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Research Article

Utilization of Deep Learning YOLO V9 for Identification and Classification of Toraja Buffalo Breeds

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Abstract

This study aims to develop and evaluate a buffalo breed detection system that supports the cultural practices of the Toraja community, particularly in the context of the Rambu Solo' ceremony. The ceremony places significant importance on the types of buffaloes used, as each breed symbolizes different social statuses and cultural meanings. In response to the need for an accurate and efficient identification method, this research utilizes the YOLOv9 (You Only Look Once version 9) deep learning model to detect and classify Toraja buffalo breeds. A dataset comprising 2,656 annotated images was used, representing five distinct buffalo categories: bongga sori, bonga ulu, moon, saleko, and todi. The images were collected from both field documentation and online sources. The YOLOv9 model was trained across 90 epochs, aiming to achieve high accuracy in breed detection and classification. The evaluation results demonstrate the model's strong performance, achieving a precision of approximately 0.9 and a recall of 0.8. These metrics indicate the model's ability to correctly identify the buffalo breeds with a high degree of reliability. However, during the training process, certain patterns of overfitting and underfitting were observed, suggesting that the model's performance could still be improved. These issues can potentially be addressed by increasing the volume and diversity of training data, applying data augmentation techniques, and fine-tuning hyperparameters to achieve a more balanced generalization. Overall, the findings show that YOLOv9 is a promising tool for supporting cultural preservation through technology by automating the identification of buffalo types used in traditional ceremonies. This system can assist in maintaining the accuracy and consistency of buffalo classification according to local customs. Future research is recommended to explore broader datasets, compare alternative object detection algorithms, and develop an integrated application for practical field use.

Keywords: Classification; Deep Learning; Object Detection; Toraja Buffalo; YOLOv9.

Introduction

Toraja, a region in Indonesia, is renowned for its unique cultural practices, particularly its distinctive beliefs surrounding death and the afterlife. One of the most significant cultural traditions still practiced by the Toraja people is the Rambu Solo' ceremony, a ritual that honors the deceased and guides them to the afterlife, a realm known as Puya, or heaven [1], [2]. Rooted in the ancient teachings of Aluk Todolo, the traditional belief system of the Toraja before the advent of Christianity, this ceremony underscores the importance of death in Torajan society, contrasting with other Indonesian tribes, such as the Bugis Makassar, who emphasize marriage as a key cultural rite [3].

Central to the Rambu Solo' ceremony is the buffalo, an animal symbolizing wealth, power, and social status within Torajan culture. The ceremony's execution reflects the social hierarchy of the Torajan people, which is divided into four levels [4]. The highest caste, Tana' Bulawan/To Parengge, requires up to 100 buffaloes for the ritual, while the Tana' Bassi/Tomakaka (middle nobility) and Tana' Karurung/To Pa'todokan (commoners) require fewer buffaloes, but must still select specific breeds, including bongga sori, bonga ulu, moon, saleko, and todi buffaloes. The lowest caste, Tana' Kua-kua/Kaunan (servant/slave class), traditionally uses only one buffalo for the ceremony [5], [6], [7].

Despite the cultural importance of buffalo selection in the Rambu Solo' ceremony, many Torajans struggle to identify the appropriate buffalo breeds, which can lead to errors in ceremony execution and compromise the authenticity of the tradition [8], [9], [10]. Rambu Solo' in the Perspective of Toraja Young Generation. This challenge underscores the need for a reliable, real-time system that can assist in the accurate identification and classification of buffalo breeds according to the family's social status [1], [11].

This research aims to address this need by developing and evaluating a detection system using the YOLOv9 method, tailored specifically to identify Toraja buffalo breeds in real-time [12], [13]. By answering key research questions such as the accuracy of the YOLOv9 model in detecting and classifying different breeds, its utility in

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simplifying the recognition process for the community, and its performance in real-world conditions this study hypothesizes that the YOLOv9 model will effectively meet these challenges [14].

The scope of this research includes the collection and analysis of images of various Toraja buffalo breeds, labeled according to their type. However, this study also acknowledges limitations, such as the potential lack of diversity in the dataset, which may not fully capture all environmental and lighting variations. Further customization of the model may be necessary to enhance its accuracy in diverse field conditions.

This research contributes to the advancement of object detection technology by applying the YOLOv9 method to a culturally significant context, enabling the real-time recognition of Toraja buffalo breeds. Additionally, it supports the preservation of Torajan cultural heritage by facilitating more accurate and culturally aligned execution of the Rambu Solo' ceremony. Through this dual contribution, the study offers both a technical solution and a means of preserving an essential aspect of Torajan culture.

Method

This research is designed to develop and test a Convolutional Neural Network (CNN) model using the Yolov9 algorithm for multilabel classification of Toraja buffalo images [15], [16]. The study employs a quantitative approach, with data-based experiments to evaluate the model's performance in image classification [17]. he research design includes data collection, pre-processing, model development, model training, performance evaluation, and result analysis, as outlined in **Figure 1**.

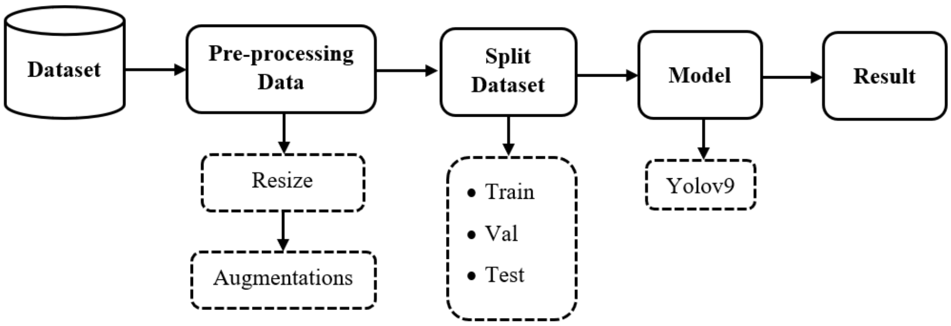
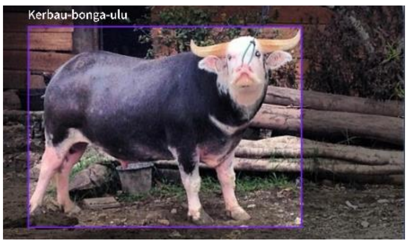


Figure 1. Research Design

A. Dataset Collection

The dataset used in this study comprises 2,656 images of Toraja buffaloes, sourced from both field documentation and the internet. Each image is labeled into one of five categories: bongga sori buffalo, bonga ulu buffalo, moon buffalo, saleko buffalo, and todi buffalo, as shown in **Figure 2**. To ensure that the model is trained with diverse and comprehensive data, the sample selection aimed to represent each buffalo category adequately. The data collection process included several critical steps: Image Capture: Images were taken from various angles and under different lighting conditions to introduce variability in the dataset. Manual Labeling: Each image was manually labeled to ensure accurate classification by type. Data Sourcing: Additional images were gathered from reliable internet sources to expand the dataset. Data Verification and Validation: The collected data underwent verification to confirm its quality and accuracy. This process involved cross-checking labels with expert knowledge of Toraja buffalo types and ensuring that images met the required standards for resolution and clarity before they were used in model training.

(a) bonga sori buffalo



(b) bonga ulu buffalo

(c) white buffalo

(d) saleko buffalo

(d) todi buffalo

Figure 2. Toraja Buffalo Label

B. Data Pre-processing

The data analysis method in this study includes several important stages to ensure accuracy and optimal model performance.

First, a pre-processing process was performed where all collected images were resized to a size of 640 x 640 pixels to ensure consistency in data input to the model [18]. In addition, the images were normalized to reduce variations in luminance and color, which can affect model performance. Data augmentation is also performed to increase the variety and amount of training data [19]. Augmentation techniques used include saturation (to adjust the intensity of colors), exposure (to change the level of luminance), blur (to simulate blurry image conditions), and noise (to add random noise into the image) [20]. These augmentations help the model to be more resilient to variations in real conditions.

Furthermore, The dataset was divided into three subsets: training data (90%), validation data (5%), and test data (5%). This split was determined based on best practices in deep learning, where the majority of the data is allocated for training to allow the model to learn effectively from a large sample [21]. The validation set was used to tune hyperparameters and prevent overfitting during training, ensuring that the model generalizes well to unseen data [22]. The test set, kept separate from the training and validation processes, served to provide an unbiased evaluation of the model's performance once training was completed [23]. This ratio was chosen to balance the need for a substantial training set while retaining sufficient data for reliable validation and testing. [18].

The YOLOv9 model, known for its speed and accuracy in object detection tasks [24], was used for training . Training was conducted over 90 epochs, a duration selected based on preliminary experiments, which showed this was sufficient for the model to converge without overfitting. YOLOv9's architecture, which includes CSPDarknet as the backbone, PANet as the neck, and YOLO Head for final prediction, was well-suited for this multilabel classification task.

C. Deep Learning

YOLOv9 is the latest version of the You Only Look Once (YOLO) family of object detection models designed to provide fast and accurate object detection by utilizing CSPDarknet architecture as the backbone [25], PANet as the neck, and YOLO Head for final prediction [26], [27]. The model offers high inference speed and superior detection accuracy thanks to the Cross-Stage Partial Connections technique for feature extraction and Path Aggregation Network for multiscale feature fusion [28]. YOLOv9 supports multilabel classification and real-time object detection [29]. With configurations that include Binary Cross-Entropy Loss and Adam Optimizer, YOLOv9 is trained to optimize precision, recall, and MAP in detecting and classifying objects [30]. The architecture of Yolov9 can be seen in **Figure 3**.

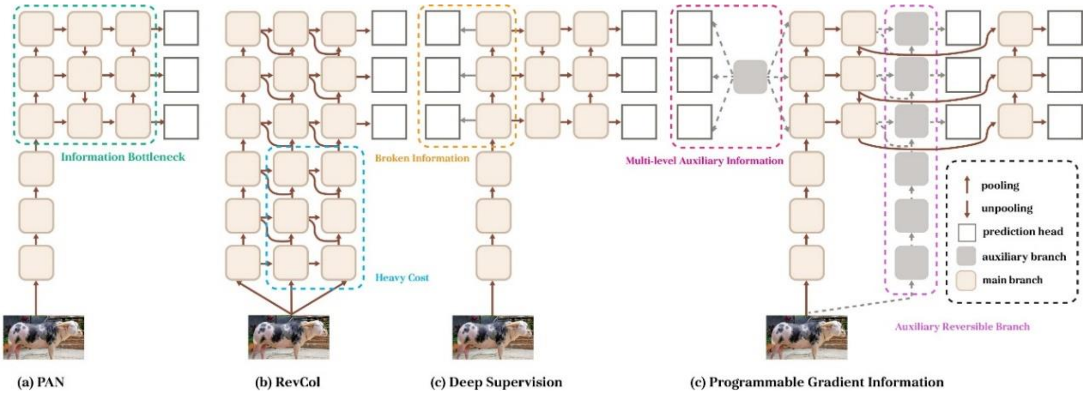


Figure 3. Yolov9 Architecture

D. Evaluation Metrics

In this research, the model performance is evaluated using several key metrics: loss, precision, recall, and Mean Average Precision (MAP).

Binary Cross-Entropy Loss: his metric measures the prediction error for binary classification tasks, guiding the training process to correct errors [31]. BCE is formulated as Equation 1:

$$L = -\frac{1}{N}\sum_{i=1}^{N}(y_i \log(p_i) + (1 - y_i)\log(1 - p_i)) \quad (1)$$

Where L is the loss value, N is the number of samples, y_i is the original label, and p_i is the prediction probability for the positive class. BCE measures the average difference between the actual label and the model prediction, helping in the training process to correct errors.

This metric assesses the proportion of correct positive predictions, crucial for ensuring the accuracy of the multilabel classification [32]. Precision is formulated as Equation 2:

$$Presisi = \frac{TP}{TP+FP} \quad (2)$$

Where TP is True Positives (number of correct positive predictions), and FP is False Positives (number of incorrect positive predictions).

Recall This metric evaluates the model's ability to correctly identify all positive instances in the dataset [33]. Recall is formulated as Equation 3:

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

Where FN is False Negatives (the amount of positive data that is misclassified as negative).

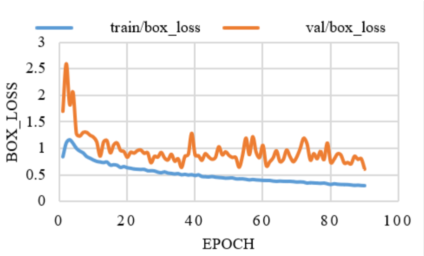
MAP MAP provides an overall performance measure by averaging the precision-recall curve across all classes. MAP is formulated as Equation 4:

$$MAP = \frac{1}{n}\sum_{i=1}^{n} AP_i \quad (4)$$

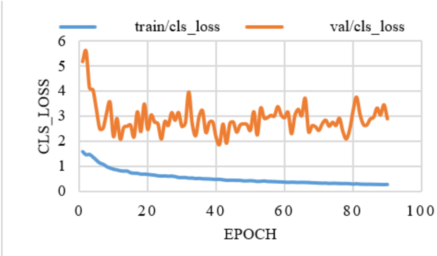
Where n is the number of classes and AP_i is the Average Precision for class i.

Results and Discussion

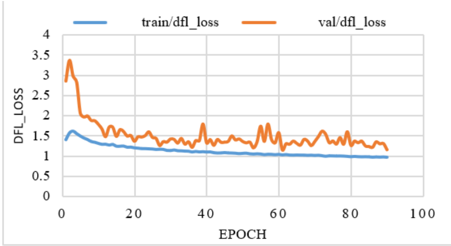
This study processed a dataset of 2,656 images of Toraja buffaloes, categorized into five distinct labels: bongga sori buffalo, bonga ulu buffalo, moon buffalo, saleko buffalo, and todi buffalo, using the YOLOv9 CNN model. The model was trained for 90 epochs, aiming to optimize performance in detecting and classifying Toraja buffaloes.



(a) box_loos



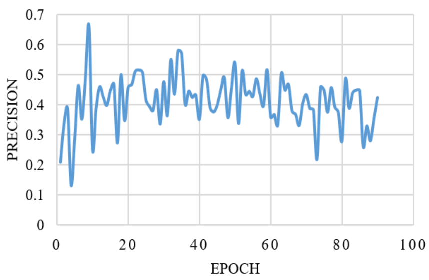
(b) cls_loss



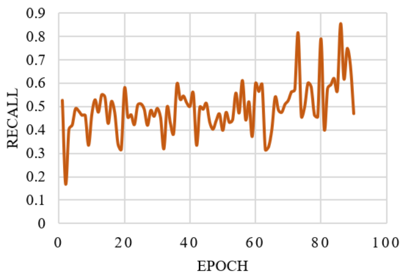
(c) dfl_loss

Figure 4. Loss Metrics Chart

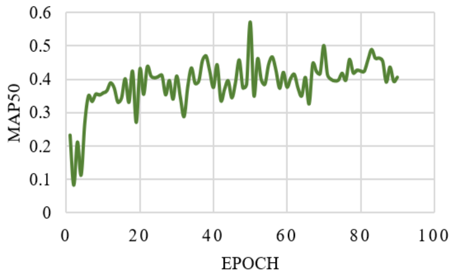
Figure 4 presents three loss metric graphs: Box Loss, CLS Loss, and DFL Loss, which illustrate the model's performance during training and validation. Box Loss measures how accurately the model predicts bounding box locations, CLS Loss evaluates classification accuracy, and DFL Loss combines these aspects. The higher Box Loss compared to CLS Loss suggests challenges in predicting bounding box locations, possibly due to an unbalanced dataset, suboptimal anchor boxes, or other model parameters. A relatively lower DFL Loss indicates that the YOLOv9 model generally performed better in location prediction and classification, despite these challenges.



(a) Precision



(b) Recall



(c) MAP

Figure 5. Evaluation Metrics Chart

In **Figure 5**, the precision and recall metrics reveal the model's strengths and limitations. Precision reached a maximum of approximately 0.9, showing the model's effectiveness in correctly identifying buffaloes. However, a slight decrease in precision at higher epochs indicates potential overfitting, where the model becomes too specialized to the training data. The recall, with a maximum value around 0.8, suggests the model's ability to detect most buffaloes in the images, though a slight dip at higher epochs hints at underfitting, where the model fails to generalize to new data effectively. These results suggest that while the YOLOv9 model performs well, there is room for improvement, particularly in enhancing generalization.

The findings align with previous studies that demonstrated the efficacy of YOLO models in complex object detection tasks. For instance, the performance of YOLOv9 in this study is consistent with the results obtained by [25], where a similar CNN-based approach was employed for multilabel classification tasks with other livestock species, showing comparable precision and recall values. However, the use of YOLOv9, a more recent version, offers significant improvements in detection speed and accuracy, reinforcing its suitability for real-time applications in livestock monitoring.

Overfitting and underfitting in this study are influenced by several factors. The relatively small dataset size may contribute to overfitting, as the model may memorize the training data rather than learning general features applicable to unseen data. Additionally, the diversity of the dataset concerning lighting, angles, and environmental conditions might be insufficient, leading to underfitting when the model encounters new scenarios. To address these issues, expanding the dataset, improving data augmentation techniques, and experimenting with different model parameters or architectures could enhance the model's ability to generalize better.

Figure 6 displays the test results, where YOLOv9 effectively detected various buffalo types with good accuracy. The blue bounding boxes indicate successful identification, along with labels and confidence scores. The model demonstrated robustness across different viewing angles, lighting, and backgrounds, showcasing its generalization capability. Nevertheless, some instances of partial detection or misclassification highlight the need for further refinement of both the dataset and the training process.

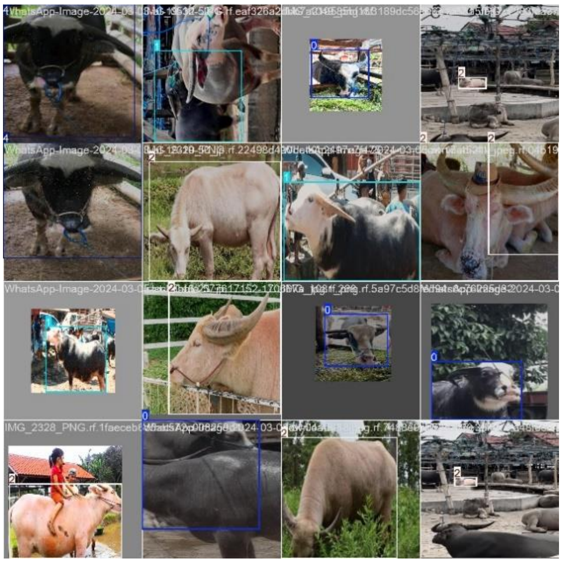


Figure 6. Testing Results

An essential outcome of this study is that the YOLOv9 model can deliver high performance in detecting and classifying Toraja buffaloes after 90 training epochs. The high precision, recall, and mAP values underline the model's potential for practical applications, such as monitoring and conserving Toraja buffalo populations. Moreover, these results affirm the hypothesis that CNN models, when trained on sufficiently large and diverse datasets, can achieve remarkable accuracy in object recognition tasks.

The practical implications of this research extend to real-world applications, where the YOLOv9 model could serve as an efficient tool for monitoring Toraja buffaloes, thereby aiding conservation efforts. Additionally, the model's framework could be adapted to identify other livestock species, expanding its utility beyond the scope of this study.

However, this study also acknowledges certain limitations, such as the dataset's restriction to five Toraja buffalo types and the lack of representation for all possible environmental conditions. The model may require further customization to handle variability in lighting, backgrounds, and viewing angles effectively. Future research should focus on expanding the dataset, testing the model in real-world conditions, improving data augmentation techniques, and exploring alternative object detection models to benchmark against YOLOv9.

Conclusion

This study successfully demonstrated that the YOLOv9 model can be effectively used to detect and classify Toraja buffalo species. The results showed that the model trained for 90 epochs was able to provide high performance in terms of precision, recall, and mAP, demonstrating the model's ability to accurately recognize various buffalo types.

The performance evaluation showed that YOLOv9 had a maximum precision of about 0.9 and a maximum recall of about 0.8, indicating the model's ability to identify and detect most of the buffaloes in the images. However, there were some indications of overfitting and underfitting, which can be addressed by increasing the dataset and model parameters. The answers to the main research questions confirmed that the YOLOv9 model can detect and classify the types of Toraja buffaloes with a high level of accuracy, and the use of this technology can make it easier for people to recognize buffalo types according to their social strata. The contributions of this research include the development of a real-time object detection system based on YOLOv9, as well as supporting the preservation of Torajan culture by providing practical solutions to recognize buffalo types in the Rambu Solo' ceremony. For future research, it is recommended to expand the dataset with more variations in environmental conditions, develop data augmentation techniques to improve the diversity and quality of the dataset, and explore other object detection models for performance comparison. Thus, this detection system can be implemented more widely and provide greater practical benefits in the conservation and preservation of Torajan cultural traditions.

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