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Development of a Raspberry Pi 4-Powered Internet of Things System for Acne-Prone Skin Health Monitoring

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ABSTRACT

This research developed an Internet of Things (IoT)-based facial skin health monitoring system, with a focus on acne-prone skin. Facial skin is categorized into three main types: normal, oily, and dry, as well as four types of acne: blackheads, papules, pustules, and nodules. The system is designed to enhance the accuracy of skin condition monitoring through facial image analysis, utilizing a dataset of 4,092 images. The high number of acne cases, especially in 12-24 year olds with 40-50 million cases in the United States, is the background of this research. Conventional skin analyzers are considered less capable of providing accurate quantitative data. Therefore, a Smart Skin Analyzer Detector was developed that uses a Raspberry Pi as a data processor. Images are taken through a webcam, analyzed, and then the results are sent to the cloud. The system is also integrated with Telegram to provide users with real-time notifications regarding their skin type and acne condition. This approach enables more effective, faster, and more affordable skin monitoring. The results demonstrate that IoT technology has significant potential in enhancing personalized and sustainable skin care.

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1. INTRODUCTION

The skin on the face is the most sensitive part of the body compared to other areas of skin, so it requires an accurate identification method to determine a person's skin condition and type [1]. Skin types such as oily, dry, and normal are often difficult to analyze without the help of digital analysis tools, because the visual characteristics of skin vary greatly between individuals [2]. According to the Global Burden of Disease report, acne is one of the most common skin disorders in the 15–40 age group, with an estimated 40–50 million cases each year in the United States and a prevalence of 85% in the 12–24 age range [2]. The high prevalence suggests that acne is a significant health issue, not just an aesthetic concern.

Various skin analysis devices available on the market, such as digital microscope-based Skin Analyzers, have limitations in providing accurate measurements, are expensive, and do not support real-time monitoring [3]. In addition, the device is not yet capable of producing quantitative output that can be processed digitally or automatically sent to users. Therefore, IoT technology offers a more effective, efficient, and sustainable solution for digital skin condition monitoring [4].

Several previous studies related to acne detection have been conducted using the Deep Learning approach, including the Convolutional Neural Network (CNN) method used by Sudana Putra et al [5] with 100% training accuracy, 88% testing accuracy, and research by Arifianto & Muhimmah [6], which implements TensorFlow with a sensitivity of 77.3% and an accuracy of 63.2%. The YOLOv8 model has been used by Meilita et al [7] to detect skin diseases in cats with high performance, but it has not yet been applied to humans. Previous research shows that image detection technology has developed rapidly, but there has been no research that integrates YOLOv8-based acne detection technology into a real-time IoT system using Raspberry Pi.

From this research gap, research was developed to design a Raspberry Pi 4-based acne monitoring system with the YOLOv8 algorithm, which is capable of automatically detecting skin type and acne type thanks to edge computing processing [8] In addition, integration with the Telegram application allows users to receive real-time notifications without the need for expensive devices or external servers. Thus, this research provides a modern solution that is fast, economical, and relevant for beauty practitioners and general users alike.

2. RESEARCH METHOD

This study consists of facial skin types and types of acne, the samples taken in this study are facial skin types, which are divided into 3 classes of normal skin, oily skin, and dry skin while the types of acne are divided into 4 classes namely blackheads, papules (papule), pustules (pustule) and nodules (nodule). A total of 4,092 face samples were used in this study.

1. YOLOv8 model trained by running Python code on the Google Colab platform [9].
2. Code editing and script development is done using Visual Studio Code (VS Code).
3. Execution of program scripts is done through the command prompt (CMD) interface..
4. Data analysis of facial skin types and acne types will be sent from the Raspberry Pi 4 to be analyzed and sent via the Telegram application.

The flowchart and block diagram used in this study are presented in Figures 1 and 2.

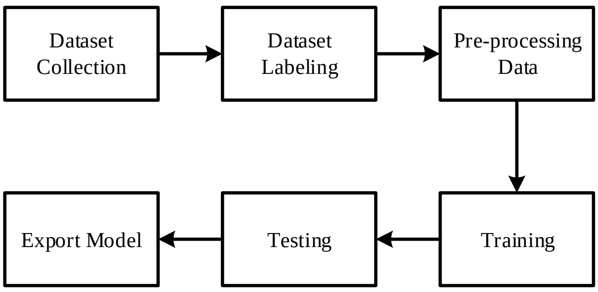


Figure 1. YOLO Block Diagram

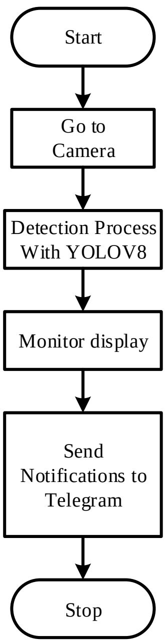


Figure 2. Flowchart of acne skin monitoring system

Each image is labeled using the YOLO annotation standard [10]. The preprocessing stages include resizing, augmentation, cropping, and image quality enhancement according to the procedures in Zhou's research [11]. The YOLOv8 model was trained using Google Colab with 100 epochs and a batch size of 16 based on the latest generation YOLO architecture recommendations. The Raspberry Pi 4 is used as an edge computing device because it has the ability to run lightweight deep learning models with low power consumption [12]. IoT integration is carried out using the Telegram API for automatic notification delivery [13].

2.1. You Only Look Once (YOLO)

YOLO is a method in computer vision used for real-time object detection in images or videos [14]. YOLO has the advantage of being able to detect objects in one pass (one "look"), making it very fast compared to other methods that require multiple stages of processing.[15], YOLO approaches the problem of object detection in a very efficient and effective way[16]

2.2. YOLOv8

YOLOv8 is the latest generation of the YOLO object detection algorithm developed by Ultralytics in 2020. As the successor to YOLOv7, this model introduces several significant improvements, particularly in terms of accuracy, processing speed, and implementation flexibility. Thanks to these updates, YOLOv8 exhibits superior performance compared to its previous version, particularly in terms of inference speed and object detection accuracy. This makes it highly suitable for application in real-time systems that require fast response and high precision [17]. Table 1 is a YOLO comparison.

Table 1. YOLO Comparison

Model	Speed	Accuracy	Flexibility
YOLOv1	Medium	Medium	Low
YOLOv2	Fast	High	Medium
YOLOv3	Very fast	High	High
YOLOv4	Very fast	Very high	High
YOLOv8	Very fast	Very high	Very high

2.3. Confusion Matrix

A confusion matrix is an assessment tool that compares the model's classification results with the actual conditions. This matrix offers insights into the number of accurate and inaccurate model predictions, regarding events that took place (true positives) and those that did not happen (false positives) [18]. True Positive (TP): refers to the scenario in which the model accurately identifies an event that is indeed true. True Negative (TN): describes the situation where the model indicates that an occurrence did not happen, and it turns out that it truly did not happen. False Positive (FP): represents a case in which the model suggests that an event took place, yet it did not (often referred to as a false alarm). False Negative (FN): denotes the instance where the model fails to recognize an event that actually occurred [18].

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

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

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

$$\text{Specificity} = \frac{TN}{TN+FT} \tag{4}$$

$$\text{F1-Score} = 2x\,\frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}} \tag{5}$$

2.4. Internet of Things (IoT)

In the development of an acne facial skin health monitoring system, an IoT-based approach is employed by integrating a YOLO-based object detection algorithm with a Raspberry Pi mini-computer device. The system is designed to automatically detect various types of facial acne, including whiteheads, blackheads, pustules, papules, and nodules, through real-time image input captured by a camera. The detection process is performed locally by a Raspberry Pi using the YOLOv8 model, which is capable of recognizing objects with high accuracy and efficiency. Once the inference process is complete, the detection results, in the form of annotated images (bounding boxes and classification labels) as well as confidence level information, are stored and automatically sent via a pre-configured Telegram bot. The transmission is done using the Telegram API, which allows the system to provide instant notifications to users or medical personnel regarding detected skin conditions. Thus, this system not only functions as an automatic detection tool, but also as an IoT-based communication medium that can accelerate the decision-making process in handling acne problems. The integration between YOLO, Raspberry Pi, and Telegram makes this system effective in providing continuous monitoring, real-time notifications, and supporting data-driven skin care personalization [19].

3. RESULTS AND ANALYSIS

This research aims to identify different types of acne and facial skin types using the YOLOv8 algorithm. The detection results will be processed through the IoT system and sent as a notification to the Telegram application.

3.1. Problem dataset of acne type and facial skin type

The dataset used in this study was obtained from the Roboflow platform, which includes various types of acne, such as blackheads, papules, pustules, and nodules. Facial Skin types include dry skin, normal skin, and oily skin. According to the dataset, 4,092 pieces of acne data, along with various types of facial skin, were collected. YOLOv8 dataset can be seen in Figure 3.

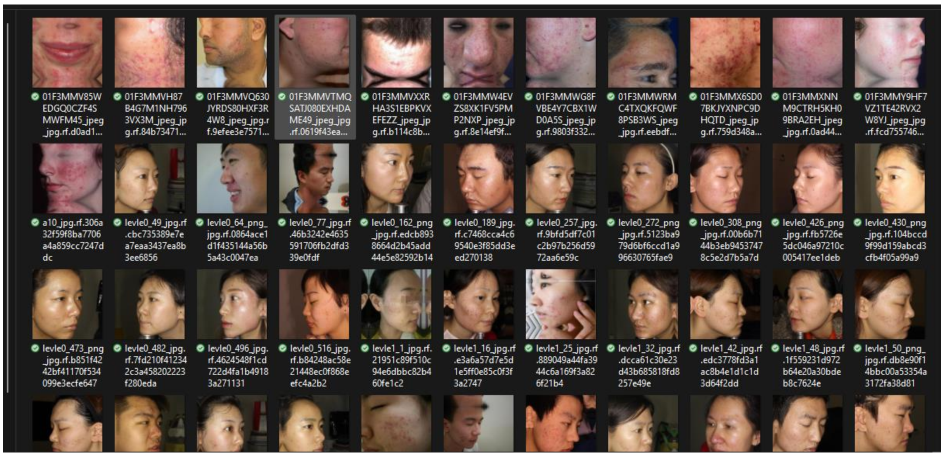


Figure 3. YOLOv8 dataset

3.2. Training data

Object detection in this study uses Intersection Over Union (IoU) and Non-Maximum Supression (NMS) to measure the bounding box ratio of objects that will be correctly predicted, These two techniques IoU and NMS work together to ensure that object detection is done accurately, avoid duplicate predictions, and increase the confidence that the detected object really matches the desired one.

3.2.1. Epoch Testing, and YOLOv8 Model

The purpose of this test is to evaluate the extent to which several parameters affect the mean Average Precision (mAP) value. The outcomes of the tests are presented in Table 2.

Table 2. Test Results

No	Image	Epoch	Batch	Folder
1	480	100	16	0.652

According to the findings presented in Table 2, a mAP value of 0.652 was obtained after the model was trained for 100 epochs, indicating that the object detection performance produced by the model is relatively good. This MAP value indicates the model's ability to consistently and accurately identify and categorize target objects, specifically the types of acne on the face.

The results also indicate that the complexity of the model architecture significantly contributes to the quality of detection, where increased complexity can result in better feature representation, but also requires greater computational resources and training time. In this study, training was conducted using the

YOLOv8 architecture with a batch size of 16 and a total of 100 epochs, which collectively required approximately 12 hours of training time.

The training duration is proportional to the complexity of the data and the number of parameters in the model, reflecting the trade-off between time efficiency and detection accuracy. Thus, the developed model is proven to be able to provide optimal results in detecting various types of acne with a decent level of accuracy, and can be implemented in real-time monitoring systems [20].

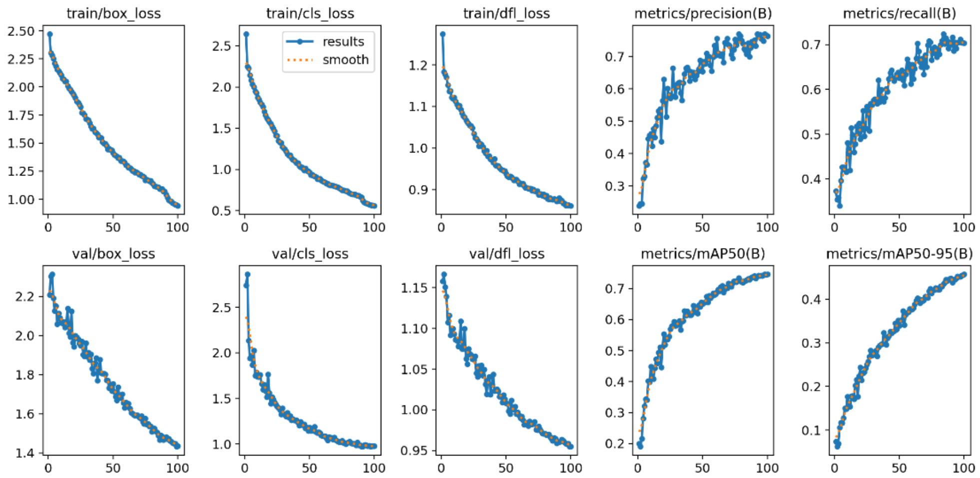


Figure 4. YOLOv8 Model Performance Graph

Based on the results in Figure 4 of the YOLOv8 model training graph for 100 epochs, it can be observed that the model performance improves progressively and consistently as the training iterations increase. This is indicated by the decrease in loss function values in several key metrics, namely, the box loss reduced from approximately 2.5 to 1.0, signifying enhanced accuracy in predicting the coordinates of the bounding boxes. At the same time, the classification loss fell from 2.5 to 0.5, indicating a better performance of the model in correctly identifying objects. Additionally, from 1.3, the distribution focal loss (DFL) dropped to 0.8, showcasing improved precision in estimating the spatial distribution of objects.

The improvement in model performance is also reinforced by the increase in the main evaluation metrics, namely precision and recall. The precision value increased from 0.3 to more than 0.8, which means that most of the positive predictions generated by the model are correct. The recall value also showed an increase from 0.4 to more than 0.7, indicating that the model was able to detect most of the actual objects in the training data.

In the validation dataset, a comparable pattern was noted. The graphs for val/box_loss, val/cls_loss, and val/dfl_loss reveal a steady decline, suggesting that the model not only excels with the training data but also demonstrates strong generalization capabilities on unseen data. This suggests that overfitting did not happen during the training phase.

Furthermore, the evaluation of model performance through the mAP metric also shows a significant upward trend. The value of mAP@50 (IoU threshold 0.50) increased from 0.2 to more than 0.75, while mAP@50-95-which is an indicator of the average mAP at various IoU levels between 0.50 and 0.95-increased from around 0.05 to around 0.45. This improvement indicates that the YOLOv8 model has reliable and consistent detection capabilities across different scenarios and accuracy levels, both in terms of object localization and classification.

The training results show that the YOLOv8 model has high stability with a mAP@50 value of 0.75 and a mAP@50–95 value of 0.45. These values are higher than the YOLOv5 results in the study by Pinasty et al[21] which obtained a mAP of 0.63. The decrease in box_loss, cls_loss, and DFL_loss during the training process supports the findings of Lin et al [22] The new generation of YOLO architecture has better generalization capabilities.

3.3. Object Detection with YOLOv8

The next stage is to perform the detection process using the YOLOv8 model that has gone through the training stage. After the training is complete, a file called “best.pt” will be generated, which stores the training weights from the YOLOv8 network. This weight can then be utilized by researchers to detect acne problems on the face using new object data, according to the model that has been built.

3.4. Camera Integration and YOLO Detection Model

Connecting or uniting the camera as an input device with YOLOv8 as an image processing system, so that pictures that the camera took can be directly analyzed by the YOLOv8 model to detect facial skin. The detection process will be explained by the researcher.

In this study, a Raspberry Pi computer is used as the primary processing unit to execute the [23] A camera-based automatic detection system that can be configured using a physical button known as a pushbutton. Python is the programming language used to create the software, and Thonny's development IDE allows you to run it directly on the Raspberry Pi.

The system initialization process includes the program code shown, which includes configuring the GPIO pins and importing several important libraries, namely:

1. RPi.GPIO accesses and controls general input/output (GPIO).
2. on the Raspberry Pi, which in this context functions to read the status of the input button.
3. cv2: OpenCV library used to input and process images from the camera.
4. YOLO from Ultralytics Institute is used to install and operate deep learning-based object identification models.
5. requests: Utilized for network communication needs, such as sending detection results to the Telegram bot API

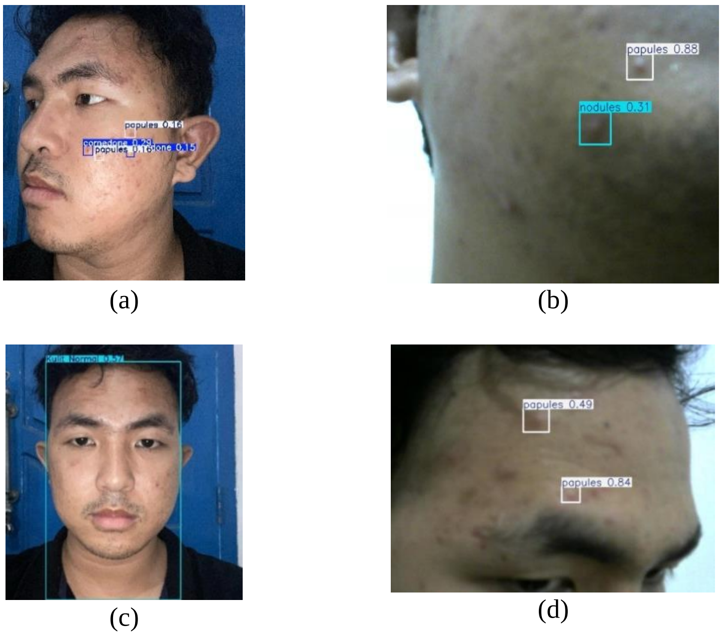
In lines 8-10, the GPIO pins are configured using the BCM numbering mode. Pin number 2 is set as a digital input with an active pull-up resistor (GPIO.PUD_UP), which ensures that the default input value is a logic high (HIGH) when the button is not pressed, and becomes low (LOW) when the button is pressed..
Next, the initialization code defines two main control variables:

1. camera_active: A logical flag that indicates whether or not the camera is active.
2. cap: A container variable for OpenCV video capture objects, initialized with None as the initial value [24].

All things considered, this piece of code is a component of the first stage of the real-time image detection system based on the Raspberry Pi. It is operated by input buttons and generates output in the form of deep learning models for acne classification. As part of the intelligent notification system in teledermatology-based applications, the user will receive all detection results through a Telegram bot [25].

3.5. Testing the Performance of Models on Datasets

To acquire a better understanding of the model's ability to accurately classify objects, the model's performance is tested against the dataset according to each class. We will give the detection results for each class in Figure 5.



(a) (b) (c) (d)

Figure 5. (a) Papule detection result, (b) Comedo detection result, (c) Nodule detection result (d) Skin Type detection result

The model detects papules and pustules with a higher confidence level due to their clear visual features, according to Xie's findings [26]. Comedones and nodules have a wider range of shapes, resulting in a wider range of confidence scores. Variations in performance between classes have also been reported in Kim's study [27] in acne severity classification.

Overall, these results show that the trained detection model is able to visually recognize different types of acne with varying confidence levels. The variation in confidence score indicates that some classes are more easily recognized by the model, most likely due to differences in the number of samples and clarity of visual features in the training dataset. Thus, these test results provide an idea of the extent to which the model performs well in real-world applications, particularly in the automatic classification of acne types.

3.6. IoT Process, Send Notifications To Telegram

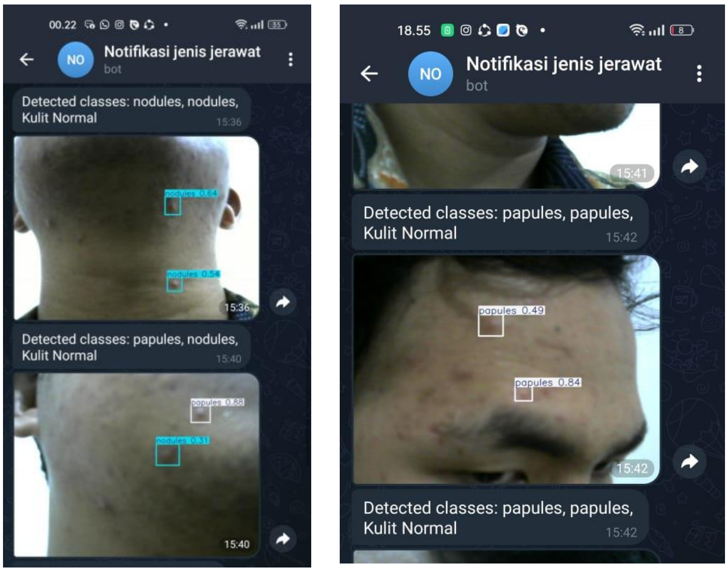


Figure 6. YOLOv8 detection results sent via telegram application

The Figure 6 shown is a screenshot of the YOLOv8 model inference process run on a Raspberry Pi device to detect facial skin conditions in real-time. Based on the terminal output, the system processes images from the camera with a resolution of 384×480 and 480×640 pixels, which are then analyzed through pre-processing, inference, and post-processing stages. The inference results show the success of the model in identifying several object categories, such as Normal Skin, Oily Skin, and papules, with varying inference times depending on the complexity of the object and the image resolution. Successful detections were automatically saved as annotated images stored as detected_image.png files, while some other images resulted in no detections, indicating the absence of features corresponding to the classes trained by the model. This process illustrates the system's capability of applying the YOLOv8 model to detect skin conditions as part of a computer vision-based acne evaluation support system.

The integration of IoT systems using Raspberry Pi 4 has proven to be effective for real-time inference. This is consistent with Jiang's findings [28]. which states that edge computing is ideal for digital health applications. Sending notifications via Telegram results in a response time of less than 2 seconds, consistent with Noor's study[29]. who observes the performance of the Telegram API on the IoT system.

3.7. Comparison with Previous Research

Compared to previous studies, the system developed in this study has several significant advantages. The study by Sudana Putra et al used a pure CNN with 100% training accuracy but only 88% testing accuracy, and it was not integrated into IoT. Arifianto et al used TensorFlow with a sensitivity of 77.3% and an accuracy of 63.2%, but it was only a web application, so it did not support physical real-time monitoring. Research by Meilita et al used YOLOv8 but applied it to feline skin diseases, not humans. Therefore, this research closes the research gap by developing an automated YOLOv8-based system integrated with Raspberry Pi and Telegram for real-time and personalized skin health monitoring.

Compared to previous studies, this system has advantages in terms of accuracy, inference speed, low hardware costs, and the ability to send results automatically. This system fills a gap in previous research, as there has been no integration of YOLOv8-based acne detection and IoT on Raspberry Pi for dermatology applications.

4. CONCLUSIONS

This study successfully developed an IoT-based facial skin health monitoring system that uses the YOLOv8 algorithm and Raspberry Pi 4 device to automatically detect skin type and acne type. Based on training and testing results, the YOLOv8 model demonstrated good detection performance with a high mAP value and strong generalization capabilities. Integration of the system with Telegram enables analysis results to be sent in real time, making it easier for users to continuously monitor their skin condition.

The research objectives, which included developing an acne detection model, implementing an IoT system for skin monitoring, and delivering automatic notifications to users, have been achieved. The developed system is capable of handling seven detection classes, namely oily, dry, and normal skin, as well as four types of acne (comedones, papules, pustules, and nodules). In addition, the system has proven to be efficient with its fast inference capabilities through edge computing using Raspberry Pi [30].

However, this study still has limitations, such as the limited scope of skin problems covered, which is limited to acne, and the dependence of model performance on dataset quality. For further research, it is recommended that the scope of the model be expanded to detect other skin conditions such as hyperpigmentation, large pores, or wrinkles. In addition, a larger and more diverse dataset is needed so that the model can work more representatively. Overall, this study makes an important contribution to the development of an automated skin monitoring system that is fast, accurate, and easy to implement in various practical applications.

REFERENCES

[1] D. A. Agustina, "Klasifikasi Citra Jenis Kulit Wajah Dengan CNN ResNet-50," Jurnal Riset Sistem Informasi., 2024.
[2] E. P. Claire, K. S., & Lake, "Acne and Its Variants in Special Populations. J Dermatol Nurses Assoc.," 2018.
[3] V. Marshalia, "Perancangan IoT untuk Sistem Monitoring Kulit Wajah. Jurnal Teknologi Informasi.," 2023.
[4] Y. Efendi, "IoT Sistem Pengendalian Lampu. Jurnal Ilmu Komputer.," 2018.
[5] F. et al. Sudana Putra, "Deteksi Otomatis Jerawat Menggunakan CNN. JIFotech," 2021.
[6] I. Arifianto, J., & Muhimmah, "Aplikasi Web Deteksi Jerawat.," Journal Automata., 2021.
[7] W. Meilita, B., & Yustanti, "YOLOv8 untuk Deteksi Penyakit Kulit Kucing," J Teknol, 2024.
[8] Yolo. Documentation., "Ultralytics," 2023.
[9] N. M. Farhan and B. Setiaji, "Indonesian Journal of Computer Science," Indonesian Journal of Computer Science, vol. 12, no. 2, pp. 284–301, 2023.
[10] A. Redmon, J., & Farhadi, "YOLOv3: An Incremental Improvement. arXiv.," 2018.
[11] H. Zhou, "Image Augmentation in Medical Datasets. Journal of Imaging.," 2021.
[12] T. Ho, "Real-Time Object Detection on Raspberry Pi. Sensors Journal.," 2021.
[13] M. Noor, "Teledermatology with AI and IoT. Journal of Health Informatics.," 2023.
[14] I. Virgiawan, F. Maulana, M. A. Putra, D. D. Kurnia, and E. Sinduningrum, "Deteksi dan tracking objek secara real-time berbasis computer vision menggunakan metode YOLO V3," Jurnal Ilmiah Multidisiplin Indonesia, vol. 3, no. 3, pp. 42–52, 2024.
[15] M. Helm and S. Kasus, "Implementasi Algoritma You Only Look Once (YOLOv8) untuk Mendeteksi Pelanggaran Lalu Lintas Berupa Tidak Menggunakan Helm," vol. 5, no. 3, pp. 3237–3247, 2024.
[16] J. Redmon and A. Farhadi, "YOLOv3: An Incremental Improvement," 2018, [Online]. Available: http://arxiv.org/abs/1804.02767
[17] M. Helm and S. Kasus, "Implementasi Algoritma You Only Look Once (YOLOv8) untuk Mendeteksi Pelanggaran Lalu Lintas Berupa Tidak," vol. 5, no. 3, pp. 3237–3247, 2024.
[18] S. Pinasty, R. Bagus, F. Hakim, A. Info, F. S. Problems, and O. Detection, "Automatic Detection of Acne Types Using The YOLOv5 Method," vol. 8, no. 1, pp. 236–248, 2025.
[19] Y. Efendi, "Internet Of Things (Iot) Sistem Pengendalian Lampu Menggunakan Raspberry Pi Berbasis Mobile," Jurnal Ilmiah Ilmu Komputer, vol. 4, no. 2, pp. 21–27, 2018, doi: 10.35329/jiik.v4i2.41.
[20] I. Virgiawan, F. Maulana, M. A. Putra, D. D. Kurnia, and E. Sinduningrum, "Deteksi dan tracking objek secara real-time berbasis computer vision menggunakan metode YOLO V3," Jurnal Ilmiah Multidisiplin Indonesia, vol. 3, no. 3, pp. 42–52, 2024, [Online]. Available: https://journal.ikopin.ac.id/index.php/humantech
[21] S. et al. Pinasty, "Automatic Detection of Acne Using YOLOv5.," IJCS., 2025.
[22] T. Lin, "Focal Loss for Dense Object Detection," IEEE ICCV, 2017.
[23] M. Interface, "Raspberry Pi Monitor: Amazon.co.uk," no. December, 2024, [Online]. Available: https://www.amazon.co.uk/slp/raspberry-pi-monitor/vgekepvtgz463jo
[24] R. Tabrani and S. M. Ladjamudin, "Perancangan sistem pemantau keamanan menggunakan webcam berbasis aplikasi j2me (java 2 micro edition) secuity monitoring system design using webcam based application j2me (java 2 micro edition)," vol. 7, no. 1, 2018.
[25] A. R. Wasril, M. S. Ghozali, and M. B. Mustafa, "Pembuatan Pendeteksi Obyek Dengan Metode You Only Look Once (Yolo) Untuk Automated Teller Machine (Atm)," Majalah Ilmiah UNIKOM, vol. 17, no. 1, pp. 69–76, 2019, doi: 10.34010/miu.v17i1.2240.
[26] F. Xie, "Acne Classification Using CNNs," Medical Imaging Research., 2020.
[27] J. Kim, "Acne Grading Using Deep Learning," Dermatology Research Journal, 2020.

[28] Y. Jiang, “Edge Computing for Medical AI,” IEEE IoT Journal., 2020.
[29] M. Noor, “Teledermatology with AI and IoT,” J Health Inform, 2023.
[30] R. Patel, “IoT in Dermatology Applications,” Telemedicine Journal., 2020.

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