Acne Type Recognition for Mobile-Based Application Using YOLO

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Abstract. Acne is a chronic skin condition that happens to most teenagers at the age of 12 and 25. Several types of acne are found as non-inflammatory and inflammatory skin disease. As the number of people facing acne problems increasing and there is the need to have an automated application for recognizing acne, this study proposed a mobile-based application that able to recognizes acne types. This study used the Deep Learning technology method, YOLOv4 in detecting and recognizing acne. There are four types of acne covered in this study which are cyst, papule, pustule, and whitehead. The dataset used for the purpose of training and testing the model is from the DermNet NZ dataset. Based on the testing conducted, the application achieved 91.25% average of accuracy. It is believe, the integration of YOLO with any existing Deep Learning approach could improve the recognition rate in future.

1. Introduction
Acne is a chronic skin condition that happens to most teenagers at the age of 12 to 25. Several types of acne are found as non-inflammatory and inflammatory skin diseases such as blackhead, whitehead, papules, pustules, nodules, and cysts [1][2]. In recent years, the process of acne analysis is done traditionally where the process of outlining the ROI is conducted manually. Accordingly, the acne spotted in the ROI will be count and mark physically on the patient's face. This manual process may lead to false acne detection and recognition. Furthermore, the similarity between one type of acne to other type of acne remain a challenging task [2][3].

Despite the challenges in the manual process of acne recognition, the need from the patient to see the dermatologist remain increasing due to high demand. It is very difficult for a patient to wait for the availability of the dermatologist [1][4]. Hence, there is a need for an automated acne type recognition application that could ease these people. The proposed automated acne type recognition could offer a high accuracy recognition of the acne type with the elimination to see the dermatologist [2].

In the literature, vast explorations have been conducted in developing an automated acne type recognition application using both non-Deep Learning and Deep Learning based approach. Among of the research that used non-Deep Learning approach are [4][5][6][7]. They implemeted Haar Features and HSV Color Model in detecting and recognizing acne type. However, these works reported to achieved in average of only 70%.

Next, the Deep Learning based approach is reported to be widely applied in the development of acne type recognition application. [8][9][10] used Convolutional Neural Network for acne type recognition in which achieved the average of 80%. On the other hand, You Look Only Once (YOLO)
algorithm is applied in broad domain specifically in object detection and object recognition task. YOLO achieved an average of 85% for accuracy [11][12].

YOLO has been broadly used since it is straightforward, and the speed of detection is very quick [13]. Due to the good reputation of YOLO, this study proposed a mobile-based application for acne type recognition using YOLOv4.

2. Methodology
This section describes the methodology used in this study. There are 3 main phases conducted in this study which are data collection, model development using YOLO, and model testing. Figure 1 shows the proposed methodology for this study. Each phase will be described subsequently.

![Figure 1. Methodology proposed for this study.](image)

2.1. Data Collection
This study covers only four types of acne which are cysts, papules, pustules, and whiteheads. Figure 2 demonstrates four types of acne covered in this study.

![Figure 2. Acne types.](image)

In this study, the dataset from Kaggle website of acne images is used for training the model. The dataset is acquired from DermNet NZ which is the dermatology website that contain many skin diseases. However, images used for this study are retrieved from acne skin disease directory only. Hence, only 215 acne images are retrieved, and these images will be grow using Roboflow before proceeding the training process later.

2.2. Model Development using YOLO
You Look Only Once (YOLO) is a Deep Learning based technique. The architecture of YOLO allows an end-to-end training and it offers high average detection and recognition accuracy [14]. In addition, YOLO also offers high speed object detection and recognition capabilities in many applications including in autonomous vehicle, intelligent system, and virtual reality application [15].

Towards the implementation of YOLO, it uses features from the entire image, and it will predict the bounding boxes concurrently. The input image will be divided into S X S number of grids and each grid will generates B bounding boxes and with their confidence scores respectively. Figure 3 shows the process of dividing the image and labelling the score accordingly.
2.2.1 Data Training
The process of data training aims to produce a custom YOLOv4 model for the acne type recognition using a pre-trained model. All images will be annotated using LabelImg and consequently all these images will be feed to the Roboflow. In Roboflow, images were split into 63% for the train, 25% for validation, and 15% for test. Roboflow will allows the datasets to grow bigger based on the augmentation functions applied to the dataset. This study applied six augmentation functions which are rotation, grayscale, saturation, brightness, blur, and noise. This will enable the model to recognize the acne more efficiently despite various condition. For the purpose to find the most optimal separation between train, test and validation image, the model is tuning using different values. This study split the train, test and validation image into 60%, 15% and 25% respectively. Table 1 records the different tuning parameter value for the training process.

| No | Process | Value Set (%) | Accuracy (%) |
|----|---------|---------------|--------------|
| 1. | Train   | 65            | 21.00        |
|    | Test    | 20            |              |
|    | Validation | 15           |              |
| 2. | Train   | 60            | 68.00        |
|    | Test    | 15            |              |
|    | Validation | 25           |              |
| 3. | Train   | 80            | 58.00        |
|    | Test    | 10            |              |
|    | Validation | 10           |              |

3. Result and Discussion
This section discusses the accuracy testing and confusion matrix calculation conducted.

3.1. Accuracy Testing
As the prototype completed, the mobile application had to go through accuracy testing. This will make sure that all the objectives of the project stated are satisfied. The accuracy is identified by using a smartphone real-time camera move over a laptop screen displaying acne images. Table 2 shows sample accuracy testing of the system.
The overall quantity of images used to test the accuracy of the application is 80 images. Some of the prediction results generated from the table are false. The reason for the result considered false because the application misrecognized the acne type. For example, the acne type is papule but the result on the bounding box identified as cyst. This could be happened since cyst and papule seems similar to each other but different in size might confuse the application then produced a false result. To infer the overall accuracy result for each type of acne, the accuracy percentage is computed by using the formula as shown in Equation (1).

\[
\text{Accuracy} (\%) = \frac{\text{Number of correct prediction}}{\text{Total number of all cases of prediction}} \times 100
\]  

From equation 1, the number of correct predictions is the number of images with correct recognition that denoted as True. As a result, 73 out of 80 images achieved True and yields to 91.25% of accuracy.

3.2. System Output

This part addresses the results of the system testing carried out on the mobile application for acne type recognition that has been developed. 80 acne type real-time images of which 20 images were used for four categories. The columns are being used in the confusion matrix to show the Actual classes, while rows are used to indicate the predicted outcomes produced by the application. The confusion matrix outcomes are shown in Table 3.

### Table 2. Sample accuracy testing

| No | Real-time Image | Expected Result | Actual Result | Accuracy | Result |
|----|-----------------|-----------------|---------------|----------|--------|
| 1. | ![Image](image1.png) | Cyst | Cyst | 94.28% | True |
| 2. | ![Image](image2.png) | Papule | Papule | 63.20% | True |
| 3. | ![Image](image3.png) | Papule | Cyst | 61.39% | False |
Table 3. Confusion matrix

|       | Cyst | Papule | Pustule | Whitehead | Total |
|-------|------|--------|---------|-----------|-------|
| Cyst  | 17   | 19     | 17      | 20        | 20    |
| Papule| 59   | 57     | 60      | 57        | 20    |
| Pustule| 1   | 3      | 0       | 3         | 20    |
| Whitehead| 3  | 1      | 3       | 0         | 20    |
| Total | 18   | 22     | 17      | 23        | 80    |

The correct classification is noted along the upper-left to lower-right diagonals. This means that the correct classification is 17, 19, 17, and 20 respectively for the cyst, papule, pustule, and whitehead. Next, Table 4 presents the summary of the confusion matrix result obtained.

Table 4. Summarization of Confusion Matrix Result

|       | Cyst | Papule | Pustule | Whitehead |
|-------|------|--------|---------|-----------|
| TP    | 17   | 19     | 17      | 20        |
| TN    | 59   | 57     | 60      | 57        |
| FP    | 1    | 3      | 0       | 3         |
| FN    | 3    | 1      | 3       | 0         |

The accuracy, sensitivity and specificity of the mobile application Acne Type Recognition was analyzed quantitatively. The aggregate results obtained are represented in Table 5.

Table 5. Summarization of Confusion Matrix Result

| Type of Acne | Accuracy (%) | Sensitivity (%) | Specificity (%) |
|--------------|--------------|-----------------|-----------------|
| 1. Cyst      | 85.00        | 85.00           | 98.33           |
| 2. Papule    | 95.00        | 95.00           | 95.00           |
| 3. Pustule   | 85.00        | 85.00           | 100.00          |
| 4. Whitehead | 100.00       | 85.00           | 95.00           |
| Average      | 91.25        | 87.50           | 97.10           |

The average accuracy of the Acne Type Recognition Mobile Application is 91.25%, as seen in Table 5. It means that in understanding four distinct forms of acne, the suggested YOLO algorithm is able to return great results. In addition, to achieve high successes at 87.5% and 97.1% percent respectively, the average percentage of sensitivity and specificity values are also evaluated. In a nutshell, the YOLO algorithm's overall performance is known to be powerful and capable of correctly recognizing both the positive and negative classes, regardless of the distance and illumination barrier.

4. Conclusion
This study proposed the application of the real-time acne type recognition using YOLO algorithm. The cyst, papule, pustule, and whitehead are four types of acne utilized in this study. Using a confusion matrix, the performance of the YOLO acne type recognition is analyzed.

The general average accuracy percentage represented a very high accuracy of 91.25%. It is concluded that YOLO algorithm has a remarkable success in detecting the acne types. It is believed the convergence of YOLO algorithm with any current Deep Learning technique could enhance the performance of the identification.

5. Acknowledgement
All authors would like to thank Universiti Teknologi MARA Cawangan Melaka for the research funding and support.
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