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PAPER

Design and Development of an Artificial Intelligence–Based Image Measurement System to Support Medical Procedures

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ABSTRACT

This project seeks to create and develop a measurement system utilizing artificial intelligence (AI) technology to facilitate applications in medical procedures, specifically for assessing wound size to improve treatment planning and decision-making. The implemented system utilizes the You Only Look Once (YOLO) v8 model for precise wound recognition and measurement, alongside a MySQL database for organized wound data storage, facilitating effective analysis and management of wound information. The development process commenced with the acquisition of wound image data and the training of the YOLOv8 model to enhance its ability to accurately detect and measure wound size. The system's performance was evaluated in terms of accuracy and processing stability. The findings indicated an average accuracy of 84.5% and a confidence stability rate of 83% for the image processing capabilities of YOLOv8. The system also enables organized data storage and retrieval, thereby supporting decision-making in medical treatment procedures. Performance testing indicated that the system processes images efficiently and effectively, suggesting its applicability in medical practice, including monitoring treatment progress and adjusting treatment plans based on real-time data. This study emphasizes the potential of AI technology and systematic data management to improve the quality of medical care. The proposed method functions as an effective tool to enhance the accuracy and efficiency of wound measurement, presenting significant implications for the future of medical practice.

KEYWORDS

smart wound scan, convolutional neural network (CNN), consult, medical procedure

1 INTRODUCTION

Wound management remains a significant clinical challenge due to the biological complexity of tissue repair, the heterogeneity of wound types, and the high

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risk of infection and delayed healing [1], [2]. Effective wound care requires accurate assessment, appropriate treatment planning, and continuous monitoring throughout the healing process. In clinical practice, wound evaluation often relies on visual inspection and manual measurement, which may introduce subjectivity and inter-observer variability. Therefore, multidisciplinary collaboration among healthcare professionals is essential to ensure reliable wound assessment and effective treatment management [3]. With the increasing prevalence of chronic wounds and the expansion of home-based healthcare services, there is a growing need for technological solutions that support efficient wound monitoring and documentation [4], [5].

To address these challenges, various digital health technologies have been developed to support wound documentation and clinical decision-making. Mobile health platforms and smart wound care systems have demonstrated improved accessibility and efficiency in wound monitoring workflows [6]. Clinical mobile applications have been designed to facilitate structured wound nursing management and provide real-time decision support [7]. Web-based wound assessment systems enable standardized documentation and centralized data management, thereby improving continuity of care among healthcare teams [8]. Related studies in the online-journals.org journal family have also shown that Artificial Intelligence (AI) and mobile technologies can support medical image analysis, computer-aided diagnosis, and intelligent healthcare service delivery [39], [40]. Web-based optical character recognition (OCR) and health data recording systems have also been applied to support structured data extraction and digital medical documentation workflows [9], [10].

In recent years, AI-based image analysis has emerged as a promising approach for improving wound assessment and clinical decision-making. Numerous studies have explored the application of machine learning and deep learning models for wound classification, segmentation, and healing prediction [11]–[14]. AI-driven wound analysis systems have shown potential to improve diagnostic consistency and reduce variability among clinicians [15], [16]. However, successful implementation in healthcare requires reliable validation procedures, consistent dataset preparation, and well-structured evaluation frameworks to ensure clinical applicability and robustness [17], [18]. Recent algorithm-based image selection studies further highlight the importance of image quality, dataset screening, and clinically meaningful visual data in medical imaging workflows [41]. Accurate AI-based characterization of wound size and tissue composition has been highlighted as important for clinically meaningful wound assessment and longitudinal monitoring [19].

Deep learning techniques, particularly convolutional neural networks (CNNs), have significantly advanced the field of medical image analysis. CNN-based architectures enable automatic extraction of hierarchical visual features from medical images, allowing accurate identification of complex patterns such as tissue structures and wound boundaries [21]. Numerous review studies have confirmed the effectiveness of deep learning techniques across various medical imaging applications, including disease detection, segmentation, and classification [22]–[25]. Early studies demonstrated the feasibility of using CNN-based models for automated wound detection and dermatological image analysis [26]–[28]. However, conventional CNN classification models primarily focus on image-level classification and often lack precise spatial localization capabilities, which are essential for accurate wound boundary detection and quantitative wound size estimation.

Object detection frameworks address this limitation by enabling simultaneous localization and classification of target objects within an image. Among these approaches, the You Only Look Once (YOLO) architecture has gained significant attention due to its ability to perform real-time object detection with high computational efficiency. Since its introduction, the YOLO family of models has evolved considerably, with recent versions such as YOLOv8 providing improved detection accuracy, faster inference speed, and enhanced scalability [29]. Comparative studies have shown that newer YOLO models outperform earlier versions in various applications, including agricultural disease detection, industrial inspection, and medical image analysis [30]–[32]. These improvements make YOLOv8 particularly suitable for healthcare applications that require accurate object localization and rapid image processing.

Recent research has increasingly explored the application of YOLO-based models for wound detection and assessment. Hybrid architectures combining YOLOv8 with segmentation networks have been proposed to support chronic wound diagnosis and monitoring [33]. YOLOv8-based systems have also demonstrated promising results in pressure injury detection and assessment [34]. Furthermore, automated wound detection systems designed for multi-ethnic datasets have shown improved model generalizability across diverse patient populations [35]. Advanced image analysis techniques, including image fusion and measurement algorithms, have been introduced to enhance wound size estimation accuracy [36]. Dataset construction and region-of-interest detection strategies have also contributed to improving model training and evaluation processes [37]. In addition, multi-scale attention mechanisms have been applied to improve wound detection performance in clinical imaging environments [38].

1.1 Research gap

Despite the progress achieved in AI-assisted wound assessment, several limitations remain. First, many existing studies emphasize wound classification or detection accuracy but provide limited discussion of clinically usable wound size estimation, which is necessary for monitoring healing progression over time [26], [33], [36]. Second, AI-based wound analysis models are often evaluated using experimental datasets without sufficient description of dataset composition, annotation consistency, and validation procedures. Third, several systems remain at the prototype or model-evaluation level and are not fully integrated with database-backed clinical documentation platforms [17], [20].

Therefore, this study aims to develop and evaluate a YOLOv8-based Smart Wound Scan system for automated wound localization, image-based wound size estimation, and structured clinical data management. The main contribution is the integration of an AI detection module with a web-based wound management platform, allowing wound images, measurement results, and clinical records to be stored and reviewed within a unified workflow.

2 METHOD

The methodology of this study was designed to develop and evaluate an AI-assisted wound assessment system that integrates wound image detection, size estimation, web-based data management, and clinical record storage. The methodological process consisted of six main stages: dataset preparation, wound image annotation, image preprocessing, YOLOv8 model training, system integration, and performance evaluation.

The following subsections describe the computational principles, dataset preparation, OpenCV-based preprocessing workflow, model training configuration, system architecture, and evaluation procedures used in this study.

2.1 CNN

Convolutional neural networks constitute a foundational deep learning methodology for image analysis and form the core computational framework of most modern medical imaging systems. A principal advantage of CNNs is their capacity to automatically learn hierarchical feature representations from raw pixel data, facilitating the extraction of low-level features (e.g., edges and textures) as well as higher-level semantic patterns without the need for manual feature engineering.

This capability is particularly important in wound and dermatological imaging due to the diverse appearance of wounds across patients, anatomical regions, lighting conditions, and stages of healing. CNN-based models can identify clinically significant features such as tissue texture, wound margins, granulation patterns, and color variations. In this study, CNN principles serve as the architectural foundation of the YOLOv8 model employed for automatic wound detection and localization. Previous research has demonstrated the effectiveness of CNN-based techniques for wound classification, segmentation, and image analysis, thereby supporting their use in AI-assisted wound assessment systems.

2.2 YOLO

You Only Look Once is a single-stage object detection framework designed to perform object localization and classification within a single inference pass. This architecture enables high computational efficiency, making YOLO particularly suitable for real-time or near–real-time clinical applications.

The proposed system employs YOLOv8 to automatically detect and localize wound regions in uploaded images. The model generates bounding box coordinates and confidence scores, which are subsequently used for wound measurement and database storage. Automated localization eliminates the need for manual region-of-interest selection, reduces inter-observer variability, and provides a consistent spatial reference for quantitative analysis. Recent advancements in YOLO architectures have improved detection accuracy and robustness across diverse imaging conditions, supporting their integration into AI-based wound management systems.

2.3 Regression and its application in this study

Regression methods provide a quantitative framework for modeling relationships between variables and are commonly employed in medical imaging to translate numerical outputs into clinically meaningful units.

In this study, regression techniques are applied during the calibration and validation phases to relate pixel-based measurements derived from bounding box outputs to actual wound dimensions expressed in centimeters or millimeters. Accurate wound size estimation is essential for monitoring healing progression and evaluating treatment effectiveness. Regression-based error analysis is conducted to assess agreement between algorithm-generated measurements and clinician-measured reference values, thereby ensuring the reliability and clinical applicability of the proposed system.

2.4 Relationship between image resolution and physical dimensions

The relationship between image resolution and physical dimensions is a critical consideration in image-based wound measurement systems. Image resolution determines the spatial detail available for boundary detection, while physical size defines the mapping between pixel distances and real-world dimensions.

Wound images captured using different devices under varying acquisition conditions may exhibit inconsistencies in resolution and scaling. If not properly addressed, these inconsistencies may result in biased size estimation. In this study, calibration and normalization procedures are incorporated to establish a consistent pixel-to-length conversion factor prior to measurement computation. Previous research highlights the importance of standardized preprocessing and calibration strategies to ensure reliable quantitative analysis across heterogeneous imaging conditions.

2.5 Physical size calculation

Physical size calculation refers to the conversion of pixel-level measurements into real-world units that are meaningful in clinical practice. In wound assessment, this conversion is essential because treatment planning depends on accurate evaluation of wound dimensions and their changes over time.

Although DPI-based conversion provides a theoretical relationship between pixels and physical units, practical accuracy depends on calibration reliability and acquisition conditions. Therefore, the proposed system incorporates validated size computation procedures and quantitative error analysis to ensure that estimated wound dimensions accurately reflect clinical reality. This approach aligns with methodological recommendations in AI-based wound measurement research, which emphasize the necessity of quantitative validation for longitudinal monitoring and clinical decision support.

2.6 Workflow of the health record system utilizing OCR technology (N&B RSU System)

The N&B RSU health record system utilizes OCR technology to extract structured clinical data from scanned or uploaded health records. This project integrates the OCR module into the wound management platform to enable automated data entry and minimize manual transcription errors.

The process begins with the upload of digital health record images. The OCR engine analyzes the image to identify textual regions, recognize characters, and convert them into machine-readable text. The extracted data, including patient identifiers, wound assessment notes, and clinical measurements, are then validated and stored in the database. This structured data integration facilitates linkage between wound images and associated clinical records, thereby enhancing documentation accuracy and supporting longitudinal patient monitoring.

This OCR-assisted workflow improves data integrity and reduces administrative burden while ensuring interoperability with the AI-driven wound detection module.

2.7 Personal data protection act B.E. 2562 (2019): PDPA

The use of digital wound images and associated clinical data in AI-based systems requires strict compliance with personal data protection regulations, as such information may be classified as sensitive health data. Thailand's PDPA provides a legal framework governing the collection, processing, storage, and disclosure of personal data.

In this study, PDPA compliance is ensured through data anonymization, secure database storage, controlled user authentication, and restricted access privileges. Patient-identifiable information is separated from wound image data wherever possible, and system access is limited to authorized users through role-based authentication mechanisms. These measures are particularly important for web-based wound management platforms that support multi-user access and long-term data storage.

By incorporating data protection principles into the system architecture, the proposed platform ensures secure handling of sensitive health information throughout the system lifecycle.

2.8 Materials and equipment

This study involved the design and implementation of an AI-based wound assessment and digital management system. Both software and hardware components were selected to support model development, image preprocessing, web application implementation, database management, and experimental evaluation.

The software environment included Python, OpenCV, YOLOv8, PHP, HTML, CSS, JavaScript, MySQL, XAMPP, and Visual Studio Code. Python was used to implement and test the YOLOv8 model for wound localization and measurement. OpenCV was used in the image preprocessing workflow, including image resizing, grayscale conversion, histogram analysis, Gaussian blur filtering, adaptive thresholding, and morphological operations. PHP managed server-side scripting and database communication, while HTML, CSS, and JavaScript supported the front-end interface. MySQL stored wound images, measurement outputs, clinical records, and user information.

System development and model training were conducted on an ASUS A15 notebook equipped with an AMD Ryzen 7 4800H processor, 16 GB RAM, and an NVIDIA GeForce RTX 3050 Laptop GPU. This configuration supported YOLOv8 training, inference, web application testing, and database operation under local server conditions.

2.9 Project design methodologies

This study centers on the design and development of an AI–based system for wound identification, wound size estimation, and digital wound record management. The workflow includes dataset preparation, AI model training, image preprocessing, system architecture design, database implementation, and functional validation.

The dataset consisted of wound and non-wound images collected from clinical image sources provided by the Faculty of Nursing, Rangsit University, and publicly accessible dermatological images from the DermNet repository. Patient-identifiable information was excluded before system development. Images were manually annotated using bounding boxes to identify wound regions or non-wound regions. Figure 1 illustrates the overall project workflow, including dataset preparation, AI-based processing, measurement output generation, and result storage.

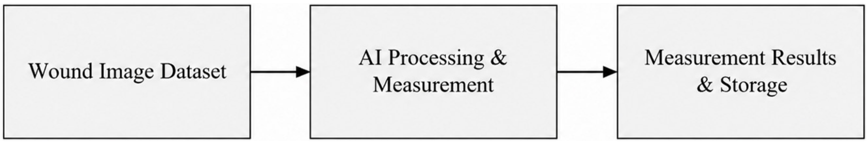

Fig. 1. Overall workflow of the proposed Smart Wound Scan project

2.10 Image processing and AI-driven wound detection

The system analyzes uploaded wound images using a YOLOv8-based object detection model. After image upload, the input image is processed through the OpenCV preprocessing pipeline and forwarded to the AI detection module. The YOLOv8 model localizes the wound area using bounding box prediction and returns the detected class, confidence score, and bounding box coordinates.

If the uploaded image is classified as a wound image, the detection result, measurement output, and processed image are stored in the database for clinical review and longitudinal monitoring. If no wound is detected, the system reports a non-detection result and terminates the measurement process. Figure 2 illustrates the image processing and AI-driven wound detection workflow.

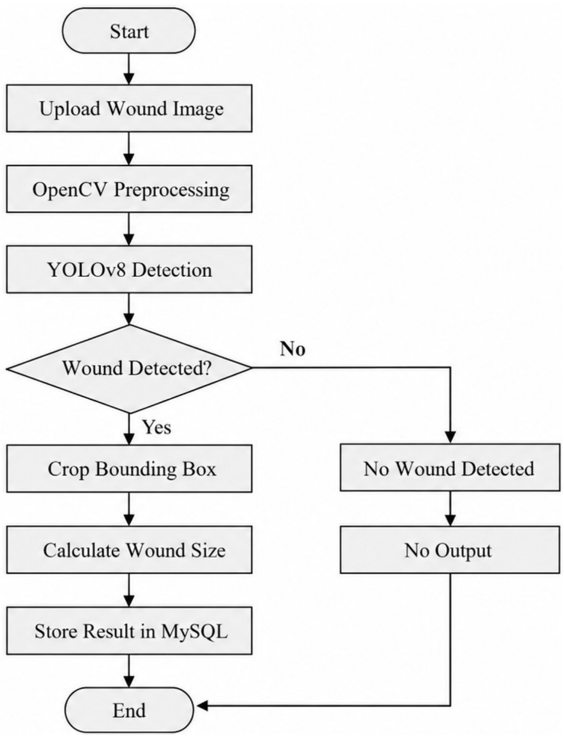

Fig. 2. Image processing and AI-driven wound detection workflow

2.11 Dataset preparation and annotation

Wound images were collected in standard formats (.jpg and .png) from clinical image sources and publicly accessible dermatological repositories. The dataset contained both wound and non-wound images to support detection and negative class recognition. Images were uploaded to the Roboflow platform for dataset management, annotation, preprocessing, and export.

Each image was manually annotated using bounding boxes. For wound images, bounding boxes were placed around the visible wound boundary as consistently as possible. Annotation consistency was reviewed by checking bounding box placement, class labels, and image quality before training. Preprocessing and augmentation, including resizing, normalization, rotation, flipping, and brightness adjustment, were then applied. Figure 3 summarizes the dataset preparation and annotation workflow.

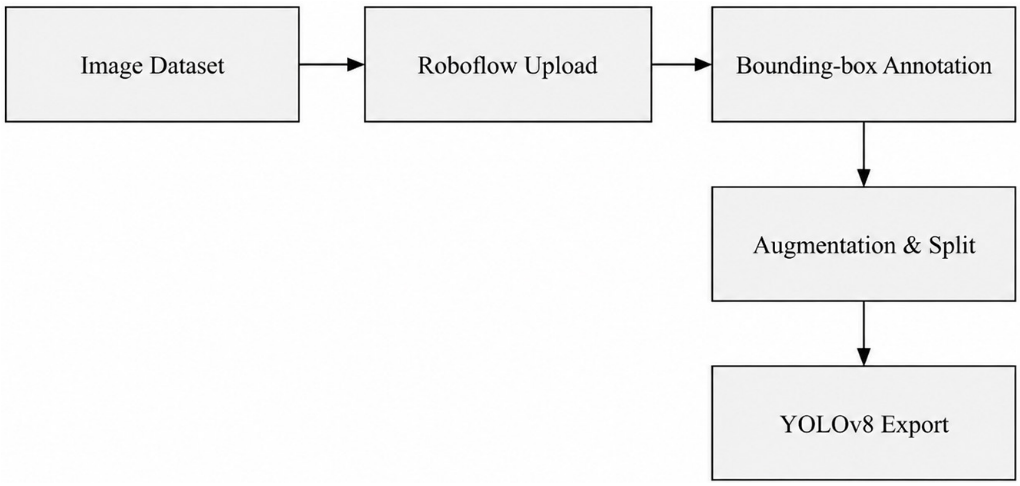

Fig. 3. Dataset preparation and annotation workflow

2.12 Training and evaluation of the YOLOv8 model

The annotated dataset was divided into training and validation subsets using a 70:30 ratio. The training set contained 2,940 images, while the validation set contained 1,260 images, for a total of 4,200 images. All images were resized to 640×640 pixels to conform to the YOLOv8 input specification. The model was trained for 200 epochs, and the best-performing model weights were selected for integration into the Smart Wound Scan system. Evaluation used precision, recall, mAP, classification behavior, and measurement accuracy compared with ruler-based reference measurements. Figure 4 illustrates the YOLOv8 model training and validation workflow used in this study.

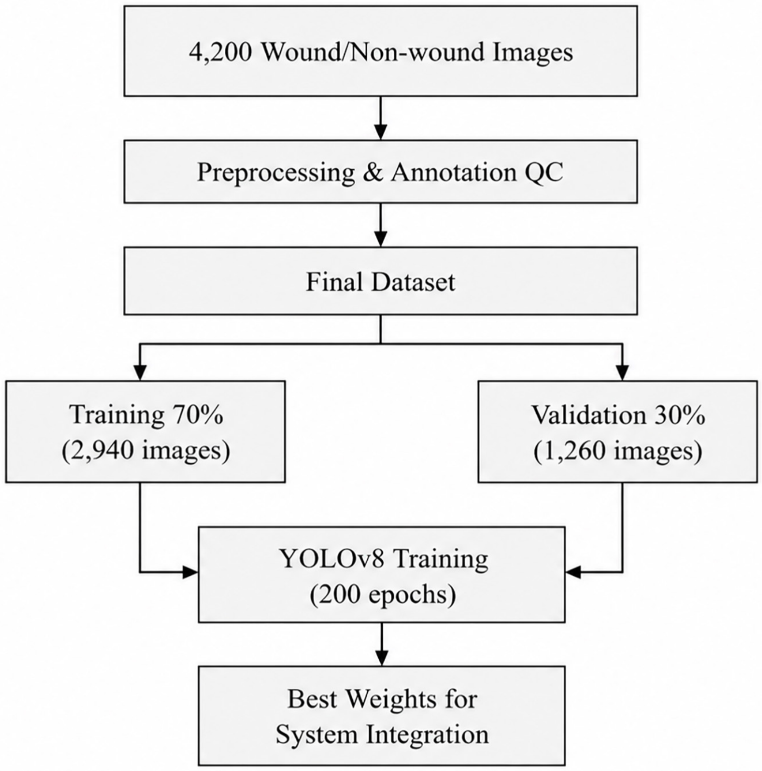

Fig. 4. YOLOv8 model training and validation workflow

2.13 Image pre-processing

Prior to model inference, input images were processed using OpenCV-based preprocessing operations. Each image was resized to 640×640 pixels, converted to grayscale, and evaluated using histogram analysis. Gaussian blur filtering was applied to reduce noise, adaptive Gaussian thresholding was used to minimize uneven illumination, and morphological opening was applied to refine edge structures before YOLOv8 inference. The complete OpenCV-based preprocessing workflow is summarized in Figure 5.

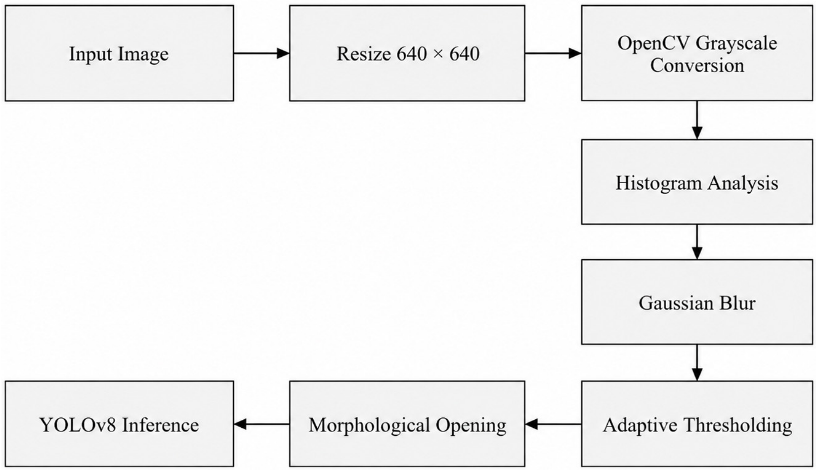

Fig. 5. OpenCV-based image preprocessing pipeline

2.14 Post-processing and output generation

During post-processing, image pixel values were normalized from 0 to 1 to improve inference stability. The processed image arrays were converted into PyTorch tensors and passed to the YOLOv8 model. The model generated wound class labels, confidence scores, and bounding box coordinates, which were used to estimate wound width and height before storage in the MySQL database. Figure 6 presents the post-processing and YOLOv8 inference workflow, including normalization, tensor conversion, and generation of class labels, bounding box coordinates, and confidence scores.

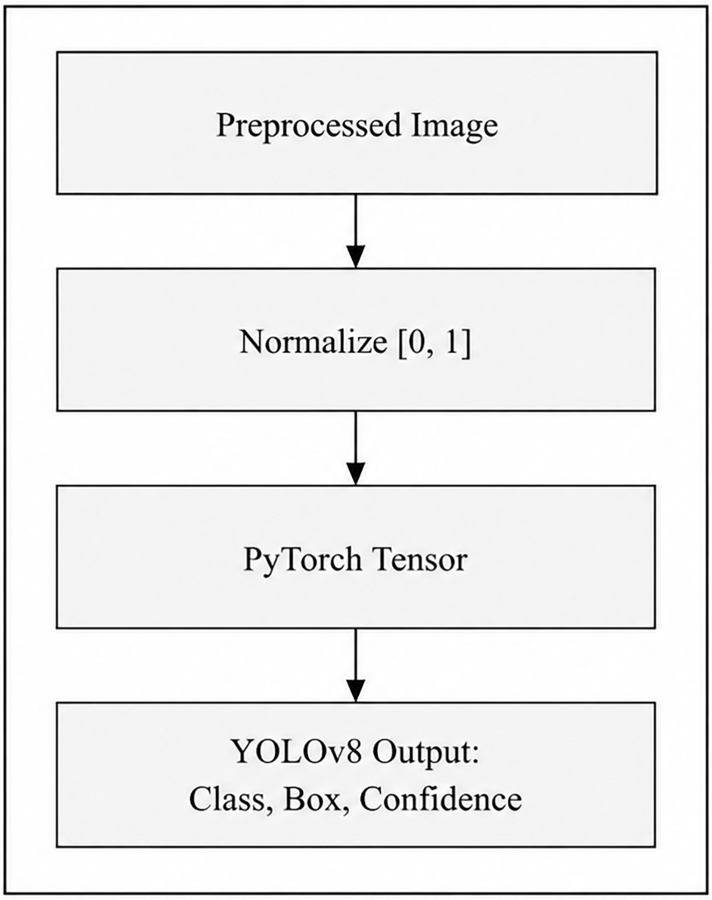

Fig. 6. Post-processing and YOLOv8 inference workflow

2.15 System architecture design

The system architecture consists of three integrated components: a web-based user interface, a MySQL database, and an AI image analysis module implemented in Python. The web interface allows authorized users to register, log in, upload wound images, view results, and review clinical records according to role-based access privileges. The AI module performs OpenCV-based preprocessing and YOLOv8-based wound detection, while the database stores user information, wound images, measurement values, detection results, and clinical documentation. The integrated Smart Wound Scan system architecture is illustrated in Figure 7.

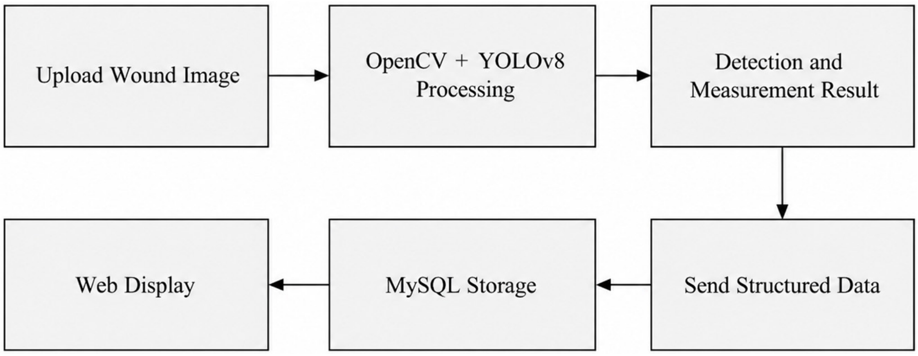

Fig. 7. Integrated smart wound scan system architecture

2.16 Data flow design

The data flow of the Smart Wound Scan system describes how wound images and associated clinical data move through the system. At Level 0, the system interacts with three primary user groups: administrator, medical staff, and patient. At Level 1, the process is decomposed into registration, login, image upload, result display, and storage, ensuring that wound images are linked with patient records and procedure reports under role-based access control. Figure 8 shows the Level 0 data flow diagram of the Smart Wound Scan system, whereas Figure 9 presents the Level 1 data flow diagram with the internal processes of registration, login, image upload, result display, and data storage.

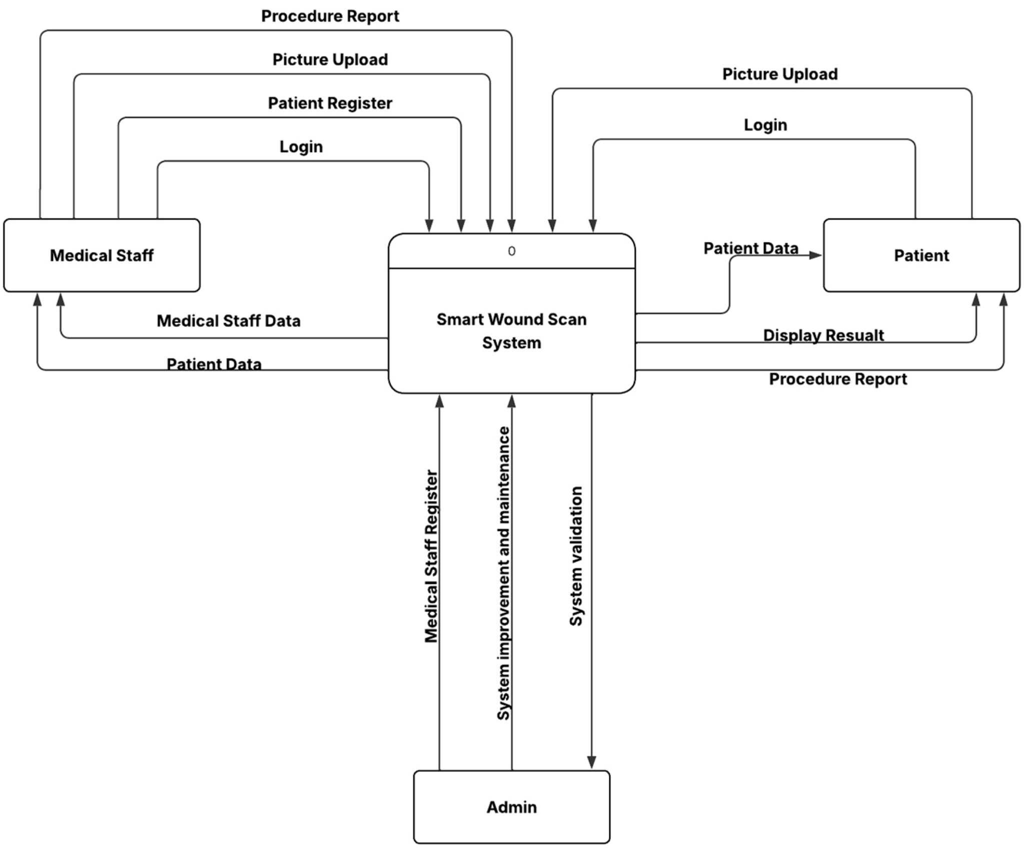

Fig. 8. Data flow diagram level 0 of the Smart Wound Scan system

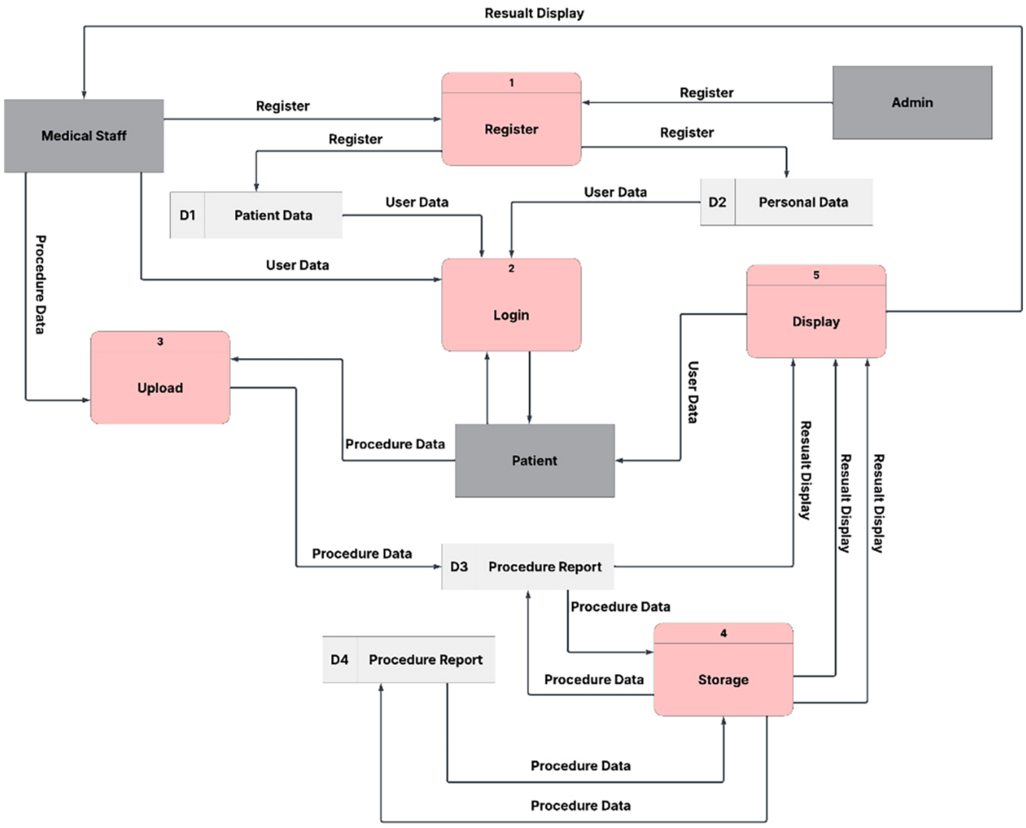

Fig. 9. Data flow diagram level 1 of the Smart Wound Scan system

3 RESULTS

The proposed Smart Wound Scan system was evaluated in terms of system functionality, wound size estimation performance, image acquisition sensitivity, YOLOv8 detection performance, and overall model behavior. The evaluation focused on whether the web-based system could support role-based access, wound image upload, clinical documentation, and result storage, and whether the AI module could detect wound regions and produce measurement outputs that were reasonably consistent with ruler-based reference measurements.

3.1 System functional evaluation

Role-based access control was tested across three user groups: administrator, healthcare professional, and patient. The functional scope of each role was verified based on whether the role could access specific modules, including authentication, registration, profile management, patient record access, wound image upload, clinical review, and record maintenance. Table 1 summarizes the verified access privileges.

Table 1. Role-based access privileges in Smart Wound Scan

Functionality	Administrator	Healthcare Professional	Patient
Login	✓	✓	✓
Registration	✓	✓	–
Home page access	✓	✓	✓
View own profile	–	✓	✓
View registered patients' profiles	✓	✓	–
View own treatment records	–	–	✓
View registered patients' treatment records	✓	✓	–
Edit treatment records	✓	✓	–
Delete treatment records	✓	✓	–
Upload images	✓	✓	✓
Clinical assessment/consultation	✓	✓	–
Logout	✓	✓	✓

Table 1 summarizes the verified access privileges for the three user groups. The results show that administrator and healthcare professional roles can manage patient profiles and treatment records, while patients can access their own profile, upload images, and view their own treatment records. These access restrictions support secure clinical workflow management and prevent unauthorized modification of wound records.

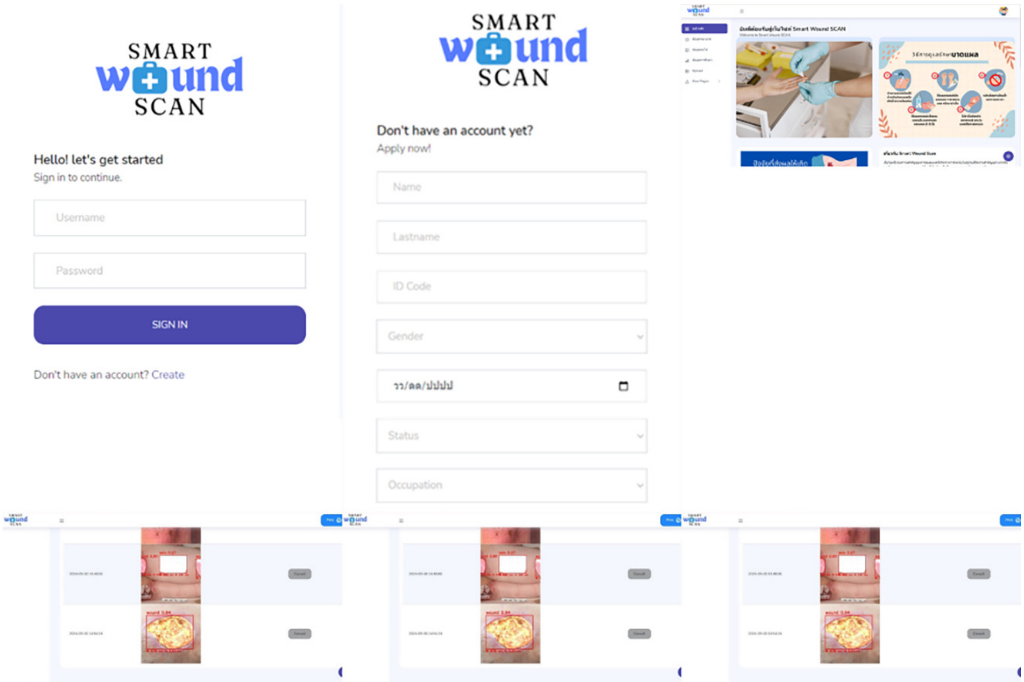

Fig. 10. Overview of the Smart Wound Scan web application workflow

Figure 10 presents an overview of the Smart Wound Scan web application workflow, including authentication, role-based access, image upload, AI-assisted wound analysis, structured storage, and clinical review. The functional evaluation confirmed that the web application can support end-to-end wound monitoring and record management within the proposed system.

3.2 Wound size estimation performance

Wound size estimation was assessed by comparing system-generated measurements against ruler-based reference measurements. The comparison was reported for two axes: X axis, representing wound width, and Y axis, representing wound height or length. Percent error was calculated as follows:

$$\text{Percent error (\%)} = |\text{System measurement} - \text{Ruler measurement}| / \text{Ruler measurement} \times 100$$

Table 2. Measurement comparison between ruler reference and Smart Wound Scan at 30 cm (n = 10)

Image	X (Ruler, cm)	X (System, cm)	Y (Ruler, cm)	Y (System, cm)	Accuracy (%)	Error X (%)	Error Y (%)
1	6.00	6.22	2.70	3.31	88	2.20	6.10
2	11.00	11.88	7.20	7.46	91	8.00	3.61
3	12.10	12.01	7.40	7.38	90	0.74	0.27
4	9.90	9.95	9.20	9.05	89	0.51	1.63
5	7.00	6.54	8.10	7.70	88	6.57	4.94
6	7.70	7.78	8.50	8.50	74	1.04	0.00
7	8.50	8.47	6.90	6.83	88	0.35	1.01
8	8.10	8.10	6.00	6.16	66	0.00	2.67
9	4.50	4.95	5.00	6.01	84	10.00	20.20
10	6.20	6.03	5.00	5.37	91	1.70	3.70

Table 2 presents the measurement comparison at the recommended capture distance of 30 cm. Across the ten test images, the system achieved a mean measurement accuracy of 84.90%, with a mean X-axis error of 3.11% and a mean Y-axis error of 4.41%. Image 9 showed a higher Y-axis error, suggesting that wound boundary ambiguity, image quality, or perspective distortion can affect measurement reliability. Representative measurement outputs are presented in Figures 11, 12, and 13, corresponding to Images 1–3, respectively, and showing ruler-based reference measurements and YOLOv8-generated wound detection outputs.

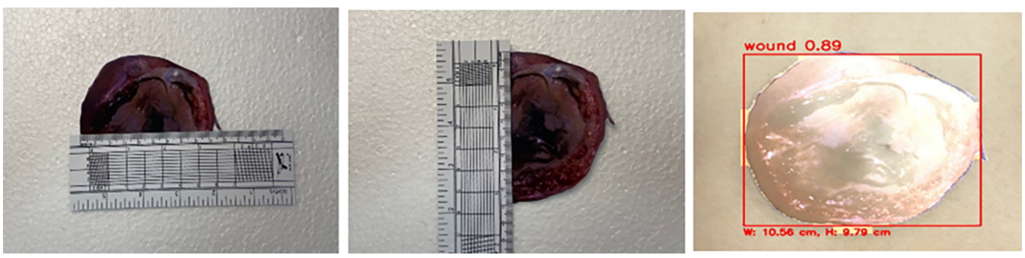

Fig. 11. Example measurement outputs for image 1

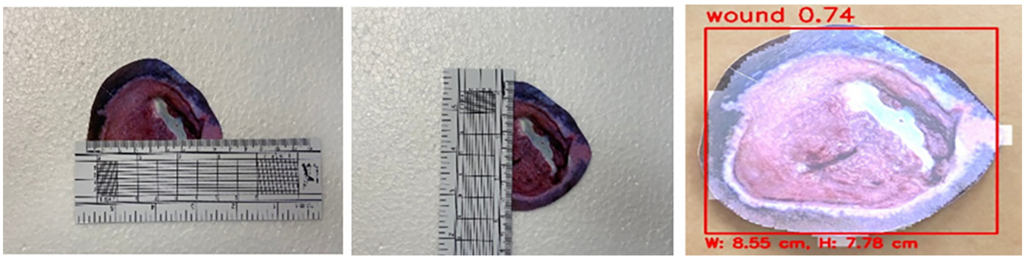

Fig. 12. Example measurement outputs for image 2

Fig. 13. Example measurement outputs for image 3

To assess image acquisition sensitivity, measurements were evaluated at 25 cm, 30 cm, and 35 cm. Table 3 summarizes the mean accuracy obtained at each capture distance.

Table 3. Mean measurement accuracy across different capture distances

Capture Distance (cm)	Mean Accuracy (%)
25	82
30	85
35	81

The highest mean accuracy was observed at 30 cm, indicating that this distance provides a suitable balance between image scale, boundary visibility, and perspective stability. Therefore, 30 cm was selected as the recommended capture distance for the proposed system.

The YOLOv8 model was trained using 4,200 images split into training and validation subsets, as shown in Table 4. The training set contained 2,940 images, and the validation set contained 1,260 images.

Table 4. Dataset split for model development

Subset	Number of Images	Percentage (%)
Train	2,940	70
Validation	1,260	30
Total	4,200	100

The training process was conducted over 200 epochs. Figure 14 shows the training curves, which indicate that precision, recall, and mAP improved during training and stabilized toward later epochs.

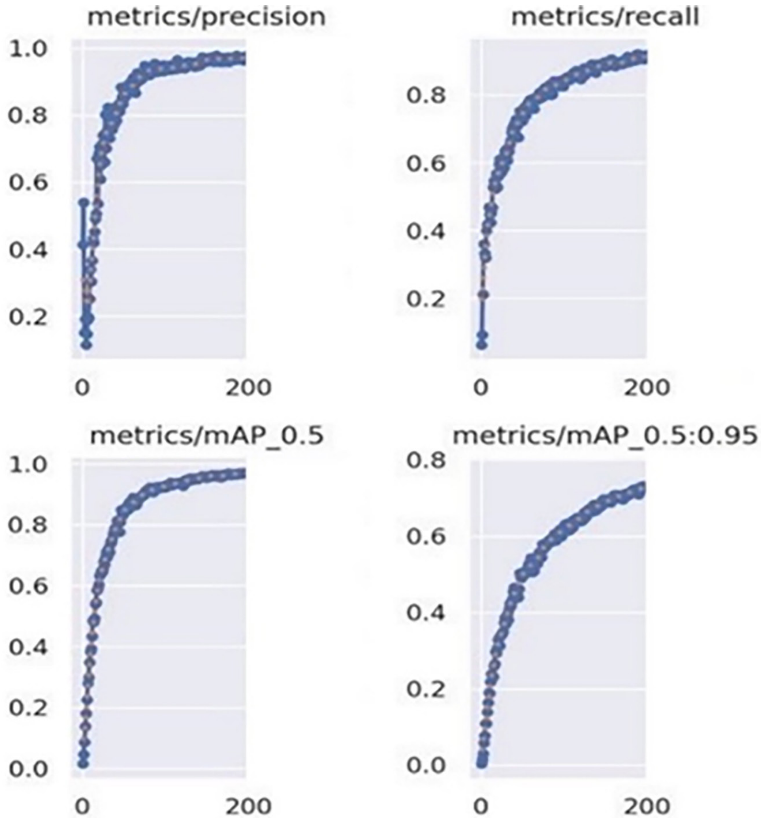

Fig. 14. Training curves of the YOLOv8 model over 200 epochs

Detection performance for the primary wound class showed maximum precision of approximately 86.3% and recall of approximately 100%. However, the mAP value was approximately 0.433 at an IoU threshold of 0.5. This result indicates that the model was highly sensitive in detecting wound presence but still had limitations in localization precision and bounding box consistency. Figure 15 presents the precision–recall and mAP curves.

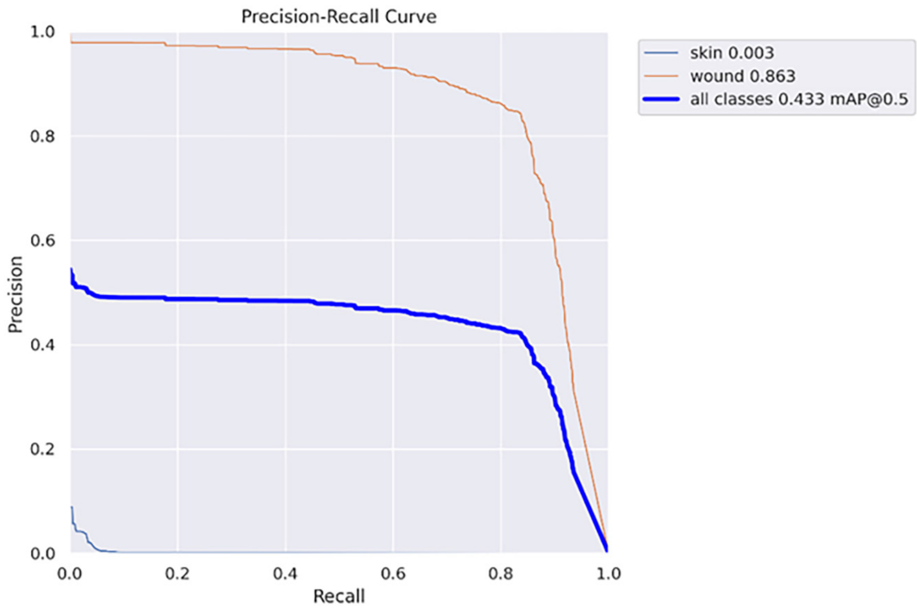

Fig. 15. Precision–recall and mAP curves of the YOLOv8 model

Classification behavior further indicated strong recognition of wound images, with residual false positives where skin was misclassified as a wound. Figure 16 presents the confusion matrix, and Figure 17 presents the overall and per-class metric report. Table 5 summarizes the investigated procedures and overall system performance, including functional testing, measurement accuracy, YOLOv8 detection performance, and classification behavior.

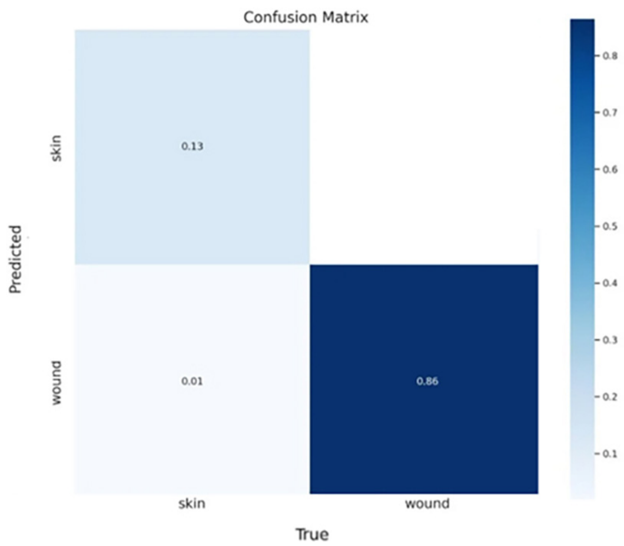

Fig. 16. Confusion matrix for wound and non-wound classification

```
Overall Accuracy: 0.8333
Overall Precision: 0.8333
Overall Recall: 0.8333
Overall F1 Score: 0.8333

Per-Class Metrics:
Class 0: Precision: 1.0000, Recall: 1.0000, F1 Score: 1.0000
Class 1: Precision: 0.6667, Recall: 1.0000, F1 Score: 0.8000
Class 2: Precision: 1.0000, Recall: 0.5000, F1 Score: 0.6667
```

Fig. 17. Overall and per-class performance metrics

Table 5. Summary of investigated procedures and system performance

Evaluation Procedure	Metric	Reported Outcome
Functional system testing	Role-based access control	Verified
Measurement at 25 cm	Mean accuracy	82%
Measurement at 30 cm	Mean accuracy	85%
Measurement at 35 cm	Mean accuracy	81%
Measurement at 30 cm	Mean X-axis error	3.11%
Measurement at 30 cm	Mean Y-axis error	4.41%
YOLOv8 wound detection	Precision (maximum)	86.3%
YOLOv8 wound detection	Recall (maximum)	100%
YOLOv8 wound detection	mAP@0.5	0.433
Classification behavior	Overall accuracy	83.33%
Classification behavior	Skin misclassified as a wound	~13%

4 DISCUSSION

The findings demonstrate that the Smart Wound Scan system can support AI-assisted wound monitoring by integrating YOLOv8-based image analysis with a structured web-based data management workflow. Compared with many AI wound assessment studies that focus mainly on model-level performance, the proposed system emphasizes practical integration by combining wound detection, size estimation, role-based access control, result visualization, and database-backed clinical documentation. This workflow supports continuity of care and creates a practical foundation for longitudinal wound monitoring.

The detection results show high recall, indicating that the YOLOv8 model was able to identify most wound regions in the evaluated images. However, the moderate mAP value suggests that localization quality remains a limitation. This discrepancy between high recall and moderate mAP indicates that the model may detect wound presence effectively but may not always predict bounding boxes with sufficient spatial precision. In wound measurement applications, inaccurate localization can directly affect size estimation. Possible causes include annotation inconsistency, wound boundary ambiguity, lighting variation, skin-tone diversity, background complexity, and class imbalance between wound and non-wound samples.

Alternative methodologies may improve future performance. Segmentation-based approaches such as U-Net, Mask R-CNN, or YOLOv8-seg could provide more precise wound boundary estimation than bounding box detection, particularly for irregular wound shapes. However, these methods require pixel-level annotation and higher computational resources. Before clinical deployment, further validation should include larger and more diverse datasets, expert-reviewed annotations, standardized image acquisition protocols, physical reference markers, controlled lighting, and prospective evaluation in real healthcare settings.

5 CONCLUSION

This study presented the Smart Wound Scan system, an AI–based wound measurement and management platform that integrates YOLOv8-based wound detection with a web-based clinical data management workflow. The system allows authorized users to upload wound images, automatically detect wound regions, estimate wound size, store measurement results, and review clinical records. The highest mean measurement accuracy was obtained at a capture distance of 30 cm, with a mean accuracy of approximately 85%. The YOLOv8 model demonstrated strong detection sensitivity, but the moderate mAP value indicates that localization quality and bounding box consistency still require improvement. The main contributions are: (1) development of a YOLOv8-based wound localization workflow; (2) implementation of image-based wound size estimation; (3) integration with a role-based web platform and MySQL database; (4) evaluation using measurement accuracy, capture distance sensitivity, detection metrics, and system functionality; and (5) identification of practical limitations for future clinical validation.

6 ETHICAL STATEMENT

This study has been approved by the Research Ethics Office of Rangsit University (RSUERB) under the certification number RSUERB2024-021 as a study that does not fall under the category of human research.

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