Acne Severity Classification on Mobile Devices using Lighweight Deep Learning Approach

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***Abstract*—Acne is a prevalent skin condition affecting millions of people globally, impacting not just physical health but also mental well-being. Early detection of skin diseases such as acne is important for making treatment decisions to prevent the spread of the disease. The main goal of this project is to develop an Android mobile application with deep learning that allows users to diagnose skin diseases and also detect the severity level of skin diseases in three levels: mild, moderate, and severe. Most of the deep learning methods require devices with high computational resources which hardly implemented in mobile applications. To overcome this problem, this research will focus on lightweight Convolutional Neural Networks (CNN). This study focuses on the efficiency of MobileNetV2 and Android applications that are used in this project to detect skin diseases and severity levels. Android Studio is used to create a GUI interface, and the model works perfectly and successfully by using TensorFlow Lite. The skin disease images of acne with severity levels (mild, moderate, and severe) achieve 92% accuracy. This study also demonstrated good results when it was implemented on an Android application through live camera input.**

***Keywords*—Acne detection; severity level; MobileNetV2; convolutional neural network**

I. INTRODUCTION

Skin diseases are conditions that affect your skin and cause rashes, inflammation, itchiness, or other skin changes. It can be our genetics that causes skin disease, while other reasons may be due to lifestyle. While genetics and hormonal fluctuations play a significant role in acne development. Acne skin disease occurs when a pore that is blocked with oil and dead skin cells becomes reactive, leading to acne. Blackheads are entirely closed pores, while whiteheads are open pores that have turned dark. Acne, which most frequently appears on your face, chest, and back, is caused by bacteria and hormones [1]. Dermatologists often evaluate the severity of acne in a clinical setting. The skin conditions were commonly identified using standard procedures like physical exams, blood tests, and biopsies. During the clinical examination, the specialist uses the methods and equipment for diagnosing the skin lesion based on their experience, expertise, and precision. This method might result in incorrect diagnoses, pointless follow-up procedures, a delay in starting the right therapy, and the spread of illness. Although medical technology based on lasers and photonics has helped to identify skin illnesses considerably more quickly and effectively, the cost remains expensive for most of patients. The severity level of acne is divided into four levels: grade 1 (mild), grade 2 (moderate, or pustular acne), grade 3 (moderately severe, or nodulocystic acne), and grade 4 (severe nodulocystic acne) [2].

Acne detection using deep neural networks is a promising method to be accurate and faster than traditional state-of-the-art methods [3]. Common feature based like color and texture analysis observes the limitations including lower accuracy and precision values in certain channels and the impact of lighting conditions on color values and classification accuracy [4]. Deep learning methods are known to be provided with vast amount of training data in order to achieve high accuracy and avoid overfitting (a condition where training model performed too well on a particular set of data, and not on the other sets of data). Acne segmentation and manual grading of lesion skin for quantitative assessment of acne severity is a very crucial task. The effectiveness of segmentation method may vary depending on dataset quality, size and diversity [5]. Accurate assessment of acne severity aid dermatologists in determining the suitable treatment required for the patients. Hence, smartphone-based acne detection app helps individuals to track disease progress and assess treatment effectiveness [6]. Users can take prompt action on early detection to prevent its worsening and potential scars. The benefits of the apps include privacy where maybe some of the people may not feel comfortable discussing skin problems face-to-face. Visiting experts might also be costly and time consuming for the appointment. Therefore, app-based detection provides a more cost-effective alternative and also maintains privacy. The apps will allow dermatologists to engage with their patients, giving fast responses and feedback, thus significantly addressing their patients' needs.

Previous work on skin disease using machine learning algorithm focuses on high-resolution images and severe levels of skin disease [7]. Especially on acne detection, various types of skin color and low-resolution images such as from low specification camera phone, low lighting conditions are very limited in the public image database. Skin detection is very well-known as a challenging problem due to several factors such as illumination, pose variations, skin color, age and complex background. Machine learning based tools can complement medical image assessment and help users spot potential issues early on. Therefore, research in skin lesion problems mainly utilizing machine learning methods. A hybrid approach of deep learning and Support Vector Machine (SVM) is proposed for multi-class skin lesion classification [8]. Since acne is the most common skin disease, severity of acne problems is necessary to assess the efficacy of medical treatment procedures. Maroni et al. develop an automatic extraction, detection and counting of skin lesions for acne severity [9]. Preprocessing of blob detection minimizes the time taken for acne spot marking. There are limited public datasets available with various image conditions. Zhang et. al [10] construct CNN pre-trained VGG16 model on small dataset for severe level of acne vulgaris. Malgina et al. [11] trained CNN model and customized dataset mapping based on severity stages of acne lesions. Ensemble neural network was then proposed in two phases of experiment in order to calculate the number of acne severity and position the acne detection boxes simultaneously [12]. Most of the mentioned research previously achieved high accuracy and good performance results in acne lesions detection. However, it remains challenging for acne detection in complex conditions, within special application scenarios and managing the computational time of the training.

Mobile-based skin detection starts emerging due to the potential to reach a vast and diverse user worldwide. Mobile-based applications are more accessible and convenient without the need for specialized equipment and can be accessed anytime and anywhere. Velasco et al. implemented CNN MobileNet to create a skin disease classification system on an Android application [13], [14]. CNN improved the capability of the machine learning framework and achieved the best training precision to classify various classes of skin disease [15], [16]. Zhao et al. extract selfie image features using ResNet 152 pre-trained model to learn the target severity level from labeled images [17]. However, none of the previous work on acne detection and assessment for real mobile apps evaluates on classification image time average. Hence, lightweight models are more effective to be deployed into mobile applications. Lightweight deep learning models are designed to be more efficient, consuming fewer resources with less computational power. This ensures that the model can run smoothly on mobile devices without draining the battery quickly or causing significant slowdowns.

This paper focuses on creating a lightweight CNN model to classify acne by its level of severity which is usable in devices with low computational resources such as smartphones. In this paper, the data augmentation method is implemented with transfer learning on the CNN model to discover the performance in terms of accuracy and further optimise it before being transferred in TensorFlow Lite. The model is implemented in a mobile application. Overall, the main contributions of this study include:

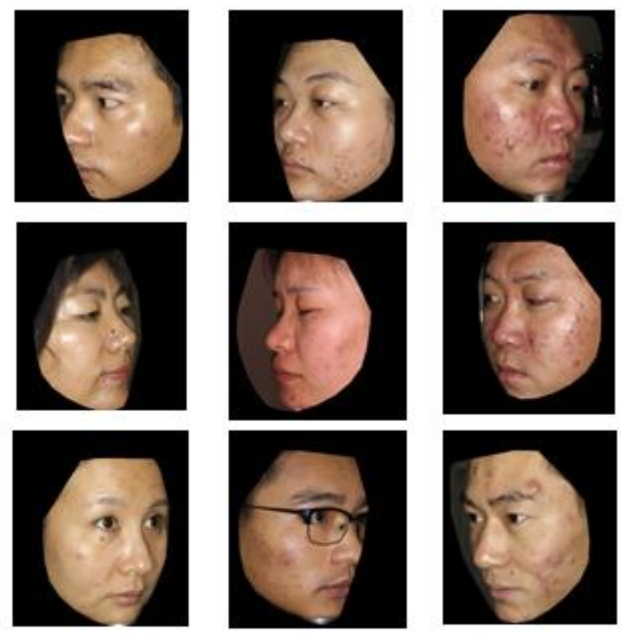
- Perform acne detection with severity levels and testing the effect of transfer learning using lightweight CNN,
- Implement image augmentation method, test and validate its influence in acne detection and severity level classification,
- Optimize the model on changes in performance accuracy and speed for the best model to be deployed in a mobile application,
- Designed application interface and creating a mobile Android application for acne detection and severity level classification.

This proposed method proved capable in improving classification accuracy and achieved fast processing speed of captured image using MobileNetV2. Therefore, it may be studied further in another related research of detection using mobile-based applications development.

II. MATERIALS AND METHODS

A. Dataset Collection

In this project, datasets were acquired and collected from open source and dermatology sources Dermnet where publicly available in www.kaggle.com, namely the acne grading dataset. Fig. 1 shows an example dataset image of an acne problem with several severity levels. The image is gathered for training purposes and obtained from public dermatologist sources online. The stage development of acne lesions is categorized into three levels: (1) mild acne has only a few blackspot as well as small pimples, (2) moderate acne has many blackspot as well as large pimples, and (3) severe acne has many blackspot, blackheads, large and inflamed pimples and cysts [18]. The total images uploaded and trained are 1139 images. There are 388 images of acne with mild severity, 474 images of acne with moderate severity, and 277 images of acne with severe severity.



(a) (b) (c)

Fig. 1. Sample datasets datasets from left are acne with (a) mild severity, (b) moderate severity and (c) severe level.

The image contains an image of a body part that is affected by the skin disease acne. The images were saved in JPG (Joint Photographic Group) format with 2320 × 3160 pixels resolution and labelled. For the dataset, the images are split with a ratio of 6:2:2 for training, testing and validation sets respectively.

B. Proposed Method

The proposed method consisted of two main steps, (1) deep learning steps and (2) the implementation step which involved the development of an Android application for the created CNN model to be deploy in real mobile. The entire process is illustrated in Fig. 2, depicting the workflow of the proposed method. Initially, load the dataset and generate data augmentation. Details of the implementation of augmentation method are in Section II(C). The total dataset exhibits slight class imbalance across severity levels. Subsequently, the dataset is partitioned into distinct sets for training, validation, and testing purposes. The MobileNetV2 model, selected for its lightweight architecture, is then implemented and trained using the training dataset. The process is repeated for the rest of validation and testing dataset. The evaluated model is saved and deployed in a real mobile. Finally, the random image contained various backgrounds with complex context and skin color was tested to determine the robustness of the mobile applications.

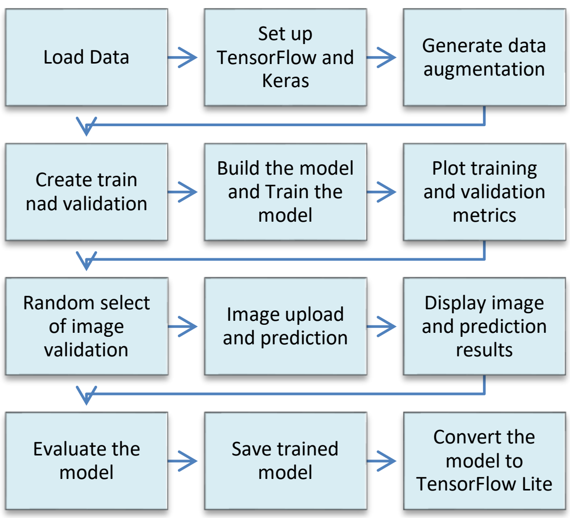


Fig. 2. Overview of proposed method.

C. Data Augmentation

Initially, loaded dataset needs to perform data augmentation techniques in order to handle the limited amount of data used. Given the limited amount of data available, data augmentation techniques are employed to generate additional samples while maintaining label integrity. It involves applying various transformations to create new samples while preserving the label information. This process was only done on training and validation dataset. Specifically, the augmentation process involves rotation, flipping, zooming, brightness/contrast adjustments and Gaussian blur. Rotation randomly rotates images to simulate different facial orientations, while flipping mirrors images horizontally and vertically for varied perspectives. Zooming adjusts image scale to simulate varying distances from the subject, and brightness/contrast modifications accommodate different lighting conditions. Gaussian blur is applied to simulate varying image clarity.

These techniques collectively enrich the dataset, providing the model with diverse examples to learn from, thereby improving its robustness and generalization capability. Hence, new images are generated from the original dataset as illustrated in Fig. 3 and Fig. 4. This augmentation strategy results in a total of nine augmented images in addition to the original image for each image in the training dataset, effectively expanding the dataset size and improving data generalization. By augmenting the dataset in this manner, the proposed model is better equipped to handle challenges such as overfitting and class imbalance, ultimately enhancing its performance in acne severity classification tasks on mobile devices.

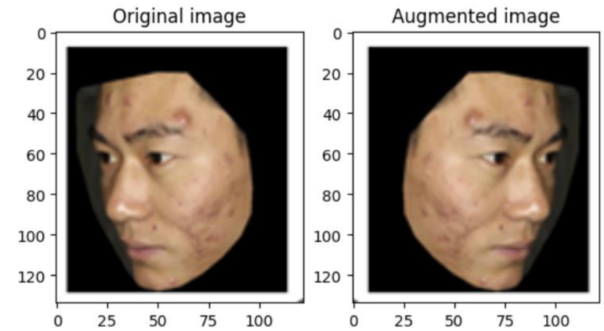


Fig. 3. The original image and augmented image (flip image).

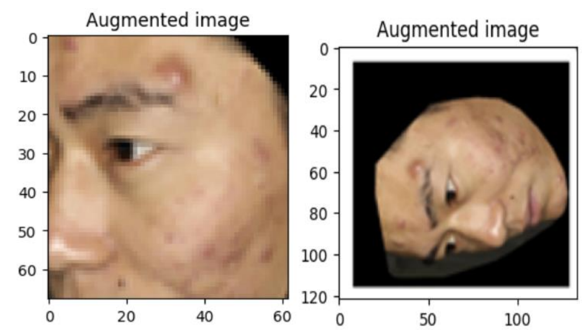


Fig. 4. Augmented image after zoom (left) and rotate (right).

D. Framework of Proposed Model

The integration of the feature extractor layer based on the MobileNetV2 model represents a significant advancement in acne detection methods for mobile devices [19]. By incorporating the powerful feature extraction capabilities of the pre-trained MobileNetV2 model, the proposed framework leverages learned representations to enhance the accuracy of acne severity classification. The addition of this layer ensures that the model can effectively capture relevant features from input images, enabling more precise and reliable classification of acne severity levels. Moreover, the lightweight nature of the MobileNetV2 architecture makes it suitable for deployment on Android devices, ensuring efficient processing and optimal performance even with limited computational resources. This new framework for acne detection on mobile devices holds promise for improving accessibility to dermatological assessment tools and empowering individuals to monitor their skin health conveniently using their smartphones.

MobileNetV2 is specifically designed to excel on mobile devices, employing a streamlined architecture built on depthwise separable convolutions, which significantly reduces computational costs compared to traditional convolutions [20]. The architecture of MobileNetV2 comprises three fundamental building blocks: deep separable convolution, linear bottlenecks, and inverted residuals. In these blocks, 3 x 3 depth-wise separable convolutions are utilized to achieve substantial computational efficiency gains, up to eight to nine times compared to regular convolutions. The inverted residual mechanism establishes direct connections between bottleneck layers, contributing to the architecture's efficiency. Within the

53-layer MobileNetV2 architecture, an initial full convolutional layer is followed by 19 residual bottleneck layers, as depicted in Fig. 5. This modified MobileNetV2 architecture enhances the model's ability to accurately detect acne lesions while maintaining computational efficiency, making it well-suited for deployment on mobile devices.

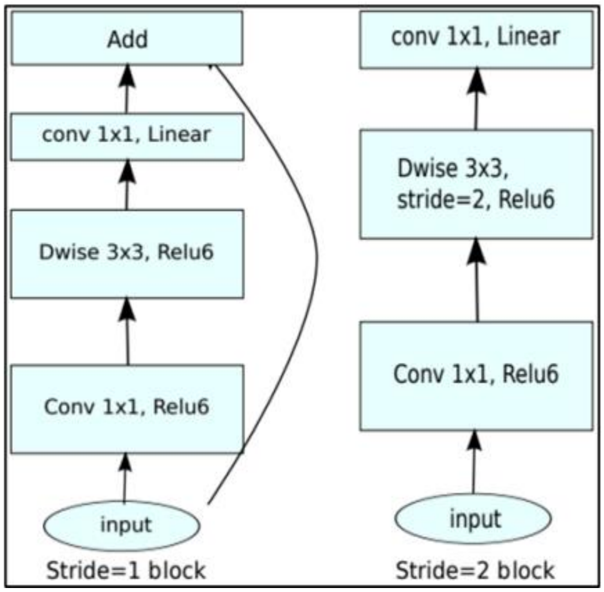


Fig. 5. Model architecture of MobileNetV2.

TABLE I. DEPTHWISE CONVOLUTION LAYERS

Output Size	Layer
224×224	Image
112×112	3×3 Conv, 32, /2
56×56	3×3 DWConv, 32, /2
	1×1 Conv, 64
28×28	3×3 DWConv, 64, /2
	1×1 Conv, 128
	3×3 DWConv, 128
	1×1 Conv, 128
14×14	3×3 DWConv, 128, /2
	1×1 Conv, 256
	3×3 DWConv, 256
	1×1 Conv, 256
7×7	3×3 DWConv, 256, /2
	1×1 Conv, 512
	$4 \times$ 3×3 DWConv, 512 1×1 Conv, 512
	3×3 DWConv, 512
	1×1 Conv, 1024
1×1	Global Average Pooling
	1000-d fc, Softmax

While Table I shows the modified depth-wise separable convolutions layers to optimize the training cost. The model weight and architecture are saved once the confusion matrix has analysed the performance test data. The model is modified into a "FlatBuffer" (.tflite) that TensorFlow Lite provides to be installed on mobile devices. The (.tflite) model is loaded, and Kotlin and C++ are used to run the interpreter. The interpreter module is then used in conjunction with the operation kernels after that. The interpreter will make use of the Android Neural Networks API for hardware acceleration (NNAPI). The Android Neural Networks API (NNAPI) is capable of inference in the areas of behavior prediction, picture 25 categorization, and the choice of an appropriate response to a search query. With the help of this API, computing effort may be split across neural network hardware, ondevice CPUs, and graphics processing units (GPUs).

E. Training Model

The training of the proposed model was done using Google Colab with Python programming and a runtime pre-configured with machine learning and AI libraries such as TensorFlow, Matplotlib, and Keras. For the hyperparameters setting, the Stochastic Gradient Descent (SGD) optimizer with 0.0001 learning rate and fined tuned to 0.9 momentum. The SGD optimizer is a powerful and widely used optimization algorithm. The drawback is SGD convergence is slower and requires several fine-tuned of hyperparameters setting.

The learning rate was fined tuned to 0.0001 step size to help the model optimized and find better solutions. As a smaller learning rate was set, a larger epoch, specifically 100, was used in order to enable the model to reach a state of convergence. The batch sizes were used to allow better generalization and the experiment has been carried out with different batch sizes. Smaller batch sizes might lead to more noise in gradients, while larger batch sizes will improve the convergence but require more memory. The last important parameter setting is training epochs which influences how many times the model sees the entire dataset. The hyperparameter configuration can be viewed in Table II.

TABLE II. HYPERPARAMETER SETTINGS

Hyperparameter	Value
Epoch	100
Batch Size	8
Optimizer	SGD
Momentum	0.9
Learning Rate	0.0001

F. Application Interface

The application interface is designed to provide users with intuitive functionality through three main buttons: "Select Photo," "Start Camera," and "Detect." Users have the option to upload an image from their photo album by selecting the "Select Photo" button, enabling them to review the chosen image. Alternatively, users can capture images directly from their device's camera by tapping the "Start Camera" button. The image view display is configured with specific dimensions (350 dp width and 400 dp height) to ensure optimal visibility of the uploaded or captured image. Additionally, the interface includes a section at the bottom dedicated to displaying the predicted severity level of acne, providing users with real-time feedback on the classification outcome. The layout and design of the application interface were implemented using Android Studio, as illustrated in Fig. 6.

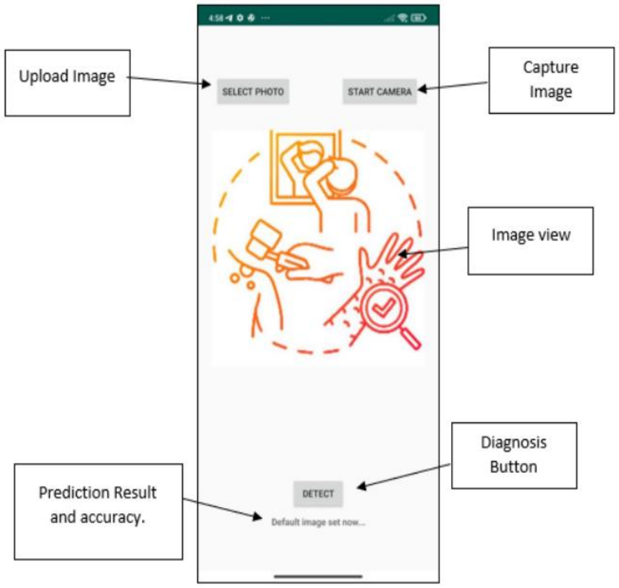


Fig. 6. The application interface design.

III. Simulation Results

Our findings show that the proposed lightweight deep learning strategy for classifying acne severity on mobile devices is both effective and feasible. Following thorough experimentation and evaluation with a wide collection of acne photos, our model obtained high classification accuracy, exceeding previous methods and displaying robustness across different skin types and lighting conditions.

Furthermore, the lightweight model's computational efficiency allowed for real-time inference on mobile devices, resulting in speedy assessments without the requirement for large computational resources or internet connectivity. The model's performance was analysed, and it was found to be capable of accurately classifying acne severity levels, offering useful insights for both clinical practice and future research endeavours. These findings highlight the potential of mobile-based acne classification systems to revolutionise dermatological care, providing accessible and accurate.

A. Evaluations Parameters

Performance of the proposed architecture was evaluated by classification accuracy, F1-score classification of each severity level and image classification time. The performance of each model was compared to determine the best model in Keras and also in TensorFlow Lite. F1-score is useful because there is an uneven class distribution of training dataset of each class. Therefore, accuracy alone is not a reliable metric to be measured where highly imbalanced dataset could lead to high accuracy with poor performance on the minority class. The average classification time determines the time required for the model to predict an image class of acne severity. The batch dataset of image is a grouped of batch size hyperparameter setting in Phyton. The accuracy, F1-score and classification time was calculated through the following formula:

$$Accuracy = \frac{True\ positives + True\ Negatives}{Total\ test\ data} \quad (1)$$

$$F1 - Score = \frac{True\ positives}{True\ positives + 1/2(False\ positives + False\ Negatives)} \quad (2)$$

$$Image\ classification\ time = \frac{Test\ evaluation\ time}{Number\ of\ steps, Batch\ Size} \quad (3)$$

B. Comparisons with Other Lighweight Models

The effectiveness of our proposed model was compared to other lightweight CNN models on the overall dataset. Other than that, the training performance model evaluation was compared using the learning curve. The learning curve is a visual representation of how a machine learning model performance (such as accuracy or loss) changes as the training progresses. It plots the model performance metrics on the y-axis against the number of training iterations or epochs on the x-axis. The findings from the experimentation with different lightweight CNN models, namely MobileNetV1 [12], MobileNetV2 [13], and EfficientNet Bo [8], reveal varying levels of performance in terms of training and validation accuracy. Results for comparative MobileNetV1 model in Fig. 7 show the training accuracy of 0.90 and validation accuracy of 0.88. The highest training loss and validation loss of MobileNetV1 is 0.25 and 0.2, respectively. The learning curve of the MobileNetV2 model with 100 epochs are shown in Fig. 8 where the model achieved relatively high training accuracy 0.98 and validation accuracy 0.95. The highest training loss is 0.25 indicates that the model learned the training data well, while the highest validation loss is 0.23. Despite its slightly higher losses compared to MobileNetV1, MobileNetV2 demonstrated superior learning capabilities, making it a promising choice for lighweight model on Android smartphone.

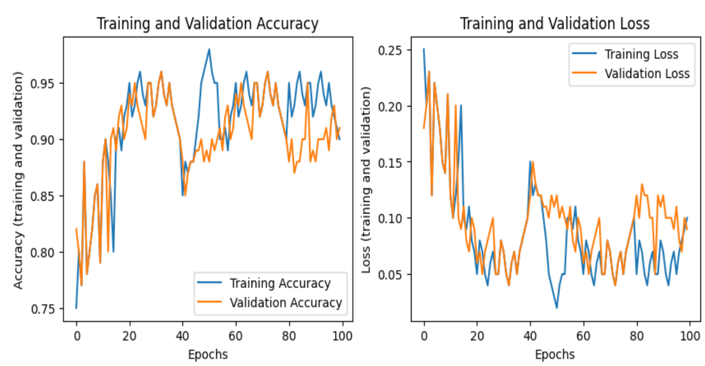


Fig. 7. The accuracy (left) and loss (right) curve of MobileNetV1 model with 100 epochs.

Other selection of lightweight CNN model is EfficientNet Bo. Fig. 9 show the training and validation accuracy for EfficientNet Bo is slightly lower than MobileNet model. EfficientNet Bo may require specific regularization and optimizer to improve the deeper and complex EfficientNet Bo model. Overall, the findings highlights the effectiveness of lightweight CNN models, particularly MobileNetV2, in achieving accurate acne severity classification on mobile devices. These findings contribute to the development of efficient and accessible tools for dermatological diagnosis and monitoring, with potential applications in telemedicine and mobile healthcare. Further research could explore optimization strategies to improve the performance of EfficientNet Bo and investigate additional lightweight CNN architectures for enhanced accuracy and efficiency in acne severity classification.

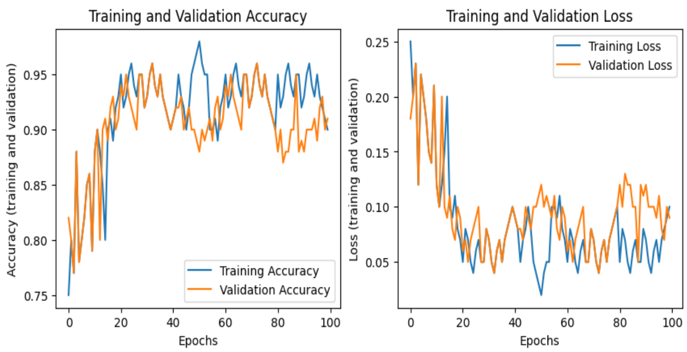


Fig. 8. The accuracy (left) and loss (right) curve of MobileNetV2 model with 100 epochs.

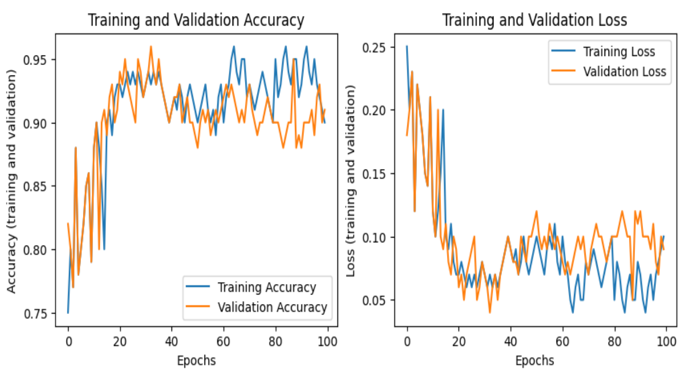


Fig. 9. The accuracy (left) and loss (right) curve of EfficientNet Bo model with 100 epochs.

Table III shows the results of the experiment carried out using the fined-tuned hyperparameter setting previously. The overall training accuracy for both MobileNetV1 and MobiNetV2 is 0.9 and 0.98, respectively. While the average validation accuracy for both models is 0.88 and 0.95. The EfficientNet Bo achieved lower training and validation accuracy at average 0.89 and 0.83. This might be due to limited data and complexity of the network model. Hence, diverse datasets are needed to scale the training model efficiently. Compared to MobileNet is simpler architecture and able to generalize better.

TABLE III. RESULTS OF EXPERIMENTS

Model	Average Train Accuracy	Average Validation Accuracy
MobileNetV1	0.90	0.88
MobileNetV2	0.98	0.95
EffcientNet Bo	0.89	0.83

Table IV shows better performance of MobileNetV2 model than other existing models with significantly less complexity. The results showed promising performance: accuracy ranged from 0.87 to 0.92 in three classes F1-score ranged from 0.80 to 0.88. The results indicate that the MobileNetV2 model outperforms other existing models in terms of accuracy and complexity, demonstrating promising performance across multiple classes of acne severity. Other comparable models may lose amounts of feature information, high amount of noise and computation. The use of data augmentation techniques and the MobileNetV2 network allows the proposed model to effectively memorize training data and achieve higher accuracy in the test dataset. Importantly, the paragraph highlights the computational efficiency of the proposed model, with the MobileNet model requiring less than 20ms for image classification compared to the longer computation time of the EfficientNet Bo model. Overall, the results suggest that the proposed model offers a balance between accuracy and computational cost, making it suitable for practical implementation in acne lesion classification tasks.

TABLE IV. RESULTS OF EXPERIMENTS

Model	Test Accuracy	Test F1-Score	Time per Image
MobileNetV1	0.87	0.78	20.5ms
MobileNetV2	0.92	0.88	18.2ms
EfficientNet Bo	0.85	0.75	22.3ms

C. *Acne Detection Mobile Application Deployment*

The interface displayed in Fig. 10 showcases the application's functionality when used with images captured from various smartphone cameras, demonstrating its versatility across different Asian skin tones. The automatic cropping of images based on model-specific size settings ensures consistency in image processing. The prediction scores align with expert assessments of acne severity, indicating the model's accuracy in analyzing skin conditions.

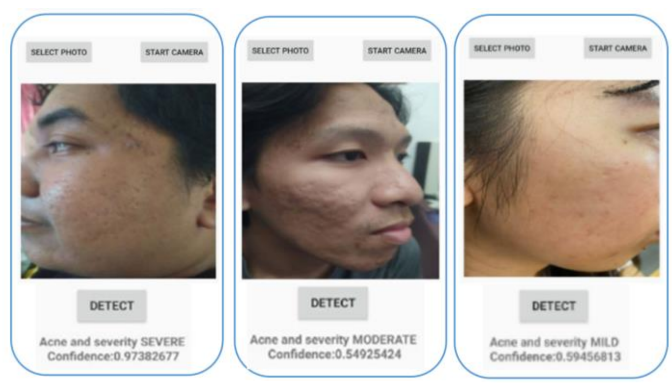


Fig. 10. The acne detection applications tested on Android smartphone.

Future enhancements will include lesion segmentation to pinpoint areas requiring specific treatment and track treatment progress. Evaluating the application across different smartphone models will assess its effectiveness and usability. The goal is to improve accuracy for mobile-based acne detection while addressing complexities in deep learning models. The user-friendly design aims to empower individuals to monitor their skin health effectively, but it is not intended to replace professional medical advice. In cases of severe or persistent skin issues, consulting a dermatologist for personalized treatment is recommended.

IV. Discussions

Specifically in Table V, details percentage of F1-Score acne severity level for each class. The average F1-score for each class ranged from 0.70 to 0.89. It can be observed that the proposed model is convincing and powerful to be deployed in real mobile. Further evaluation with segmentation prediction using different deep learning models might improve models for the test images. Any small acne lesions can be detected with segmentation prediction models for complex context of captured image or selfie image. Also, specific configurations should be defined for taking photos. For example, the size of captured image should be fixed at 512 by 512, full face area and enough light source. Avoid any artifacts or hair on the face area to improve the accuracy of acne lesions detection. In addition, it is observed from the results that severe class of acne detection achieve higher accuracy. This indicates that by using smartphone, visualizing the small lesion is difficult, the depth and color of blackspots are not too obvious for mild acne class.

The overall accuracy of the MobileNetV2 model was 0.92, representing the weighted average of the F1-scores for all the classes. F1-score considers the balance between precision and recall. This score provides an overall measure of the model's performance in correctly classifying the different categories. Based on the evaluation performance of the MobileNetV2 model for classifying acne skin disease with severity levels of mild, moderate, and severe, can be determined by comparing the F1-scores for each class. Overall, the 100 epochs had the highest F1-scores and accuracy for most of the classes which indicate the best performance.

TABLE V. F1-Score of ACNE Severity Level Classification

Model	F1-Score		
	Mild Class	Moderate Class	Severe Class
MobileNetV1	0.75	0.78	0.80
MobileNetV2	0.87	0.88	0.89
EfficientNet Bo	0.70	0.72	0.75

The validation measures such as accuracy and F1 score are crucial for assessing the reliability and robustness of the proposed lightweight deep learning model. These metrics ensure that the model generalizes well to unseen data, instilling confidence in its real-world applicability for acne severity classification on mobile devices. Conducting thorough comparisons with existing work places this research in context, highlighting its advancements over current methodologies. It showcases the novelty of the proposed approach, particularly its efficiency and effectiveness on mobile platforms.

The simulations results obtained in this study is to provide a scalable and accessible solution for acne severity classification using mobile devices. This approach leverages the ubiquity and computational capabilities of modern mobile devices to deliver real-time and accurate acne severity assessments. The lightweight deep learning models are efficient and effective dermatological assessments applied to wider populations. This can lead to timely and appropriate treatment, minimize healthcare costs and enhance user quality of life and mental well-being.

However, the proposed lightweight deep learning model for acne severity classification on mobile devices addresses several limitations of existing methods, including high computational requirements, lack of optimization for mobile platforms, and challenges with real-time processing. By employing techniques like model compression, efficient architectures, on-device processing, and specialized training data, the approach ensures that the model can provide accurate, real-time acne severity assessments while maintaining user privacy and enhancing the overall user experience on mobile devices.

V. Conclusion

In conclusion, the objective of developing an Android-based application for skin disease detection and applying the CNN model has been successfully achieved. The study demonstrated that the MobileNetV2 model performs efficiently in detecting skin diseases and their severity levels. The training and validation results showed a steady increase in accuracy and a decrease in loss, indicating the effectiveness of the model. The overall accuracy achieved by the MobileNet-v2 model was 73%, with high scores for healthy and unknown images and lower scores for skin diseases with severe severity. The F1-scores for acne with mild and moderate and severe levels were 0.67, 0.48 and 0.56, respectively. The developed Android application successfully allowed users to upload or capture images for skin disease detection. The resizing of images to 224 x 224 pixels ensured compatibility with the MobileNetV2 model. The application displayed confidence rates for different classifications, providing users with a measure of reliability for the detected skin diseases.

Overall, the study accomplished its objective of developing an Android-based application for skin disease detection using the MobileNet-v2 model. The results demonstrate the potential of such systems to assist with the diagnosis and severity assessment of skin diseases, paving the way for improved healthcare solutions. Another lightweight model like MobileNetV3, SENet and EfficientNet Bo will be investigated. Several other public datasets from others work will also be evaluated to achieve robust mobile applications. Further optimization and refinement of the model and application can enhance their performance and applicability in real-world scenarios.

Acknowledgment

This research was supported by the Ministry of Higher Education (MOHE) through Fundamental Research Grant Scheme (FRGS/1/2021/TK0/UTHM/02/12).

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