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TICKCOUNT: AN APPROACH FOR AUTOMATIC TICK COUNTING IN CATTLE

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ABSTRACT

Ticks are a significant concern in livestock production, contributing to health complications and economic losses. Early detection is essential for effective management, yet manual tick counting is labor-intensive and prone to human error. This study aims to develop an automated method for detecting and counting ticks on cattle using artificial intelligence, thereby enhancing precision livestock farming and promoting sustainable animal health practices. An artificial intelligence model based on advanced mathematical optimization and deep learning techniques was implemented for automatic object detection and counting. The system was trained on 48 annotated images selected from a dataset of 500 photographs captured under field conditions at the Brazilian Agricultural Research Corporation. Annotation was performed in a supervised learning framework focusing on a single target class: tick. The proposed artificial intelligence model achieved a detection accuracy of 0.91. The model demonstrated robustness in identifying ticks under consistent lighting and background conditions. This performance highlights the potential of deep learning for automating tick detection in real-world scenarios, offering a faster and more objective alternative to manual methods. The proposed approach shows promise for improving cattle management through automated tick detection. However, the model's generalizability may be constrained by the homogeneity of the dataset, which included only one breed and uniform environmental conditions. Future research should incorporate more diverse images and explore real-time applications on mobile devices or drones.

KEYWORDS: Animal Health; Artificial Intelligence; Deep Learning; Parasites; Precision Livestock Farming.

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1. INTRODUCTION

Ticks are hematophagous ectoparasites capable of transmitting a wide range of infectious agents to humans and animals (Nogueira *et al.*, 2023). Owing to this vectorial capacity, they are considered among the most epidemiologically significant arthropods worldwide, second only to mosquitoes in global public health importance (Yang *et al.*, 2021; Fei *et al.*, 2024). Their blood-feeding behavior required to complete each developmental stage can lead to local inflammation, secondary infections, reduced body condition, and anemia in infested animals, in addition to affecting productivity, with estimated reductions of up to 90.2 liters (L) of milk per cow annually (Marques *et al.*, 2020; Pérez-Otáñez *et al.*, 2024).

The distribution and abundance of ticks are modulated by environmental conditions, host-related characteristics, and human activities (Yang *et al.*, 2020), all of which influence their ecology, epidemiological patterns, and pathogen transmission dynamics (Clarke-Crespo *et al.*, 2020). Among these factors, climatic variables play a decisive role in tick development and survival (Tian *et al.*, 2023), as they determine geographical range, vectorial capacity, physiological responses, and overall survival probabilities (Fei *et al.*, 2024; Khwarahm, 2023). Parameters such as temperature, humidity, and precipitation are critical for maintaining essential biological processes, including growth, development, and persistence in the environment (Ma *et al.*, 2024).

Host diversity, anthropogenic landscape modifications, and ecological characteristics of the environment also have a direct influence on tick distribution patterns and population dynamics. Understanding the interactions among these factors is crucial for identifying regions at higher risk of tick infestation and tick-borne diseases, as well as for designing evidence-based prevention and control strategies (Khwarahm, 2023; Fei *et al.*, 2024). In this regard, multiple studies have evaluated habitat suitability for various tick species, highlighting the importance of environmental variables such as humidity, temperature, precipitation, vegetation type, soil moisture, and land-use patterns (Uusitalo *et al.*, 2022; Ma *et al.*, 2024).

To anticipate spatial distributions and analyze the ecological determinants of tick presence, numerous studies have employed environmental suitability models also referred to as species distribution models (Kopsco *et al.*, 2022; Pérez-Otáñez *et al.*, 2024; Tarekegn *et al.*, 2025). These tools allow researchers to project both current and future distributions under different environmental conditions (Wang *et al.*, 2024). Among them, the Maximum Entropy algorithm (MaxEnt) has proven highly effective for estimating potential distributions using presence-only data (Yang *et al.*, 2021). Its high predictive power and robust performance have been well documented (Wang *et al.*, 2024; Fei *et al.*, 2024), as it estimates optimized probability distributions through the principle of maximum entropy, integrating presence records with key environmental variables (Leta *et al.*, 2013; Wang *et al.*, 2024).

Moreover, MaxEnt has outperformed other ecological suitability modeling approaches used in both fauna and flora (Tesfamariam *et al.*, 2022), owing to its ability to handle continuous and categorical environmental variables, work effectively with limited datasets, generate jackknife analyses, and produce accurate predictions even when sampling records are spatially dispersed (Wan *et al.*, 2020; Fei *et al.*, 2024). Its continuous probabilistic outputs also facilitate interpretation and provide detailed information on habitat suitability across space (Fei *et al.*, 2024).

Tick populations and the diseases they transmit pose a major concern for farmers in rural areas. Their impact results in considerable economic losses worldwide, estimated at approximately 30 billion USD (Monakale *et al.*, 2024). Enhancing control programs requires early identification and quantification of infestations. Traditionally, this is achieved by counting 4–8 millimeter (mm) engorged female ticks by palpating one side of the animal and extrapolating the result to the entire body (Cortivo *et al.*, 2016). Although widely accepted, this method has major limitations, including being time-consuming, laborious, and susceptible to psychophysical and optical biases (Barbedo, 2017).

In recent years, the incorporation of new technologies has driven significant advances across multiple productive sectors, including livestock farming. Artificial intelligence has emerged as a promising tool to address several management challenges (Ezanno *et al.*, 2021). In this context, Barbedo *et al.* (2016) explored the use of infrared imaging for tick detection in cattle; however, the correlation between automated detection and the actual number of ticks did not exceed 0.75. Concurrently, major advances in computer vision have considerably improved object detection performance (Diwan *et al.*, 2023). With the introduction of the You Only Look Once (YOLO) algorithm (Redmon *et al.*, 2016) and its subsequent versions, both detection accuracy and inference speed have substantially increased. For example, Mekhalfi *et al.*, (2021) demonstrated that YOLOv3 outperformed Mask R-CNN in detecting circular patterns in desert agricultural fields, while Araujo- Junior *et al.*, (2023) showed that YOLOv5 is suitable for detecting and counting sprouted clones of plant material.

Given these advancements, there is a clear need to develop automated and reliable tools capable of identifying and quantifying ticks rapidly, accurately, and with minimal human intervention. Such approaches have the potential to enhance epidemiological surveillance, support decision-making, and reduce economic losses associated with tick infestations. For these reasons, the aim of this study was to develop an artificial intelligence based model that, using the YOLOv5 algorithm, enables the automatic detection and quantification of ticks in cattle through image analysis. The study was conducted in 2021 at the research laboratory of the Federal University of Rio de Janeiro.

2. MATERIALS AND METHODS

Experimental site

The study was conducted at Embrapa Southern Livestock (Embrapa Pecuária Sul), a research unit of the Brazilian Agricultural Research Corporation (Embrapa), located in Bagé, Rio Grande do Sul, Brazil. Embrapa is a federal institution linked to the Ministry of Agriculture, Livestock and Food Supply, responsible for coordinating agricultural research across Brazil (Fig. 1).

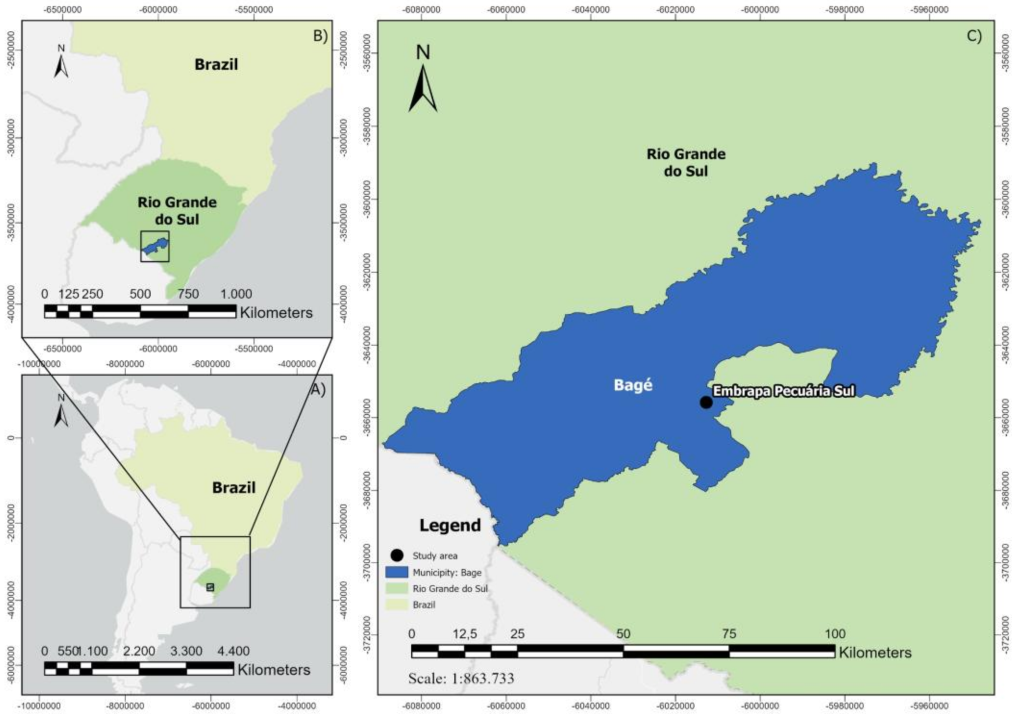

Figure 1: Geographic location of Embrapa Pecuária Sul.

Dataset description: The image database comprises 500 photographs of one hundred Brangus cattle (heifers and steers), either infested or non-infested with the tick *Rhipicephalus (Boophilus) microplus*. This breed was selected due to its typically dark coat, which may hinder visual tick detection. Images were captured during handling activities at Embrapa Pecuária Sul (Latitude: -31.34777777, Longitude: -54.01333333) between 8:30 and 11:30 AM on November 27, 2019. Environmental conditions included ambient temperatures ranging from 16.7 to 19.1 degree Celsius (°C), relative humidity between 77 and 95 percent (%), wind speeds between 1.2 and 4.1 meters per second (m/s), and skin surface temperatures from 27.7 to 32.7 °C (Barbedo *et al.*, 2017). Images were acquired using a consumer-grade mobile smart device equipped with a high-resolution Red Green and Blue (RGB) camera. Photographs were captured at an average distance of approximately 1 meter from the animals, ensuring sufficient spatial detail for object-level annotation and detection.

Image annotation

Tick annotation was performed using the labeling tool labellmg (version 1.8.6). A single class named “tick” was defined. Images were annotated in YOLO format, with bounding boxes drawn around each tick (Fig. 2).

Figure 2: Annotation of ticks detected in an image.

Object detection approach

The YOLO object detection model, a single-stage detection algorithm, was employed. YOLO predicts multiple bounding boxes and class probabilities within a single image (Yue *et al.*, 2022), making it suitable for detecting multiple ticks simultaneously. The architecture used (Fig. 3) includes 24 convolutional layers, four max-pooling layers, and two fully connected layers. YOLO has evolved through more than ten versions, each with increasing depth and feature extraction capabilities (Li *et al.*, 2022). This study utilized YOLOv5, maintaining its original structure but adjusting the number of training epochs to 100, as demonstrated in (Araujo Junior *et al.*, 2023). To reduce the required training samples, transfer learning was applied (Hosna *et al.*, 2022), following approaches by Valente *et al.* (2020) and Mu *et al.* (2020). A pre-trained model based on the Microsoft Common Objects in Context (MSCOCO) dataset was fine-tuned for tick detection. The dataset was split into training and testing sets in an 80:20 ratio.

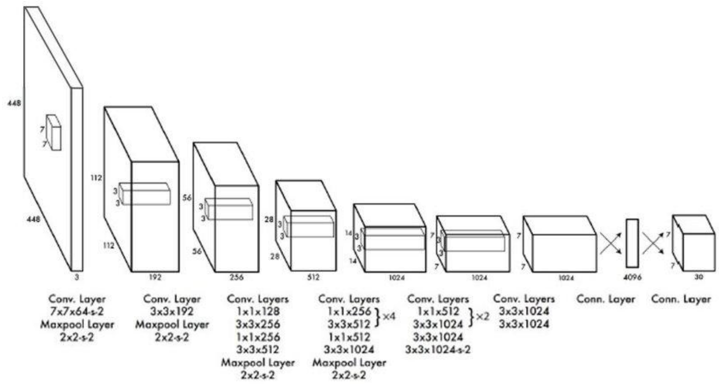

Figure 3: YOLO network architecture (Omidi et al., 2021).

Experiment

From the dataset, 48 images were randomly selected and annotated, containing a total of 795 ticks of varying sizes. Descriptive statistics of tick counts per image are presented in Table 1.

Table 1: Descriptive statistics of the number of ticks in the training images.

Minimum	Q_1	Median	Mean	Q_3	Maximum	Standard Desviation
1	5	7	8.5	16.56	21	125

Development Environment

The model was developed using Google Colab, a cloud-based computational platform that provides access to high-performance hardware resources. The experimental environment included 12.7 gigabytes (GB) of system Random Access Memory (RAM), an NVIDIA Tesla GPU with 15 GB of dedicated memory, and approximately 78 GB of available storage. This configuration enabled efficient training and evaluation of deep learning models using high-resolution input images. All experiments were implemented in Python (version 3.10.0). The primary libraries used included Pandas (version 1.5.3) and NumPy (version 1.22.4) for data handling and numerical computations, Matplotlib (version 3.7.1) for visualization, PyTorch (version 2.0.0) as the deep learning framework, Scikit-learn (version 1.2.2) for auxiliary machine learning utilities, and Keras (version 2.12.0) for additional neural network components.

3. RESULTS AND DISCUSSION

Model training

The initial configuration of training parameters for the YOLOv5 model played a crucial role in determining its detection performance and convergence behavior. Appropriate selection of hyperparameters is essential in object detection tasks, particularly when dealing with small targets embedded in complex backgrounds, such as ticks on cattle fur (Diwan *et al.,* 2023). Training was conducted for 100 epochs, a value commonly adopted in YOLO-based applications to allow sufficient feature learning while avoiding unnecessary overfitting (Chen *et al.,* 2022; Wang *et al.,* 2022). A batch size of 4 was selected to balance computational efficiency and GPU memory constraints, enabling stable gradient updates during training, as recommended for high-resolution image processing tasks (Li *et al.,* 2022). All input images were resized to a uniform resolution of 2560 × 2560 pixels. High-resolution inputs are particularly beneficial for detecting small objects, as they preserve fine-grained visual details that may be lost at lower resolutions (Mu *et al.,* 2020; Mekhalfi *et al.,* 2021). This choice allowed accurate localization of ticks while maintaining computational feasibility within the available hardware resources.

Model initialization employed pretrained YOLOv5 weights derived from large-scale datasets, following a transfer learning strategy. Transfer learning has been shown to significantly improve convergence speed and detection accuracy when training data are limited, especially in agricultural and biological imaging contexts (Hosna *et al.,* 2022; Valente *et al.,* 2020). An initial learning rate of 0.01 was adopted and dynamically adjusted using a cosine annealing scheduler. Learning rate scheduling techniques such as cosine annealing promote smoother convergence and reduce the risk of training instability or premature convergence to suboptimal minima (Wang *et al.,* 2022). The AdamW optimizer was used due to its ability to combine adaptive learning rates with effective weight decay, improving generalization and mitigating overfitting in deep convolutional networks (Diwan *et al.,* 2023). To further enhance model robustness, L2 regularization and moderate data augmentation were applied. Geometric transformations and color-based augmentations increased sample diversity and improved the model's ability to generalize under varying illumination and background conditions, which are typical in real-world livestock environments (Chen *et al.,* 2022; Li *et al.,* 2022).

Evaluation and analysis of experimental outcomes

In object detection and segmentation tasks, model performance is governed by the combined optimization of multiple loss functions, each addressing a specific component of the learning process. The integration of localization, classification, and distribution-aware losses is particularly important when detecting small objects embedded in complex backgrounds, as is the case with tick detection on cattle (Diwan *et al.,* 2023).

The bounding box loss (box_loss) evaluates the accuracy of object localization by measuring discrepancies between predicted and ground truth bounding boxes. This loss accounts for both the spatial positioning and geometric dimensions of the detected objects. Specifically, it penalizes errors in the predicted center coordinates (x, y) through distance-based measures, as well as deviations in width $(w)$and height (h), thereby ensuring precise spatial alignment between predicted and reference bounding boxes (Wang *et al.,* 2022).

The segmentation loss (seg_loss) quantifies the accuracy of the predicted segmentation masks by assessing the overlap between model outputs and ground truth annotations. This component is essential for differentiating target objects from background regions, particularly in visually heterogeneous scenes. Segmentation loss functions typically combine pixel-wise classification losses with overlap-based measures, enabling robust delineation of object boundaries, even for small and partially occluded targets (Mekhalfi *et al.,* 2021; Chen *et al.,* 2022).

The classification loss (cls_loss) measures errors in the predicted class probabilities, guiding the model toward accurate categorical discrimination. Although the present study considers a single target class ("tick"), cls_loss remains important for reducing misclassification and improving confidence in object identification, especially in environments containing visually similar distractors such as wounds, dirt, or insects (Diwan *et al.,* 2023).

In addition, the distributed focal loss (dfl_loss) was employed to enhance the model's sensitivity to class imbalance and localization uncertainty. Unlike traditional regression-based losses, dfl_loss models bounding box predictions as probability distributions, allowing the network to focus more effectively on difficult samples and underrepresented patterns. This characteristic is particularly beneficial for detecting small and sparsely distributed objects, as commonly encountered in agricultural and livestock imaging applications (Li *et al.,* 2022; Wang *et al.,* 2022). By jointly optimizing these loss functions, the YOLOv5 model achieved balanced performance across localization, segmentation, and classification tasks.

This multi-loss strategy contributed to stable training behavior and robust detection performance in visually complex and heterogeneous field environments, supporting its suitability for real-world livestock monitoring applications.

The segmentation loss (seg_loss) measures the discrepancy between the predicted segmentation masks and the corresponding ground truth annotations, serving as a key indicator of model performance in image segmentation tasks. Accurate segmentation is particularly important for detecting small and partially occluded objects, as it enables the model to precisely delineate target regions from complex backgrounds, a common challenge in livestock and agricultural imaging (Mekhalfi *et al.,* 2021). In this study, seg_loss integrates two complementary components: cross-entropy loss and Dice loss. Cross-entropy loss evaluates pixel-wise classification errors by comparing the predicted class probabilities with the ground truth labels at each pixel location. This loss function is effective in ensuring global classification consistency across the image and is widely used in semantic and instance segmentation tasks (Chen *et al.,* 2022).

Dice loss, on the other hand, quantifies the spatial overlap between the predicted and ground truth masks, providing a robust measure of segmentation accuracy that is less sensitive to class imbalance. This characteristic is especially relevant when segmenting small objects, where foreground pixels constitute only a minor fraction of the image and boundary precision is critical (Mu *et al.,* 2020; Li *et al.,* 2022). By emphasizing overlap rather than absolute pixel counts, Dice loss improves the model's ability to capture fine-grained object boundaries. The combined use of cross-entropy loss and Dice loss allows the model to balance global pixel-level classification accuracy with precise boundary delineation. This composite approach enhances segmentation robustness in heterogeneous and visually complex environments, such as those encountered in precision agriculture and livestock monitoring, where variations in texture, illumination, and background clutter are prevalent (Diwan *et al.,* 2023).

The classification loss (cls_loss) evaluates the model's ability to correctly assign class labels to detected objects by comparing predicted class probabilities with the corresponding ground truth categories. This loss function plays a central role in ensuring reliable categorical identification, as it directly influences the confidence and correctness of each detected instance (Diwan *et al.,* 2023).

In this study, cls_loss is computed using cross-entropy loss, which quantifies the divergence between the predicted probability distribution over the target classes and the true class labels. Cross-entropy loss penalizes incorrect predictions in proportion to their associated confidence scores, thereby encouraging the model to improve its discriminative capability during training (Chen *et al.,* 2022). This mechanism is particularly effective for stabilizing classification performance in object detection frameworks such as YOLO. Although the proposed model focuses on a single target class ("tick"), cls_loss remains essential for minimizing false detections and improving confidence calibration. In complex field environments, visual elements such as wounds, dirt, insects, and variations in fur texture may exhibit features similar to the target object. The optimization of cls_loss helps the model to distinguish true ticks from visually similar non-target patterns, thereby reducing misclassification errors (Wang *et al.,* 2022). By guiding the network toward accurate categorical assignments, cls_loss contributes to the overall robustness and reliability of the detection pipeline. This aspect is particularly important in agricultural and livestock monitoring applications, where even a small number of false classifications may lead to incorrect infestation assessments and suboptimal management decisions (Diwan *et al.,* 2023).

The distributed focal loss (dfl_loss) was incorporated to address challenges associated with localization uncertainty and class imbalance in object detection tasks. Unlike conventional regression-based loss functions that treat bounding box coordinates as deterministic values, dfl_loss models localization targets as probability distributions. This distributional formulation allows the network to capture fine-grained spatial uncertainty and improves its sensitivity to difficult-to-localize objects (Li *et al.,* 2022). By adopting a probabilistic perspective, dfl_loss enhances model robustness when dealing with heterogeneous datasets and sparse target distributions, which are common in agricultural and livestock imaging applications. In such scenarios, target objects often occupy a small portion of the image and may be partially occluded or visually blended with the background. The use of dfl_loss mitigates training bias by reducing the disproportionate influence of easily detected samples and encouraging the model to focus on challenging instances (Wang *et al.,* 2022; Diwan *et al.,* 2023). This loss function is particularly beneficial for detecting small and clustered objects, where precise localization plays a critical role in overall detection performance. In applied contexts such as precision agriculture, remote sensing, and livestock monitoring, distribution-aware losses have been shown to improve generalization and localization accuracy under complex visual conditions (Li *et al.,* 2022). The combined analysis of the loss components highlights their complementary roles in optimizing model performance. While box_loss ensures accurate spatial localization of predicted bounding boxes and seg_loss improves object delineation, dfl_loss contributes significantly to enhancing robustness and precision, especially in scenarios involving small targets and complex backgrounds. During training, substantial improvements were observed across all loss components. Specifically, box_loss decreased by 57.60% and seg_loss by 68.88%, indicating enhanced localization and segmentation accuracy. In parallel, dfl_loss exhibited a marked improvement, reflected by an increase in mAP@0.5:0.95, which denotes higher precision across a range of intersection-over-union thresholds. Similar trends were observed on the validation set, where box_loss and seg_loss declined by 59.55% and 60.33%, respectively, and dfl_loss showed a comparable increase in precision.

These results confirm that the model effectively learned relevant feature representations and achieved stable convergence through the integrated optimization of multiple loss functions. The observed performance gains validate the effectiveness of the configured training strategy and suggest that distribution-aware loss formulations such as dfl_loss are well suited for object detection tasks in visually complex livestock environments.

Training progression and accuracy

Since the number of annotated images required to achieve satisfactory detection performance was not known a priori, the model was trained in successive stages with increasing dataset sizes. This incremental training strategy allowed the evaluation of the relationship between training data availability and detection accuracy, a common practice in deep learning applications involving limited annotated datasets (Hosna *et al.,* 2022). Initial training using 10 annotated images yielded a detection accuracy of 0.52, indicating that the model was able to capture only basic visual features of the target object. When the number of annotated images was increased to 20, detection accuracy improved substantially to 0.79, reflecting enhanced feature learning and improved generalization.

Finally, training with 48 annotated images resulted in a detection accuracy of 0.91, demonstrating a clear performance gain associated with the availability of additional labeled data. This progressive improvement in accuracy is consistent with findings reported in agricultural and biological imaging studies, where incremental increases in training data combined with transfer learning lead to significant performance gains, even when the total dataset size remains relatively small (Mu *et al.,* 2020; Valente *et al.,* 2020; Araujo Júnior *et al.,* 2023). These results highlight the effectiveness of the adopted training strategy and confirm that the pretrained YOLOv5 architecture was able to leverage limited data efficiently. The final training process using 48 images and 100 epochs required 2.871 hours of computational time. The model weights corresponding to the highest detection accuracy achieved during training were retained and subsequently used for inference and evaluation on validation data. This selection strategy ensured that the best-performing model configuration was employed for all reported experimental results.

Evaluation of metrics

After evaluating the metrics, it was observed that the model detects ticks with an accuracy of 0.91. The loss values (Fig. 4A-D), decrease in the training data and show a trend toward stabilization in the validation data. A lower loss value indicates higher model accuracy (Chen *et al.*, 2022). This justifies stopping training near 100 epochs. Similarly, recall indicates the number of ticks in the image that were correctly detected, while mean Average Precision (mAP) calculates the average precision values, which exceed 0.8 (Fig. 4F-G). This demonstrates that the proposed approach provides reliable results for tick detection and counting. The model's true positive rate is 0.91, with a false negative rate of 0.09. This means that 9% of the ticks in the image were not recognized by the model as ticks. On the other hand, the true negative rate, corresponding to the image background, was 1.0, indicating that in the test images, the model did not mistakenly classify the animal or environment as ticks.

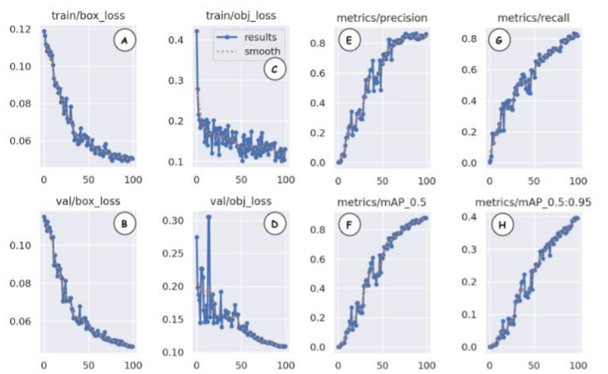

Figure 4: Results of metrics evaluation.

Model Utilization

In the validation images below, it can be observed that the model successfully identifies ticks (Fig. 5). In Fig. 5A, the model detects a tick despite the animal having lighter-colored fur. In Fig. 5B-C, the model correctly ignores flies on the animal, not confusing them with ticks. Similarly, in Fig. 5D, skin wounds on the animal are correctly ignored.

Even when images contain additional elements such as vegetation, wood, wounds, or dirt that could cause confusion, the model does not misclassify them as ticks. Furthermore, despite variations in lighting, shadowed areas, and exposure differences, the model continues to detect ticks accurately.

The model was also tested on a YouTube video featuring a tick-infested dog. Despite not being trained on dog images, the model successfully detected ticks on this animal (Fig. 6A, Supplementary Video 1). Additionally, the model was tested on another YouTube video featuring a bovine of a different breed, with varying distances from the camera (Fig. 6B, Supplementary Video 2). In Fig. 6, some ticks are not detected by the model, possibly because it was not trained on images containing a high density of ticks clustered together.

Figure 5: Validation images.

Figure 6: Model test on a dog and bovine of a different breed.

Comparison with results from the literature

Table 2 summarizes a comparative analysis between the proposed TickCount framework and previously reported approaches for automated tick detection, infestation estimation, or tick-related image classification. The comparison considers application context, image acquisition modality, task definition, and reported performance metrics, allowing a structured evaluation of methodological and practical differences across studies.

Table 2: Comparative analysis of automated tick detection and counting approaches.

Application context	Image type	Task	Key performance metrics	Counting error (MAE)	Reference
Cattle (thermography)	Infrared	Parasite load estimation	Qualitative results	Not reported	Cortivo *et al.*, 2016
Cattle (infrared monitoring)	Infrared	Detection and infestation estimation	Correlation with manual counts ≤ 0.75	Approximate	Barbedo *et al.*, 2017
Isolated tick images	RGB (smartphone)	Species classification	Validation accuracy≈85%	Not applicable	Xu *et al.*, 2021
Crowdsourced tick images	RGB	Species classification	Accuracy=87.84%; F1=87.73%	Not applicable	Justen *et al.*, 2021
Cattle (thermal imaging)	Infrared	Convolutional Neural Network (CNN)-based detection	Validation accuracy≤ 75%	Not reported	Mudau *et al.*, 2022
Isolated tick images	RGB	Tick detection	Detection accuracy 98.5%	Not reported	Akgül and Kaya, 2022
Cattle in field conditions	RGB (smartphone)	Detection and automatic counting	Accuracy=0.91; Recall > 0.80; mAP > 0.80	Not reported (future work)	This study

*Where ≤ is "less than or equal to"; ≈ is "approximately equal to"; = is "equal to"; > is "greater than".

Although counting error metrics such as mean absolute error (MAE) are commonly used in object counting problems, most existing studies on tick detection do not report per-image counting errors. Consequently, a direct quantitative comparison based on MAE was not possible. In this study, evaluation focused on object-level detection accuracy, recall, and mAP, which are more suitable for assessing the reliability of automated tick detection in real-world livestock environments. A comparison with related studies highlights the contribution of the proposed TickCount approach. Previous works have mainly focused on infrared-based detection or indirect infestation estimation. For instance, Barbedo *et al.* (2017) reported a maximum correlation of 0.75 between automated detection and manual counting using infrared imagery, indicating limitations in accurately quantifying tick loads. Similarly, Cortivo *et al.* (2016) demonstrated the feasibility of thermographic analysis but did not achieve object-level detection or precise counting. More recent deep learning approaches have primarily addressed tick classification or detection under controlled conditions. Mudau *et al.* (2022) obtained validation accuracies below 75% using CNNs on infrared images, while Akgül and Kaya (2022) reported high detection accuracy using YOLOv3 on curated RGB datasets. However, these studies were not designed for real-world cattle infestation quantification.

4. CONCLUSIONS

This study introduced TickCount, an automated framework for tick detection and counting in cattle based on an artificial intelligence model grounded in deep mathematical learning architectures. By leveraging RGB images acquired under real field conditions and integrating advanced object detection mechanisms, the proposed approach provides a practical and scalable alternative to traditional manual tick inspection methods.

The experimental results demonstrated that the developed system achieved a detection accuracy of 0.91, with recall and mean average precision values exceeding 0.80. These metrics indicate that the model is capable of reliably identifying ticks under heterogeneous environmental conditions, including variations in lighting, background elements, fur color, and the presence of visually similar distractors such as wounds, dirt, and insects. The robustness observed during validation confirms the model's capacity to generalize beyond controlled laboratory scenarios and operate effectively in practical livestock management contexts.

A key contribution of this work lies in shifting from indirect infestation estimation approaches—such as thermography or infrared-based correlation models—toward direct object-level detection and automated counting. Unlike previous methodologies that rely on correlation with manual inspection or qualitative parasite load assessment, TickCount enables explicit localization and quantification of individual ticks. This object-level precision represents a significant advancement for precision livestock farming and environmental management.

From an environmental science perspective, early and accurate tick detection plays a critical role in sustainable livestock production systems. Tick infestations are associated not only with animal health deterioration and economic losses, but also with increased use of acaricides and chemical control measures. Excessive or poorly targeted application of chemical treatments can contribute to environmental contamination, acaricide resistance, and negative ecological impacts. By enabling timely and objective infestation assessment, automated detection systems such as TickCount may support more rational and targeted intervention strategies, reducing unnecessary chemical usage and promoting environmentally responsible parasite management.

Furthermore, the use of consumer-grade RGB imaging devices demonstrates that advanced monitoring solutions do not require specialized or costly equipment. This accessibility enhances the scalability of the approach, particularly in low- and middle-income agricultural systems where technological resources may be limited. The integration of artificial intelligence into livestock monitoring therefore aligns with broader goals of sustainable agricultural intensification and digital transformation in environmental management.

Despite these promising outcomes, certain limitations must be acknowledged. The training dataset was relatively limited in size and diversity, consisting primarily of a single cattle breed and a restricted range of environmental conditions. Although the model exhibited encouraging generalization when tested on different animal species and breeds, broader validation across diverse geographical regions, infestation densities, coat colors, and climatic conditions is necessary to confirm robustness at larger scales.

Additionally, while object-level detection metrics were thoroughly evaluated, counting-specific error measures such as Mean Absolute Error (MAE) were not computed due to the absence of detailed per-image manual counting annotations. Future research should incorporate systematic ground-truth counting to enable quantitative benchmarking against object counting standards. Expanding the dataset and incorporating semi-supervised or active learning strategies may further enhance detection performance while reducing annotation effort.

Future developments may also explore real-time deployment on mobile devices, edge-computing platforms, or unmanned aerial systems (drones), allowing large-scale herd monitoring with minimal human intervention. Integration with environmental data—such as temperature, humidity, and vegetation indices—could further support predictive modeling of infestation risk, linking computer vision-based detection with ecological and epidemiological forecasting frameworks.

In conclusion, TickCount contributes to the advancement of environmentally sustainable livestock management by providing a reliable, scalable, and automated solution for tick detection and quantification. The integration of artificial intelligence and accessible imaging technology offers significant potential for improving epidemiological surveillance, optimizing parasite control strategies, and reducing environmental impacts associated with livestock production systems. Continued methodological refinement and large-scale validation will further consolidate the role of AI-driven monitoring tools in sustainable animal health and environmental management.

AUTHOR CONTRIBUTIONS

F. Jimenez Ochoa, as corresponding author, was responsible for data analysis and manuscript writing. F. Fuentes Gandara contributed significantly to the creation of tables and figures and participated in manuscript writing. S. Da Silva Camargo contributed to research supervision and data interpretation. F. Flores Cardoso participated in developing the research proposal and critically reviewed the manuscript.

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CONFLICT OF INTEREST

The authors declare no potential conflict of interest regarding the publication of this work. In addition, the ethical issues including plagiarism, informed consent, misconduct, data fabrication and, or falsification, double publication and, or submission, and redundancy have been completely witnessed by the authors.

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