae	Variable-sized, dry skin patches that are moderately lighter in colour than the surrounding skin
Mycetoma	A variety of fungi and bacteria	A growing large lump that covers smaller lumps releases a yellow or blood-coloured discharge that could contain the microcolonies of the pathogenic organisms
Scabies	Sarcoptes scabiei	Small, itchy lumps with curly lines and some of which contain pus

The skin-NTDs are commonly co-endemic in numerous regions and often go unreported or lack consistent monitoring by surveillance programs [4]. In such a context, computer-

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aided diagnosis (CAD) approaches [6, 8-11] can play a crucial role in identifying skin-NTDs, especially in low-income and developing countries. They will be supportive for frontline medical staff and patients as an effortless and cost-effective way of diagnosis. These approaches utilize computer vision and machine learning algorithms to automatically recognize skin-NTDs.

Most of the current CAD approaches are designed to recognize common skin diseases, such as Acne, Eczema, Shingles, Sunburn, Dermatitis, and Skin cancers. Compared to them, the number of skin-NTDs detection approaches is considerably low due to the lack of attention on these diseases and unavailability of benchmark datasets. Automated CAD approaches treat skin-NTDs detection as an image classification task, training a machine learning model with either skin lesion images or microscopic images. Although a few skin-NTDs detection approaches have been proposed in the past, the majority of them [12-15] have focused on individual Neglected Tropical Skin Diseases using binary classification models.

In this study, a deep learning classifier has been built to detect five skin-NTDs that are mostly spread in low-income countries. The proposed model is designed to operate on skin lesion images, as these images can be easily obtained by anyone without incurring additional costs or expert knowledge. As the first step of this study, publicly available skin lesion images have been collected, and a dataset has been built. In addition to the original images, data augmentation techniques are used to generate additional images and enhance the generalization capability of the proposed model. Then the EfficientNet [16] pre-trained model is utilized to build an image classifier. As the final step of the proposed work, a visualization technique has been developed to identify the areas of the skin affected by Neglected Tropical Skin Diseases. The proposed approach will help a large number of people since the early detection of Neglected Tropical Skin Diseases is challenging in many countries due to the shortage of experts and equipment. Additionally, the proposed work will help medical practitioners in identifying the most influential regions in skin images.

II. BACKGROUND

Many researchers have focused on specific skin-NTDs and proposed binary classification models to distinguish skin-NTD images from other skin images. Arce-Lopera et al., [12] developed a mobile application for diagnosing cutaneous leishmaniasis using the pre-trained VGG-19 model and showed 93% of classification accuracy. Hu et al., [17] have proposed a methodology to detect Buruli ulcer lesion borders using image processing techniques and an SVM classifier. Recently, Barbieri et al., [14] proposed a Convolutional Neural Network (CNN) based approach that combines image and clinical data to detect leprosy, achieving a classification accuracy of 90% and a detection accuracy of 96.46%. While these approaches have demonstrated improved performance in detecting individual Neglected Tropical Skin Diseases, an effective CAD system is expected to accurately identify multiple skin-NTDs using a single model due to the high similarity in symptoms among these diseases, which often poses challenges even for human experts in visual recognition.

Some researchers have developed automated systems to detect multiple skin-related NTDs by treating disease detection as a multi-class classification problem. A few sets of researchers have used traditional machine learning techniques to classify the skin-related NTDs. Recently, Nyatte et al., [6] proposed a real-time diagnosis approach for three skin-related NTDs: Buruli ulcer, Cutaneous Leishmaniasis, and Leprosy. As the first step in their work, a dataset of skin lesion images was created for these diseases. Subsequently, a set of image processing algorithms was applied for feature extraction. Their SVM-based classifier achieved an overall classification accuracy of 96%. Similar to their work, Joshi et al., [18] proposed a decision tree-based classification approach for melanoma, eczema, and leprosy. Ahmed et al., proposed a model based on Transductive Support Vector Machine for classifying 24 different skin disease images, including leprosy and scabies. Banerjee et al., [19] employed a multi-level support vector machine classifier to categorize images of tinea versicolor, vitiligo, and leprosy. Goma et al., [20] used SVM and artificial neural networks classifiers to recognize the skin diseases in the Philippines. Although SVM and other traditional classifier-based approaches are simple and fast for real-time disease recognition, their overall recognition performance is considerably limited due to poor generalization capabilities and reliance on pre-processing techniques.

A few recent researchers have utilized deep learning models to recognize multiple skin-NTDs through a single classification model. Yotsu et al., [8] proposed a CNN classifier to detect five skin NTDs: leprosy, Buruli ulcer, yaws, mycetoma, and scabies. They focused on darker-toned skin and hence conducted the data collection in Ghana and Ivory Coast. Their ResNet-50 based classifier demonstrated a classification accuracy of 70% on the test data. Mondal et al., [10] employed the DenseNet-121 pre-trained model and a Generative Adversarial Network to classify vitiligo, tinea versicolor, and leprosy. Differing from other deep learning-based approaches, Akmalia et al., [21] employed Local Binary Patterns for feature extraction, and then used a CNN model for classifying urticaria, dermatitis, abscess, herpes, pyoderma and scabies. The AlexNet pre-trained model is utilized in [22] to classify low-quality lesion images. Akyeramfo-Sam et al., [23] devised a real-time web-based system for the classification of acne vulgaris, atopic dermatitis, and scabies. Although these CNN-based multi-class classification approaches are capable of efficiently detecting several skin NTDs at a time, they still fall short of the recognition capabilities of dermatologists.

Although a considerable number of skin disease detection approaches have been proposed in the past, it is evident that only a few approaches have been developed specifically to detect Neglected Tropical Skin Diseases, which have notably received limited attention from the research community. This study seeks to address this significant research gap, with a keen focus on five select skin NTDs, which have largely been underrepresented in existing literature.

In the following subsections, the details of the EfficientNet [16] pre-trained model architectures and visualization techniques are presented, as they are utilized in the proposed approach.

A. EfficientNet and Deep Transfer Learning

Over the last ten years, deep learning-based models have exhibited remarkable performance in image classification tasks compared to traditional machine learning algorithms. During this period, although numerous Convolutional Neural Network (CNN) based models were proposed, the

EfficientNet model stands out as superior due to its exceptional classification accuracy on the ImageNet [24] dataset using a smaller parameter count compared to others.

Until recently, researchers believed that increasing the number of convolutional layers in an image classification model was the only way to capture discriminative and strong features [25]. As a result, they proposed deeper CNN models with more than 100, 150, or even 200 layers, examples of which include DenseNet-161 and ResNet-200. Although increasing the number of layers has been beneficial for improving model accuracy, it has also led to an increase in the computational complexity of the model due to the larger number of parameters. Unlike previous deeper CNN models, EfficientNet increased the model size in a uniform way, called compound scaling, by expanding its depth, width, and resolution. The compound scaling mechanism of EfficientNet has helped achieve state-of-the-art classification accuracy in ImageNet with a model size almost six times smaller in terms of the number of parameters compared to other CNN architectures. By increasing the compound scaling factor from 1 to 8, eight EfficientNet models have been proposed, known as EfficientNet-B0 through EfficientNet-B7. These EfficientNet models significantly outperform models of similar size in terms of classification accuracy and speed. The details of EfficientNet models are summarized in Table II.

TABLE II: SUMMARY OF EFFICIENTNET MODELS

EfficientNet Model	No. of FLOPs (Billions)	No. of Parameters (Millions)	Top-1 Accuracy on ImageNet
B0	0.39	5.3	77.1%
B1	0.70	7.8	79.1%
B2	1.0	9.2	80.1%
B3	1.8	12	81.6%
B4	4.2	19	82.9%
B5	9.9	30	83.6%
B6	19	43	84.0%
B7	37	66	84.3%

The process of moving acquired knowledge from one domain to another is referred to as transfer learning. In deep transfer learning, the knowledge of a pre-trained network, which was trained on a massive dataset, is transferred to another similar task. Deep transfer learning techniques have been employed in the proposed work to classify images of skin-NTDs, addressing the data deficiency issue and contributing to achieving the highest classification accuracy. Pre-trained EfficientNet models from the ImageNet dataset were employed in this study to classify skin-NTD diseases due to their exceptional classification accuracy and reduced parameter count.

B. *Visualization Techniques in Deep Image Classification*

CNNs demonstrate remarkable performance in image classification tasks for a long period. However, their decision-making process is frequently viewed as a black box, which poses challenges in interpreting how and why they reach specific predictions. In certain applications, understanding which features or regions of an image have the most significant contribution to classifying a particular class is important.

Recently, several visualization techniques [26, 27] have been proposed to understand the decisions of deep learning-based image classification models. CAM[27] and Grad-CAM[26] are two well-known visualization techniques used to elucidate the classification decisions of a CNN classifier.

Fig. 2. Sample images of the collected dataset. First row to fifth row: Buruli ulcer, Cutaneous Leishmaniasis, Leprosy, Mycetoma, and Scabies.

The fundamental concept behind CAM involves utilizing the weights from the fully connected layers to generate a weighted sum of feature maps within the last convolutional layer. This summation emphasizes the portions of the input image that exert the most pronounced influence on the ultimate classification determination. Although CAM is simple and computationally efficient, it requires changing the network architecture, making it less flexible for use with various CNN architectures, including EfficientNet. Grad-CAM is a follow-up approach of CAM that does not require modifying the architecture of the neural network. Grad-CAM employs the gradients of the final convolutional layer in the model to generate a heat map for a specific target class.

In this study, Grad-CAM was utilized to generate heat maps for skin-NTDs, as it demonstrates superior performance without requiring any additional training or modification of the classification network.

III. METHODOLOGY

In this study, a CNN-based image classifier was fine-tuned to identify skin-NTDs from skin lesion images. Although more than seven diseases are categorized as skin-NTDs, the CNN classifier was trained to identify five diseases based on their prevalence in the Asian region: Cutaneous Leishmaniasis, Buruli ulcer, Leprosy, Mycetoma, and Scabies. Since no public benchmark dataset is available, skin lesion images were collected from the internet and subsequently labeled to create a dataset with the assistance of a dermatologist. In addition to the original images, additional images are generated by using data augmentation techniques. All EfficientNet pre-trained models were used to train a classifier, and the best one was selected based on the experimental results. Finally, the Grad-CAM visualization technique is utilized to identify the most discriminative regions for classifying a particular skin-NTD and to elucidate the classification decisions of the proposed model. The details of the proposed methodology are described in the following subsections.

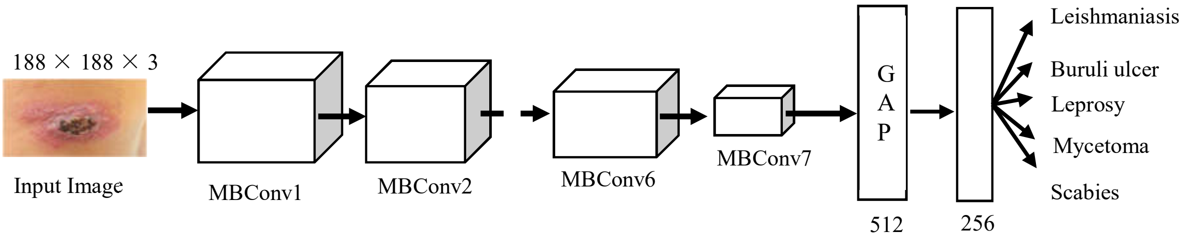

Fig. 3. Block diagram of the proposed CNN classifier model architecture. It includes mobile inverted bottleneck convolution (MBConv) blocks for feature extraction and three fully-connected layers for classification. Additionally, we replaced the flatten layer with a Global Average Pooling layer in between convolutional and fully-connected layers.

A. Data Collection and Dataset Creation

A total of 869 images of the five skin-NTDs have been collected, as detailed in Table III. These images were collected from webpages that do not have any copyright restrictions. Most of the images were taken from the DermNet [28] webpage. After collecting the data, the images were resized to a fixed size, labeled, and then 80% of them were used for training, while the remaining 20% were used for testing. Fig. 2 shows some of the images collected for our dataset.

TABLE III: DETAILS OF THE CREATED SKIN-NTD DATASET

Skin-NTD	**Training Images**	**Testing Images**
Cutaneous Leishmaniasis	128	33
Buruli ulcer	132	34
Leprosy	127	33
Mycetoma	132	33
Scabies	173	44
Total	**692**	**177**

B. Data Augmentation

Additional skin lesion image samples have been generated from the originally collected images using data augmentation techniques. From an original image, seven images are generated using rotation, width shifting, height shifting, zooming, shearing, and horizontal and vertical flips operations. These additionally generated images help improve the generalization capability of the CNN classifier and mitigate the impact of overfitting.

C. Architecture of the CNN classifier

The original EfficientNet architecture was modified and subsequently fine-tuned to classify images of skin-NTDs. The block diagram of the proposed CNN classifier is illustrated in Fig. 3.

The EfficientNet pre-trained models have a set of Mobile Inverted Bottleneck Convolutions (MBConvs) for feature extraction. Generally, increasing the number of feature channels is used to capture more complex features, but this also leads to an increase in the computational complexity of the model. To address this issue, EfficientNet uses inverted residual connections in MBConv blocks by increasing the number of channels in the initial part of the block and then reducing them using a 1 × 1 convolution. In addition to the inverted residual connections, EfficientNet introduces linear bottleneck layers in MBConv layers, which are designed to have a linear activation function to reduce the computational complexity of the model. Due to the residual connections and linear bottleneck layers, MBConv blocks are efficiently able to extract features with fewer computational resources.

In this study, the entire family of pre-trained EfficientNet models were utilized and ultimately selected one based on its validation accuracy. Although all of the EfficientNet pre-trained models have MBConv blocks, these blocks differ from one another because they are scaled with different compound scaling factors. We removed the fully-connected layers from all of these pre-trained models and then added three new fully-connected layers with 512, 256, and 5 neurons, respectively. In addition to those modifications, the Flatten layer was replaced with a Global Average Pooling layer [29], as it helped reduce the number of parameters in the fully-connected layers.

D. Training

The EfficientNet pre-trained models were trained for a fixed number of iterations using the training set of the constructed dataset. Deep transfer learning techniques are utilized to fine-tune the pre-trained models with a fewer number of training samples. Feature extraction layers, such as MBConv blocks, are frozen during fine-tuning, while the fully-connected layers are trained to learn the classification of skin-NTDs. Training is stopped at a specific iteration based on the validation accuracy to prevent overfitting. The best performing model is evaluated using the test data.

E. Grad-CAM based Visualization

In the final phase of the proposed methodology, a visualization technique was developed to explain the classification decisions of the proposed model based on the Grad-CAM technique.

In the first step of visualization, gradient score of a skin-NTD class was obtained from the last convolutional layer features of the proposed CNN classifier. Next, the gradients of that skin disease class were Global Average pooled generate a one-dimensional vector containing information about how specific feature channels influence the classification for that particular skin disease class. In the next step of visualization, the acquired one-dimensional vector is multiplied with the features from the final convolutional layer of the model to generate the heat map for that class. Finally, the generated heat map is normalized, resized, and then overlaid onto the original input image to identify the most discriminative regions.

The best-performing EfficientNet model was used to generate visual images of the skin-NTD classes. By analysing an input skin image and the corresponding image generated using Grad-CAM based technique, the most discriminative regions influencing the classification of a particular disease class were identified.

Fig. 4. Grad-CAM based visualization. First row: Original images, second row: Corresponding generated images.

IV. Results and Discussion

A. Implementation Details

The proposed CNN classifier is trained for 50 iterations and the best performing model was used to evaluated the test data. Since the number of input samples are few, the model was trained with the batch size of 8. The model is designed and trained using the Keras library. The model is trained using the categorical cross-entropy loss function with a learning rate of 0.0001. The network is trained using the Adam optimizer. For reproducibility, the code for this work is publicly sourced (https://github.com/pabasar/skin-ntd-detection).

B. Evaluation Metrics

The performance of the proposed CNN classifier was evaluated by utilizing accuracy, precision, and recall as metrics. These measurements are calculated in the following manner:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}, \tag{1}$$

$$Precision = \frac{TP}{TP + FP}, \tag{2}$$

$$Recall = \frac{TP}{TP + FN}. \tag{3}$$

$$F1\,Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{4}$$

In these equations, TP denotes true positives, TN denotes true negatives, FP denotes false positives, and FN denotes false negatives. The accuracy was used to assess the overall performance of the model and employed precision and recall to evaluate the individual disease detection performances. The F1 score is also used to measure model performance since the class distribution is imbalanced.

C. Experimental Results

As stated in the methodology, all the EfficientNet pre-trained models were fine-tuned and the best model was chosen based on the experimental results. All the EfficientNet models are trained in a similar manner, with regards to learning rate, batch size, and other hyper parameters. The average test accuracy of these pre-trained models are given in Table IV.

TABLE IV: AVERAGE TEST ACCURACY OF THE EFFICIENTNET PRE-TRAINED MODELS

EfficientNet Model	Average Accuracy (%)
B0	90.40
B1	90.96
B2	91.52
B3	91.53
B4	90.40
B5	89.83
B6	89.83
B7	89.27

Based on the average test accuracy, we selected EfficientNet-B3 as the best performing model and used it to compare performances with similar approaches. Table V provides a summary of the individual disease detection performances of the proposed EfficientNet-B3 based classification model.

TABLE V: CLASSIFICATION PERFORMANCES OF EFFIENCINTNET-B3 MODEL

Disease	Precision	Recall	F1-Score
Cutaneous Leishmaniasis	0.97	0.82	0.89
Buruli ulcer	0.80	0.97	0.88
Leprosy	0.97	0.88	0.92
Mycetoma	0.91	0.94	0.93
Scabies	0.95	0.95	0.95

Although the proposed classifier is developed to classify five selected skin-NTDs and evaluated on the newly collected dataset, the performances of similar skin disease classification approaches were compared and reported the results in Table VI. Based on our knowledge, none of the previous approaches considered skin-NTDs, which we have included in this study. Since these approaches evaluate their models on different datasets and classify a different set of skin diseases, comparing the accuracies of these approaches does not accurately reflect their disease recognition performances.

TABLE VI: COMPARISON WITH SIMILAR APPROACHES. N/G DENOTES NOT GIVEN

Study	No. of Classes	No. of Images in Dataset	Overall Classification Accuracy (%)
[8]	5	1,709	70.00
[10]	4	876	94.24
[30]	24	812	94.00
[18]	3	N/G	87.00
[19]	3	876	91.38
[31]	5	350	93.30
[21]	6	72	92.00
[23]	3	254	85.90
[12]	2	2,022	93.00
[15]	2	150	91.60
[14]	2	1,229	90.00
Ours	5	869	91.53

The results of the Grad-CAM based visualization technique are depicted in Fig. 4. We have used the test set of our dataset to generate these images. From the generated images, it is evident that skin diseases with distinct and large moles having clear boundaries are more easily classified than diseases with small moles.

D. Discussion

This study aims to detect five skin-NTDs from skin lesion images. To achieve high accuracy with a smaller number of training samples and less computational complexity, the pre-trained EfficientNet-B3 model was used. The proposed model is capable of detecting one of the five skin-NTDs in real-time.

Although the proposed model demonstrated good classification accuracy, its overall performance was influenced by several factors. Since skin lesion images were gathered from diverse sources, they exhibit variations in lighting conditions, zoom levels, and skin tone colours. These factors can significantly impact the classification performance, as this study's objective is to train the model without any pre-processing, thereby enabling real-time detection. Furthermore, it is evident that the classification scores for Buruli ulcer disease are slightly lower than those for Buruli ulcer disease are slightly lower than those for other diseases, primarily due to its visual appearance being highly similar to that of Cutaneous Leishmaniasis.

It is also observed that although the proposed Grad-CAM based visualization technique is used to highlight the most influence regions in the image, it is not very much accurate as fewer number of images are used to train the model. We intend to incorporate a greater number of samples in the training process and enhance the visualization as part of the future work in this study.

V. Conclusion

In this study, a CNN-based classification approach is proposed to detect five neglected skin diseases that have not received much consideration in previous research: Cutaneous Leishmaniasis, Buruli ulcer, Leprosy, Mycetoma, and Scabies. Due to the absence of available benchmark datasets, a dataset was developed with 869 images. The family of pre-trained EfficientNet models were employed in this study and the EfficientNet-B3 was chosen based on the experimental results. The proposed classification model achieves an overall classification accuracy of 91.53% on the test data. In addition to classification, a visualization technique was developed to identify the most influential regions in input images for a skin disease. The proposed work will be beneficial to frontline medical staff and local residents in low-income countries.

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