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YOLOv8-Based Object Detection for Automated Cattle Sex Identification in Tomohon City

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Abstract: *Accurate identification of cattle sex is essential in livestock management to support proper data recording and strategic decision-making. Conventional identification methods are often time-consuming and dependent on human expertise, which may reduce efficiency and accuracy. Therefore, this study aims to develop an automated cattle sex identification system using an object detection approach based on the YOLOv8 algorithm. The dataset consisted of primary images collected directly in Tomohon City using a smartphone camera and secondary images obtained from the Roboflow platform. All images were annotated with bounding boxes and classified into two categories: male and female cattle. The dataset was divided into training, validation, and testing sets with a ratio of 70:20:10. Model training and evaluation were conducted using the Roboflow platform, and the final model was integrated into a web-based system to enable real-time detection. The experimental results show that the proposed model achieved 97.1% precision, 92.5% recall, and 98.7% mean average precision (mAP). These findings indicate that the system performs reliably and can serve as an effective tool to support livestock data management in Tomohon City.*

Keywords: *cattle, object detection, sex identification, YOLOv8.*

1. Introduction

Livestock farming in Tomohon City consists of dairy cattle, beef cattle, and working cattle, which contribute to the local economy through milk and meat production, agricultural activities, and biogas generation from cattle waste [1], [2]. These contributions highlight the importance of efficient livestock management systems. However, field observations indicate that cattle data collection and identification in Tomohon City are still conducted manually, increasing the risk of recording errors, data inconsistency, and inefficient monitoring processes [3], [4]. Web-based systems have been widely implemented to improve data management efficiency, accuracy, and accessibility [5], [6]. Accurate cattle sex identification is also important for breeding management, population monitoring, and production planning, emphasizing the need for a more automated livestock identification system.

Recent developments in smart agriculture have encouraged the adoption of computer vision–based approaches for automated livestock monitoring and identification [7]. Previous studies have applied object detection techniques for cattle monitoring using aerial images [8], breed identification [9], and livestock health monitoring [10]. Despite this, studies specifically focusing on automated cattle sex identification in the local context of Tomohon City remain limited. Therefore, this study proposes a YOLOv8-based object detection system integrated into a web-based platform for automated cattle sex identification to support more efficient livestock data management.

2. Literature Review

Traditional livestock identification methods, such as ear tagging and RFID-based systems, have been widely used for animal tracking and farm management [12], [13]. However, these approaches require additional hardware infrastructure and remain vulnerable to tag damage, loss, and data inconsistency. Therefore, computer vision–based approaches have attracted increasing attention in livestock management applications. Computer vision–based object detection enables automatic object recognition and localization within digital images [14], [15]. Compared with image classification, object detection provides both categorical and spatial information, making it suitable for automated animal monitoring applications [16], [17].

Several studies have applied deep learning approaches for livestock identification and monitoring. In livestock management, object detection has demonstrated significant potential for automated monitoring, population tracking, and visual-based data collection [18]. In addition, computer vision technologies support livestock management decision-making by providing consistent and real-time visual data [19]. Previous studies developed cattle identification systems using muzzle-based biometric patterns [20], [21], body feature recognition and deep feature fusion methods [22], and YOLO-based real-time livestock detection models [18]. However, most previous studies primarily focused on cattle detection, breed recognition, or individual identification rather than automated cattle sex identification. Studies specifically addressing image-based cattle sex identification remain limited, particularly in local livestock management contexts such as Tomohon City.

The YOLO algorithm is widely used for object detection because it performs localization and classification within a single-stage architecture, enabling faster processing and better computational efficiency than two-stage detectors such as R-CNN and Faster R-CNN [23], [24]. Recent developments in YOLOv8 further improve detection accuracy, inference speed, and object localization performance under varying environmental conditions [25]. These advantages make YOLOv8 suitable for livestock monitoring and automated cattle sex identification systems. Unlike previous studies that mainly focused on RFID-based systems and general livestock identification, this study proposes a YOLOv8-based automated cattle sex identification system integrated into a web-based platform to support more efficient livestock data management. Roboflow was utilized to support dataset management, image annotation, preprocessing, and model training processes [26]–[28].

3. Methods

A. Data Description

This study utilized 602 cattle images consisting of 282 male and 320 female cattle images. The dataset included 129 images collected directly from cattle farms in Tomohon City using smartphone cameras under real farm conditions, while the remaining images were obtained from publicly available datasets on the Roboflow platform to increase image diversity and support model generalization. The images included variations in lighting conditions, camera angles, object distances, cattle orientation, and background complexity to represent practical livestock environments. Duplicate and highly similar images were manually filtered to reduce overfitting risks. All images were annotated using bounding box techniques and classified into two categories: male and female cattle. Annotation was manually performed by the researcher using Roboflow and validated through repeated checking to maintain labeling consistency. Male and female cattle were identified based on visible anatomical characteristics, including body shape, horn structure, and genital region visibility when observable. The dataset was divided into training, validation, and testing sets using a 70:20:10 ratio, resulting in 428 training images, 121 validation images, and 53 testing images.

B. Research Location

Field data collection was conducted at several cattle farms located in Tomohon City, North Sulawesi, Indonesia, including farms in Central Tomohon District and South Tomohon District. These locations were selected to represent variations in livestock environmental conditions and cattle management practices within Tomohon City. The observed cattle mainly consisted of Ongole cattle raised under semi-intensive farming systems, where cattle are typically grazed in open areas such as plantations or grass fields during daytime and returned to enclosures for feeding and management activities. Images were collected during daytime using smartphone cameras from multiple viewing angles and distances to represent actual livestock management conditions. Variations in natural lighting, cattle orientation, outdoor farm environments, and background complexity were intentionally included during image acquisition to improve dataset representativeness and support model robustness under practical field conditions.

C. Research Methods and Evaluation

This study applied the Extreme Programming (XP) methodology, consisting of planning, design, coding, and testing stages. The planning stage involved analysing livestock identification problems and determining system requirements. The design stage focused on developing the web-based system architecture and YOLOv8 integration workflow. The coding stage included implementation of the YOLOv8 model, backend development, and image processing mechanisms, while the testing stage evaluated both system functionality and model performance. The XP approach was selected because it supports flexible and iterative system development. The study utilized the YOLOv8 algorithm for real-time cattle detection and sex identification. YOLOv8 was selected because of its lightweight architecture, fast inference capability, and suitability for real-time object detection systems. As a single-stage object detection framework, YOLOv8 simultaneously performs object localization and classification in a single process, enabling efficient image processing under practical livestock farming conditions. Detailed model training and implementation procedures are presented in the following section.

C.1 Processing and Annotation

Before model training, all collected images underwent preprocessing and annotation using the Roboflow platform. Bounding box annotation was manually performed by the researcher to label cattle objects into male and female categories based on visible anatomical characteristics and field information obtained during data collection. Repeated validation and rechecking were conducted to minimize labeling errors and maintain annotation consistency across the dataset. However, variations in body posture, viewing angles, partial occlusion, lighting conditions, and image quality presented challenges in visually distinguishing male and female cattle during the annotation process. The annotated dataset enabled the YOLOv8 model to learn object localization and classification features simultaneously. Subsequently, the dataset was divided into training, validation, and testing subsets for model training and performance evaluation.

C.2 Model Training and Implementation

The YOLOv8 model was trained using the Roboflow platform due to its lightweight computational performance, fast inference capability, and suitability for real-time detection systems. Training was conducted using 100 epochs, an input image size of 640×640 pixels, and a batch size of 16. The optimizer configuration and learning rate were automatically managed using the platform's default training settings and were not explicitly provided in the training interface. Data augmentation techniques, including horizontal flipping, brightness adjustment, and rotation, were applied to improve model robustness under varying environmental conditions such as lighting, viewing angles, and background complexity. A confidence threshold of 0.25 and an IoU threshold of 0.5 were applied during detection and evaluation. Training was performed in a cloud-based GPU environment, with a total duration of approximately 32 minutes.

The trained YOLOv8 model was subsequently integrated into a web-based system for automated cattle sex identification. The system consisted of a frontend user interface and a backend image-processing module developed using Python. Users uploaded cattle images through the web interface, after which the system processed the images using the trained YOLOv8 model and displayed prediction results along with confidence scores. The workflow included image upload, preprocessing, model inference, and result visualization, as illustrated in Figure 1.

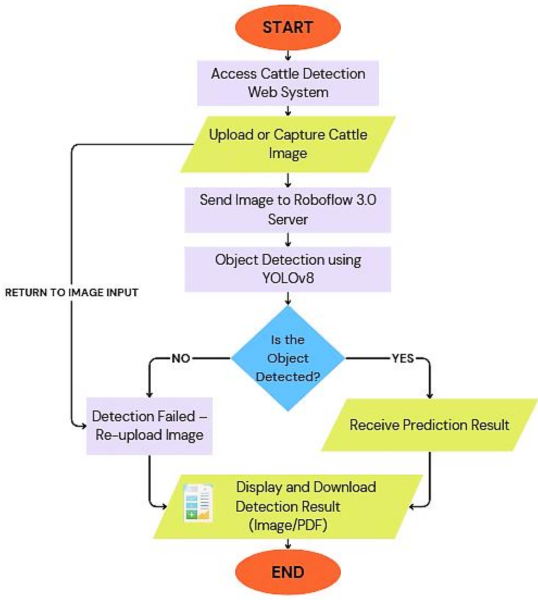

Figure 1. Flowchart of the web-based cattle detection system using YOLOv8

Figure 1 presents the overall system workflow, including image input, object detection, decision handling, and prediction result visualization.

C.3 Evaluation Method

Model performance was evaluated using precision, recall, F1-score, and mean Average Precision (mAP), which are commonly used metrics in object detection and classification tasks. Precision measures prediction accuracy, recall evaluates the ability to identify relevant objects, while the F1-score provides a balance between both metrics. mAP was used to assess overall detection performance across confidence thresholds. In addition to the overall evaluation, per-class analysis was conducted for male and female cattle to assess class-specific detection capability. A confusion matrix was also used to identify potential misclassification patterns between classes. Evaluation was performed using unseen testing images under varying real-world conditions, including differences in lighting, background complexity, viewing angles, object distances, partial occlusion, and image quality, to assess model robustness in practical livestock farm environments.

Error analysis was further conducted to identify factors contributing to detection inaccuracies, particularly under challenging conditions such as low lighting, overlapping cattle positions, partial body occlusion, and extreme side-view angles that may reduce the visibility of anatomical characteristics used for cattle sex identification. Although the testing dataset size remained relatively limited, it was considered sufficient for preliminary evaluation. Future studies are recommended to utilize larger and more diverse datasets to improve model generalization and evaluation reliability.

4. Results and Discussion

A. Model Performance

The YOLOv8 model performance was evaluated using precision, recall, F1-score, and mean Average Precision (mAP) metrics based on the testing dataset. The evaluation results are presented in Table 1.

Table 1. Model Performance Evaluation Result

Metric	Value
Precision	97.1%
Recall	92.5%
F1-score	94.7%
mAP	98.7%

The evaluation results (Table 1) indicate that the model achieved high detection performance, with precision, recall, F1-score, and mAP values of 97.1%, 92.5%, 94.7%, and 98.7%, respectively. These results demonstrate the model's capability to accurately classify cattle sex while maintaining consistent object detection performance under varying environmental conditions. To further analyze classification performance and identify potential misclassification patterns between male and female cattle classes, a confusion matrix evaluation was conducted, as presented in Figure 2.

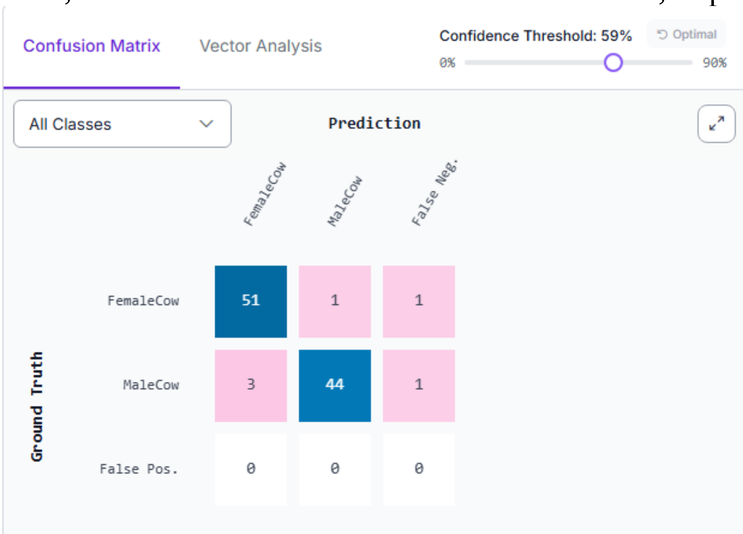

Figure 2. Confusion matrix of cattle sex identification using the YOLOv8 model

The confusion matrix in Figure 2 shows that the model correctly classified most cattle images. A total of 51 female cattle and 44 male cattle were correctly predicted. In total, 95 out of 101 images were classified correctly. Misclassifications occurred in six cases, including one female cattle misclassified as male, three male cattle misclassified as female, one female cattle classified as another class (false negative), and one male cattle classified as another class (false negative). These results indicate that the model achieves good overall classification performance, although minor misclassifications still occur across both classes. In addition to overall classification analysis, per-class performance evaluation was conducted separately for the MaleCow and FemaleCow classes to assess class-specific detection capability.

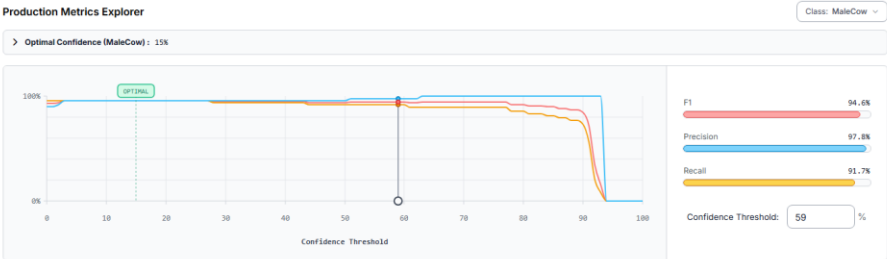

Figure 3. Performance metrics for the MaleCow class

Figure 4. Performance metrics for the FemaleCow class

The MaleCow class (Figure 3) achieved a precision of 97.8%, recall of 91.7%, and F1-score of 94.6%, whereas the FemaleCow class (Figure 4) achieved a precision of 94.4%, recall of 96.2%, and F1-score of 95.3%. Although slight performance differences were observed between classes, both categories demonstrated high detection capability. These findings indicate that the YOLOv8 model was able to distinguish male and female cattle effectively under varying farm conditions, lighting variations, and image characteristics.

Furthermore, the overall detection consistency and robustness of the model were evaluated through mAP performance analysis, as illustrated in Figure 5.

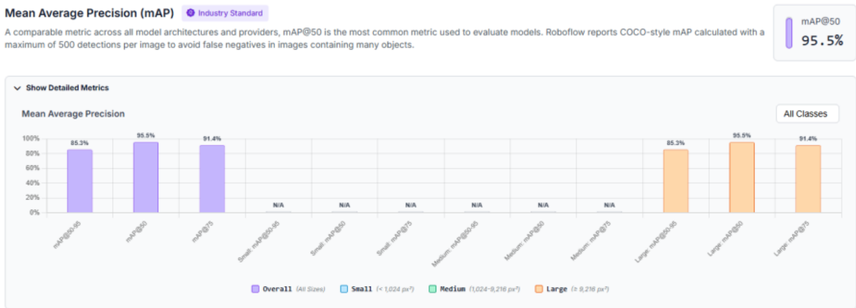

Figure 5. mAP performance analysis of the YOLOv8 model

The mAP evaluation results (Figure 5) indicate that the YOLOv8 model achieved stable detection performance across different confidence thresholds during testing. The high mAP value demonstrates the model's capability to accurately localize and classify cattle objects under varying farm conditions, including differences in illumination, viewing angles, object distances, and background complexity. Several detection inaccuracies were still observed under challenging conditions such as partial body occlusion, overlapping cattle positions, low image quality, insufficient lighting, and extreme side-view angles that reduced the visibility of anatomical characteristics used for cattle sex identification. Although these conditions affected detection performance in certain scenarios, the overall results demonstrate that the YOLOv8 model achieved reliable performance for automated cattle sex identification under the evaluated dataset conditions.

Error analysis indicated that lighting conditions were among the main factors affecting detection performance. In several testing scenarios, excessive lighting exposure reduced the visibility of anatomical characteristics required for cattle sex identification, causing inaccurate detection or classification results. Under such conditions, the system displayed a notification requesting users to upload or capture another image with improved visibility. Nevertheless, the YOLOv8 model generally demonstrated stable detection capability across normal farm environments and practical testing scenarios.

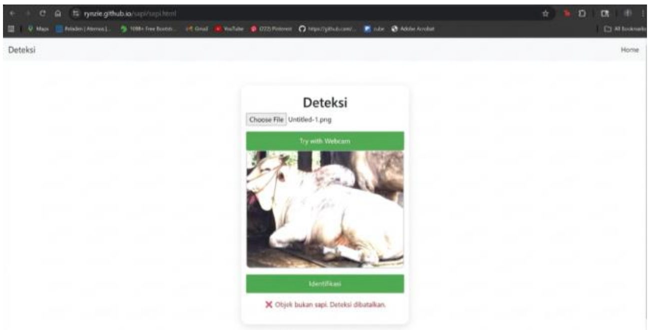

Figure 6. Example of detection failure under excessive lighting conditions causing unsuccessful cattle identification.

As illustrated in Figure 6, excessive lighting exposure caused image overexposure and reduced the visibility of important anatomical characteristics used for cattle sex identification. Consequently, the system was unable to generate an accurate prediction and prompted the user to provide another image with better lighting conditions. These findings highlight the importance of image quality and environmental lighting in supporting reliable cattle detection performance. Although the evaluation results demonstrate promising detection capability, several limitations remain in this study. The testing dataset consisted of only 53 unseen images, which may still limit model generalization capability. In addition, variations in image acquisition conditions, particularly excessive lighting exposure, may affect detection accuracy in certain situations. Therefore, future studies are recommended to utilize larger and more diverse datasets, conduct broader real-world testing, and evaluate system performance under more varied environmental conditions to improve model robustness and implementation reliability.

B. Detection Results

In addition to quantitative performance evaluation, further analysis was conducted to observe the practical detection capability of the developed system through image-based cattle identification within the web-based environment. The detection results demonstrate how the trained YOLOv8 model performs in identifying and classifying cattle sex under practical usage conditions.

Figure 7. Cattle detection results using YOLOv8, showing a male cow (left) and a female cow (right)

Figure 7 illustrates successful cattle detection and classification using the YOLOv8 model. The male cow was identified with a confidence score of 86%, while the female cow obtained a confidence score of 83%. In both cases, the bounding boxes accurately localized the detected cattle objects, indicating that the model operated effectively under practical farm conditions. These results demonstrate the model's capability to distinguish male and female cattle under varying image acquisition conditions, including differences in pose, background characteristics, and illumination.

C. System Evaluation and Discussion

In addition to model performance evaluation, the developed system was further assessed through functional testing to evaluate its reliability and practical implementation capability under actual usage conditions.

Table 2. Functional Testing Results of the Cattle Detection System

No.	Test Scenario	Expected Output	Result
1	Image upload	The system receives and processes the image	Successful
2	Object detection	The bounding box appears on the detected object	Successful
3	Sex identification	The correct label (male/female) is displayed	Successful
4	Confidence score display	The confidence score is shown	Successful
5	No object detection	The system displays a failure message	Successful
6	Re-upload after failure	System reprocesses the new image	Successful

According to Table 2, all system functionalities operated as expected, including image upload, object detection, cattle sex identification, and output visualization. The system also handled error conditions effectively by providing appropriate feedback when no cattle object was detected and allowing users to re-upload images. The results indicate that the web-based system successfully integrated the YOLOv8 detection model into a functional image-processing workflow. In addition to supporting automated cattle sex identification, the system provided stable interaction between image input, model inference, and result visualization under practical usage conditions. Compared with manual identification methods, the system offers faster processing and reduces the possibility of human error during livestock data recording and identification processes.

To further evaluate the practical implementation capability of the developed system, processing time analysis was conducted to measure the duration required for image upload, model inference, result generation, and output visualization during the cattle identification process. The evaluation was performed on both laptop and smartphone devices to assess system responsiveness under different usage conditions.

Processing time evaluation on the laptop device was conducted using Chrome DevTools to measure the duration of each processing stage within the web-based cattle detection system. The measured stages included image upload and preprocessing, model inference, result visualization, and data download. The evaluation results are presented in Table 3.

Table 3. Processing time evaluation results on laptop device

No.	Processing stage	Processing time (seconds)
1	Image upload and preprocessing	5s
2	Model inference and detection process	11s
3	Result visualization	3s
4	Detection result download	16ms
	Total Processing time	19.016s

Based on the evaluation results on Table 3, image upload and preprocessing required approximately 5 seconds, while the model inference and detection process required approximately 11 seconds. Result visualization required approximately 3 seconds, whereas the download process required only 16 milliseconds. Overall, the total processing time from image upload to final detection output was approximately 19.016 seconds on the laptop device. These findings indicate that the developed system is capable of performing automated cattle sex identification within an acceptable processing duration for practical web-based implementation. In addition to laptop-based testing, processing time evaluation was also conducted on a smartphone device to compare system responsiveness across different platforms. The evaluation results demonstrated that the smartphone device achieved faster processing performance under the tested conditions.

Table 4. Processing time evaluation results on smartphone device

No.	Processing stage	Processing time (seconds)
1	Image upload and preprocessing	404ms
2	Model inference and detection process	4.78s
3	Result visualization	<1s
4	Detection result download	3s
	Total Processing time	8.148s

The smartphone-based evaluation (Table 4) showed that image upload and preprocessing required approximately 404 milliseconds, while the model inference and detection process required approximately 4.78 seconds. Result visualization was displayed almost instantly after the detection process was completed, whereas the detection result download process required approximately 3 seconds. Overall, the total processing time was approximately 8.184 seconds. Compared with laptop-based testing, the smartphone device demonstrated faster response time during the cattle identification process, indicating good system adaptability and responsiveness across multiple device platforms.

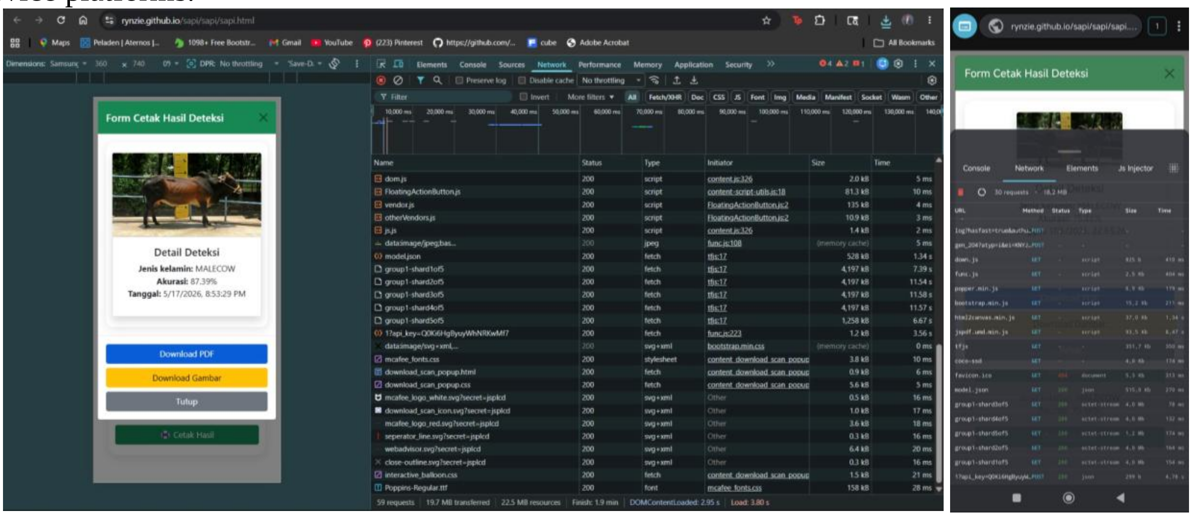

Figure 8. Processing time evaluation: on a laptop device (left); on a smartphone device (right)

Figure 8 presents the processing time evaluation results obtained from laptop- and smartphone-based testing environments. The screenshots illustrate the duration required for image upload, model inference, result generation, and output visualization during the cattle detection process. Based on the evaluation results, the smartphone device demonstrated a faster overall response time than the laptop device under the tested conditions.

The differences in processing duration between devices may be influenced by hardware specifications, browser optimization, network stability, and system resource allocation during the testing process. Nevertheless, both testing environments successfully executed the complete detection workflow, including image upload, cattle detection, classification, and result visualization, indicating stable practical implementation capability of the developed system. To further illustrate the practical implementation of the developed system, the web-based user interface is presented in Figure 9.

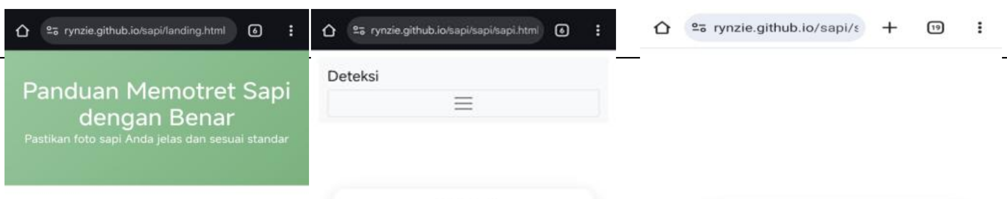

Figure 9. Web-based interface of the cattle detection system: Image upload interface (left- middle); Detection result interface (right).

The web-based interface enables users to upload cattle images and obtain automated cattle sex identification results through the integrated YOLOv8 detection model. As shown in Figure 9 (left-middle), the interface provides an image upload feature that allows users to capture or select images for the identification process. The uploaded images are subsequently processed by the trained YOLOv8 model within the web-based system environment.

During the processing stage, the model generates detection outputs consisting of bounding boxes, predicted class labels (male cow or female cow), and confidence scores. However, as illustrated in Figure 9 (right), the user interface displays only the final classification results and confidence scores to simplify user interaction and improve readability. An example of detailed detection visualization with bounding boxes is presented in Figure 7. The interface was designed to support practical usability through responsive image upload functionality, rapid access to detection results, and straightforward user interaction across multiple device platforms. In addition, the detection results can be saved in image or PDF format, supporting documentation and livestock data management activities in practical farm environments.

5. Conclusions

This study developed a YOLOv8-based cattle sex identification system integrated into a web-based platform to support automated livestock management in Tomohon City. The evaluation results demonstrated that the YOLOv8 model was capable of identifying and classifying male and female cattle with stable detection performance under varying practical image acquisition conditions. The main contribution of this study lies in the implementation of a YOLOv8-based object detection model for automated cattle sex identification using cattle image datasets collected from local farm environments. In addition, the developed web-based system provides practical functionalities, including image upload, automated detection, prediction result visualization, and output management to support digital livestock data handling.

System evaluation further demonstrated that the developed platform operated consistently across multiple devices and was capable of processing cattle object detection within acceptable response times during testing. However, several limitations remain in the present study. The testing dataset size was still relatively limited, and certain environmental conditions, particularly excessive lighting exposure, were found to affect detection performance. Moreover, broader usability evaluation and more comprehensive real-world field testing are still required to further validate the system's robustness and practical implementation capability. Future studies are recommended to utilize larger and more diverse datasets, perform more extensive field evaluations under broader environmental conditions, and further optimize system performance for more reliable livestock management applications.

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