

AI And IoT Based E-Dermatology System for Facial Skin Condition Analysis and Skincare Recommendation

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Abstract—Facial skin problems are among the most common health issues experienced by the Indonesian population, while access to affordable and reachable dermatological consultation remains limited. This study develops an AI- and IoT-based E-Dermatology system that integrates a YOLOv8 object detection model to identify facial skin conditions, a Fuzzy Logic algorithm to classify severity and determine skincare recommendations, and an ESP32-based Moisture Click sensor connected through the MQTT protocol to measure facial skin moisture in real time. The system is intended to help users independently monitor facial skin condition without requiring specialized medical expertise. Testing results show that the YOLOv8 model achieved a precision of 0.862, a recall of 0.812, and a mAP@50 of 0.865, with the best-performing training weights reaching a peak precision of 0.878; the Fuzzy Logic algorithm reached a 100% match rate against scikit-fuzzy validation across 10 classification test scenarios, supported by a membership-function-level validation that matched scikit-fuzzy on 100% of tested points for the triangular function and 90% for the trapezoidal function; the Moisture Click sensor obtained an accuracy of 80.91% with a MAPE of 19.09% compared to a commercial instrument, and a MAPE of 1.24% compared to a clinical image-based skin analyzer; and User Acceptance Testing on 20 respondents produced satisfaction scores between 93% and 97% across all functionality aspects. These results indicate that the proposed AI- and IoT-based E-Dermatology system is feasible and effective as a self-service tool for facial skin analysis and skincare recommendation.

Keywords— *E-Dermatology, facial skin condition, Fuzzy Logic, IoT, Moisture Click sensor, skincare recommendation, YOLOv8.*

I. INTRODUCTION

Facial skin condition is one of the most frequently reported health concerns among Indonesians, yet affordable and easily accessible dermatological consultation remains a challenge for many people [1]. Common problems include acne, hyperpigmentation (dark spots), and wrinkles, caused by clogged pores, excess melanin production, and reduced collagen respectively [2], as well as dark circles, which are commonly associated with thinning periorbital skin and poor local blood circulation [3]. Because professional consultation is not always reachable, an automated system capable of analyzing facial skin condition and suggesting an appropriate skincare response, built upon artificial intelligence and machine-learning techniques [4], is highly desirable. Such a system needs to combine an objective visual-assessment mechanism with contextual physiological information, since a purely image-based diagnosis cannot account for the role of environmental exposure and skin hydration in determining an appropriate treatment recommendation.

Several prior studies have applied computer-vision and machine-learning techniques to facial skin analysis. A CNN-based approach combined with Hough Circle Transform achieved 99.8-100% accuracy for acne detection, but used a limited dataset without varying lighting conditions [5]. A Support Vector Machine model using Histogram of Oriented Gradient features reported 98% accuracy in classifying three skin problems, yet was not implemented as a ready-to-use application [6]. An AI-powered acne grading system based on

ResNet-50 obtained a lesion-detection precision of 0.507 and recall of 0.775 but relied on clinical imaging rather than a direct IoT sensor [7]. An IoT- and YOLOv5-based monitoring system achieved a precision of 0.894 for new acne lesions, though evaluation was limited to visualization without considering external factors [8]. Finally, a CNN (VGG16) Android application reported 97% accuracy in detecting acne, dark spots, puffy eyes, and wrinkles, but used only image input without environmental sensors or fuzzy reasoning [9]. None of these works combines visual detection, an expert decision layer, and a physical moisture sensor in one real-time system.

To address this gap, this study designs and implements an E-Dermatology system that integrates three complementary technologies: a YOLOv8 object-detection model to localize and classify visual skin anomalies (acne, wrinkles, dark circles, and dark spots); a Mamdani Fuzzy Logic engine that combines the visual detection results with environmental and physiological sensor readings (skin moisture and UV index) to determine severity level and recommend an active skincare ingredient; and an ESP32-based Moisture Click sensor that transmits real-time moisture data through the MQTT protocol to a desktop application built with Python and CustomTkinter. The contribution of this research is therefore the integration of AI-based visual detection, expert-system reasoning, and IoT sensing into a single, real-time, self-service facial skin analysis tool, together with an empirical evaluation of detection

accuracy, decision-logic validity, sensor accuracy, and end-user acceptance.

The remainder of this paper is organized as follows. Section II describes the research method, including the research stages, system and hardware design, software design, and the testing procedures used to evaluate each subsystem. Section III presents the results of YOLOv8 training and detection, Fuzzy Logic decision validation, application implementation and User Acceptance Testing, and Moisture Click sensor accuracy testing, together with the corresponding discussion. Section IV concludes the paper and outlines directions for future development.

II. METHOD

A. Related Work

Table I summarizes prior studies on facial skin-condition detection that motivate the design choices of this research.

TABLE I
SUMMARY OF RELATED WORK

Ref.	Method	Result / Limitation
[5]	CNN+Hough	99.8-100% acc.; limited dataset
[6]	HOG+SVM	98% (3 probs.); no app
[7]	ResNet-50	P 0.507, R 0.775; clinical imgs only
[10]	YOLO	General skin-disease classes; not facial-cosmetic focused
[8]	IoT+YOLOv5	P 0.894; no ext. factors
[9]	CNN(VGG16)	97% (4 probs.); no sensor/fuzzy

Unlike these works, the present study combines visual detection (YOLOv8), an expert decision layer (Fuzzy Logic), and a physical moisture sensor (Moisture Click via ESP32/MQTT) into a single real-time desktop application, while also reporting a formal validation of the fuzzy decision logic against a reference scikit-fuzzy implementation. In addition, the teler dermatology concept proposed by Panagoulas et al. [11], which uses a multimodal transformer to analyze visual and descriptive data simultaneously for dermatological diagnosis, supports the broader feasibility of AI-assisted self-monitoring tools as an early step before users seek direct medical consultation, which is the same motivation underlying the system developed in this study. Fuzzy Logic and low-cost embedded sensors have each been explored separately for skin-related decision support: Dite Arum et al. [12] applied Fuzzy Logic to recommend a facial serum product based on user-reported skin needs, while Eka Nindiya et al. [13] built an ESP32-based device with a light sensor to classify facial skin type. Neither work, however, integrates visual object detection, expert-system reasoning, and a physical moisture sensor into one application, which is the gap this study addresses.

B. Research Type and Stages

This research is a development research (R&D) study aimed at designing and implementing a camera- and sensor-based prototype for facial skin-condition detection. YOLOv8 acts as the visual detector for acne, wrinkles, dark circles, and dark spots, while a capacitive moisture sensor supplies non-

visual supporting information. The output of the study is a hardware prototype together with a desktop application for visualizing the detection results[14]. Furthermore, the system integrates image-processing technology and intelligent decision-making methods to improve the accuracy and reliability of skin-condition assessment. Facial images captured by the camera are processed using the YOLOv8 model to identify and classify visible skin problems, whereas the moisture sensor provides additional data regarding skin hydration levels. The combination of visual and sensor data is then analyzed using the Fuzzy Logic method to generate skincare recommendations based on the detected skin condition. Through this approach, the proposed system is expected to provide users with a practical and accessible tool for preliminary skin analysis and personalized skincare recommendations in real time.

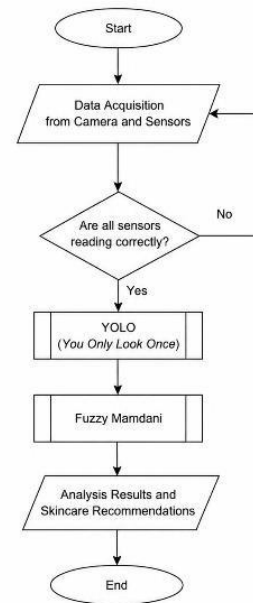


Figure. 1. Flowchart of the research stages.

As shown in Figure. 1, the research stages begin with a literature study, hardware and software design, and the collection and labeling of an acne, wrinkle, and dark-circle dataset for YOLO training. After the prototype is completed and the sensor is integrated, moisture data from the sensor together with YOLO visual detection results are processed using the Mamdani Fuzzy method to generate a skincare-ingredient recommendation. The results are then evaluated to draw the final conclusion of the system.

As part of the validation phase, testing was conducted using five images that had previously been used as ground-truth data. The system's detection results were compared with the original annotations to evaluate the model's consistency after implementation in the application. In addition, testing was conducted under various lighting conditions to determine the effect of light intensity on the model's ability to consistently detect the number of skin-colored objects in real-world usage scenarios. With the completion of the visual detection testing, secondary data testing, and lighting variation testing, the

YOLO model testing phase is now complete, and the model is ready to be used as the visual detection component in the next phase of system testing.

C. System Design

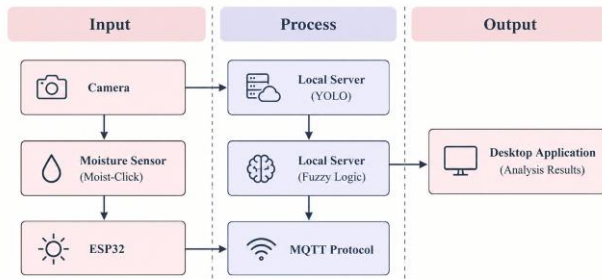


Figure. 2. System block diagram.

The block diagram in Figure. 2 represents the integrated architecture connecting IoT hardware with machine learning to generate a personalized skin-care recommendation. The system flow begins with data acquisition through a camera for facial-condition detection and a moisture/UV sensor for physical skin parameters; both inputs are managed by an ESP32 microcontroller. Data are transmitted through the MQTT protocol using a HiveMQ broker to the desktop application, where object detection by the YOLOv8 model and expert-rule calculation by the fuzzy-logic engine are performed. The final output is an automatically tailored skincare-ingredient recommendation based on the user's real-time skin and environmental condition.

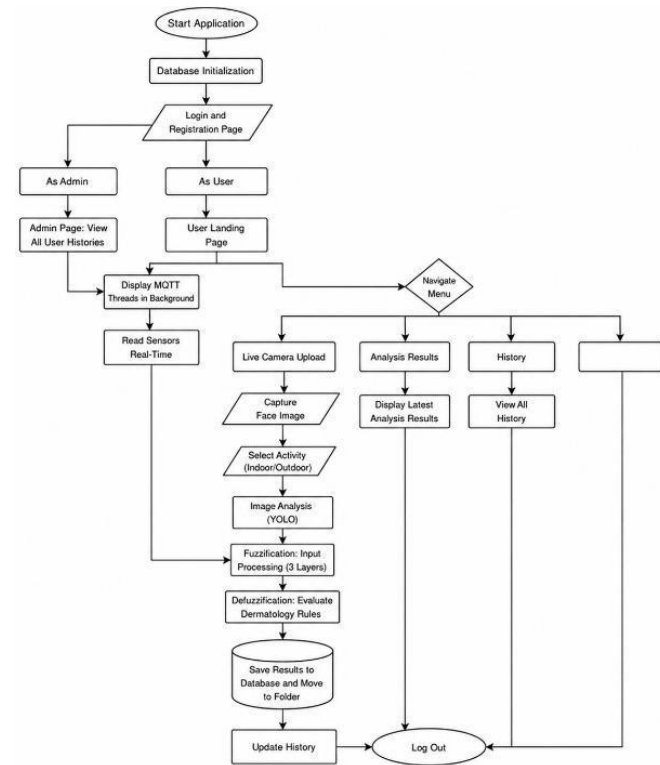


Figure. 3. System flowchart.

Figure. 3 illustrates the working flow of the facial skin-analysis system using camera and sensor inputs to produce a fuzzy-based skincare recommendation. The system receives two main inputs: a facial image from the camera and a skin-moisture reading from the Moisture Click sensor. After both data sources are confirmed to be valid, the facial image is processed using YOLO to detect skin conditions (acne, wrinkles, dark circles, dark spots). The visual data are then combined with the sensor data and analyzed using Mamdani fuzzy logic to produce the final decision, namely the skin-condition analysis and the recommended active skincare ingredient, displayed in real time.

D. Hardware and Application Design

The main hardware component is an ESP32-C3 Super Mini microcontroller, used as the central processing and wireless-communication unit [15]. The Moisture Click sensor [16] is connected to the microcontroller through the I2C interface, as summarized in Table II.

TABLE II
WIRING CONFIGURATION

Component	Pin	Function	ESP32
Moisture Click	3.3V	Power	3V3
	GND	Ground	GND
	SDA	I2C data	GPIO21
	SCL	I2C clock	GPIO22

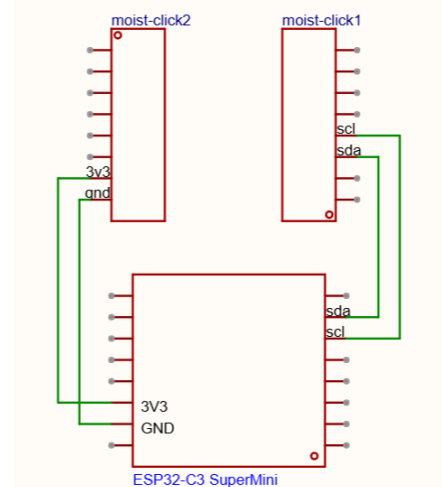


Figure . 4. Hardware schematic of the sensor circuit.

Based on the schematic and wiring diagrams, Figure 4 shows the hardware design to be implemented. The 3.3V and GND pins serve as the power supply and ground lines for the sensor module, respectively, while the SDA and SCL pins function as bidirectional data communication lines for the I2C protocol, where SDA (Serial Data) carries humidity measurement data from the sensor to the microcontroller, and SCL (Serial Clock) provides a clock signal that synchronizes data transmission timing between the two devices.

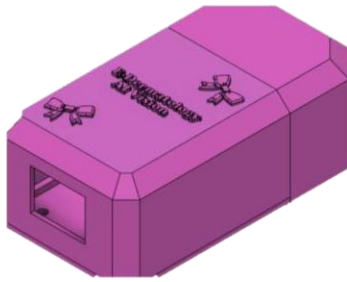


Fig. 5. Physical device design.

On the software side, the desktop application focuses on an intelligent and responsive Graphical User Interface, built in Python using the CustomTkinter library[17]. The overall workflow starts with user authentication, which automatically triggers real-time transmission of moisture data through MQTT in the background. When a user performs a test-either by uploading a photo or scanning the face through a live camera-the image is processed by the YOLO computer-vision model to detect and count skin anomalies such as acne, wrinkles, dark spots, and dark circles. These visual extraction variables are then combined with the physical sensor reading and evaluated by the Fuzzy Logic algorithm, which aligns expert rules to produce a precise skin-condition diagnosis and skincare recommendation. The final result is displayed on the result interface and archived in the database as a digital record retrievable from the history page.

Communication between the ESP32 microcontroller and the desktop application relies on the lightweight MQTT publish-subscribe protocol, brokered through a public HiveMQ instance. The ESP32 continuously publishes the moisture and UV readings to a dedicated topic at a fixed interval, while the desktop application subscribes to the same topic so that the latest sensor values are always available in the background, independent of whether the user is actively performing a scan. This decoupled architecture was chosen so that sensor connectivity issues, such as a temporary Wi-Fi disruption, do not block the visual-detection and fuzzy-inference pipeline, since the last known sensor value can still be used while the connection is being re-established.

All detection results, sensor readings, and the corresponding skincare recommendations are stored in a local relational database, allowing each user to retrieve past scan records from the history page sorted by date. An administrator role is also implemented to allow inspection of aggregate usage records across all registered users, primarily for monitoring and quality-assurance purposes during the testing phase of this research.

E. System Testing Procedure

Four main tests were carried out: YOLO visual-detection testing, Fuzzy decision-system testing, application/UAT testing, and skin-moisture sensor testing, performed separately to ease error identification for each component.

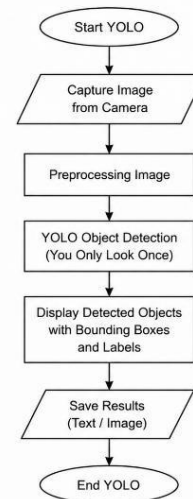


Figure 6. YOLO testing sub-process flowchart.

Visual-detection testing aims to determine how accurately the model identifies objects in user images. After an image is fed into the model, the system generates a bounding box with a class label and confidence value, which is then compared with the manually annotated ground-truth label.

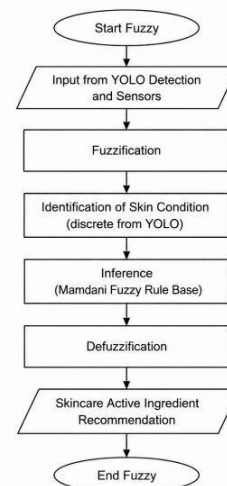


Figure 7. Fuzzy classification testing sub-process flowchart.

Fuzzy-system testing validates the accuracy of the locally implemented Fuzzy Logic algorithm by comparing its decision output against the standard scikit-fuzzy library executed in a Google Colab environment, using 10 patient-data scenarios with varying input parameters.

Application testing was carried out through a User Acceptance Test (UAT) questionnaire distributed to 20 respondents, evaluating user interface, functional ease, AI diagnosis clarity, and history/database management using a 1-5 Likert scale. Sensor testing compared the moisture percentage measured by the Moisture Click sensor with a commercial Digital Skin Analyzer at three facial zones (forehead, cheek, chin) for each respondent.

F. Evaluation Metric for the Moisture Sensor

Sensor accuracy was evaluated using the Mean Absolute Percentage Error (MAPE), a scale-independent error metric widely used in statistics and machine learning [18]:

$$\text{MAPE} = (100/N) \sum |y_n - \hat{y}_n| / y_n \quad (1)$$

where N is the number of samples, y_n is the actual reading from the commercial device, and $\hat{y}_n$ is the predicted reading from the Moisture Click sensor. Because the system measures three facial zones (forehead, cheek, chin) for each of the 20 respondents, the total number of samples is $N = 60$. Sensor accuracy is then obtained as $\text{Accuracy} = 100\% - \text{MAPE}$.

III. RESULTS AND DISCUSSION

A. Place, Time, and Dataset Configuration

The research was conducted over 11 months, from July 2025 to May 2026, mainly at the campus of Politeknik Negeri Malang for software development, dataset acquisition, and system-integration testing. Prior to training, 1,499 facial images were annotated into four skin-problem classes and split using the hold-out method, as summarized in Table III.

TABLE III
DATASET DISTRIBUTION

Data Category	Images	Percentage
Training Set	1312	88%
Validation Set	125	8%
Testing Set	62	4%
Total	1499	100%

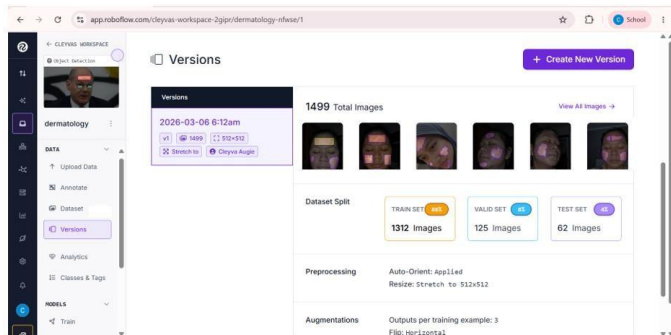


Figure 8. Sample of the labeled dataset in Roboflow.

The training set (88%) was used as the primary data for model learning, the validation set (8%) was used to evaluate performance and tune hyperparameters during training, and the testing set (4%) was used to assess the model's ability to predict previously unseen data.

B. YOLOv8 Training and Detection Performance

Training was performed using the Ultralytics framework in Visual Studio Code with Python. The model was trained for 50 epochs with a batch size of 16, an initial learning rate (lr0) of 0.01, and an input image size of 640×640 pixels, across four target classes: acne, wrinkles, dark circles, and dark spots. The total training time was 42,772 seconds (11.882 hours).

TABLE IV
FINAL MODEL PERFORMANCE (EPOCH 50)

Evaluation Parameter	Final Value
Precision	0.862
Recall	0.812
Epoch 50	0.878

As shown in Table IV, the model achieved a high precision (86.2%) and a recall of 81.2%, indicating that the resulting detections rarely produce false positives while still capturing most true skin-condition instances. Training was configured with a patience value of 50 to guard against overfitting; because this value matched the total number of epochs, the schedule completed all 50 epochs without triggering an early stop, and the best-performing weights (best.pt) were therefore obtained exactly at the final epoch of training.

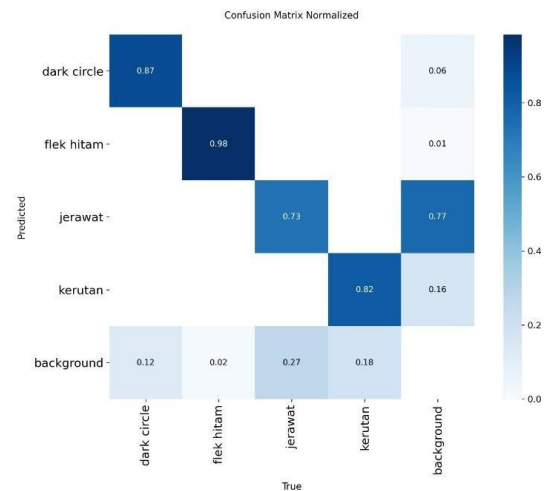


Figure 9. Normalized confusion matrix.

The diagonal of the confusion matrix in Figure 9 shows the strongest recognition for the Dark Spot class at 98%, followed by Dark Circle (87%) and Wrinkle (82%), while Acne obtained the lowest recognition rate (73%), with 27% of acne instances misclassified as background. This pattern reflects the higher visual ambiguity and biological variability of acne lesions compared with the other three classes, while the overall structure confirms a robust detection architecture.

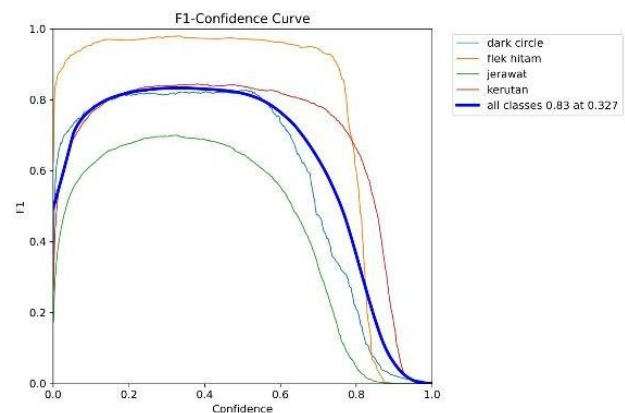


Figure. 10. F1-confidence curve.

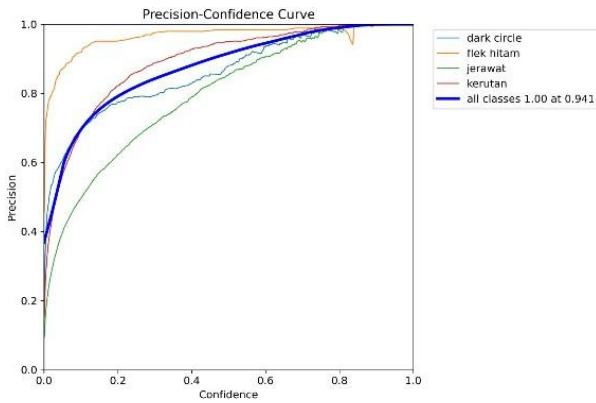


Figure. 11. Precision-confidence curve.

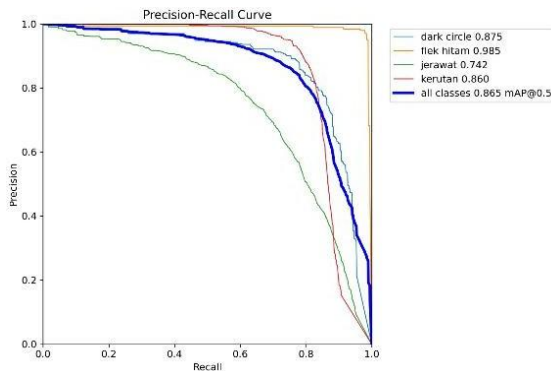


Figure. 12. Precision-recall curve.

The F1-confidence curve (Figure. 10) shows that the model sustains a peak balanced F1-score of 0.83 at a confidence threshold of 0.327. The precision-confidence curve (Fig. 11) indicates that the system can reach a maximum precision of 1.00 (100%) at a confidence threshold of 0.941, meaning that at high-confidence predictions the model's false-positive rate approaches zero, at the cost of fewer detected objects. The precision-recall curve (Fig. 12) reports an overall mAP@50 of 0.865, with the Dark Spot class reaching the highest reliability (0.985), followed by Dark Circle (0.875) and Wrinkle (0.860), while Acne remained the most challenging class (0.742). The recall-confidence curve shows that recall reaches 0.94 (94%) across all classes at a confidence threshold of 0, then decreases as the confidence threshold is tightened, which is an expected trade-off that prevents excessive false-positive detections. Taken together, the mAP@50 of 0.865 confirms that the two-dimensional YOLOv8 localization integrated into the desktop E-Dermatology system is reliably validated for use as the visual front-end of the Fuzzy Logic decision stage.

As an additional check, the trained model was validated against secondary data: five previously labeled images already used in the training dataset were re-submitted to the application through its normal upload workflow, and the resulting detections were compared with their original ground-truth annotations across 16 total annotation points. The application correctly reproduced 13 of the 16 points (81.25%), with full agreement on three of the five images and partial agreement on

the remaining two, indicating that the deployed model generally reproduces its training-time annotations well, though a small number of points—typically low-visual-salience or small objects—were not consistently redetected.

The model's sensitivity to lighting conditions was also tested using a lux meter following the SNI 7062:2019 illuminance-measurement procedure, at four illuminance levels (20, 50, 80, and 100 lux) [19]. The average detection confidence increased with illuminance, from 0.266 at 20 lux to 0.649 at 100 lux, with a minor, non-anomalous dip at 80 lux (0.576) relative to 50 lux (0.590). This confirms that detection confidence is positively correlated with lighting intensity, with the steepest drop occurring under low-light conditions (20 lux), which is consistent with the acne class's higher misclassification rate observed in the confusion matrix above and underscores the importance of adequate lighting for reliable real-world use.

C. Fuzzy Logic Decision Validation

This test validates the accuracy of the Fuzzy Logic algorithm implemented in the E-Dermatology application through a two-stage independent cross-validation against the scikit-fuzzy library executed in Google Colab, so that any source of error could be isolated precisely: (1) a numeric validation of the triangular (trimf) and trapezoidal (trapmf) membership functions that underlie every fuzzy variable in the system, and (2) an end-to-end classification validation using 10 simulated patient scenarios involving six input variables: acne count, wrinkle area, dark-circle area, dark-spot area, moisture level, and UV index. The scenarios range from an extreme low (Case 3: a clean, healthy-skin condition) to a heavy complication case (Case 10, where every parameter indicates a problem simultaneously), ensuring that all expert rules are exercised.

For the first stage, both functions were evaluated using a representative parameter set at 10 test points spanning each function's domain. The triangular function matched the scikit-fuzzy output on all 10 points (100%), confirming that its formula is free of computational defects. The trapezoidal function matched on 9 of the 10 points (90%); the single deviation occurred exactly at the boundary point where the plateau parameters c and d were equal, a degenerate case in which the trapezoid's descending edge disappears. At that point the system's implementation evaluates the condition $x \geq d$ before treating the value as part of the plateau, so it returns 0, whereas scikit-fuzzy treats the same point as belonging to the plateau and returns 1. This deviation does not affect any of the 10 classification scenarios in the second stage, since no combination of user inputs falls exactly on that degenerate boundary, but it is noted here as a target for correction in a future revision of the implementation.

For the second stage, across all 10 test scenarios, the locally implemented Fuzzy Logic decision output matched the scikit-fuzzy validation result with no deviation, yielding a 100% match rate. This confirms that the classification-level behavior of the E-Dermatology system is equivalent to the standard scientific scikit-fuzzy implementation for the operating range exercised by the test scenarios, and therefore the inference engine is reliable for real-world deployment.

The fuzzy engine implements a Mamdani Fuzzy Inference System, which consists of a fuzzifier, a rule base, and a defuzzifier [20]. Six crisp input variables—acne count, wrinkle area, dark-circle area, dark-spot area, moisture level, and UV index—are first converted into linguistic degrees of membership

(e.g., Low, Medium, High) using linear and trapezoidal membership functions, three examples of which are shown in Figs. 13-15. The rule base then evaluates a set of IF-THEN expert rules, formulated together with a dermatology practitioner consulted during system validation [21], to determine the

appropriate severity category and corresponding skincare-ingredient recommendation for each combination of inputs. Finally, the defuzzification stage converts the aggregated fuzzy output back into a discrete, human-readable recommendation label, such as those listed in the comparison results above.

In addition to the numerical validation described above, the complete IF-THEN rule base was independently reviewed and validated by a licensed aesthetic-dermatology practitioner from Radiance Rejuvenation and Anti-Aging Center, who assessed whether each rule's input-condition combination and resulting severity classification and skincare-ingredient recommendation were clinically appropriate. This expert review is documented in a formal Expert System Validation Letter issued by the practitioner [21]. The validation was conducted as a single, comprehensive review and approval of the finalized rule base rather than a repeated before/after numerical test; a quantitative comparison between the fuzzy system's recommendations and an independent dermatologist's assessment across a larger patient sample is identified as a direction for future work.

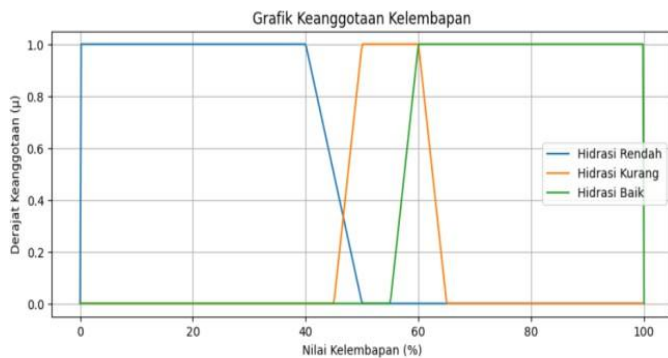


Figure 13. Membership function of skin-moisture level.

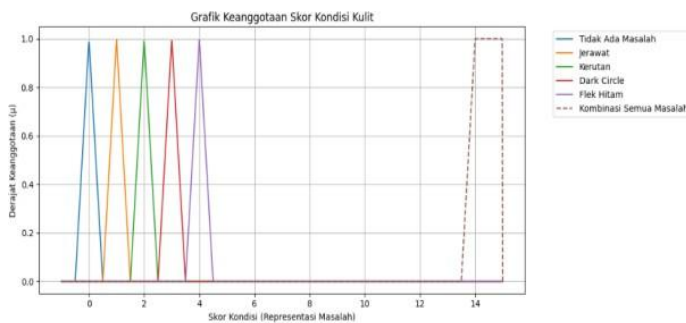


Figure 14. Membership function of facial skin condition.

ambiguity in interpretation for value ranges that are never used in the actual system implementation.

D. Application Implementation and User Acceptance Testing

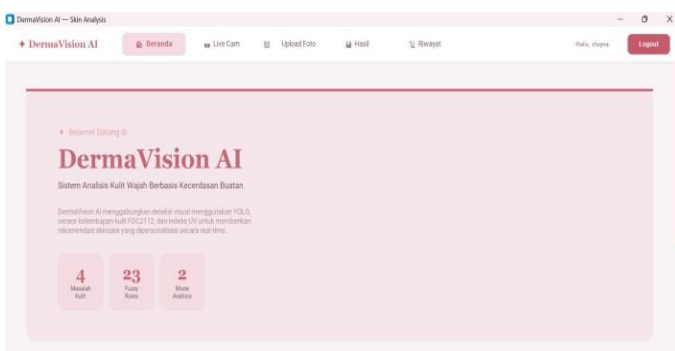


Figure 16. Home dashboard of the DermaVision AI application.

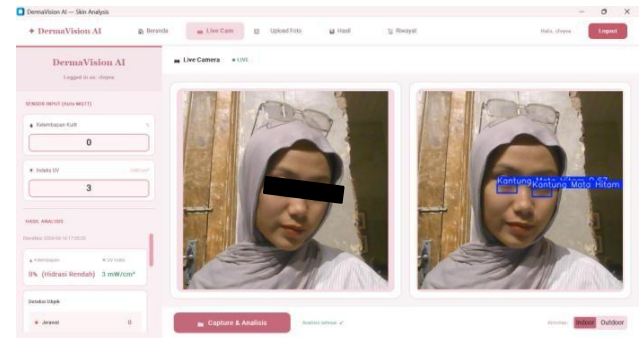


Figure 17. Live-camera skin-scanning page.

The GUI bridges the YOLOv8 detection model, sensor hardware, and tiered fuzzy logic into a single intuitive diagnostic experience. The application is organized into functional modules: user authentication (login/registration), a home dashboard, image-acquisition modules for live-camera and upload scanning (with pre-scan moisture/UV sensor integration and an indoor/outdoor UV context toggle), a detailed result page, and a history module supporting both regular-user and administrator roles.

A User Acceptance Test (UAT) was carried out with 20 respondents using a 10-item questionnaire on a 1-5 Likert scale, covering registration/login ease, dashboard appearance and navigation, color/layout/icon design, environmental-sensor instructions, scanning process, diagnosis-detail access, fuzzy-logic decision clarity, YOLO bounding-box visualization, history storage, and skincare-recommendation history.

Figure 15. Membership function of UV exposure index.

The UV Exposure index variable in the system implementation has only two definite crisp values, namely 0 (indoor conditions) and 1 (outdoor conditions), as a result of the user's manual selection in the application. Therefore, the UV membership function is designed using a narrow triangular shape centered precisely on these two values, as shown in Table 3.6, following a similar approach applied to the Facial Skin Condition variable (Table 3.5). This approach was chosen to represent discrete (rather than continuous) input values, while avoiding

TABLE V
SUMMARY OF UAT RESULTS

Evaluation Aspect	Accept. (%)
User interface (UI)	95.00
Functional ease	94.00
AI diagnosis clarity	94.00
Fuzzy decision clarity	93.00
History data mgmt.	96.00-97.00

As shown in Table V, every evaluated aspect received an acceptance score between 93% and 97%, with the history-management feature (storage and retrieval of recommendation records) receiving the highest score, and the fuzzy-logic decision clarity the lowest, though still strongly positive. Overall, the distribution indicates a very favorable user response across all components of the system.

E. Moisture Sensor Accuracy Testing

The Moisture Click sensor was validated using two comparison schemes. The first scheme compares it against a widely used commercial reference, and the second scheme compares it against a clinical, image-based skin analyzer as a more medically representative reference.

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In the first scheme, the sensor was compared with a commercial Digital Skin Analyzer at three facial zones (forehead, cheek, chin) for 20 respondents, producing 60 paired measurements. For example, for Respondent 1 at the forehead zone, the commercial device read 32% while the Moisture Click sensor read 28%, giving $|32 - 28| / 32 \times 100\% = 12.50\%$ error for that single sample. Summing the percentage error across all 60 samples gave a total of 1145.30, so the mean error was $\text{MAPE} = 1145.30 / 60 = 19.09\%$.

Table VI reports the calibration comparison between the Moisture Click sensor and the commercial Digital Skin Analyzer used as the reference instrument, with each respondent's value averaged across the three measurement zones (forehead, cheek, chin) from the full 60-sample zone-level dataset.

TABLE VI MOISTURE SENSOR CALIBRATION RESULTS (MOIST-CLICK VS. DIGITAL SKIN ANALYZER)

Respondent	Average Moist-Click (%)	Average Skin Analyzer (%)	Average MAPE (%)
R1	27.33	31.00	10.65
R2	29.67	29.33	23.45
R3	27.00	24.00	19.54
R4	40.33	41.33	10.55
R5	50.67	55.67	10.97
R6	56.33	55.00	10.74
R7	22.67	30.67	24.02
R8	25.67	27.67	9.05
R9	33.33	37.00	11.97
R10	34.00	34.33	6.86
R11	28.33	29.33	3.01
R12	37.00	35.33	6.20
R13	16.00	14.33	31.01
R14	30.67	28.00	8.23
R15	32.33	29.33	10.16
R16	36.00	34.33	4.65
R17	39.00	36.00	8.52
R18	13.33	10.33	29.09
R19	25.33	20.67	49.17
R20	24.00	14.67	93.94

The largest per-respondent deviation occurred for Respondent 20, where the cheek-zone reading (38% sensor vs. 11% reference) contributed a disproportionate share of that respondent's average error; excluding this single zone, the remaining 59 samples give a MAPE of 15.25%, indicating that a small number of contact-pressure-sensitive outliers, rather than a systematic sensor bias, account for a meaningful share of the overall error.

Sensor accuracy against the commercial reference was therefore $\text{Accuracy} = 100\% - 19.09\% = 80.91\%$, indicating that the Moisture Click sensor produces moisture readings reasonably close to the commercial reference instrument. Discrepancies between the two devices can be attributed to differences in sensor sensitivity, skin-surface condition during

measurement, the applied contact pressure, and natural moisture variation between facial zones, since forehead, cheek, and chin do not always exhibit identical moisture characteristics.

In the second scheme, the sensor was compared with a clinical image-based analyzer for 4 respondents. Because the clinical device produces a single representative moisture value per respondent from a whole-face image, the Moisture Click value used for comparison was the average of the same respondent's three zone-level readings (forehead, cheek, chin), so that both values covered an equivalent area. Across the four respondents, MAPE ranged from 0.00% (perfect agreement) to 2.58%, with an overall mean MAPE of 1.24%, indicating that the sensor's readings are consistently close to the clinical reference. The markedly lower MAPE obtained in this second scheme, compared with the 19.09% obtained against the commercial device, suggests that the choice of reference instrument itself materially affects the apparent accuracy of the sensor.

G. Discussion

Compared with the related work summarized in Table I, the YOLOv8 detection module in this study ($\text{mAP}@50 = 0.865$) performs within the same range reported for prior IoT-based skin-detection systems such as the YOLOv5 implementation in [8] (precision 0.894 for new acne lesions), while additionally covering four classes simultaneously rather than acne alone. The CNN-based approaches in [5], [9], and [7] report higher single-class accuracy (97-100%) but were evaluated on more constrained datasets or did not integrate a physical sensor or an expert decision layer. The present system therefore trades a small amount of raw classification accuracy for a substantially wider functional scope: simultaneous multi-class visual detection, a validated fuzzy decision layer, and a real-time IoT moisture measurement, all combined in one self-service desktop application.

The 100% match rate obtained for the end-to-end classification validation indicates that the rule base was correctly transcribed from the reference scikit-fuzzy design, so any future discrepancy observed in the field is more likely attributable to sensor noise or visual misdetection than to the inference logic itself. The single deviation found at the membership-function level (the trapmf degenerate-boundary case) is local to one edge condition and did not affect any of the 10 classification scenarios, but it is still a useful finding: it shows that testing at the level of the underlying formulas can surface issues that scenario-level testing alone would miss. Likewise, the consistently high UAT scores (93-97%) suggest that the GUI design choices-particularly the automatic background sensor synchronization and the unified live-camera/upload workflow-were well received by end users, while the comparatively lower score for fuzzy-logic decision clarity (93%) suggests that the textual explanation accompanying each recommendation could be made more detailed in future revisions.

Finally, the moisture-sensor MAPE of 19.09% against the commercial device is higher than the sub-10% error typically reported for laboratory-grade capacitive moisture meters, which is expected given that the Moisture Click sensor used in this prototype is a low-cost, general-purpose module rather than a dermatology-grade instrument. The relatively large error observed for a few individual samples indicates that inconsistent contact pressure and skin-surface conditions during manual measurement contribute more to the overall

error than the sensor's intrinsic noise floor, consistent with the explanation above. Notably, the same sensor achieved a substantially lower MAPE of 1.24% against the clinical image-based analyzer, which indicates that the choice of reference instrument itself has a strong influence on the apparent accuracy figure, and that the commercial-device comparison likely represents a more conservative (stricter) estimate of the sensor's real-world error.

Overall, the four evaluation results-YOLOv8 detection performance, fuzzy-logic validation, application usability, and sensor accuracy-are mutually reinforcing: a reliable visual front-end feeds accurate input variables into a logically verified decision engine, which in turn is presented to the user through an interface rated highly across all usability dimensions. The main weak point identified is the moisture sensor's accuracy, which, while still acceptable for indicative self-monitoring purposes, should be the primary target for hardware-level improvement in any subsequent iteration of the system.

IV. CONCLUSION

The design of an E-Dermatology system integrating a YOLOv8 detection model, a Fuzzy Logic algorithm, a Moisture Click sensor, and a desktop GUI has been realized as a single system capable of analyzing facial skin condition and providing real-time skincare recommendations, demonstrating that the integration of computer vision based detection, expert fuzzy reasoning, and low-cost IoT sensing is technically feasible for a self-service facial skin-monitoring application. The YOLOv8 detection model achieved a precision of 0.862, a recall of 0.812, and a mAP@50 of 0.865, with the best-performing training weights reaching a peak precision of 0.878; the Fuzzy Logic algorithm achieved a 100% match rate against scikit-fuzzy validation across 10 classification test scenarios, supported by a membership-function-level validation that matched scikit-fuzzy on 100% of tested points for the triangular function and 90% for the trapezoidal function; User Acceptance Testing on 20 respondents produced satisfaction scores of 93%-97% across all functionality and usability aspects; and the Moisture Click sensor achieved an average MAPE of 19.09% (80.91% accuracy) relative to a commercial instrument and a substantially lower MAPE of 1.24% relative to a clinical image based skin analyzer. These results indicate that the resulting system is well received by end users despite using consumer grade hardware rather than clinical-grade instrumentation, and that a locally implemented expert system decision layer can reliably reproduce the behavior of an established reference library. Future work should add a standardized skin-contact procedure and periodic recalibration mechanism for the moisture sensor, a local offline data buffer on the ESP32 to handle Wi-Fi disruption, an interactive onboarding guide to improve first-time-user navigation, particularly improved detection reliability for the acne class, which recorded the lowest per-class average precision (0.742) among the four target conditions, and a larger, more diverse dataset across skin tones and lighting conditions to support a future mobile-based deployment.

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REFERENCES

- [1] A. Prameswari, "Riset Membuktikan Ini Masalah Kulit Paling Sering Dialami Orang Indonesia," Wolipop – Detikcom.
- [2] M. Lusiana, S. St, and M. T. Pd, Buku Ajar Perawatan Kulit Wajah.
- [3] A. Goldust, M. Goldust, and U. Wollina, "Periorbital Hyperpigmentation—Dark Circles under the Eyes; Treatment Suggestions and Combining Procedures," *Cosmetics*, pp. 1-12, 2021, doi: 10.3390/cosmetics8020026.
- [4] A. A. Hania, "Mengenal Artificial Intelligence, Machine Learning, Neural Network, dan Deep Learning."
- [5] F. Sudana Putra, D. Otomatis Jerawat Wajah, and M. P. Kurniawan, "Deteksi Otomatis Jerawat Wajah Menggunakan Metode Convolutional Neural Network (CNN)," *JIFOTECH (J. Inf. Technol.)*, vol. 1, no. 2, 2021.
- [6] C. D. Sinaulan and A. Hantara, "Model Klasifikasi Permasalahan Kulit Wajah Menggunakan Metode Support Vector Machine," *J. Pendidik. dan Kewirausahaan*, vol. 9, no. 1, pp. 297-308, Oct. 2021, doi: 10.47668/pkww.v9i1.246.
- [7] J. Li et al., "Development and validation of an artificial intelligence-powered acne grading system incorporating lesion identification," *Front. Med.*, vol. 10, 2023, doi: 10.3389/fmed.2023.1255704.
- [8] V. Marshalia and D. M. Fathurahman, "Perancangan Pemanfaatan IoT dan Machine Learning Untuk Sistem Monitoring Kesehatan Kulit Wajah Berjerawat," 2024.
- [9] R. S. Sinta Puspito Rini, "Aplikasi Pendeteksi Masalah Kulit Wajah Menggunakan Algoritma CNN Berbasis Android," *J. Kreat. Teknol. dan Komput.*, vol. 16, p. 28, 2025.
- [10] M. S. E.-Sayed Amer, "Enhanced Model for Classifying Skin Diseases Using YOLO Technique," *Int. J. Res. Sci. Innov.*, vol. XII, no. XV, pp. 645-654, 2025, doi: 10.51244/ijrsi.2025.121500058p.
- [11] D. P. Panagoulas, E. Tsourelis-Nikita, M. Virvou, and G. A. Tsihrintzis, "Dermacen analytica: A novel methodology integrating multi-modal large language models with machine learning in dermatology," *Int. J. Med. Inform.*, vol. 199, p. 105898, 2025, doi: 10.1016/j.ijmedinf.2025.105898.
- [12] A. S. Dite Arum, U. Nurannisa, and R. Alamsyah Putra, "Sistem Pendukung Keputusan Pemilihan Serum Avoskin yang Sesuai dengan Kebutuhan Kulit Wajah Menggunakan Logika Fuzzy," 2023.
- [13] J. S. Eka Nindiya, Miftakhul Maulidina, and M. Dewi Manikta Puspitasari, "Rancang Bangun Alat Pendeteksi Tipe Kulit Wajah Berbasis ESP32 Dengan Sensor Cahaya TSL2561," 2026.
- [14] Ade Rahayu, "Metode Penelitian dan Pengembangan (R&D): Pengertian, Jenis dan Tahapan," *DIAJAR J. Pendidik. dan Pembelajaran*, vol. 4, no. 3, pp. 459-470, 2025, doi: 10.54259/diajar.v4i3.5092.
- [15] "ESP32-C3-MINI-1 Datasheet," Version 2.0, Espressif Systems.
- [16] T. Click and T. Click, "Moisture Click."
- [17] A. Ma'arif, "Buku Ajar Pemrograman Lanjut Bahasa Pemrograman Python," Univ. Ahmad Dahlan, p. 62, 2020.
- [18] P. M. Swamidass, "Mean Absolute Percentage Error (MAPE)," *Encycl. Prod. Manuf. Manag.*, vol. 3, pp. 462-462, 2025, doi: 10.1007/1-4020-0612-8_580.
- [19] M. H. Alfayyadh and H. Aprilianto, "Sistem Pengenalan Wajah Untuk Akses Data Dengan Metode Local Binary Pattern Histogram," *Progresif J. Ilm. Komput.*, vol. 17, no. 1, p. 47, 2021, doi: 10.35889/progresif.v17i1.572.
- [20] Y. A. R. L. Altien J. Rindengan, Buku Sistem Fuzzy. CV. Patra Media Grafindo Bandung, 2024.
- [21] M. Prabacita, "Surat Validasi Sistem Pakar oleh Radiance Rejuvenation and Anti-Aging Center," 2026.