Automatic Detection of Acne Types Using The YOLOv5 Method

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ABSTRACT

Acne is very common due to several factors such as hormones, hygiene, and environmental exposure. This research aims to develop an automatic detection system for facial skin problems using the You Only Look Once v5 (YOLOv5) algorithm, focusing on the problem of acne types on acne-prone faces, and this research is the latest research that has never been done before. The research methodology was carried out by taking datasets directly on acne faces, with a sample of 1230 images. The research process includes data collection, labeling using the Roboflow platform, dividing the dataset into training, testing, and validation data, and implementing the YOLOv5 algorithm using Google Colab. The research stages include data input, object labeling, dataset configuration, YOLOv5 preparation, modeling, model testing, hyperparameter tuning, and model performance evaluation. The results of this study resulted in an accuracy rate seen based on the mapped value of 87.6%, so this can be considered that the model is considered good in detecting the type of acne on facial skin problems in accordance with testing on data, and this model can be implemented to automatically detect facial skin problems, especially on faces with acne, in the future.

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1. INTRODUCTION

Object detection is an important task in computer vision that aims to recognize and identify instances of visual objects of a certain category (such as humans, animals, or vehicles) in digital images [1]. This time, object detection can be performed on facial skin in computer vision, which focuses on recognizing and identifying areas of human facial skin in digital images or videos.

The skin is a part of the body that reflects a person's health and vitality, so taking care of facial skin is an important aspect of self-care. Skin is complex, elastic, sensitive, and varies based on factors such as age, race, and physical condition. Each individual has different skin types, such as oily, normal, dry, and sensitive skin. This difference causes the skin problems experienced by each person to vary, so the need for facial skin care is in accordance with the existing facial skin problems [2].

Skin that is prone to oiliness and acne, especially in adolescents aged 13 years and over, really needs care with the first step, namely the use of skincare regularly, and then further care can be done by doing treatment according to needs [3]. Mishael Octaviany, who has experience in the field of non-surgical aesthetic treatments and joined Maharis Clinic in 2020 to become Head Doctor at Clinic de Votre Peau, revealed that the prevalence rate of acne is 64% in their 20s, 43% in their 30s, and 1.7% in their 50s and above. In addition, acne usually occurs due to several factors, namely hormones, skin hygiene, sun exposure, and inappropriate cosmetic products [4]. Information sourced from the human health consultation platform, Halodoc, states that there are several types of acne that are often experienced by humans, namely whiteheads, blackheads, papules, pustules, and nodules [5]. However, in addressing this issue, knowledge of the type of acne suffered is necessary, so facial skin care for acne problems is generally carried out after a direct examination of a person's face to detect the type of acne problem because acne has many types, and each requires a different approach. However, this detection process takes time. To accelerate the detection of acne-prone facial skin issues, advanced detection technology based on machine learning can be used [6]. Based on the problems and strategies based on automatic detection that have been previously described, the researchers have a research objective focused on the evaluation and recommendation of appropriate beauty treatments in taking preventive actions against acne-prone facial skin issues quickly and accurately.

Machine Learning (ML) is a branch of artificial intelligence that allows computer systems to learn and improve their performance automatically based on data, without the need to be explicitly programmed for each specific task [7]. In the ever-evolving digital era, the volume of human-generated data is rapidly increasing, making ML a highly relevant tool for addressing complex challenges in various fields, particularly in the detection of facial skin problems. Good classification implementation minimizes training errors and improves test accuracy on unknown datasets. Before that, researchers conducted dataset labeling with the help of an object detection platform, Roboflow [8].

Roboflow is a platform designed to facilitate the development of object recognition and image classification models in the field of computer vision. The platform offers a comprehensive solution, from dataset management to model training and deployment. In dataset management, Roboflow allows users to upload images, adjust their size, as well as add the necessary annotations to train the object recognition model [9]. Annotation can be done manually or using the tools available on the platform, making the process more efficient and accurate. Once the image classification is done, the next step is object detection using the You Only Look Once (YOLO) algorithm [10].

YOLO is a deep learning algorithm applied to detect objects in real time by using an artificial neural network (neural network) on an image [11]. The YOLO algorithm has been applied in various studies. The YOLO method can detect an object with accurate results and a very fast detection time. Currently, there are several versions of the YOLO algorithm, ranging from YOLOv1, YOLOv2, and YOLOv3 to YOLOv8 [12].

YOLOv5 has become very popular due to its ease of use as well as improvements in terms of speed and accuracy. YOLOv5 offers several model sizes (s, m, l, x) that allow users to balance between speed and accuracy as needed. This model is capable of reaching speeds of up to 10 frames per second (FPS). In addition, YOLOv5 has a very small file size, almost 90% lighter [13].

Research conducted by Mulyana and Rofik in 2022 [14] on the implementation of real-time detection of vehicle type classification in Indonesia using the YOLOv5 method. The study has concluded that the detection of vehicle types using the YOLOV5 method runs well, and the accuracy value is quite high. In addition, another study researched by Malik in 2023 [9] on human face identification using YOLO frameworks with the scale modifier method as preprocessing in real-time found that this study showed an average accuracy rate of 94.19% in identifying 20 human faces, based on three tests on each side. The test results show a precision value of 0.91 and a recall of 0.91.

Other research conducted by Hidayat in 2023 [13] on the implementation of the YOLO V5 algorithm for monkey type classification, using mAP (mean average precision) from 3805 training data, resulted in a very high value in classifying monkey types, which reached 99.5%. In addition, there is research conducted by Arvio et al. in 2024 [15] on the Efficient YOLO v5 Algorithm for Identifying Defective Masks on Production Machines. It was found that each model has advantages and disadvantages, where YOLOv5n has a fast computation time of 146 ms with 96.6% accuracy, while YOLOv5m shows the highest accuracy, reaching 100% but with a computation time of 537 ms. Therefore, YOLOv5n is more suitable for detecting defects in mask production at a rate of 100 masks per minute. Based on previous research, there has been no research on the automatic detection of facial skin problems using the YOLOv5 method. This research focuses more on the level of accuracy of the results of detecting facial skin problems in evaluating beauty treatments, especially on facial problems that have acne.

2. MATERIAL AND METHOD

The population in this study consists of facial images that include the types of acne experienced by students of the Faculty of Mathematics and Natural Sciences, Islamic University of Indonesia. The samples used in this study are facial images categorized into five classes, namely blackhead, whitehead, papule, pustule, and nodule found on students of the Statistics Study Program at the Islamic University of Indonesia. In this study, a total of 1,230 facial image samples were used. The data collection technique used in this research is image capture. The tools and methods for organizing data used in this research are as follows:

1. Image data acquisition of various acne types was performed using an iPhone 13 smartphone camera with 12 Megapixel (MP) camera specifications.
2. Dataset preprocessing involved importing images, labeling, resizing, augmentation, flattening, cropping, enhancing image quality, and exporting the dataset using Roboflow software.

3. The YOLOv5 model was trained by executing Python code on the Google Colab platform.
4. Code editing and script development were conducted using Visual Studio Code (VS Code).
5. The program script was executed via the Command Prompt (CMD) interface.

The algorithm used in this research is presented in the following diagram.

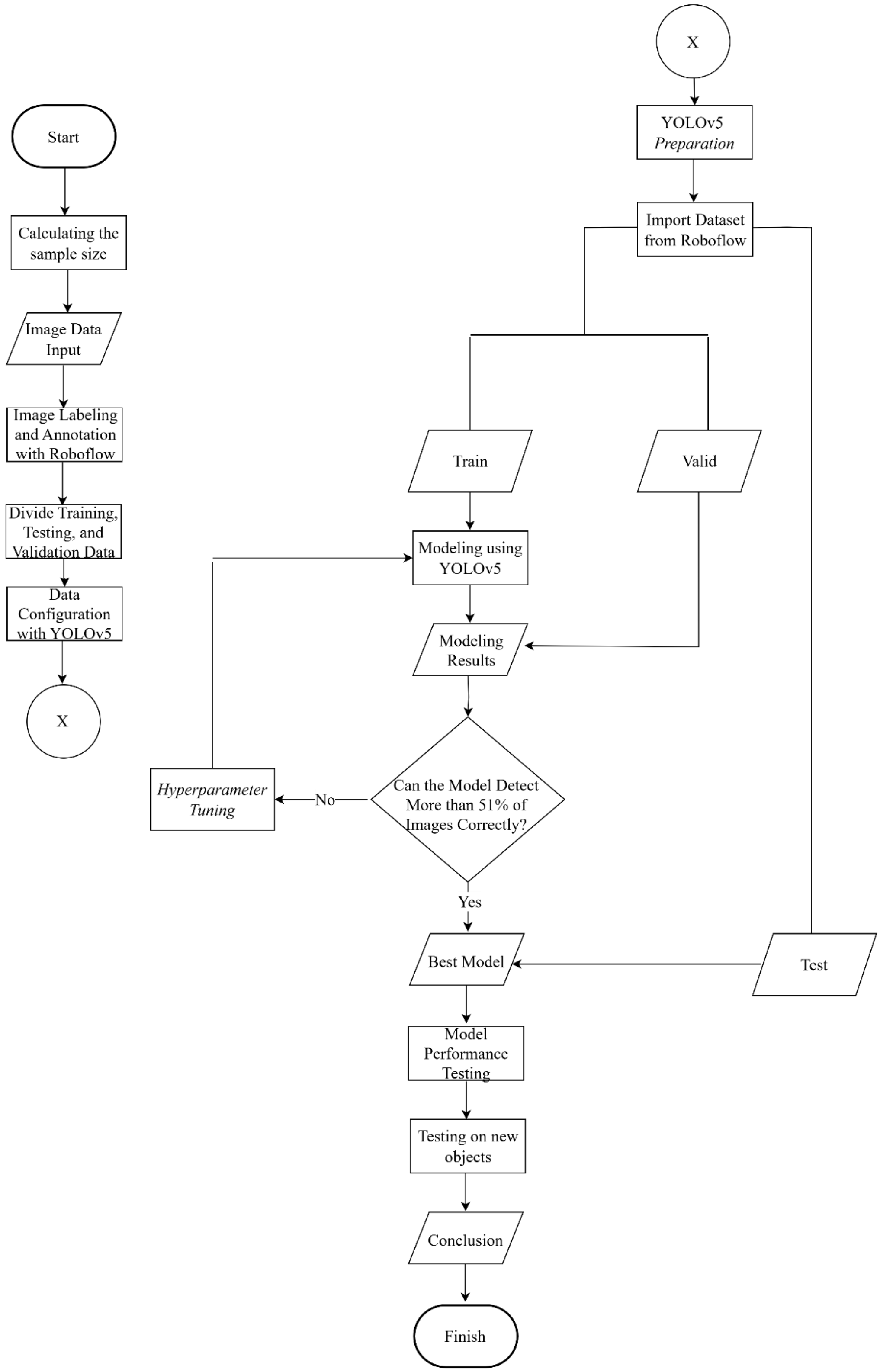


Figure 1. Research Flowchart

Based on the diagram in Figure 1, the research stages carried out are as follows.
1. Calculates the number of samples to be used in object detection.
2. Input image data for acne facial skin problems.
3. Manually label the image dataset object with the following criteria:
   a. Blackhead: This acne is usually found in areas with larger oil glands, such as the cheeks, forehead, chin, and nose. These pimples are characterized by a black or dark brown color because the top of the pore remains open, allowing the mixture of sebum and dead skin cells to oxidize.
   b. Whitehead: This acne has white or slightly yellowish characteristics because the top of the pore is tightly closed so that it can prevent oxidation. For its size, it is small, but if you touch it directly, you can feel it.
   c. Papule: This pimple is characterized by small red or pink bumps and does not contain pus but will be painful to the touch.
   d. Pustule: This pimple is the result of the development of papule acne, which is small but the lump contains pus.
   e. Nodules: These pimples are large, red, and hard bumps. This acne feels very painful to the touch or often painful if not touched and forms deep below the surface of the skin.
4. Annotate images using Roboflow software.
5. Divide the data into training, testing, and validation data.
6. Configure data or adjust datasets according to the YOLOv5 format.
7. Perform YOLOv5 preparation by copying the YOLOv5 git repository to Google Colab.
8. Import data into Google Colab using Roboflow API code.
9. Conducting the modeling stage with the process of creating, adjusting, and evaluating algorithms on training data.
10. The best model was obtained from the validation results.
11. Conducting model testing by testing and evaluating model performance to be able to make predictions on testing data.
12. Perform hyperparameter tuning by changing the parameters in the testing process if the detection result is less than 51%.
13. Conducting detection tests on acne-prone facial skin problems in real-time.
14. The results of model evaluation on testing data were obtained in the form of accuracy, F1-score, precision, and recall.

2.1 Counting the Number of Samples

The data adequacy test was carried out to determine the number of images needed in the training of the acne face detection model by associating it with the specified number of classes (k). Several factors must be considered, such as model complexity, number of classes, proportion of classes, and accuracy goals. However, the researcher must find out the number of samples using the Cochran formula 1 [16].

$$n = \frac{Z^2 pq}{e^2} \tag{1}$$

Where n is the number of samples required, Z^2 is the z-score for the 95% confidence level (1.96), p is true odds, q is the wrong chance (1-p), and e is the margin of error.

After obtaining the proportion of samples per class, the next step is to determine the total number of samples with the following calculations as equation 2.

$$\text{Total Sample} = n \times k \tag{2}$$

Where n is the number of samples per class, and k is the number of classes.

If the class distribution is unbalanced, the class with the smallest number of images will determine how many total images are needed by taking more images for a sparse class or using oversampling or data augmentation techniques to balance the number of images between classes.

2.2 You Only Look Once (YOLO)

You Only Look Once (YOLO) is a program that aims to detect objects quickly. The model applied to YOLO is an image of several locations and scales, where the area with the highest level of accuracy of the detection results is considered a good detection result. YOLO relies heavily on the input image because there are several grid cells with the same number of small boxes, either rows and columns or S x S. Each grid cell has an important role in predicting the number of bounding boxes and the confidence value for each bounding box so that the confidence score can represent how accurately the model can detect objects contained in the bounding box and a value to estimate the accuracy of the bounding box itself. The confidence score value can be defined as equation 3 [17].

$$\text{Confidence score} = \Pr(\text{Class}) \,.\, \text{IoU}_{\text{Pred}}^{\text{Truth}} \tag{3}$$

Where Pr (Class) is probability or confidence in the prediction result, and $\text{IoU}_{\text{Pred}}^{\text{Truth}}$ is measures the extent to which a prediction matches the truth.

If no object is detected by the grid cell, then the confidence value will be equal to the Intersection Over Union (IOU) between the ground truth and the prediction box.

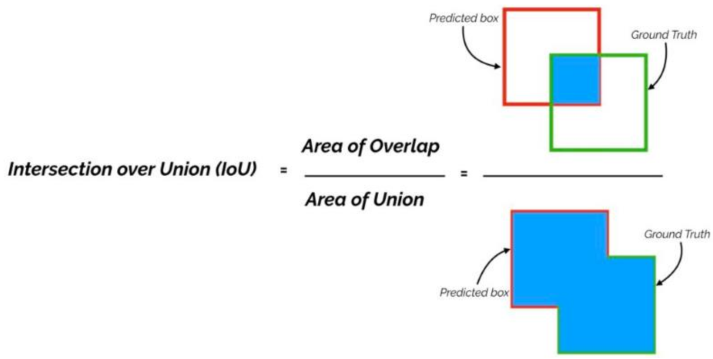


Figure 2. Intersection Over Union (IOU) Calculation [18]

Intersection Over Unian is a calculation method to measure the accuracy of object detection on a dataset. In this case, the IoU will make a comparison between the bounding box in the actual data and the bounding box in the prediction data. Here is the workflow of the YOLO algorithm.

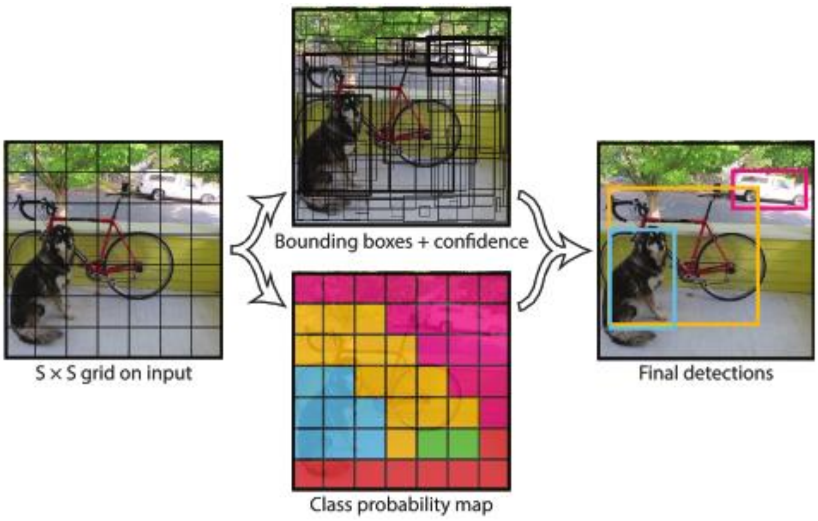


Figure 3. YOLO Algorithm Workflow [19]

Based on Figure 3, the YOLO process is carried out by dividing the input image into small boxes of 7 x 7 first, then obtaining the prediction results of bounding boxes and confidence from the processing results, after which it shows the chance of predicting the object class, and then the last one is obtained the final object detection results along with the confidence value and the object class [20].

YOLO is a technique that uses an artificial neural network approach in detecting image objects. The network used by YOLO has 24 convolutional layers followed by two fully connected layers, so to reduce the depth of feature maps, several layers are reduced to 1x1, which is then followed by 3x3 layers. The following is the architecture of the YOLO network, can view figure 4 [21].

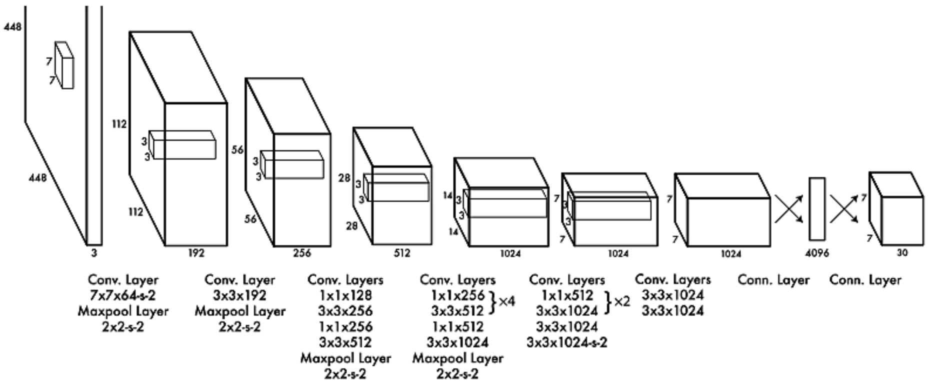


Figure 4. YOLO Network Architecture [22]

Convolution here can be interpreted as the process of getting pixels based on the value of the pixel itself as well as other pixels by using a matrix called the kernel to represent weights. The operation is carried out by multiplying the points in three dimensions of the image matrix, which is input by starting from the upper left corner of 3x3. The size of the matrix is then multiplied by the 3x3x3 kernel filter. The first convolution operation is performed using a one-dimensional kernel filter on a one-dimensional image matrix so that the output of the convolution operation will produce a feature map with a size of 3x3. The training process aims to find the optimal weight and the best kernel filter in detecting the image objects that have been inputted [23].

2.3 YOLOv5

YOLOv5 is one of the fixes that have been done before. The principle of the YOLO algorithm is to detect objects by evaluating a grid of pixels based on their color and shape so that they can be trained to detect and classify damage to buildings. Here is the architecture of YOLOv5 [15].

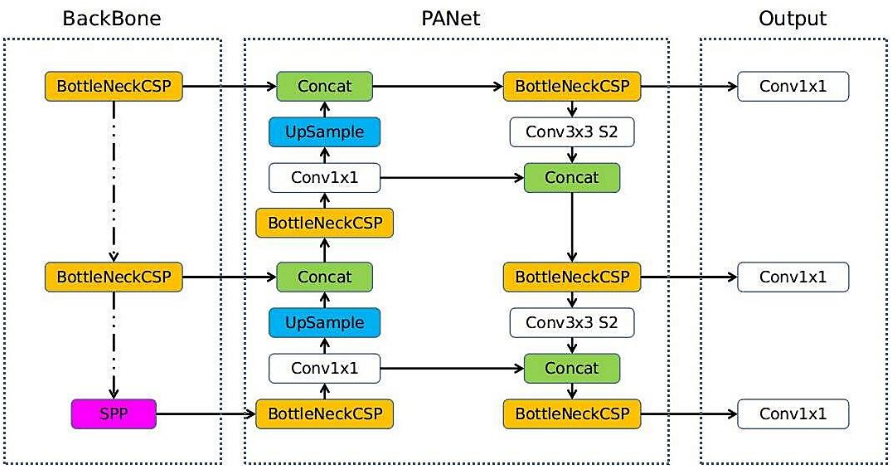


Figure 5. YOLOv5 Architecture [23]

Figure 5 shows that the process cannot consume a large dataset compared to CNNs that do not use YOLO, so in this case, YOLO is the most advanced method to speed up the object detection process. YOLOv5 has the advantage of faster detection speed because it only requires a lower inference time compared to other versions of YOLO, namely with a time range of 1 ms to 3.25 ms, and the mAP value given is not too different between YOLOv5 and the next version. Besides that, YOLOv5 has the advantage of a lighter model with a smaller size than the previous version. This is evident from the comparison of the type and performance of the YOLO version in the figure 6 [23].

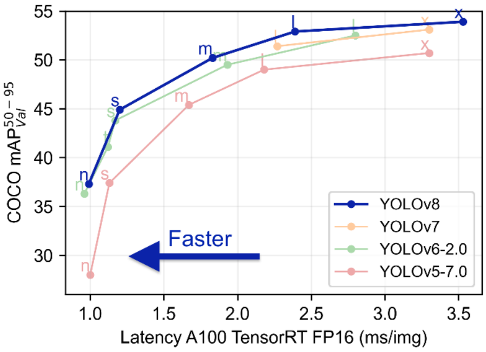


Figure 6. YOLO Type and Performance [23]

2.4 Confusion Matrix

The confusion matrix can provide information in the form of the results of comparisons between classifications carried out by the model. The confusion matrix has calculations by comparing the total number of correct classifications for events that occurred (true positives) compared to events that did not occur (false positives), as well as the total number of false classifications for events that occurred (false negatives) compared to events that did not occur (false positives). The following is an overview of the confusion matrix table 1 [23].

Table 1. Confusion Matrix

Confusion Matrix		Current	
		Positive (1)	Negative (0)
Predictions	Positive (1)	TP	FP
	Negative (0)	FN	MR

Based on the table, there are four components in the confusion matrix, namely True Positive (TP), which is a model for predicting correctly and indeed correctly; True Negative (TN), which is a model that predicts correctly and indeed is proven wrong; False Positive (FP), which is a model that predicts correctly even though it is wrong; and the last one is False Negative (FN), which is a model that predicts wrong when it is true. The calculation of the confusion matrix to determine the values of accuracy, precision, recall, and F1 score can be seen in the following equations 4-7 [23].

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{TN} + \text{FN}} \tag{4}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{5}$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{6}$$

$$\text{F1} - \text{Score} = 2 \times \frac{(\text{Precission} \times \text{Recall})}{(\text{Precission} + \text{Recall})} \tag{7}$$

Accuracy is the ratio of predicted results that are correct (positive and negative) to total data. Furthermore, there is a recall, which is a positive estimate of the total positive data. Precision is the ratio of the correct forecast positive outcome to the total positive forecast. Then the last one is the F1-Score, which is a comparison between the average precision results and recalls. F1-Score has a value ranging from 0 to 1, where 0 is the lowest value, while 1 is the highest value. F1-Score can represent that the classification model has good precision and recall [18].

The focus of the researcher in this case is to use an evaluation matrix on the detection object using mAP (mean average precision). mAP is generally used to evaluate models on machine learning, such as YOLO, R-CNN, and other machine learning models. Calculate the mAP score by looking for the average precision (AP) value first in each class.

$$AP = \sum_{k=1}^{N} (R_k - R_{k-1}).P_k \tag{8}$$

Where N is the number of data points (threshold) for the calculation of precision and recall, k is the point or threshold certain, R_k is the value recall at the point of k, P_k is the value precision at the point of k, and R_{k-1} is the change in value recall from the point of k−1 to the point of k

The result of the average precision value is then averaged by the number of classes that have been predetermined. The following is a formula for finding the value of the accuracy level of the object detection results [23].

$$mAP = \frac{1}{N}\sum_{i=1}^{N} AP_i \tag{9}$$

Where N is total specified classes, AP is average precision, and I is an index of each class.

3. RESULTS AND ANALYSIS

In this study, researchers will detect the type of acne in facial skin problems using the YOLOv5 algorithm with PyTorch in the Google Collaboratory.

3.1 Dataset of Acne-Type Problems on the Face

The dataset used in this study is secondary data obtained from the Kaggle platform related to various types of acne, such as blackhead, whitehead, papule, pustule, and nodule. Based on the dataset, 1241 datasets were obtained for acne image data. Additionally, before detecting objects, the researchers will calculate the number of samples per class using the Cochran formula found in equation (1). We assume that the smallest proportion of a class is 20% according to the number of classes (p=0.2) and obtained $n \approx 246$. Researchers needed a minimum of about 246 images per class to qualify using a 95% confidence level and a 5% margin of error. With the minimum total number of images calculated using equation (2), a total sample of 1230 was obtained for the 5 classes. Based on these results, a total of at least 1230 images were obtained to detect five types of acne, such as blackhead, whitehead, papule, pustule, and nodule, with good accuracy and balanced data distribution.

3.2 Preprocessing Dataset

At this stage, data preprocessing will be carried out, which includes object labeling, image resizing, and dataset distribution in the form of training, testing, and validation. The researcher resized the image size to pixels 640×640. The selection of the size considers the balance between relevant pixel information and ensuring the performance of the YOLOv5 object detection algorithm. This time, the researcher divided the dataset with a comparison of 70% with a total of 861 images of training data, 20% of validation data with a total of 246 images, and 10% of testing data with a total of 123 images.

The labeling process is carried out based on the YOLO output format, which consists of the results of object classification, the x and y coordinates of class objects, and the width and height of class objects. The labeling on the object consists of five classes, namely blackhead, whitehead, papule, pustule, and nodule. The results of this labeling are then stored in a single folder containing image files of acne facial skin problems based on their type.

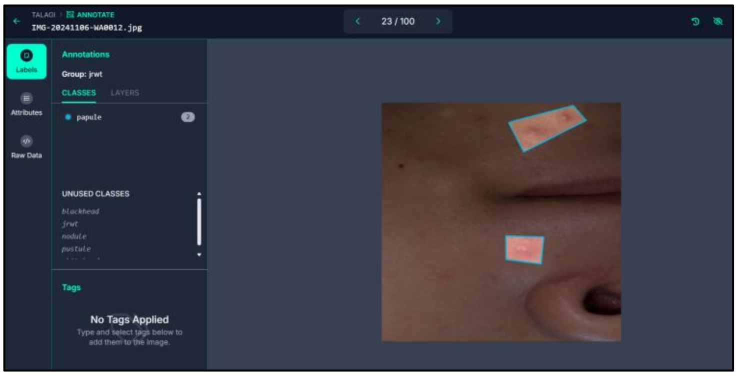


Figure 7. One of the Results of Labeling Objects on Images

Based on Figure 7, the labeling results on all images will be obtained in a file with the format ".txt", which is the basis for the detection object results in the training data with the YOLOv5 model.

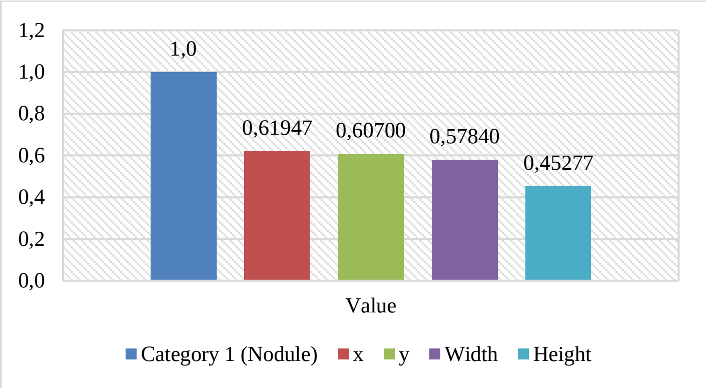


Figure 8. Visualization of one of the Object Labeling Results in the Image

In Figure 8, it can be interpreted that the contents of the data labeling file are as follows. (1) 1: The class number of the output object is included in category 1, namely the type of acne nodule. (2) 0.61947: The horizontal position (x) of the center point of the bounding box is a proportion of the width of the image. (3) 0.60700: The vertical position (y) of the center point of the bounding box as the height proportion of the image. (4) 0.57840: The width of the bounding box is a proportion of the width of the image, and (5) 0.45277: The height of the bounding box is the proportion of the height of the image.

3.3 Training Data

Object detection in this case uses Intersection Over Union (IOU) and Non-Max Suppression to measure the ratio of bounding boxes on an object that will be correctly predicted if the IOU is valued $> 0.5 - 0.9$. When an object has confidence > 0.5 value, it is given a bounding box on the object. And vice versa, if < 0.5, then it will be assumed that the object is not detected or background.

3.3.1 Epoch Value Testing, Batch, and YOLOv5 Models

This test was carried out to determine the influence of several parameters on the mAP value. The test results are presented in the table 2.

Table 2. Test Results

No.	Image	Epoch	Batch	folder
1	640	100	16	0.876

Based on Table 2, it can be seen that the mAP obtained with 100 epochs is 0.876, so the level of accuracy in the detection results is said to be a good result and the resulting model shows that the complexity of the model can affect the detection quality. Training data using YOLOv5 with a batch size of 16 and 100 epochs, the run time takes about 34.14 minutes.

Table 3. YOLOv5 Modeling Results

Class	Images	Instances	P	R	mAP50	mAP50-95
All	249	295	0.903	0.827	0.876	0.443
Blackhead	249	49	0.979	0.953	0.981	0.520
Nodule	249	54	0.977	0.786	0.887	0.440
Papule	249	68	0.845	0.868	0.853	0.397
Pustule	249	77	0.742	0.710	0.729	0.270
Whitehead	249	47	0.975	0.817	0.932	0.587

Based on the output, it can be seen that the performance of YOLOv5 that has been carried out can detect objects in the form of blackheads, obtaining 97.9% accuracy, 95.3% recall, 96.6% F1-Score, and an mAP value of 98.1%; nodule objects obtained 97.7% accuracy, 78.6% recall, F1-Score 87.1%, and the mAP value was 88.7%; the papule object obtained a precision of 84.5%, recall 86.8%, F1-Score 85.6%, and the mAP value of 85.3%; the pustule object obtained a precision of 74.2%, recall 71%, F1-Score 72.6%, and an mAP value of 72.9%; and the whitehead object obtained a precision of 97.5%, recall 81.7%, F1-Score 88.9%, and an mAP value of 93.2%. Here is a performance graph of the YOLOv5 model.

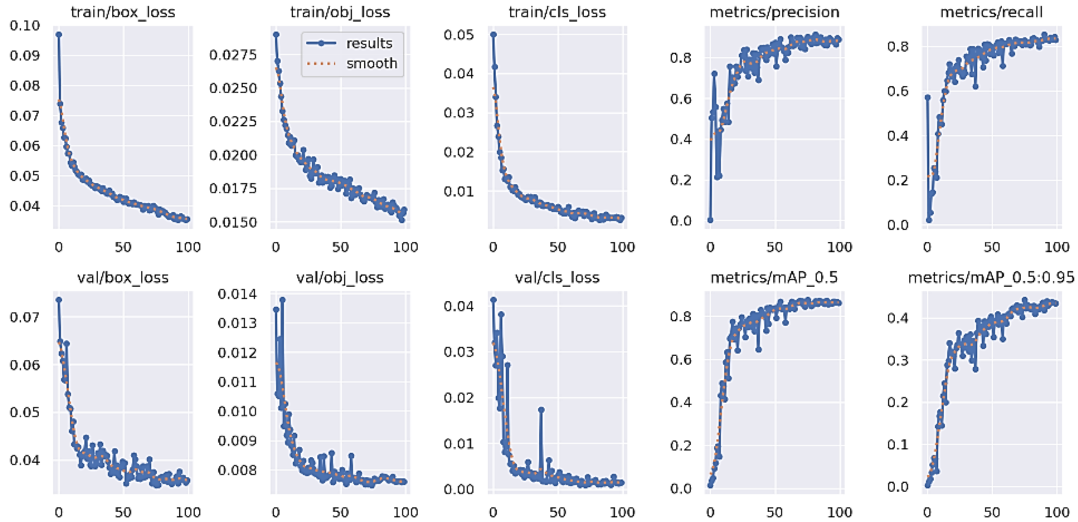
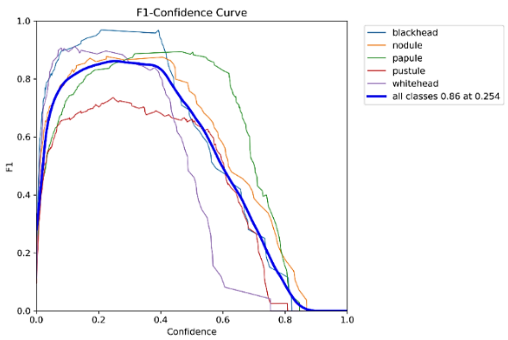
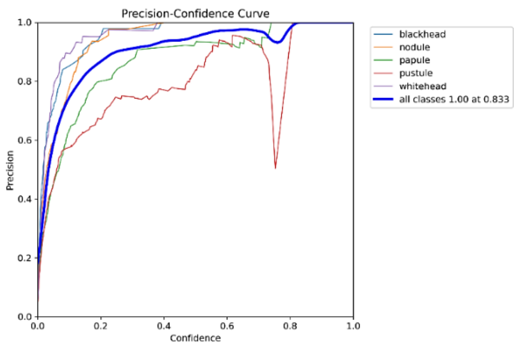


Figure 9. YOLOv5 Model Performance Graph

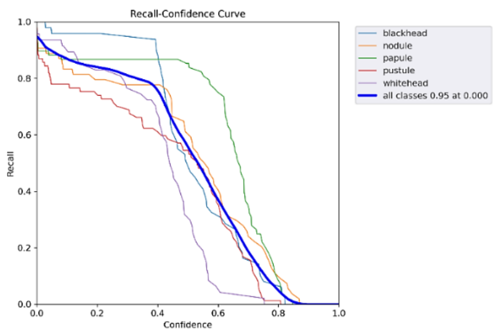
Figure 9 is a box, object, and classification chart that represents changes that occur in the loss value. At the beginning of the training, the loss was around 0.9, but as the epoch progressed, the loss dropped to close to 0, around 0.04. The train/obj_loss graph on the training data decreases as the epoch progresses, from 0.0275 at the beginning of the training to close to 0 around 0.015, which shows that the model is getting better at detecting the presence of objects. Precision increases close to 0.85 when the epoch reaches 100, so the model has a fairly high level of accuracy, i.e., about 80% of all positive detections are correct. The recall value also increased steadily and reached about 0.8 by the end of the training, which means that the model managed to find about 80% of all objects that should have been detected. In the graph, the mAP increases significantly, indicating that the model is getting better at detecting objects.



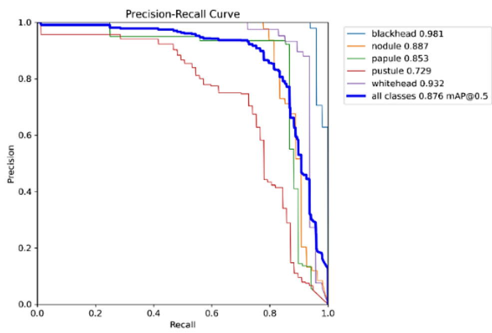
(a)



(b)



(c)



(d)

Figure 10. (a) F1-Confidence Value (b) Precision-Confidence Value (c) Recall-Confidence Value (d) Precision-Recall Value

Figure 10 (a) above confidence shows how confident the model is that the prediction is correct, and the value ranges from 0 to 1. It can be seen that F1-Confidence reached a high of 0.86 in the entire class when the confidence value was 0.254. Figure 10 (b) shows that the precision for all classes reaches its highest value when the confidence threshold value is at 0.833, as indicated by the thick blue line (aggregate of all classes). Figure 10 (c) interprets that the graph between confidence and recall in all classes has a recall value of 0.95 when confidence is 0. A high recall indicates the model's ability to detect most (or all) positive cases. When the confidence value is close to 1, the recall decreases for each class, as more positive cases no longer meet the confidence threshold. Figure 10 (d) shows the Precision-Recall curve, which illustrates the relationship between precision and recall. High precision means that most positive predictions are correct. A mAP@0.5 value of 0.876 indicates the average area under the Precision-Recall curve for all classes, provided that the prediction is considered correct if it has an IoU of at least 50% with ground truth.

3.4 Object Detection with YOLOv5

Next is the detection process using YOLOv5, which has been trained. After running, a "best.pt" file will be obtained in which there is a weight of the training data on the YOLOv5 network. Researchers can carry out the process of detecting acne problems on the face with a new object using weights on the training tissue.

3.5 Model Performance Testing against Datasets

Model performance testing on the dataset is seen on each class, which provides a comprehensive overview of the model's ability to accurately identify objects. The results of detection in each class will be explained by the researcher in the figure 11.

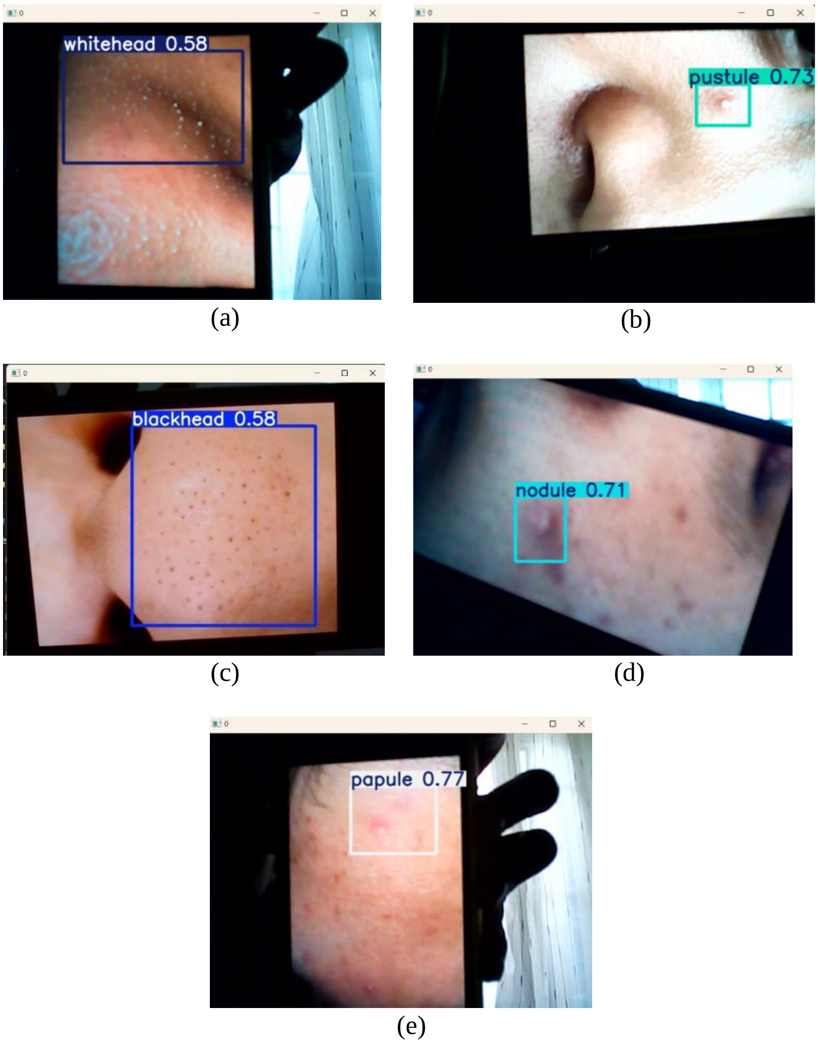


Figure 11. (a) Whitehead Detection Results (b) Pustule Detection Results (c) Blackhead Detection Results (d) Nodule Detection Results (e) Papule Detection Results

Based on the detection results, the average detection performance is above 0.50, so in this case, the network can recognize features of various types of acne, such as whitehead, pustule, blackhead, nodule, and papule well, which can then be evaluated and recommend suitable beauty treatments to take preventive actions against facial acne problems quickly and accurately. Some recommendations that researchers might provide for whiteheads and blackheads include regularly cleansing the face and using products containing salicylic acid to help clear the pores. Then, for pustule and papule types of acne, extra attention is needed with the use of products containing benzoyl peroxide or salicylic acid, which can reduce inflammation and kill acne-causing bacteria. It is also important not to squeeze acne to avoid worsening the condition or leaving marks. Next, the last type is a nodule, which requires maintaining skin cleanliness regularly and avoiding excessive stress, as stress can trigger the appearance of this type of acne. Thus, by maintaining the proper skincare routine, avoiding internal and external triggers, and using appropriate products. However, if the acne has reached a severe stage, researchers recommend seeking professional treatment from a dermatologist for optimal results.

4. CONCLUSION

Based on the description of the previous chapter in the study, it can be concluded that the test results were obtained using several parameters such as 100 epochs, batches of 16, and the YOLOv5 model that the dataset on the system successfully detected the type of acne on facial skin problems consisting of the types of acne "blackhead", "whitehead", "papule", "pustule", and "nodule" according to their respective performance levels, so, in this case, it can be said that the system can help to automatic detection of acne types and test results obtained using the YOLOv5 model as a whole produced an mAP value of 87.6% with a precision value of 90.3%, recall 82.7%, and F1-Score of 86.3% so that this can be considered that the model is considered good in detecting acne types in facial skin problems according to the test on the data. Although this research is about automated detection of facial skin problems using the YOLOv5 method, which has not been studied by anyone, there may still be limitations in this research related to other facial skin issues such as dark spots (hyperpigmentation), large pores, oily skin, dryness, and others, making it possible to expand the model.

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