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Image-based Detection and Classification of Poultry Diseases from Chicken Droppings in Open House Poultry Farms

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Abstract - Monitoring chicken health is essential for maintaining the production efficiency of poultry farms and meeting the demand for poultry products. Previous studies have explored various methods, including utilizing sound, behaviour, and the shape of the chickens, as well as the conditions of their droppings, to assess chicken health. In this research, we monitor chicken droppings as a reliable indicator of chicken health. We develop an automated system for detecting chicken droppings and identifying health conditions, specifically in open house poultry farms in Malaysia. Open poultry houses are the most common design in Malaysia due to their lower construction and maintenance costs, a more natural environment for the chickens, and greater space to roam. However, the design of open poultry houses, which utilizes evenly gapped wood slat flooring, compounds the problem of automatically distinguishing new droppings from dirty flooring. In our work, data consisting of chicken dropping images from a poultry farm in Malaysia were collected for analysis. We used the YOLOv5n algorithm for detecting chicken droppings and distinguishing between healthy and sick chickens based on observable features such as the colour and shape of their droppings. Our proposed architecture, which used the YOLOv5n algorithm, can accurately detect chicken droppings and classify them into three health classes (coccidiosis, healthy, and other unhealthy), with an accuracy rate of up to 94.9%. By leveraging advanced computer vision techniques, poultry farmers can benefit from timely and accurate health assessments, leading to improved productivity and animal welfare in open house poultry farming systems.

Keywords— Poultry Diseases, Chicken Droppings, Image-based Detection, YOLOv5n, Open House Poultry Farms

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1. INTRODUCTION

Poultry farming stands as a fundamental pillar of global agriculture, playing an indispensable role in meeting the burgeoning demand for animal protein worldwide and this market is rapidly growing. According to [1], consumption is expected to increase from $384.95 billion in 2024 to $410.98 billion in 2025. Within the Malaysian agricultural landscape, poultry farming assumes significant importance, evidenced by compelling statistics. In 2022, Malaysia had over 293 million chickens in stock, showing growth from approximately 284.57 million the year before. Over the past decade, there has been a consistent rise in chicken stock levels [2]. Furthermore, the exponential rise in chicken production aligns seamlessly with the escalating per capita consumption of poultry meat among Malaysians, reaching an estimated 50 kilograms per person as of 2023 [3].

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The health and productivity of poultry are paramount, directly impacting the economic viability of poultry farms and the quality of poultry products. Traditional methods of monitoring chicken health in open house poultry farms have relied predominantly on manual observation, a process that is both time-consuming and susceptible to human error. However, with the advent of artificial intelligence (AI), computer vision, and Internet-of-Things (IoT), there exists novel and transformative approaches in monitoring chicken health in modern poultry farms [4-9].

Open house poultry farms have been around for a long time in Malaysia. Compared to closed houses, open house poultry farms are much more cost-effective in terms of various ancillary costs. However, integrating modern technology in open houses can be more challenging. For instance, automated analysis and processing of chicken droppings, which serve as important indicators of the chickens' health status, using modern tools such as computer vision, deep learning, and machine learning are problematic. These poultry houses are built of wood, with gapped wooden slats on the floor, making droppings detection using deep learning difficult. In contrast, closed house poultry or any other type farms have plain, solid floors without gaps, making detection much easier.

The aim of our research is to address the challenges of utilising computer vision to detect and classify chicken droppings in open house poultry farms in Malaysia. In our proposed system, we used the YOLOv5n model, which is highly efficient in terms of both accuracy and speed. YOLOv5n is an object detection model capable of distinguishing between healthy and unhealthy droppings with a high precision rate.

By utilizing this advantage of deep learning technology, we can contribute to the poultry industry by improving animal care and enhancing production efficiency, ultimately having a large-scale impact on the productivity of poultry farming.

2. LITERATURE REVIEW

The global poultry industry is rapidly expanding, leading to an increasing need for improved poultry health monitoring techniques. Computer vision, deep learning, object detection, and similar technologies have the potential to improve animal welfare, including chickens in poultry farms. By using various object detection models, thermal monitoring systems, and audio-based models, it is becoming easier to monitor chicken health, sometimes in real time [10]. This review provides an analysis of modern methods, such as temperature monitoring, audio analysis, droppings examination, and posture estimation [4], [5], [11] which are useful for detecting abnormalities in poultry.

2.1 Temperature Monitoring

Wang et al. [12], Noh et al. [13] and Chuang et al. [14] have contributed to the field of thermal imaging for poultry health monitoring. Wang et al. [12] proposed a method where an improved YOLOv8n-mvc model was developed to measure body temperature of chicken by infrared thermography and achieved high accuracy. Noh et al. [13] developed a real-time surveillance system using thermal cameras to monitor poultry body temperature, enabling early detection of avian influenza. Similarly, Chuang et al. [14] developed a similar system for geese, utilizing convolutional neural network (CNN) algorithms to accurately detect individual body surface temperature variations in poultry, which positively impacts early disease detection methods.

2.2 Audio-based Monitoring

Another method for diagnosing poultry diseases is audio signal processing, which can be used to identify the sounds of sick chickens, as demonstrated by Quintana et al. [15]. Using a solar-powered system and decision tree models, they achieved 86.1% accuracy in detecting sick chickens based on different sounds. Another study in this field, conducted by Jakovljević et al. [16], utilised the Support Vector Machine (SVM) algorithm to monitor chicken stress sounds, achieving an accuracy range of 63% to 83%. Furthermore, Carpentier et al. [17] and Huang et al. [18] have contributed to this field of audio-based detection methods by monitoring chicken sneezing sounds, achieving precisions of 88.4% and 90%, respectively. Another work done by Sun et al. [19] using random forest model to analyse sound based on audio-based monitoring method and achieved accuracy of 91.14%. E. Hassan et al. [20] proposed a deep learning-based audio classification model where they included Burn Layer which improved model performance and achieved accuracy of 98.55%.

2.3 Pose Estimation

Poultry health can sometimes be determined by assessing posture and analysing behaviour. Research by Hilmi et al. [21], Fang et al. [22], [23], Xie and Chang [24], K. S. Chemme and R. J. Alitappeh [25] and Fang et al. [26] focuses on pose estimation and behaviour analysis using different such as ResNet, Deep Neural Network (DNN), and YOLOv8 models. They achieved high accuracy in predicting illness in chickens by monitoring abnormal behaviour and variations in body shape.

2.4 Droppings Analysis

Computer vision and deep learning applications have proven highly effective in chicken dropping analysis for poultry health monitoring. Different colours of chicken droppings indicate various health conditions, such as healthy, sick, or infected by a virus or disease. Vandana et al. [27] used EfficientNetB7 model based on classifying chicken diseases using dropping images and achieved accuracy of 97.07%. Chen and Yang [28] used the ResNeXt50-3A model for disease detection by identifying healthy and unhealthy chicken droppings, achieving 97.4% accuracy. Further research in this area by Mbelwa et al. [29] and Suthagar et al. [30], based on CNN models for chicken dropping classification and disease detection, achieved accuracies of 94% and up to 97%, respectively. Additionally, Widyawati and Gunawan [31] and Utomo et al. [32] used the YOLOv5 algorithm for chicken dropping detection and classification and achieved an accuracy of 89.2% and 90% respectively. Xu and Chang [33] used YOLOv7 model for chicken dropping detection and classification and achieved an accuracy of 83%.

The authors [27-30] used EfficientNetB7, ResNeXt50-3A, XceptionNet, and DenseNet, respectively. These models are all based on CNN and fall under deep learning within the machine learning category. However, YOLOv5, YOLOv7 used by the author [31-33], are an object detection and classification models within the field of computer vision.

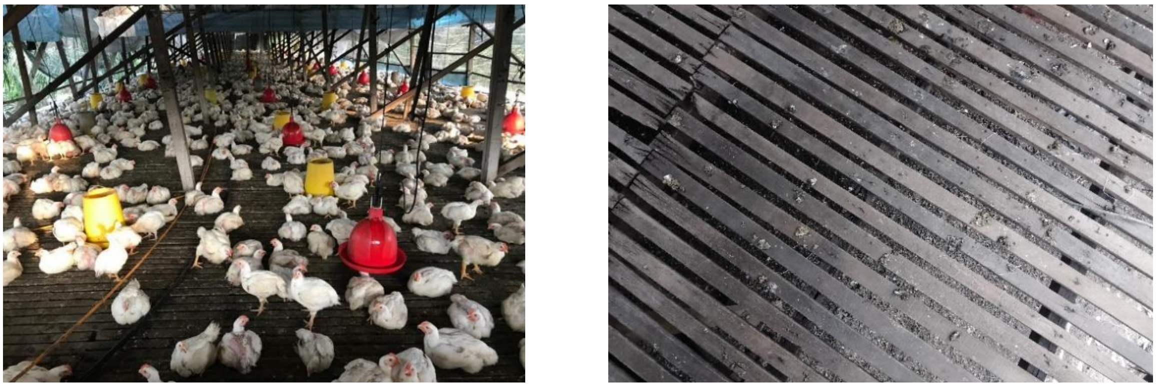
EfficientNetB7, ResNeXt50, XceptionNet, and DenseNet are powerful deep learning models that require larger datasets compared to YOLOv5 and YOLOv7 for optimal performance. These models operate in multiple stages for object detection tasks and demand significant computational power for training. Their architectures are also complex. In contrast, YOLOv5 and YOLOv7 are a single-stage object detector with a lightweight and less complex architecture, requiring less computational power compared to the other models. Additionally, it is capable of real-time detection.

Chicken droppings analysis method has some advantageous over other methods such as:

- Non-Invasive and Stress-Free: This method is completely non-invasive, causing no harm or distress to the chickens compare to other methods. This is one of the advantages over other methods such as temperature monitoring or pose estimation, which can cause stress to the chicken.
- Early Detection: When a chicken becomes sick, the colour of its droppings may change, even if it appears healthy externally. This serves as an early sign of illness. Monitoring these changes can help detect diseases early and prevent them from spreading to the entire flock.
- Real-Time Monitoring: Models like YOLO can perform real-time monitoring to detect diseases by identifying changes in chicken droppings.
- High Accuracy: This method can achieve high accuracy rates and provide detailed insights into diseases by identifying different dropping colours associated with specific illnesses.
- Cost-Effective: This approach does not require expensive equipment, such as thermal cameras for temperature monitoring or audio equipment for audio-based monitoring.
- Ease of Implementation: This method is easy to implement and does not require specialized skills.

A key distinction between our study and others lies in the background of the images used in our dataset. Unlike the relatively nondescript backgrounds in the images of other datasets, ours were derived from open house poultry farms in Malaysia, where the coop floors are constructed from wooden slats. These slats, with gaps in between as shown in Figure 1, allow the ground to be visible from the coop floor and are intended to promote better air circulation while permitting chicken dropping to fall directly on the ground, thus maintaining hygiene in the coop. This characteristic, while typical of local conditions, introduces a challenge when collecting data using a smartphone camera, as it can be difficult to focus on the droppings.

This difference in the dataset background is significant as it introduces an additional layer of complexity in achieving high accuracy, particularly in the context of open house poultry farming in Malaysia. Because of this condition, our approach has proven to be effective and efficient, making it a suitable tool for health monitoring in the poultry industry.



(a) (b)

Figure 1. Open House Poultry Farms in Malaysia: (a) Slats are Visible in The Poultry Farm, and (b) Example of Wooden Slats with Gaps in Between

3. RESEARCH METHODOLOGY

3.1 Data Collection

Smartphone cameras with a 12-megapixel resolution were utilized to capture images of chicken droppings in a commercial open house poultry farm in Malaysia. Images were taken during morning and before evening periods when chickens were grouped together, facilitating easier photo capture. Chickens are social animals and naturally tend to group together, especially during the mornings and evenings. This behaviour is primarily driven by two factors such as safety and light [34]. Chickens group together for safety from predators and due to their poor night vision. Data collection focused on chickens aged between 3 to 6 weeks, a period when they are most susceptible to clinical diseases [35]. The distance between the camera and chicken dropping was maintained to be between 20 and 25 cm.

Figure 2 shows a collection of images containing chicken droppings. The figures also show how the droppings are positioned on the wood slats, which have gaps between every slat and the ground clearly visible underneath. With guidance from the poultry farm owner and his highly experienced farmhands, and informed by references from relevant literature, we categorized our dataset into three distinct classes: *coccidiosis* (labelled as "cocci"); *healthy* (labelled as "healthy"); and *other unhealthy* (labelled as "other_unhealthy"). The classification was based on visual characteristics, such as the presence of blood, texture, and colour, which are typically sufficient to distinguish coccidiosis from other classes.

Although we collected over 600 images from the poultry farm, only 276 images were usable due to the clarity and distinctness of the droppings from the surrounding dirt and dried droppings. Of these 276 images, 80% (221 images) were allocated for the training dataset and the remaining 20% (55 images) earmarked for the validation dataset. To address the limited data, we applied data augmentation techniques as described in the next section to expand the training dataset.

3.2 Preprocessing and Augmentation

Our collected images were carefully annotated using Roboflow's [36] polygon tool, offering greater precision over traditional bounding box annotations. This allowed us to accurately outline object boundaries, especially in instances with irregular shapes or complex patterns. An example of the polygon annotation is shown in Figure 3.

(a)

(b)

(c)

(d)

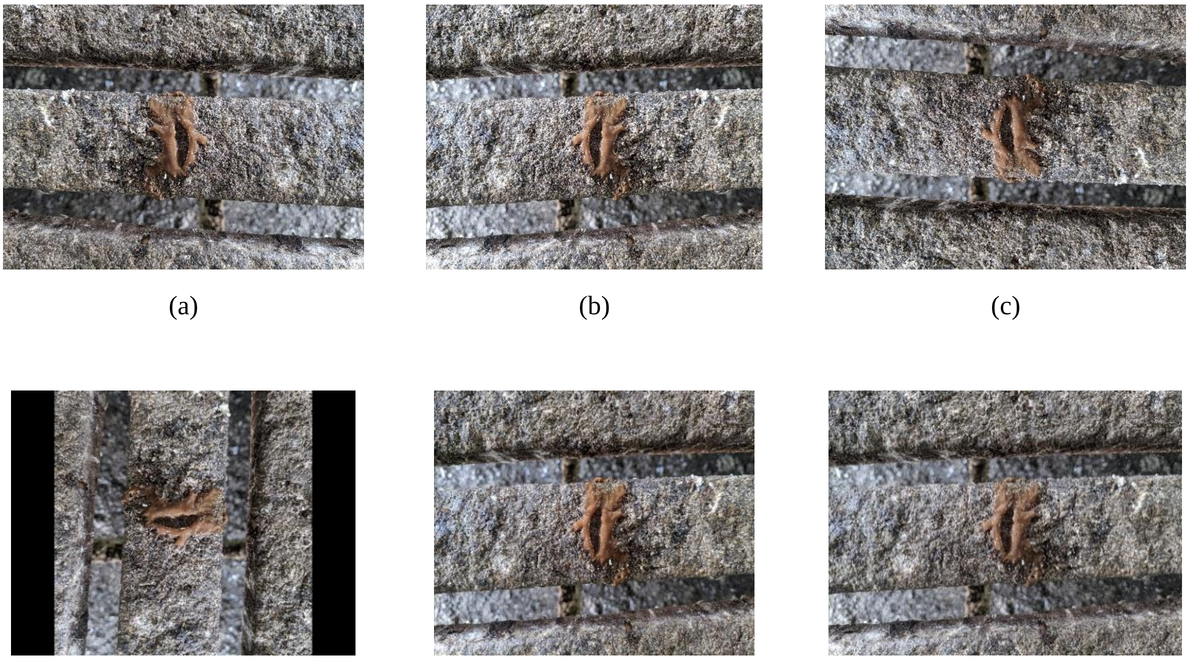
Figure 2. Samples of Chicken Droppings: (a) Healthy, (b) Coccidiosis, (c) and (d) Others (Unhealthy)

Figure 3. Data Annotation Using Roboflow's Polygon Annotation Tool

We used Roboflow for data augmentation, a key step in improving our training data. Each image was randomly modified in several ways:

- Flipping: Images were flipped both horizontally and vertically.
- Rotation: Images were rotated 90° in various directions.
- Saturation Adjustment: Saturation levels were adjusted between -25% and +25%.
- Brightness Adjustment: Brightness levels were adjusted between -10% and +10%.
- Noise Addition: Up to 0.8% of pixels in each image were subjected to noise addition, simulating natural variations.

For each image in the dataset, a random selection of these augmentations was applied. So, not all augmentations necessarily were applied to each image. For instance, for one image, it might have only been flipped horizontally and had its brightness adjusted, while for another image, it might have been rotated and had noise added. These changes created four unique versions of each image, thus increasing the dataset. Some examples of these augmentations can be seen in Figure 4.



(a) (b) (c)

(d) (e) (f)

Figure 4. Data Augmentation on Images of Chicken Droppings: (a) Original, (b) Brightness Increased by 10%, (c) Rotated Horizontally, (d) Rotated Counter-Clockwise, (e) Saturation Increased by 25%, and (f) 0.8% Added Noise

We only augmented the 221 images that were set aside as training data, expanding them to 884 images. Within the training dataset of 884 images, 192 images were in the cocci class, 336 images in the healthy class, and 356 images in the other_unhealthy class. Conversely, the validation dataset consisted of 55 images, distributed as follows: 12 images in the cocci class, 21 images in the healthy class, and 22 images in the other_unhealthy class.

3.3 Model: YOLOv5

The You Only Look Once (YOLO) algorithm, recognized for its robust object detection capabilities and high precision, was chosen as the fundamental framework for this study. Although newer versions of YOLO were available, YOLOv5 was chosen for this study due to its mature and well-documented implementation, thus making it highly accessible and suitable for the development of the initial prototype. Additionally, YOLOv5 strikes a balance between computational efficiency and performance, making it a practical choice for our specific dataset and limited hardware capabilities. Moreover, this preliminary study aims to demonstrate the feasibility of the proposed approach.

While image classification models such as EfficientNetB7, ResNet, Xception, and DenseNet may be more straightforward to implement for single-object classification (e.g., one dropping per image), we chose an object detection model like YOLO because it aligns with our broader research objective of creating a scalable solution for real-world applications. An object detection model offers greater flexibility and adaptability, particularly for future iterations of our work, where images may contain multiple droppings or require spatial localisation for further analysis.

Figure 5 represents YOLOv5 architecture. The YOLOv5 model is designed with a three-part structure: the BackBone, PANet, and Output sections, each containing key layers that contribute to effective object detection.

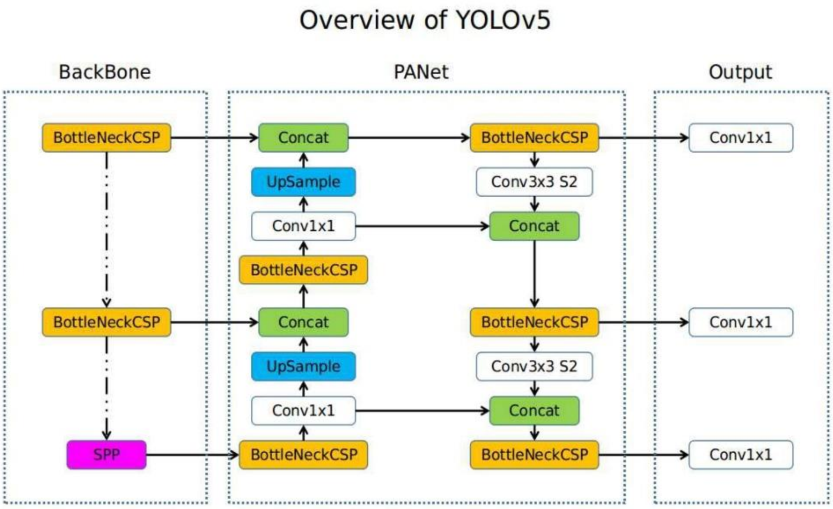


Figure 5. Overview of Model Structure of YOLOv5 [37]

YOLOv5's model architecture is designed in such way which makes it more efficient object detection. In its Backbone section, it uses BottleNeckCSP layers to extract essential features from images, identifying key patterns. The Spatial Pyramid Pooling layer enhances this process by analysing features at multiple scales, which making the model to adapt to different image sizes.

The PANet section further refines these features by up sampling low-level features and combining them with high-level features through concatenation, effectively integrating information from different scales. Finally, 1x1 convolutional layers refine the combined features.

Finally, the output section processes these refined features using BottleneckCSP and 1x1 convolutional layers. Two stages of 3x3 convolutional layers provide the final level of refinement before the model generates the detection output. This combination of layers enables YOLOv5 to achieve accurate object detection by effectively capturing and processing multi-scale information.

For our training, we opted for the YOLOv5n model, a balanced variant within the YOLOv5 family. This choice considered the trade-off between model size and performance, making it suitable for our resource constraints. We initiated the training with a standard command which is given below:

```
!python train.py --batch-size 16 --data data/saheb_data.yaml --img 640 --cfg models/yolov5n.yaml --weights 'yolov5n.pt' --name saheb_dataset_yolov5_884_55 --hyp data/hyps/hyp.scratch-low.yaml --cache --epochs 300 --patience 300
```

Our model training was customized with the following settings:

- Batch Size: We used a batch size of 16, processing 16 training examples at a time.
- Data: Our training utilized our own dataset, covering object detection
- Image Size: Input data images were resized to 640 pixels.
- Weights: We initialized the model with the 'yolov5n.pt' pre-trained weights.
- Epochs: Training was conducted for 300 epochs, allowing the model to iterate through the entire dataset 300 times.
- Patience: We set early stopping with a patience of 300 epochs which is same as training epochs.

We proposed this training strategy to improved performance and accuracy of YOLOv5n with data augmentation and a pre-trained weight.

3.4 Performance Evaluation

Evaluating the effectiveness of object detection models like YOLOv5, which relies heavily on performance metrics. We will describe in detail how we calculated precision, accuracy, recall, and F1-score.

Accuracy assesses how well the model's predictions match the actual values. In object detection, it is determined by the ratio of correctly identified bounding boxes to the total number of ground truth bounding boxes as described in Equation (1).

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \tag{1}$$

As shown in Equation (2), accuracy measures the accuracy of positive prediction by calculating the ratio of correctly identified positive cases (true positives) to the total number of instances classified as positive (including both true positives and false positives).

$$\text{Precision} = \frac{TP}{TP+FP} \tag{2}$$

Recall, also known as sensitivity, evaluates the ability of a model to correctly identify positive cases among all true positive cases. The recall calculation is presented in Equation (3).

$$\text{Recall} = \frac{TP}{TP+FN} \tag{3}$$

The F1 score represents the harmonic mean of precision and recall, effectively balancing these two metrics, as shown in Equation (4). This measure is particularly valuable in situations where the class distribution is uneven.

$$\text{F1 Score} = \frac{2\times Precision\times Recall}{Precision+Recall} \tag{4}$$

4. RESULTS AND DISCUSSIONS

We used the YOLOv5n model for the object detection task, training it for a total of 300 epochs. The model's performance was carefully evaluated using multiple evaluation metrics.

Our model achieved a mean average precision (mAP) of 94.9% at an Intersection over Union (IoU) threshold of 0.5. This result demonstrates the effectiveness of the model in object detection, demonstrating high precision and recall, reflecting its strong overall performance.

Figure 6 represents the balance between precision and recall across different thresholds. Each curve depicts the classification performance of the model for each individual category. The area under the curve (AUC) reflects the overall average performance of the model. Overall average of mAP@0.5 is 0.949. The model is particularly effective in identifying all three classes. The “all classes” or otherwise known as “overall average’ score indicates excellent performance across all categories which is shown in Table 1.

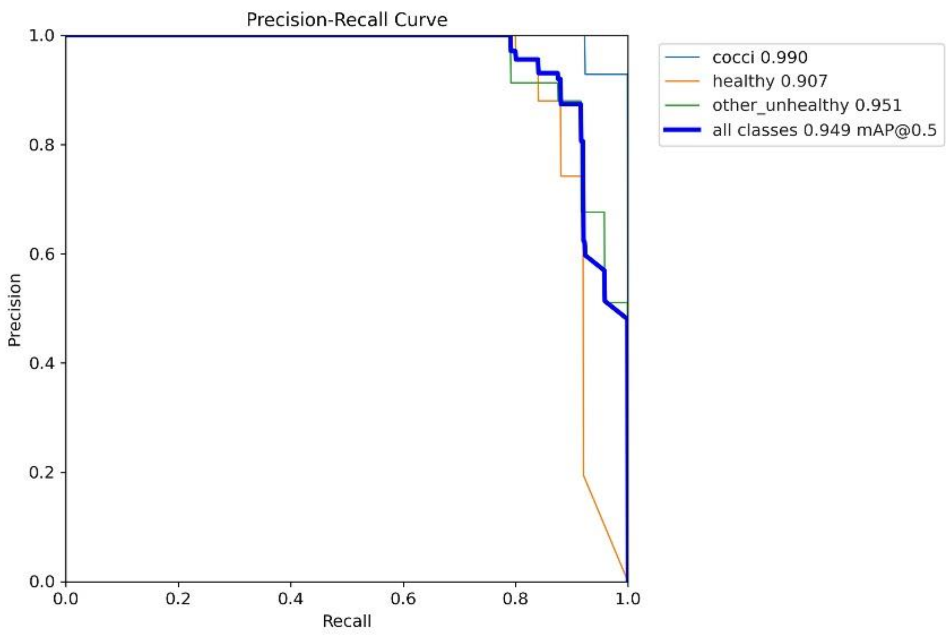


Figure 6. Precision-Recall Curve

Table 1. YOLOv5n Model Classification Performance Metrics

Class	Precision	Recall	@mAP0.5
cocci	0.905	1	0.99
healthy	0.919	0.84	0.906
other_unhealthy	0.909	0.83	0.951
Overall average	0.911	0.89	0.949

From Figure 7, the graph illustrates how the F1 score varies with different confidence thresholds for each category, indicating the model's precision and robustness in classification. For "all classes", the F1 score reaches 0.90 at a confidence level of 0.653. The peak F1 score for "all classes" suggests a strong balance between precision and recall at the specified confidence level.

The confusion matrix in Figure 8 shows that 92% of actual cocci instances were correctly identified, 84% of actual healthy instances were correctly identified, and 92% of actual other_unhealthy instances were correctly identified.

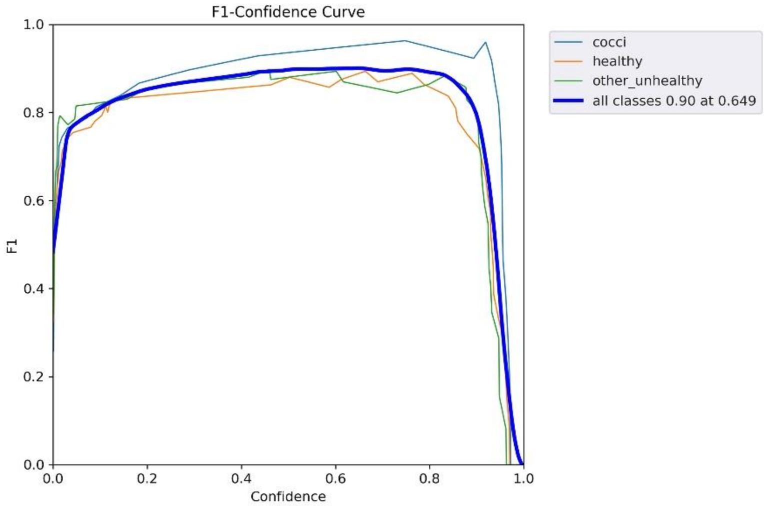


Figure 7. F1-Confidence Curve

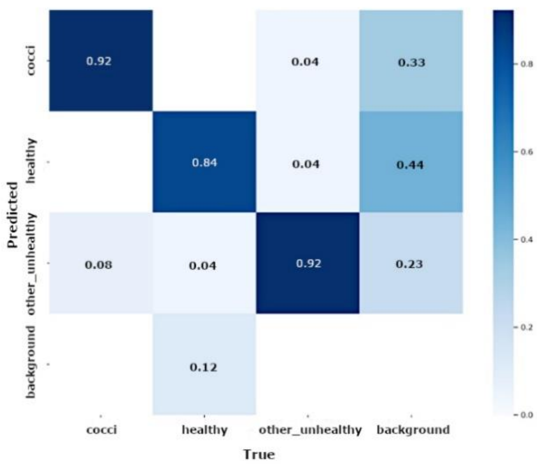


Figure 8. Confusion Matrix

Figure 9 represents the performance of the model over 300 training epochs. The graph typically shows a rapid increase in mAP at the beginning of training as the model learns from the data. As training progresses, improvements in mAP become more incremental, and the curve plateaus, indicating that the model is converging and further training yields little improvement in performance.

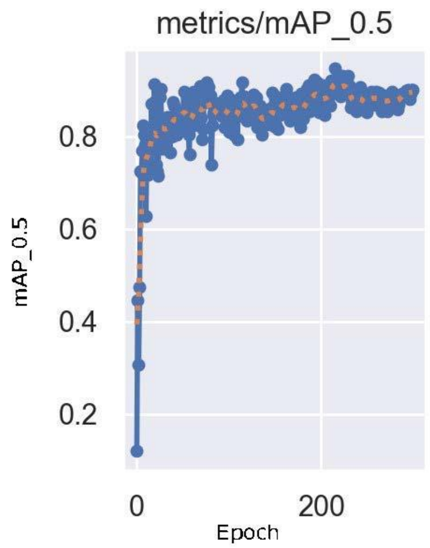


Figure 9. mAP 0.5 per Epoch Graph

Figure 10 represents visual output from the YOLOv5n model after training. It is a collage of 16 smaller images because we set batch size to 16. The YOLOv5n model has made predictions on these images, which are represented by the differently coloured bounding boxes with their respective labels. Each bounding box is associated with a label such as healthy, cocci, and other_unhealthy, indicating the model's prediction of the condition of the surface in that area. 0.4 to 0.9 scores beside each label represents the model's confidence in its prediction.

Figure 10. Output Results Showing the Classification of Each Chicken Dropping and its Corresponding Confidence Level

In our study, we used the YOLOv5n model to monitor poultry health, specifically focusing on detecting abnormalities in poultry through droppings analysis. Our approach differs from the existing literature in several key aspects, making it particularly suited for the conditions of open housing poultry farming in Malaysia.

- Temperature Monitoring: While Wang et al. [12], Noh et al. [8] and Chuang et al. [9] have made significant contributions in thermal imaging for poultry health monitoring, our approach focuses on droppings analysis, which provides direct evidence of poultry health conditions. This is especially relevant in the context of Malaysia's open housing poultry farming where thermal imaging might be difficult due to environmental factors.
- Audio-based Monitoring: Others [15-20] have demonstrated the effectiveness of audio signal processing techniques for disease identification in poultry. However, these methods might not be as effective in open housing conditions due to ambient noise. Our method of droppings analysis is not affected by such environmental noise, making it a more reliable approach in these conditions.
- Pose Estimation: While pose estimation and behaviour analysis approaches [21-26] have shown high accuracies, they require continuous monitoring of the poultry, which might not always be feasible in open housing conditions. In contrast, droppings analysis can be performed periodically without continuous monitoring.
- Droppings Analysis: Our work aligns with the droppings analysis approach, which is an effective health monitoring strategy in poultry farming [27-33]. However, our approach stands out due to the different condition posed by the open housing conditions in Malaysia. Unlike other studies that used datasets with solid backgrounds such as shown in Figure 11, our dataset has a background of wood slats, making it more difficult to focus on the droppings. To overcome this situation, we used a polygon annotation tool for a more precise shape of the droppings, which significantly improved our output. In contrast, other studies used a bounding box tool, which is not as precise as the polygon tool.

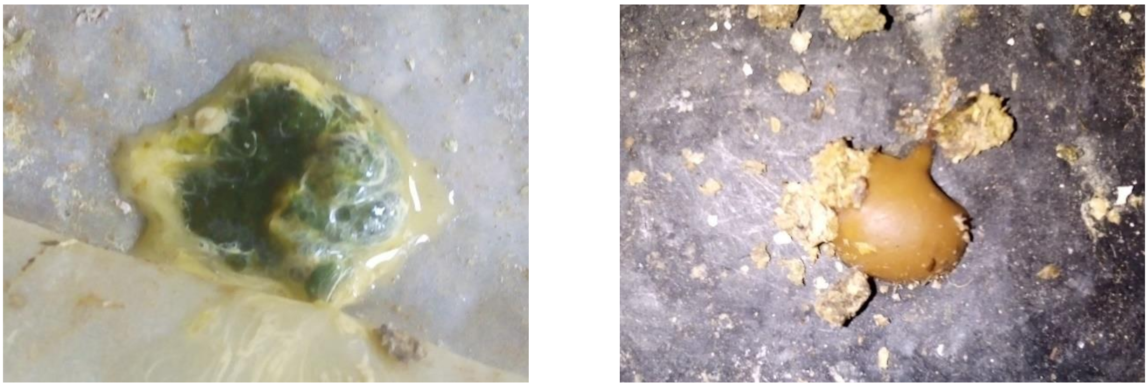
To demonstrate the feasibility and viability of this preliminary work, we performed an initial comparison of our approach with other droppings analysis methods, namely [27-33]. We focused on comparing their respective accuracy, as this metric was consistently available across all methods. Table 2 shows a summary of this comparison.

Table 2. Performance Comparison with Related Works

Authors	Model	Accuracy (%)
Vandana et al. [27]	EfficientNetB7	97.07
Chen and Yang [28]	ResNeXt50-3A	97.4
Mbelwa et al. [29]	XceptionNet	94
Suthagar et al. [30]	DenseNet	97
Widyawati and Gunawan [31]	YOLOv5	89.2
Utomo et al. [32]	YOLOv5	90
Xu and Chang [33]	YOLOv7	83
*Proposed Work	YOLOv5n	94.9

The performance of our proposed work, as shown in Table 2, is quite competitive when compared to other similar works. Our model, YOLOv5n, achieved an accuracy of 94.9%, which is higher than the 89.2% accuracy achieved by the YOLOv5 model used by Widyawati and Gunawan [31], 90% accuracy achieved by the YOLOv5 model used by Utomo et al. [32], and 83% accuracy achieved by YOLOv7 model used by Xu and Chang [33]. This demonstrates that using YOLOv5n can result in improvements over the standard YOLOv5 and YOLOv7 models.

While our proposed work's accuracy is slightly lower than 97.07% achieved by Vandana et al. [27], 97.4% achieved by Chen & Yang's ResNeXt50-3A [28] and the 97% by Suthagar et al.'s DenseNet [30], it is important to note that different models may have different strengths and weaknesses depending on the specific task and dataset. For instance, YOLO models are often favoured for real-time object detection due to their speed, even if they sacrifice a bit of accuracy. Models like EfficientNetB7, ResNeXt50-3A, and DenseNet, while accurate, are typically more computationally intensive than YOLOv5n. Furthermore, EfficientNetB7, ResNeXt50-3A, and DenseNet used a dataset that differs from ours, namely their images have solid background as opposed to wood slats as shown in Figure 11.



(a) (b)

Figure 11. (a) and (b) are Some Examples of Chicken Droppings Used in Other Datasets Where the Background is Solid or Nondescript

YOLOv5n is a lightweight model designed to operate efficiently on devices with limited computational resources, such as mobile devices and embedded systems. This is an important and practical consideration if the model is to be deployed in real-world scenarios, perhaps on edge computing devices that are cost effective, capable of performing initial data processing, and easy to scale.

Our study's unique contribution is its ability to detect chicken droppings on wood slats—a challenging task due to the gaps between slats and visibility of the ground through them. Unlike other studies with solid backgrounds, our dataset featured these slats, complicating the detection process. To address this, we used a polygon annotation tool to accurately outline the droppings, which significantly improved our results. In contrast, other studies used bounding boxes.

Furthermore, while most studies used the same dataset available on the internet, with a few mixing their own dataset with the online one, we used our own dataset collected under the conditions of open housing poultry farming in Malaysia.

While our proposed approach has been demonstrated to work, it is subject to several constraints and limitations. First, the model's robustness can be affected by the condition of the droppings and variations in environmental conditions, such as changes in lighting, which may impact the clarity and visibility of the droppings in real-world settings. In densely populated or chaotic environments, it becomes difficult to detect individual droppings, especially when they are trampled by chickens. Furthermore, our method uses an earlier version of the YOLO architecture, which, while effective, does not take advantage of the latest advances in newer versions and may be less efficient in some situations. In addition, the limited size and scope of the dataset, despite the low number of classes, may hinder the model's ability to generalize to a wider range of conditions. We acknowledge these limitations and plan to address them in the future by expanding the dataset, integrating more advanced YOLO versions, and increasing the adaptability of the model to different environmental conditions.

5. CONCLUSION

Our study highlights the effectiveness of the YOLOv5n model, particularly in poultry health assessment by analysing droppings in open house poultry farms in Malaysia. This method showed good improvements over the standard YOLOv5 model, achieving a high accuracy of 94.9% and performing on par with models such as EfficientNet-B0 and DenseNet.

Furthermore, our approach is independent, using a dataset collected from open house poultry farms in Malaysia, rather than relying solely on publicly available online datasets. This approach enabled us to train the YOLOv5n model in environment-specific conditions, resulting in improved performance in our proposed task.

Our study highlights the capabilities of deep learning models like YOLOv5n, in enhancing poultry health monitoring methods. It opens new avenues for further research and development in this field, particularly in the context of open housing poultry farming. For future work, we aim to continue refining our model and apply other preprocessing techniques that can further improve the model.

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AUTHOR CONTRIBUTIONS

Md Najmul Hasan: Software, Validation, Investigation, Data curation, Formal analysis, Writing – Original Draft.
Khow Zu Jun: Software, Methodology, Validation.
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CONFLICT OF INTERESTS

The authors declare no conflict of interest.

ETHICS STATEMENTS

This study did not require ethical approval as it involved the collection and analysis of chicken droppings, with no direct use of live animals in the experimental procedures.

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