

Internet of things and YOLOv11 for orangutan intestinal nematode parasite detection

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Article Info

Article history:

Received Feb 17, 2025

Revised Dec 30, 2025

Accepted Jan 16, 2026

Keywords:

Deep learning

Internet of things

Nematode

Parasite orangutan

Yolov11

ABSTRACT

The health of Bornean orangutans is increasingly threatened by intestinal nematode parasites, which cause significant morbidity and mortality. Traditional microscopic diagnosis is accurate but slow, labor-intensive, and impractical in remote conservation areas. This paper presents a proof-of-concept smart diagnostic automated system that integrates internet of things (IoT) enabled mobile microscopy with a deep learning model based on you only look once version 11 (YOLOv11). A publicly available dataset of 4,000 annotated parasite egg images, derived from human fecal samples and used as a proxy for orangutan infections, was employed for model training and evaluation. The proposed system achieved a mean average precision (mAP) of 0.9957 and a mean intersection over union (IoU) of 0.9098 across four target classes. Compared with prior works using YOLOv4, YOLOv5, and lightweight models, our approach provides higher segmentation fidelity and is embedded in an IoT-based framework suitable for field deployment. Importantly, a pilot test conducted in the field using real orangutan fecal samples confirmed the system feasibility, with near real-time inference (~300 ms per image) and usability by non-specialist users under low-resource conditions. While broader validation with larger orangutan specific datasets remains necessary, this study demonstrates how IoT and computer vision can be combined into a scalable diagnostic tool for wildlife health monitoring and conservation applications.

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1. INTRODUCTION

The Bornean orangutan (*Pongo pygmaeus*) is a critically endangered species that faces serious health threats from intestinal nematode parasites. These parasites can cause gastrointestinal distress, nutrient malabsorption, immunosuppression, and mortality. Research on orangutan parasites emphasizes the importance of addressing parasitic infections within orangutan populations [1] as part of comprehensive conservation and health monitoring efforts to ensure the species long-term survival [2], [3]. However, conventional diagnostic methods for detecting intestinal nematode parasites involve microscopic examination of fecal samples, which can be time-consuming, resource-intensive, and infeasible for large-scale field studies. Additionally, these methods require skilled personnel and laboratory infrastructure, both of which are scarce at remote conservation sites [4], [5]. This study addresses the challenge of developing a scalable and automated diagnostic system capable of accurately detecting parasites in low-resource field conditions.

Recent advancements in deep learning and the internet of things (IoT) have transformed computer vision and real-time data processing. For parasite detection, several models have been explored. Tchinda *et al.* [6] used wavelet transforms and neural networks for intestinal parasite classification. More recent studies applied you only look once (YOLO) version 4 for malaria parasite detection [7], YOLOv5 for intestinal parasite classification [8], and lightweight architectures for egg detection in microscopy images [9]. Parasite-attention-based models, such as YOLO-PAM [10], have further enhanced malaria detection accuracy. However, these works are mostly laboratory-based, lack integration with IoT-enabled devices, and rarely address segmentation tasks needed for morphological analysis.

This paper proposes a proof of concept IoT integrated deep learning system using YOLOv11 for automated detection and segmentation of intestinal nematode parasite eggs. Unlike prior work that focuses primarily on bounding-box detection, our approach combines portable microscopy, mobile IoT-enabled image capture, cloud-based inference, and instance segmentation to deliver both diagnostic accuracy and morphological detail. The main contributions of this paper are: i) An IoT-based system architecture for parasite image acquisition, transmission, and real-time cloud inference under connectivity-limited conditions; ii) Adaptation of YOLOv11 for high precision instance segmentation, improving beyond bounding-box detection; and iii) A pilot field deployment demonstrating feasibility and usability of the system in conservation-relevant contexts.

These contributions advance the application of IoT and deep learning within electrical and computer engineering, while addressing a critical challenge in wildlife health monitoring. The rest of the paper is structured as follows: section 2 presents the system design and dataset preparation, Section 3 reports experimental results and discussion, and Section 4 concludes with implications and future directions.

2. METHOD

2.1. System architecture internet of things and deep learning approach

The proposed system architecture integrates portable imaging hardware with IoT functionality [11], [12] and cloud-based deep learning inference to automate the detection of intestinal nematode parasites in Bornean orangutans, as shown in Figure 1. A mobile device equipped with a portable microscope captures high-resolution images of fecal samples directly in the field. These images are managed via a custom mobile application that allows users to input relevant metadata such as global position system (GPS) coordinates, observer identity, and sampling time. This application enables users to transmit image data individually or in batches. To ensure functionality in remote or connectivity-limited environments, the system supports both online and offline operation. In offline mode, images and metadata are temporarily stored locally and synchronized automatically with the server when connectivity is restored. When online, the device uploads the images to a centralized cloud server using the hypertext transfer protocol (HTTP) protocol [13]. This flexible data transmission strategy ensures uninterrupted field data collection and minimal user intervention.

On the server side, a YOLOv11n-based deep learning model [14], [15] is deployed through a representational state transfer (REST) application programming interface (API), commonly referred to as a RESTful API [16]. Once an image is received, the model performs instance segmentation to identify parasite egg locations, classify them by species, and quantify infection loads. The output includes segmentation masks, species labels, and confidence scores, which are stored in a structured format for long-term analysis and epidemiological monitoring.

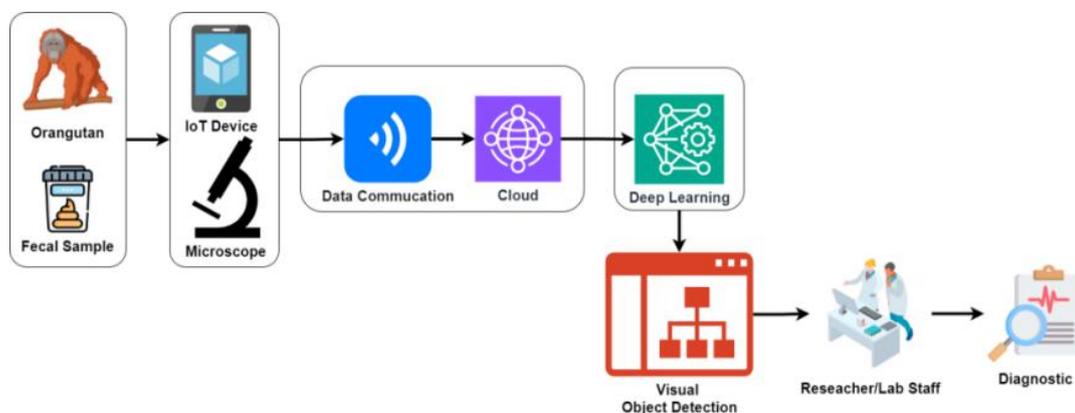


Figure 1. Overview of the automate the detection of intestinal nematode parasites in Bornean orangutans

This architecture is novel in its combination of mobile microscopy, real-time cloud inference, and segmentation-based analytics, all adapted for field-based wildlife health monitoring. Unlike prior systems that either operate in lab environments or use simpler detection methods, this approach supports real-time, field-adaptable diagnostics. It reduces the dependence on laboratory infrastructure and enables conservation teams to detect and respond to parasitic infections more efficiently, potentially improving Bornean orangutans' health outcomes in remote habitats.

In the Figure 1 depicts the entire automated pipeline for detecting intestinal nematode parasites in Bornean orangutans, beginning with fecal sample collection and microscopic imaging via an IoT-enabled device that captures high-resolution images directly from the microscope. These images are transmitted wirelessly to a cloud-based processing environment, where a deep learning inference engine which includes preprocessing, feature extraction, and object detection models optimized for microscopic morphology identifies parasite eggs and generates bounding-box predictions with confidence scores. The resulting detection output is displayed on a web-based object detection interface, allowing researchers and laboratory personnel to validate model predictions and incorporate them into diagnostic workflows for infection assessment and health monitoring.

2.2. Dataset collection nematode parasite egg

This study focuses on detecting four common intestinal nematode species known to infect orangutans: *Ascaris lumbricoides*, *Enterobius vermicularis*, hookworm eggs, and *Trichuris trichiura* [17]–[20]. These parasites contribute to significant health issues in great apes by impairing nutrient absorption, weakening immune responses, and increasing vulnerability to secondary infections. Effective detection is crucial for monitoring orangutan health, yet high quality image datasets of Bornean orangutan specific parasite eggs are not publicly available. Due to evolutionary proximity and overlapping parasite profiles between humans and non-human primates [21], it is scientifically justified to use human-derived datasets as proxies for orangutan studies. Accordingly, this research utilized the publicly available Chula-ParasiteEgg-11 dataset [22], originally introduced in a parasite classification challenge at the 2022 international conference on image processing (ICIP). This dataset comprises over 11,000 microscopy images labeled across 11 parasite species, all derived from human fecal smears, see Figure 2.

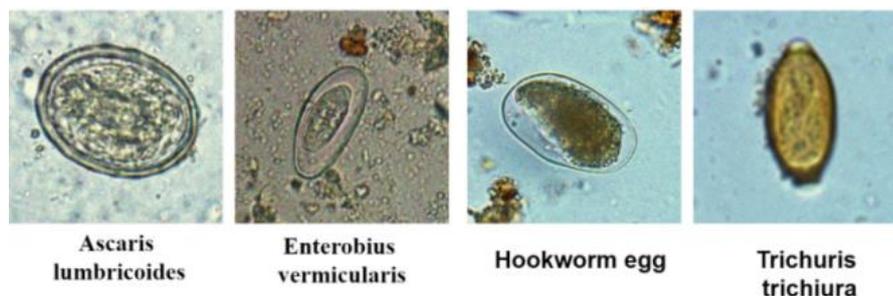


Figure 2. Microscopic images of nematode parasite eggs from the Chula-ParasiteEgg-11 dataset

For our purposes, a subset of 4,000 images was extracted, evenly distributed among the four target classes. These images capture morphological details relevant to deep learning, including variations in egg size (approximately 15-100 μm), contour, and internal structure. The dataset was chosen not only for its scale and annotation quality but also for its diversity in acquisition conditions, which is essential for building generalizable models. Images were obtained using various imaging systems, such as Olympus BX53 microscopes with Canon EOS 70D cameras, Nikon Eclipse Ni with DS-Fi2 cameras, and smartphones including the Samsung Galaxy J7 Prime, iPhone 12, and iPhone 13. Mobile imaging setups typically used a 10 \times eyepiece lens with one of the aforementioned microscopes.

As a result, the dataset includes images with varied resolution, illumination, color tone, and occasional artifacts such as motion blur or out-of-focus areas. Rather than viewing this variability as a drawback, we treated it as a strength. Exposure to images from multiple hardware configurations and environments enhances the model's ability to generalize across unseen data. In particular, this diversity simulates field conditions under which orangutan fecal samples would be collected using mobile microscopes. Therefore, the dataset's heterogeneity contributes to training a robust and adaptable segmentation model suitable for real-world deployment.

As outlined in Table 1, we constructed a balanced dataset comprising 4,000 annotated microscopy images, with 1,000 samples allocated evenly across each of the four target classes: *Ascaris lumbricoides*, *Enterobius vermicularis*, Hookworm eggs, and *Trichuris trichiura*. To ensure representative and unbiased learning, the dataset was split using stratified random sampling into three subsets: 70% for training (2,800 images), 20% for validation (800 images), and 10% for testing (400 images).

Table 1. Nematode parasite egg image datasets for training, validation, and testing

Class	Abb. in label class	Train (70%)	Validate (20%)	Test (10%)	Total number of images
<i>Ascaris lumbricoides</i>	<i>Ascaris</i>	700	200	100	1000
<i>Enterobius vermicularis</i>	<i>Enterobius</i>	700	200	100	1000
Hookworm egg	<i>Hookworm</i>	700	200	100	1000
<i>Trichuris trichiura</i>	<i>Trichuris</i>	700	200	100	1000
<i>Total</i>		2,800	800	400	4000

This stratification preserved the original class distribution in each subset, removing the need for oversampling or class weighting during training. To improve the model's generalization and robustness against variations in image capture conditions, we applied several standard data augmentation techniques. Mosaic augmentation was used to merge four random training images into a single composite, increasing contextual diversity and sample complexity. Horizontal flipping was applied to introduce spatial invariance, while random scaling simulated variations in magnification levels. These augmentations were configured directly within the YOLOv11 training pipeline using built-in parameters, ensuring efficient batch level transformation.

All images were annotated by trained parasitology experts. While the original dataset provided bounding box annotations, we converted these to instance segmentation masks using the Roboflow platform [23]. This conversion enabled the model to learn from pixel level features, which is essential for tasks requiring morphological precision. Segmentation was preferred over simple object detection because it captures not only the presence and location of a parasite egg but also its area, shape, and texture features characteristics that are crucial for quantifying infection severity and understanding parasite development stages [24]. The image segmentation is an important stage in automatic detection, identification and quantification of various type of parasite eggs in microscopic images. Different types of parasites, such as protozoa, helminths (worms) and ectoparasites and their eggs, can be observed under a microscope in human and animal faces, blood or urine samples. Microscopic images often contain multiple kinds of parasite eggs as well as other sample impurities or debris. The size, color, and texture of parasite eggs may also vary in the images depending on the sample collection and image acquisition process, making the segmentation process challenging. Various segmentation techniques such as thresholding, edge detection, and watershed have been applied in parasite egg analysis, yet focused reviews on segmentation across microscopic modalities remain scarce. In this study, we adapt core segmentation steps, including noise reduction, contrast enhancement, and morphological isolation, to the characteristics of orangutan fecal images, integrating them into our pipeline to improve detection and quantification for conservation-driven health monitoring.

Stratified random sampling was employed to divide the dataset into 70% training, 20% validation, and 10% testing subsets. This approach preserved the original class distribution across all splits, ensuring balanced representation and removing the need for additional class weighting or resampling strategies. To enhance the model's ability to generalize across varying imaging conditions, several data augmentation techniques were applied during training. These included mosaic augmentation, which increases contextual diversity by combining multiple images into one; horizontal flipping, which introduces spatial variance; and random scaling, which simulates different magnification levels [25]. These transformations were implemented using YOLOv11s built-in augmentation parameters, enabling efficient and consistent application throughout the training pipeline.

It is important to note that the training dataset consisted of human-derived parasite images, used here as proxies for orangutan infections due to strong overlap in parasite species between humans and great apes. To complement this, a separate pilot field test was conducted using real orangutan fecal samples collected from conservation areas in Central Kalimantan, Indonesia. These field samples were used exclusively for validating system performance in practical deployment scenarios and were not part of the model training dataset.

2.3. YOLOv11 training and prediction model

The YOLOv11n architecture was selected for this study due to its lightweight design and balance between computational efficiency and detection accuracy, making it particularly well-suited for real-time IoT

applications in resource-constrained field settings [26]. Model training was performed using 70% of the dataset, while the remaining 30% was used for validation and testing. To accelerate convergence and leverage prior learning, the model was initialized with pre-trained weights from the COCO dataset. Figure 3 illustrates the overall pipeline from training to inference.

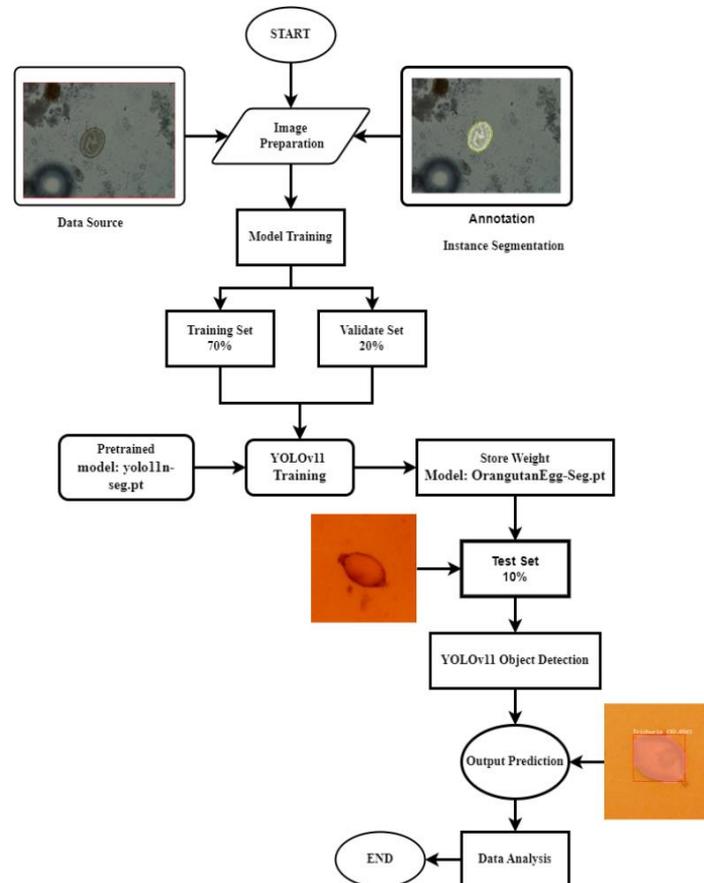


Figure 3. Flowchart depicting the data preparation and analysis pipeline for implementing the YOLOv11 model

The training was conducted over 600 epochs using a batch size of 16 and input images resized to 640×640 pixels. These parameters were chosen to maintain sufficient resolution for detecting small and complex parasite structures while optimizing graphics processing unit (GPU) memory utilization. The optimizer was configured with auto selection, a base learning rate of 0.01, momentum of 0.937, and a weight decay of 0.0005 to reduce overfitting. Validation was performed at the end of each epoch to monitor performance and detect any early signs of degradation.

To enhance generalization and model robustness, several augmentation techniques were applied during training. Mosaic augmentation was used to blend four training samples into a single image, increasing contextual complexity. Horizontal flipping introduced spatial invariance, while random scaling helped simulate variability in magnification levels. All augmentations were implemented using the built-in YOLOv11 configuration options, allowing seamless integration into the training pipeline.

The training process was accelerated using automatic mixed precision (AMP), a technique that reduces memory usage by mixing single- and half-precision calculations, thereby improving computational efficiency. Multi-graphics processing unit (GPU) training was enabled for scalability, and deterministic training settings were applied to ensure reproducibility across runs. These settings ensured that the training process was both efficient and replicable, allowing future researchers to reproduce the results under similar conditions. To support the segmentation task, several inference-specific parameters were fine-tuned.

An intersection over union (IoU) threshold of 0.7 was applied to ensure accurate alignment between predicted and ground truth masks. The system allowed a maximum of 300 detections per image and supported overlapping masks to correctly handle clustered or partially occluded parasite eggs.

Upon completion of training, the model generated a weight file encapsulating all learned parameters. This weight file was deployed to a cloud server, forming the core of the remote inference engine. When a new image is uploaded through the mobile application, the server processes the input and returns species classifications, instance counts, and segmentation masks in near real-time. This deployment strategy enables scalable, practical use in the field without requiring retraining or manual post-processing, thereby making advanced parasitological diagnostics accessible to conservation practitioners.

To comprehensively evaluate the models performance, a combination of standard metrics was employed. These included mean average precision (mAP), per-class precision, recall, and F1-score, which together assess the model's ability to accurately detect and classify parasite eggs. Additionally, IoU was used to evaluate the quality of the segmentation outputs against ground truth masks. The mAP metric provides a summary of the models performance across different precision-recall thresholds, offering a holistic view of detection accuracy. Precision and recall were calculated per class to assess the models ability to correctly identify parasite instances while minimizing false positives and false negatives. The F1-score, defined as the harmonic mean of precision and recall, offers a balanced indicator of classification accuracy particularly useful in scenarios with potential class imbalance or noise.

For evaluating segmentation quality, IoU quantifies the degree of overlap between predicted segmentation masks and ground truth annotations. This metric is critical in applications where the shape, area, or structural features of detected objects are important, such as in the morphological analysis of parasite eggs. Collectively, these metrics provide both class-level and overall assessments of the systems performance, validating its effectiveness for both object classification and pixel-level segmentation in real-world field applications

3. RESULTS AND DISCUSSION

3.1. Model performance

The YOLOv11n-based segmentation model demonstrated exceptional performance across all key evaluation metrics. The mAP reached 0.9957, indicating excellent consistency between predicted parasite detections and ground truth annotations. The mean IoU across all classes was 0.9098, reflecting a high degree of alignment between the predicted segmentation masks and actual egg boundaries critical for morphological analysis and infection load estimation.

A detailed per-class analysis further confirms the models robustness and generalizability in the Table 2. Precision was nearly perfect for all parasite categories, reaching 1 for *Ascaris lumbricoides*, Hookworm egg, and *Trichuris trichiura*, and 0.9888 for *Enterobius vermicularis*. Recall exceeded 0.99 in all cases, indicating very few false negatives. The resulting F1-scores, which balance both precision and recall, ranged from 0.9944 (*Enterobius vermicularis*) to 1 (Hookworm egg and *Trichuris trichiura*). The per-class IoU values ranged from 0.8885 to 0.9342, demonstrating that the model can effectively segment parasite shapes even when their appearances vary across images.

Table 2. Per-class model performance

Class	Precision	Recall	F1-score	IoU
<i>Ascaris lumbricoides</i>	1	0.9915	0.9957	0.9342
<i>Enterobius vermicularis</i>	0.9894	1	0.9947	0.9311
Hookworm egg	1	1	1	0.905
<i>Trichuris trichiura</i>	1	1	1	0.9049

Despite the overall strong performance, the slightly lower IoU score for *Enterobius vermicularis* (0.8885) indicates that this class may pose greater challenges for segmentation. This could be attributed to subtle variations in egg morphology, smaller size, or inconsistencies in image clarity across the dataset. Nevertheless, with all per-class IoU scores exceeding 0.88, the model demonstrates reliable capability in accurately delineating parasite shapes. These results suggest that even in the presence of imaging noise and morphological complexity, the YOLOv11-based segmentation model maintains high fidelity making it suitable for applications that require fine-grained visual analysis, such as infection load quantification or life stage estimation. Future improvements may focus on incorporating additional training samples for difficult classes or leveraging post-processing methods (e.g., conditional random fields or mask refinement networks) to further enhance mask precision. Overall, these findings validate the proposed system as a highly effective solution for automated parasite detection and segmentation, with strong implications for wildlife health diagnostics, remote disease surveillance, and longitudinal monitoring in conservation settings.

Compared with previous studies, our model demonstrates superior performance. Kumar *et al.* [7] achieved an mAP of 0.94 using YOLOv5 for intestinal parasite detection, while Xu *et al.* [10] reported an mAP of 0.92 with a lightweight architecture for microscopy-based egg detection. Parasite-attention mechanisms such as YOLO-PAM [8] achieved mAP values near 0.95 for malaria detection but were not implemented in IoT-enabled systems. Similarly, Sukumarran *et al.* [9] optimized YOLOv4 for malaria cell detection but focused on laboratory conditions. In contrast, our YOLOv11-based segmentation achieved an mAP of 0.9957 and IoU of 0.9098, providing not only higher detection accuracy but also improved segmentation fidelity, which is essential for morphological analysis.

The implications of these findings are twofold. First, the use of instance segmentation provides richer diagnostic information than detection alone, enabling estimation of parasite morphology and infection load. This level of detail is especially important for conservation health monitoring, where tracking parasite burden over time informs disease management strategies. Second, the successful integration with IoT infrastructure demonstrates that advanced deep learning models can be deployed in resource-limited environments, bridging the gap between laboratory accuracy and field applicability. While this study uses human-derived datasets as a proxy, it establishes a foundation for developing orangutan specific diagnostic systems in future research.

3.2. IoT implementation and field testing

To evaluate real-world applicability, a pilot study was carried out in the field by a research team from the University of Palangka Raya using fresh fecal samples collected from wild Bornean orangutans in conservation areas of Central Kalimantan. Images of these samples were captured using a portable digital microscope attached to a mobile device and processed through the proposed IoT deep learning pipeline. The field test aimed not at retraining the model, but at validating its robustness under realistic conditions, including variable illumination, inconsistent sample quality, and unstable network connectivity. This setup enabled assessment of usability, inference speed, and segmentation quality in authentic conservation environments.

The system successfully performed parasite classification and segmentation tasks in alignment with expert evaluations, providing additional validation of the models reliability. The model achieved an average inference time of approximately 300 milliseconds per image, measured from the point the API received the input to the delivery of the result. This response time supports near-real-time feedback, which is critical for field diagnostics. However, overall performance as experienced by end-users was affected by external variables such as image file size and network quality, which influenced upload latency and response delay.

In addition to evaluating model performance, the study conducted a formal assessment of the systems user interface, which constitutes a novel operational component within automated parasitology pipelines. Feedback obtained from field personnel indicated that the interface enabled efficient batch management, streamlined data submission from portable microscopy devices, and facilitated clear interpretation of instance-segmentation outputs. Its usability and low technical barrier further support its deployment in remote conservation settings, where diagnostic workflows must remain both reliable and accessible. The overall interface architecture and representative output visualizations are presented in Figure 4. Beyond these usability considerations, the interface also functions as an intermediary layer that links edge level data acquisition with cloud-based inference, thereby operationalizing the end-to-end IoT architecture.

As shown in Figure 4, the platform automates the organization of uploaded microscopic images into batch-level units, enabling traceable workflows suitable for longitudinal health monitoring. The system further presents annotated outputs including instance masks, class labels, and object counts in a structured format that facilitates rapid verification by field personnel or laboratory researchers. This capability is particularly important in conservation contexts, where timely assessment of parasite burden can inform decisions related to medical intervention, quarantine procedures, and broader population health management. By integrating data ingestion, cloud inference, and result visualization within a unified interface, the system provides a novel operational framework that enhances both the accessibility and reliability of automated parasite diagnostics in remote environments.

In the Figure 5 shows a representative instance segmentation output produced during the pilot deployment, in which the YOLOv11-based model successfully isolates the parasite egg from a highly heterogeneous fecal background in Figure 5. The model accurately delineates the egg boundary despite variations in illumination, debris density, and texture complexity conditions commonly encountered in field-prepared microscopic slides. During the pilot, the system achieved an average end-to-end latency of approximately 1.2-1.6 seconds per image, including wireless transmission, cloud preprocessing, and inference. Image acquisition was performed using a portable IoT microscope operating at 40× optical magnification, capturing 1280×960-pixel frames, which were then standardized to 640×640 resolution prior to inference. Segmentation performance remained stable across samples, with the model consistently generating high-confidence masks and IoU values exceeding 0.88 in field conditions, closely matching laboratory benchmarks.

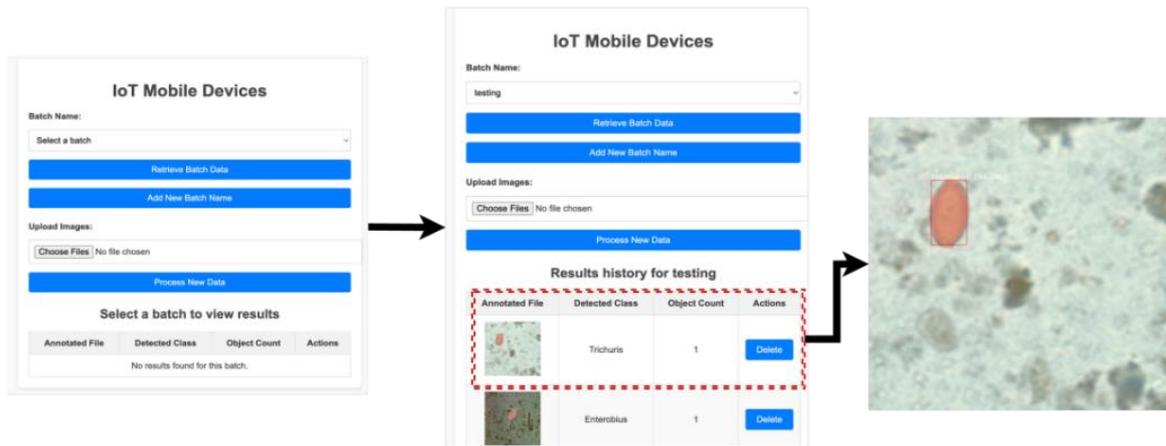


Figure 4. User interface displayed on a mobile device

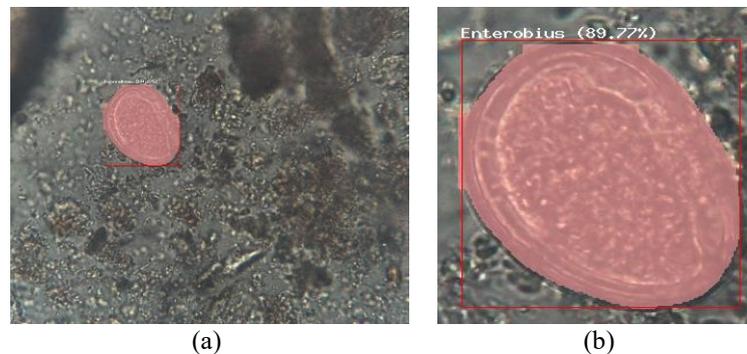


Figure 5. Segmentation results using a field-collected sample: (a) the complete image and (b) a zoomed-in view of the segmentation result

The IoT devices low-power design enabled continuous operation for 6-8 hours, supporting extended field sessions without requiring additional infrastructure. Importantly, the system preserved mask geometry and fine morphological detail, enabling downstream measurements such as egg length, width, and shape descriptors parameters relevant for species-level identification and parasite burden estimation. Collectively, these technical findings demonstrate that the integration of portable microscopy, wireless data transmission, and cloud-based deep learning inference constitutes a viable architecture for remote wildlife-health diagnostics. The combination of rapid processing, stable segmentation quality, and hardware portability underscores the systems potential for routine deployment in orangutan monitoring programs and broader conservation applications where laboratory access is limited.

4. CONCLUSION

This study presents a proof-of-concept IoT deep learning system that integrates portable microscopy with cloud-based inference for the automated detection and segmentation of intestinal nematode parasite eggs in orangutan fecal samples. By employing YOLOv11 with instance segmentation capabilities, the system moves beyond conventional bounding-box approaches and enables fine-grained morphological analysis essential for estimating parasite burden and supporting conservation-focused diagnostics. Experimental evaluation demonstrated strong performance, achieving mAP 0.9957 and IoU 0.9098, while a pilot field deployment confirmed the systems feasibility, usability, and near real-time inference in remote environments. The integration of portable imaging hardware with cloud computation underscores the potential of IoT-enabled architectures to enhance wildlife health monitoring, particularly in resource limited field conditions. The successful adaptation of YOLOv11 for detailed parasite-egg segmentation further advances automated parasitology workflows by improving both detection precision and the granularity of diagnostic information. Despite these contributions, the study is constrained by its dependence on human-derived parasite datasets as

proxies for orangutan infections. Addressing this limitation will require the expansion of training data with orangutan specific specimens and the refinement of segmentation accuracy through advanced post-processing techniques. Future research will also explore broadening the system to monitor additional parasitic and zoonotic threats relevant at the human wildlife interface, strengthening its role in conservation medicine and ecological health surveillance.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : Conceptualization

M : Methodology

So : Software

Va : Validation

Fo : Formal analysis

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R : Resources

D : Data Curation

O : Writing - Original Draft

E : Writing - Review & Editing

Vi : Visualization

Su : Supervision

P : Project administration

Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Data availability is not applicable to this paper as no new data were created or analyzed in this study.

REFERENCES

- [1] A. Panda, T. S. Djohan, W. T. Artama, and D. Priyowidodo, "Parasitic load and self-medication of Bornean Orangutan (*Pongo pygmaeus ssp. wurmbii*) in Sebangau National Park Central Kalimantan Indonesia," *IOP Conference Series: Earth and Environmental Science*, vol. 736, no. 1, p. 12055, Apr. 2021, doi: 10.1088/1755-1315/736/1/012055.
- [2] L. Patouillat, A. Hambuckers, S. Adi Subrata, M. Garigliany, and F. Brocorno, "Zoonotic pathogens in wild Asian primates: a systematic review highlighting research gaps," *Frontiers in Veterinary Science*, vol. 11, Jun. 2024, doi: 10.3389/fvets.2024.1386180.
- [3] A. Panda, A. T. S. Djohan, W. T. Artama, and D. Priyowidodo, "Home range, diet pattern and parasite's burden of the wild Bornean orangutans in Sebangau National Park Indonesia," *Animal Biodiversity and Conservation*, vol. 48, no. 1, p. e0005, Feb. 2025, doi: 10.32800/abc.2025.48.0005.
- [4] J. Dąbrowska, M. Groblewska, M. Bendykowska, M. Sikorski, and G. Gromadzka, "Effective laboratory diagnosis of parasitic infections of the gastrointestinal tract: where, when, how, and what should we look for?," *Diagnostics*, vol. 14, no. 19, Jan. 2024, doi: 10.3390/diagnostics14192148.
- [5] D. F. Parks *et al.*, "IoT cloud laboratory: Internet of things architecture for cellular biology," *Internet of Things (Netherlands)*, vol. 20, p. 100618, Nov. 2022, doi: 10.1016/j.iot.2022.100618.
- [6] B. S. Tchinda, M. Noubom, D. Tchiotsop, V. Louis-Dorr, and D. Wolf, "Erratum: towards an automated medical diagnosis system for intestinal parasitosis," *Informatics in Medicine Unlocked*, vol. 16, p. 100238, Jan. 2019, doi: 10.1016/j.imu.2019.100238.
- [7] D. Sukumarran *et al.*, "An optimised YOLOv4 deep learning model for efficient malarial cell detection in thin blood smear images," *Parasites & Vectors*, vol. 17, no. 1, p. 188, Apr. 2024, doi: 10.1186/s13071-024-06215-7.
- [8] S. Kumar, T. Arif, G. Ahamad, A. A. Chaudhary, S. Khan, and M. A. M. Ali, "An efficient and effective framework for intestinal parasite egg detection using YOLOv5," *Diagnostics*, vol. 13, no. 18, Jan. 2023, doi: 10.3390/diagnostics13182978.
- [9] W. Xu, Q. Zhai, J. Liu, X. Xu, and J. Hua, "A lightweight deep-learning model for parasite egg detection in microscopy images," *Parasites and Vectors*, vol. 17, no. 1, p. 454, Nov. 2024, doi: 10.1186/s13071-024-06503-2.
- [10] L. Zedda, A. Loddo, and C. Di Ruberto, "YOLO-PAM: parasite-attention-based model for efficient malaria detection," *Journal of Imaging*, vol. 9, no. 12, Dec. 2023, doi: 10.3390/jimaging9120266.
- [11] M. A. Rahman and M. S. Sadi, "IoT enabled automated object recognition for the visually impaired," *Computer Methods and Programs in Biomedicine Update*, vol. 1, p. 100015, Jan. 2021, doi: 10.1016/j.cmpbup.2021.100015.
- [12] I. Zualkernan, S. Dhau, J. Judas, A. R. Sajun, B. R. Gomez, and L. A. Hussain, "An IoT system using deep learning to classify camera trap images on the edge," *Computers*, vol. 11, no. 1, Jan. 2022, doi: 10.3390/computers11010013.
- [13] D. Freire-Obrégón, F. Narducci, S. Barra, and M. Castrillón-Santana, "Deep learning for source camera identification on mobile devices," *Pattern Recognition Letters*, vol. 126, pp. 86–91, Sep. 2019, doi: 10.1016/j.patrec.2018.01.005.

- [14] K. L. Tong, K. R. Wu, and Y. C. Tseng, "The device-object pairing problem: Matching iot devices with video objects in a multi-camera environment," *Sensors*, vol. 21, no. 16, Jan. 2021, doi: 10.3390/s21165518.
- [15] I. Ahmed, M. Ahmad, A. Ahmad, and G. Jeon, "IoT-based crowd monitoring system: using SSD with transfer learning," *Computers and Electrical Engineering*, vol. 93, p. 107226, Jul. 2021, doi: 10.1016/j.compeleceng.2021.107226.
- [16] S. Karlsson, R. Jongeling, A. Čaušević, and D. Sundmark, "Exploring behaviours of RESTful APIs in an industrial setting," *Software Quality Journal*, vol. 32, no. 3, pp. 1287–1324, Sep. 2024, doi: 10.1007/s11219-024-09686-0.
- [17] N. Kuze *et al.*, "Parasites found from the feces of Bornean orangutans in Danum Valley, Sabah, Malaysia, with a redescription of *Pongobius hugoti* and the description of a new species of *Pongobius* (Nematoda: *Oxyuridae*)," *Journal of Parasitology*, vol. 96, no. 5, pp. 954–960, 2010, doi: 10.1645/GE-2379.1.
- [18] E. M. Labes *et al.*, "Intestinal parasites of endangered orangutans (*Pongo pygmaeus*) in Central and East Kalimantan, Borneo, Indonesia," *Parasitology*, vol. 137, no. 1, pp. 123–135, 2010, doi: 10.1017/S0031182009991120.
- [19] A. L. Gwynn, H. C. Morrough-Bernard, A. Thornton, H. Segah, A. Azis, and F. J. F. Van Veen, "Gastrointestinal parasites of wild Bornean orang-utans (*Pongo pygmaeus*) in a habitat affected by wildfire smoke," *Global Ecology and Conservation*, vol. 55, 2024, doi: 10.1016/j.gecco.2024.e03214.
- [20] K. C. Křížová *et al.*, "First study of *Ascaris lumbricoides* from the semiwild population of the Sumatran orangutan (*Pongo abelii*) in the context of morphological description and molecular phylogeny," *Life*, vol. 13, no. 4, 2023, doi: 10.3390/life13041016.
- [21] A. Adhikari, N. P. Koju, B. Maharjan, L. Khanal, M. Upreti, and R. C. Kyes, "Gastro-intestinal parasites of urban rhesus macaques (*Macaca mulatta*) in the Kathmandu Valley, Nepal," *International Journal for Parasitology: Parasites and Wildlife*, vol. 22, pp. 175–183, Dec. 2023, doi: 10.1016/j.ijppaw.2023.10.007.
- [22] T. Suwannaphong, S. Chavana, S. Tongsom, D. Palasuwan, T. H. Chalidabhongse, and N. Anantrasirichai, "Parasitic egg detection and classification in low-cost microscopic images using transfer learning," *SN Computer Science*, vol. 5, no. 1. IEEE DataPort, 2024. doi: 10.1007/s42979-023-02406-8.
- [23] B. Dwyer, J. Nelson, and T. Hansen, "Roboflow," [Online]. Available: <https://roboflow.com> (accessed Feb 17, 2025).
- [24] K. Ray, S. Saharia, and N. Sarma, "Segmentation approaches of parasite eggs in microscopic images: a survey," *SN Computer Science*, vol. 5, no. 4, p. 401, Apr. 2024, doi: 10.1007/s42979-024-02709-4.
- [25] M. Xu, S. Yoon, A. Fuentes, and D. S. Park, "A comprehensive survey of image augmentation techniques for deep learning," *Pattern Recognition*, vol. 137, p. 109347, May 2023, doi: 10.1016/j.patcog.2023.109347.
- [26] J. Tang, C. Ye, X. Zhou, and L. Xu, "YOLO-fusion and internet of things: advancing object detection in smart transportation," *Alexandria Engineering Journal*, vol. 107, pp. 1–12, Nov. 2024, doi: 10.1016/j.aej.2024.09.012.

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