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Mobile Deep Learning Framework for Real-Time Detection of Skin Allergies and Fungal Infections Using GoogleNet

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Abstract: Dermatological disorders are represented by skin allergies and fungus, and they represent a significant percentage of this group of issues across the globe; however, the equitable access to the specialty care is not evenly distributed. Early diagnosis is necessary to prevent long-term complications, but the traditional modalities of the diagnosis are lengthy and expensive. The paper presents a detailed deep-learning-based image identification system that is designed to detect allergies and early-stage fungus on the skin using the GoogleNet architecture in MATLAB. Transfer learning can be used to reduce the scarcity of medical datasets and still maintain good classification accuracy. The suggested architecture will use a mobile application elaborated by Simulink support packages and Android Studio, hence allowing real-time inference with smartphone cameras. Standardisation of input data to the convolutional neural network (CNN) involves preprocessing protocols such as image resizing, image normalisation and image augmentation. The classifier differentiates between healthy epidermis, allergic response, and fungus before providing immediate warning, which can then be used to provide immediate medical advice. This framework is based on the prioritisation of portability, scalability and computational efficiency with the aim of reducing the use of specialised clinicians to make provisional diagnoses.

Keywords: Skin Allergies, Deep Learning, Fungal Infections, Android, Simulink.

I. INTRODUCTION

Billions of people in the world are afflicted with dermatological conditions, starting with commonplace hyperirritabilities, infections caused by mycotic infections, and neoplastic occurrences. The situation is further worsened by a global shortage of dermatologists, especially in underdeveloped areas and in the rural areas. Unattended cutaneous diseases may have degraded culmination of significant physical pain, psychological trauma, and in some cases like melanoma or deep-seated fungal infections, lethal consequences. Thus, there is a pressing need of readily available, automatic diagnostic equipment that will assist providers of primary care and laypeople to early recognize skin abnormalities. Deep learning (AI) has become a new revolution technology in the medical imaging field, with the propensity of making high-quality diagnostic assessments available to everyone [1].

Although AI has a potential in dermatology, broad adoption is faced with significant technical and practical challenges. To begin with, the training of resilient deep learning models often requires large, balanced datasets, which are uncommon in the medical field; publicly available repositories of skin lesions often consist of small sample sizes and are highly imbalanced in their classes [2]. Second, the computation required by high-performing convolutional neural networks (CNNs) is resource-intensive, which is why it is difficult to deploy such models on resource-intensive edge devices, e.g. smartphones, without specialised hardware acceleration [3]. Third, the existing automated systems usually fail under differences in the skin tone and image fidelity and deliver biased effects where the models perform poorly when dealing with underrepresented groups [4][5]. This paper addresses these issues by introducing a lightweight and mobile-friendly system that uses GoogleNet, a system that is a combination of depth and computational expediency. The vision is limited to classification of normal skin, allergic reactions and fungal infections, using a smartphone-based acquisition process.

The following salient innovations are brought out in the presented research to automated dermatological diagnosis:

1) Optimised Transfer-Learning Framework: A CNN based on GoogleNet is implemented in MATLAB, and transfer learning is used to obtain high classification accuracy despite limited and poor training data, thus reduces overfitting as is common with small-dataset settings [2].
2) Real -Time Mobile Deployment: The system closes the gap between the theoretical model design and practical implementation, with the trained network deployed to Android devices through Simulink, such that real-time frame processing and alerting without ongoing connections to the cloud are implemented

3) Accessibility-based Design: The model is designed to accommodate the standard smartphone camera and reduce its computational requirements, which makes it a cost-effective initial screening tool that directly overcomes the obstacle of the cost of ordering diagnostic modalities [6].

II. RELATED WORK

A. Deep Learning Models in Dermatology.

Use of convolutional neural networks (CNNs) to classify skin lesions has been widely studied and different networks are competing on each other in terms of the highest accuracy. VGG16, ResNet, and DenseNet, are among the models that have created a strong benchmark. As an example, Santos et al. showed the accuracy of the modified VGG16 to identify actinic keratosis and psoriasis, which highlights the applicability of transfer learning in the situations when starting with ImageNet-pretrained weights [6]. However, more sophisticated architectures are more likely to have a greater latency. Comparing several architectures (MobileNet, ResNet152 and GoogleNet) Banerjee et al. discovered that the ensemble methods (which combine texture descriptors: LBP and WLD) were able to achieve an accuracy of 91.38 but GoogleNet alone provided results of 185.06 at an equally competitive architectural footprint [7]. This implies that GoogleNet would be of use in mobile applications where speed accuracy trade-offs are important.

B. Hardware Constraints and Computational Efficiency.

The use of deep learning models in mobile devices requires careful attention to computational complexity, which is expressed in billions of operations/frame. According to Gokhale et al., CNNs have many strengths but they need a considerable amount of hardware acceleration in order to operate frame processing in real time. According to their study of Snowflake accelerator, GoogleNet requires approximately 116G–ots/s to achieve 36 frames per second which, despite having a better accuracy/computation ratio than legacy architectures such as AlexNet, is still a lot of workload on general-purpose mobile processors [3]. Optimisation methods like model compression or transfer learning that consume minimal power are, therefore, urgently needed to maintain the responsiveness of the applications and avoid battery overload when faced with constant monitoring.

C. Data Issues: Imbalance, Bias and Augmentation.

The rarity and lopsidedness of the labelled medical imagery continue to be widespread challenges in image analysis. Yao et al. argue that single-model methods are able to outperform complex combinations on small data sets with the correct regularisation (e.g., dropout) and augmentation methods in place [2]. Furthermore, training data bias has come under a lot of examination. Daneshjou et al. mention the FairSkin, where the performance of generative models and classifiers across different tones of skin has been shown to exhibit unequal variance since they are not represented sufficiently in the training data [4]. Chiu et al. find that colour difference between lesion and epidermis around it significantly affects detection efficacy besides skin tone [5]. Taken together, these papers highlight the need to perform stringent preprocessing, data augmentation, and fairness-conscious validation to guarantee diagnostic reliability with a wide range of patient demographics.

III.METHODOLOGY

A. System Architecture

The suggested system architecture is developed in the form of a sequence of pipeline that will combine image capture, preprocessing, feature-extraction, classification, and alert-generation. The process starts with the Image Acquisition Module, whereby a smartphone camera takes high-resolution images of the dermoscopic images of the corresponding area of the skin; the images are then sent to the Preprocessing Module. The Preprocessing Module performs resizing to fit the GoogleNet input requirements of 224 × 224 pixels, normalises the distributions of pixel-intensity around the mean, and noise-reduction filtering.

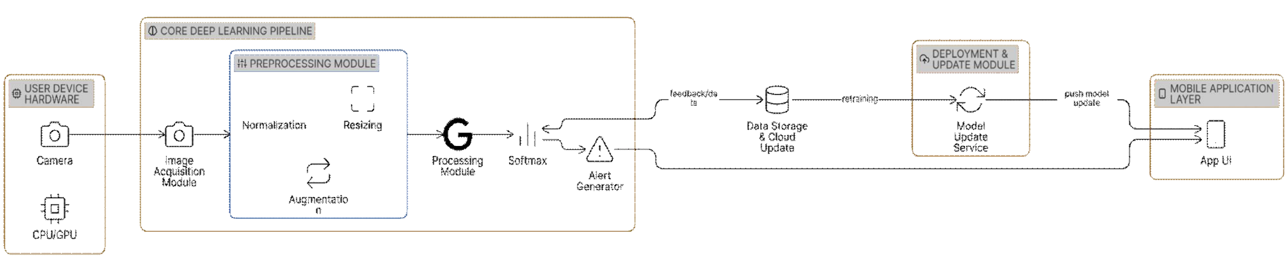

Fig. 1 Proposed System Architecture

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After preprocessing, the main Processing Module makes use of the GoogleNet convolutional neural network. Unlike linear architectures like VGG, GoogleNet has Inception modules which concurrently run convolutions with multiple receptive fields (e.g. 1 x 1, 3 x 3, 5 x 5) which allow a multi-scale capture of features, critical in distinguishing between fine fungal textures and other larger allergic rashes. The Classification Layer uses a SoftMax activation in order to generate estimates of the probability of the target phenotypes. Lastly, the Deployment Module, implemented in MATLAB and Simulink, interacts with the Android operating system to present the diagnostic results, as well as issue alerts upon diagnostic results indicating the existence of a probability of infection that exceeds a specified safety threshold. The system architecture is shown in Fig 1.

B. The algorithm and Transfer Learning Strategy.

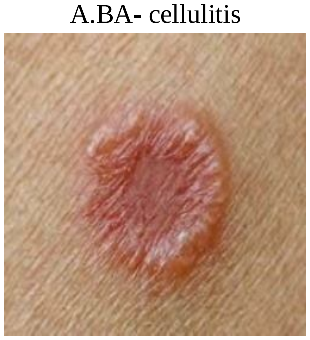
The main algorithmic paradigm is based on transfer learning, in which an existing trained model is re-used as a general-purpose feature extractor to a new task. The weight values of the convolutional backbone are also initialised with the ImageNet-trained GoogleNet checkpoint, a method that is supported by previous literature that has shown faster convergence rates, as well as higher accuracy when fine-tuning with relatively small medical data. In order to modify the architecture to classification the final fully-connected layer would be changed into an output head that would support dataset classes as shown in fig 2.

The training process follows forward propagation to produce intermediate feature maps, cross-entropy loss to measure prediction error and back-propagation using Adam optimiser to update parameters with adaptive learning rates. Data-augmentation techniques, such as rotations, zooms and horizontal flips are used in training to reduce the class imbalance and improve generalisation. This method is similar to other results of Yao et al. that augmentation is essential to over-fitting in single-model deep convolutional neural network on small datasets.

A.BA- cellulitis

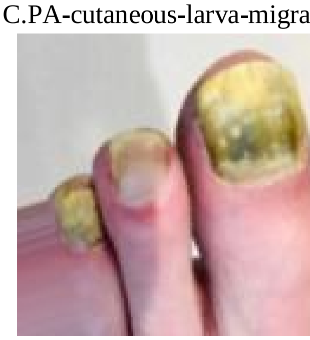
B.FU-athlete-foot

C.PA-cutaneous-larva-migrans



D.FU-ringworm

E.BA-impetigo



FU-nail-Fungus

Fig. 2 Dataset Images

C. Deep Learning Model (GoogLeNet)

It uses the GoogLeNet architecture, which has 22 layers that can be trained in the convolutional neural network. The design of it is the inception oriented version, which enables the efficient feature extraction through the use of multiple convolutional filters, specifically 1x1, 3x 5x convolutional filters, applied concurrently within each inception module. Such a setup allows the network to learn fine-grained and coarse-grained features simultaneously and also minimize computational costs and parameters. The GoogLeNet model is effective in terms of learning hierarchical feature representations using input images thereby boosting the performance of classification. The confusion matrix of training data, testing data, and the corresponding training curves are shown in Fig.3-5 as confusion matrices.

Instead of initializing the network with random weights, transfer learning is adopted because random initialization requires huge datasets as well as more computation power. The GoogLeNet model, which is pretrained with ImageNet dataset, keeps its learned feature extraction layers which identify the basic image features like edges, textures and shapes. These pretrained features are especially beneficial in the medical and agricultural image classification. The last fully connected layer, softmax layer and classification output are adjusted and changed to suit the network to classify five different categories of sugarcane disease. The approach enhances the effectiveness of training and elevates the level of classification.

The implementation of the training process is carried out in MATLAB by the application of the stochastic gradient descent with momentum (SGDM) optimizer that provides the stable convergence and the effective learning. Hyperparameters to be trained, such as the learning rate, mini-batch size, and the number of epochs, are chosen following the best practices in deep-learning. The dataset is divided into training (70 %), validation (15 %), and testing (15 %) subsets so that the evaluation of the model could be conducted properly and to prevent overfitting. The training set is used to refresh the model weights, the validation set is used to check the performance during the training and the testing set is used to see the final classification accuracy of GoogLeNet model.

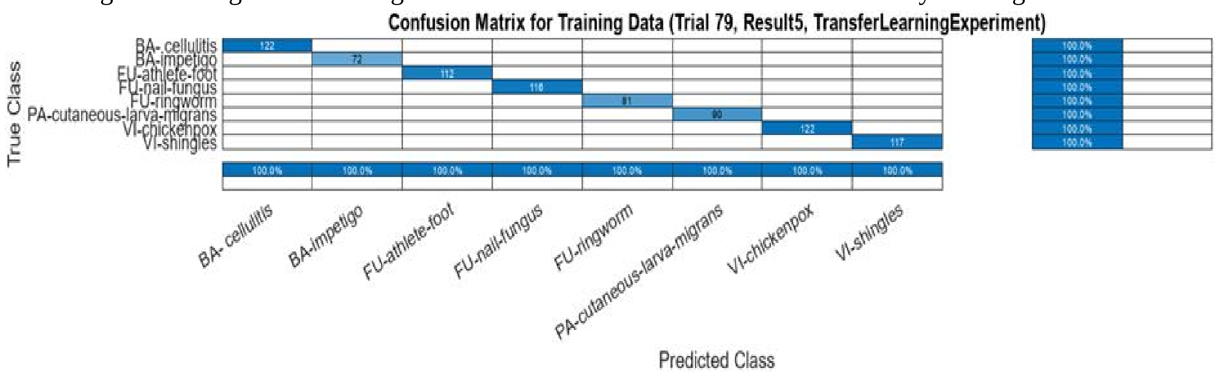


Fig. 3 Confusion Matrix for Training Data

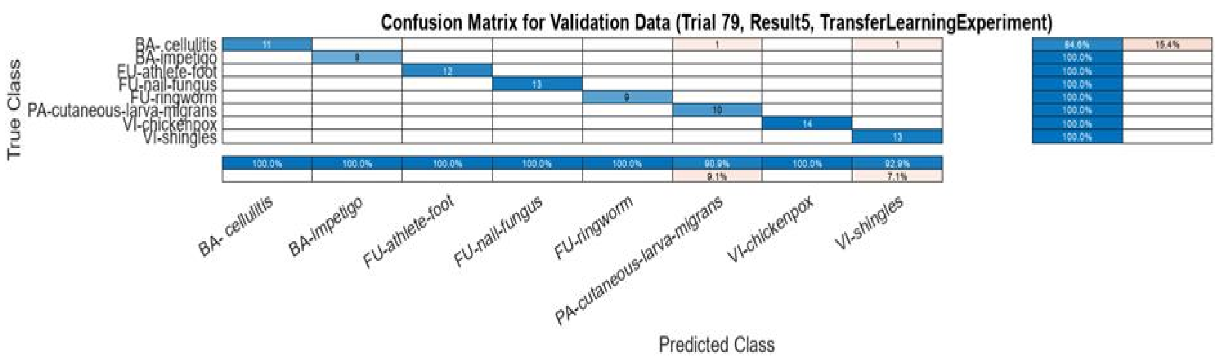


Fig. 4 Confusion Matrix for Validation Data

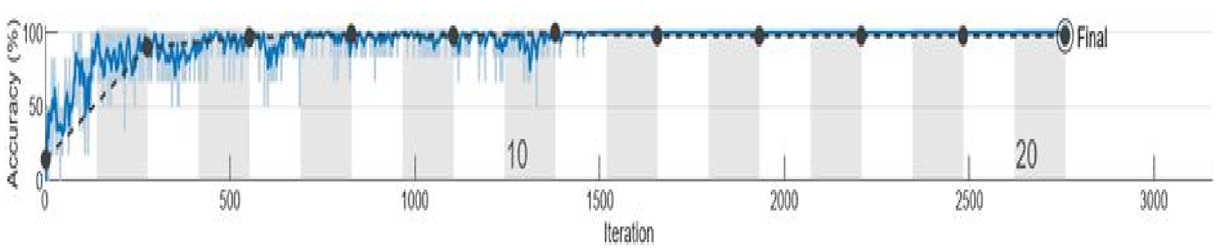


Fig. 5 Training Graph

IV. RESULTS AND DISCUSSION

A. Mobile Integration and Evaluation Plan.

The implementation of mobile applications is achieved by the use of MATLAB Support Package of Android Devices with Simulink. The Simulink model is programmed to receive a steady stream of video, process the individual frames and superimpose the output prediction on the user interface and as such, perform real-time inference. The Simulink Program Shown in Fig 6.

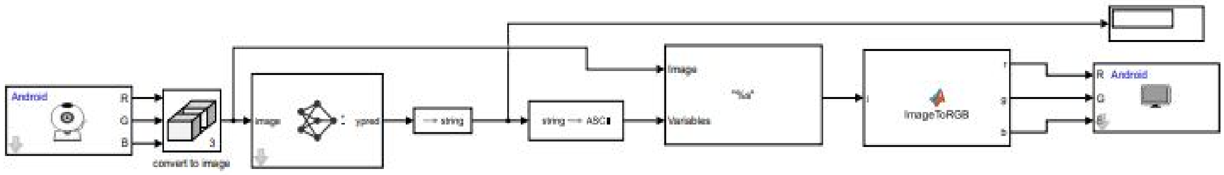


Fig. 6 Simulink Main Program

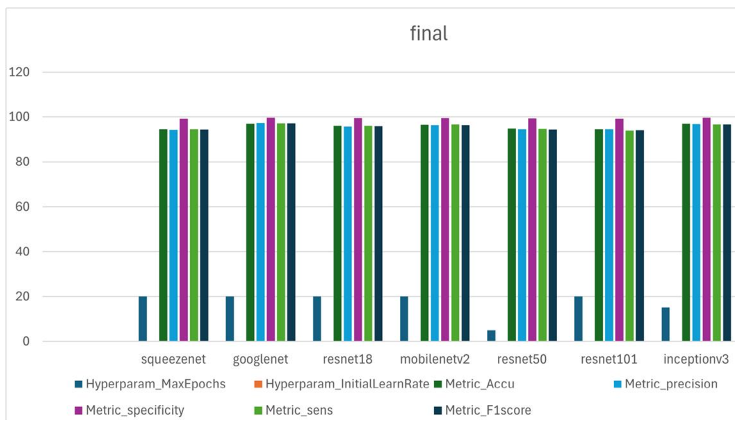


Fig. 7 Comparison of Trained models

The trained MATLAB network object is loaded into a Simulink block. System will be evaluated with a hold-out validation set and later where possible, external testing with heterogeneous datasets will be done to determine robustness. Compared graph is shown in Fig 7. Most important performance measures are as follows:

1) Accuracy - the percentage of the correctly classified cases;
2) Precision - the proportion of the number of cases correctly predicted as positive to the total
3) cases, thus saving unnecessary biopsies and patient anxiety;
4) Sensitivity (Recall) - the capability of accurate detection of real positive infections, which is a vital variable during clinical screening;
5) Specificity the capacity to detect correctly non-infected skin, thereby reducing false alarms;
6) F1 -score - the harmonic mean of recall and precision, which provides a balanced score when there is a class imbalance;

Theoretical standards developed based on similar literature indicate that, with an adequate and representative dataset, an ideally trained GoogleNet framework must reach an accuracy comparable to that of some 89% in similar dermatological classification. Android deployed results are shown in Fig 8.

Fig. 8 Real time results in android

B. Implementation and Deployment.

The implementation of this system has serious practical consequences on the accessibility of healthcare. It eases the burden on clinical facilities by letting preliminary at-home screening be performed and encouraging early intervention, which is generally less invasive and less expensive than the treatment of the advanced dermatoses. The architecture is to be cloud-based dataset updates, which means centralised retraining and constant improvement of the model and then share updates with end users. This scalability will ensure that the diagnostic capabilities keep improving with the increase in the amount of additional data. Additionally, the use of the standard smartphone hardware renders the need to use specialised medical imaging equipment inapplicable, making the solution applicable in the low-resource environment.

C. Failure Modes and Limitations.

In spite of its strength, the system has a number of weaknesses that need to be recognized. First, the quality of the image will largely depend on ambient light and the natural sharpness of the smartphone camera; the lack of optimal light and blur of the image may trigger a misclassification. Second, as stressed by Chiu et al., the colour difference between the lesions and the surrounding epidermis is a critical factor of model performance; lesions with a similar colour as the skin of the particular patient (low contrast) are very difficult to detect. Third, the training corpus may be biased against lighter skin tones due to the inherent disproportions of the training corpus; such skin-tone bias has been observed in other diagnostic AI systems and has ethical implications in regard to fair healthcare provision.

V. CONCLUSION AND FUTURE WORK

In the present research, a deep learning model has been identified to detect skin allergies and fungal infections in real-time using the GoogleNet architecture. With the capabilities of transfer learning in a MATLAB-Simulink setup, we developed a feasible procedure of implementing state-of-the-art convolutional neural networks in Android portable devices. The system architecture explicitly covers the need in portable, quick, and affordable dermatological screening. Though GoogleNet provides a strong balance between the ability to extract features and the computational efficiency, continuing issues with the balance of datasets and skin-tones represent urgent priorities in the further development. As a result, the presented system can be viewed as the step forward in AI-controlled healthcare, and it can empower people with the ability to detect issues early on and promote the overall aim of medical diagnostics accessibility. The combination of strict preprocessing process, effective model structure, and convenient mobile implementation provides a strong base of future innovations in teledermatology Continued studies are needed to take a step forward and include structured clinical information, including family history, as suggested by Jeong et al. to increase decision-making fidelity and diagnostic reliability. Furthermore, the later versions can involve hardware acceleration methods to reduce the amount of energy used on the mobile systems.

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