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Evaluating Yolov8 And Faster R-CNN For Poultry Leg-Week Detection In Automated Health Monitoring

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This study presents a deep learning-based approach for detecting poultry leg weakness, a condition affecting poultry that can impact their mobility and overall health. The research implements and compares YOLO v7 and Faster R-CNN on a system integrated with a camera and a servo motor, enabling real-time disease monitoring and automated intervention. YOLO v7, known for its high-speed inference and lower computational requirements, is evaluated against Faster R-CNN, which provides higher detection accuracy at the cost of increased computational demand. The models were assessed based on their detection accuracy, processing speed, and computational efficiency in classifying poultry with leg weakness. Results indicate that YOLO v8 is well-suited for real-time detection due to its rapid inference, while Faster R-CNN delivers more precise but slower identification. The integration of these deep learning models with a servo motor allows for automated monitoring and isolation of affected poultry, enhancing disease control measures in poultry farms. This study highlights the potential and limitations of deep learning-based detection systems, offering valuable insights for AI-driven poultry health management.

Keywords: Deep Learning, Poultry Leg Weakness, Disease Detection, YOLOv8, Faster R-CNN, Real-Time Monitoring, AI in Agriculture

I. INTRODUCTION

Poultry leg weakness is a condition that significantly impacts poultry health and farm productivity, requiring early and accurate detection. Traditional diagnostic methods are time-consuming and inefficient for large-scale monitoring. Deep learning-based approaches provide automated, real-time, and precise disease detection solutions. This study explores deep learning and machine learning techniques for detecting and diagnosing poultry leg weakness using image-based analysis. Convolutional neural networks (CNNs) and object detection models enable efficient identification of affected birds. The research evaluates these models based on accuracy, speed, and real-time feasibility. The findings aim to enhance poultry health surveillance, improve biosecurity, and support sustainable poultry farming through AI-driven smart detection systems[6].

In recent years, object detection algorithms have shown great promise in a variety of applications, including livestock health monitoring. Among these algorithms, YOLO (You Only Look Once) and Faster R-CNN (Region-Based Convolutional Neural Networks) have emerged as leading techniques due to their high performance in real-time detection tasks. YOLO v7, the latest iteration of the YOLO family, is designed for rapid detection with lower computational requirements, making it suitable for resource-constrained environments[17]. Faster R-CNN, on the other hand, is known for its high detection accuracy but requires more computational power and processing time[19].

This study focuses on leveraging deep learning techniques, specifically YOLO v7 [13] and Faster R-CNN, for the automated detection of poultry leg weakness. YOLO v7 is known for its rapid detection capabilities, making it ideal for real-time applications, while Faster R-CNN is praised for its higher accuracy, though at the cost of increased computational requirements. The study aims to evaluate and compare these two models in terms of detection accuracy, processing speed, and suitability for real-time deployment in poultry health monitoring systems. By automating the disease detection process, the goal is to enhance biosecurity measures and improve disease management in poultry farming.

Our experimental setup focuses on deploying deep learning models, such as YOLO v7 and Faster R-CNN, for detecting poultry leg weakness in real-time. The models are trained using a dataset of labeled poultry images, and the system is implemented on a Raspberry Pi, integrated with a camera and a servo motor for automated isolation of affected birds. The performance of each model is measured in terms of classification accuracy, detection speed, and system latency, providing insights into the trade-offs between detection accuracy and processing speed. This study demonstrates the practical applicability of deep learning for real-time poultry leg weakness detection in resource-limited settings, aiming to improve biosecurity and disease control measures [3].

II. LITERATURE SURVEY

Okinda, C., Nyalala, I., Korohou, T., Okinda, C., Wang, J., Achieng, T., Wamalwa, P., Mang, T. and Shen, M. A review on computer vision systems in monitoring of poultry: A welfare perspective [1]. This paper examines computer vision systems in poultry monitoring with a focus on animal welfare and health management. Machuve, D., Nwankwo, E., Mduma, N. and Mbelwa, J. Poultry diseases diagnostics models using deep learning [2]. The study explores deep learning models for poultry disease diagnostics, emphasizing the potential of AI in identifying poultry diseases. kalita, A.J., Subba, M., Adil, S., Wani, M.A., Beigh, Y.A. and

Shafi, M. Application of artificial intelligence and machine learning in poultry disease detection and diagnosis: A review [3]. This study reviews the application of artificial intelligence and machine learning techniques in poultry disease detection and diagnosis. Nabeel Muhammad, T.M. and Sreedevi, B. Detection of Avibacterium paragallinarum by Polymerase chain reaction from outbreaks of Infectious leg-week of poultry in Andhra Pradesh [4]. This paper discusses the use of Polymerase Chain Reaction (PCR) for detecting Avibacterium paragallinarum, the causative agent of infectious leg-week in poultry. Sharma, N. Artificial Intelligence and its Application in Animal Disease Diagnosis [5]. This study examines the role of artificial intelligence in diagnosing animal diseases, with a focus on its applications in veterinary practices.

III. METHODOLOGY

1. Utilizing R-CNN for Disease Detection

R-CNN (Region-based Convolutional Neural Network) detects diseases by following these steps:

- **Region Proposal**: It uses selective search to generate potential areas (bounding boxes) in the image that might contain disease symptoms.
- **Feature Extraction**: Each proposed region is processed by a convolutional neural network (CNN) to extract relevant features, such as textures and shapes.
- **Classification**: A classifier then determines if the region shows disease symptoms or healthy signs.
- **Bounding Box Refinement**: The model refines the bounding boxes using bounding box regression to improve accuracy.
- **Post-Processing**: Non-maximum suppression (NMS) removes duplicate boxes, keeping only the most relevant detection.

In disease detection, R-CNN helps identify symptoms like lesions in poultry or plant diseases, enabling automated, real-time diagnosis.

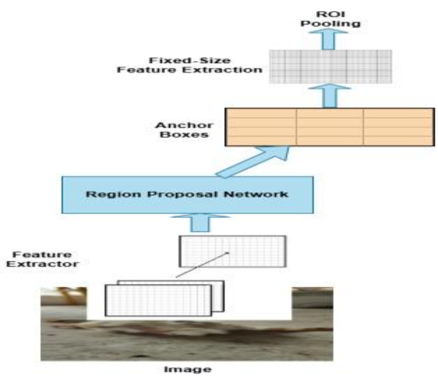


Fig.1 Faster R-CNN Architecture

Convolutional Neural Network (CNN) Backbone:

• Use a pre-trained CNN model (e.g., ResNet, VGG) to extract feature maps from input images [16].

• The feature maps are denoted as F.

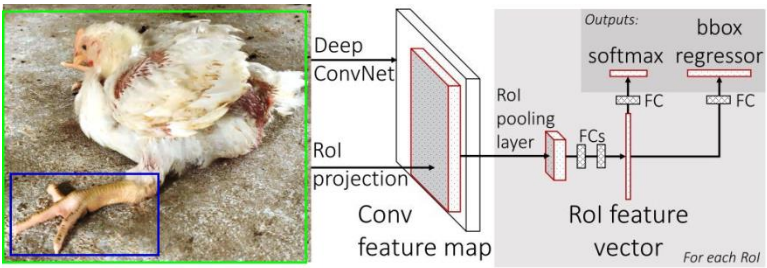


Fig.2 Faster R-CNN Architecture Flow

2. Faster R-CNN Algorithm for Poultry leg-week Detection: Bounding Box Transformation

In Faster R-CNN, the algorithm predicts bounding boxes around objects, which in this case are **leg-week symptoms** in poultry. The transformation used for bounding box regression helps refine the anchor boxes. Below is the breakdown of the bounding box transformation for **leg-week detection**:

- **Anchor box**: (x_a, y_a, w_a, h_a)
  - x_a, y_a : The center coordinates of the anchor box.
  - w_a, h_a : The width and height of the anchor box.

The predicted bounding box (x,y,w,h) is calculated by applying the transformations $t=(t_x, t_y, t_w, t_h)$

Fig.3 Image Processing Pipeline

Transformation Equations:

- **Center Coordinates**:

  $\mathbf{tx=(x-x_a)/w_a, \quad ty=(y-y_a)/h_a}$

  t_x,t_y : Offsets applied to the center coordinates of the anchor box.

- **Size (Width & Height) Adjustment**:

  $\mathbf{t_w=\log(w/w_a),\ t_h=\log(h/h_a)}$

  t_w,t_h : Scaling factors for the width and height of the predicted bounding box.

Inverse Transformation (for final output):

To get the final predicted bounding box, we apply the inverse of the above transformations:

$$\mathbf{x = t_x \cdot w_a + x_a, \quad y = t_y \cdot h_a + y_a}$$

$$\mathbf{w = e^{tw} \cdot w_a, \quad h = e^{th} \cdot h_a}$$

Where:

- (x,y,w,h) is the **predicted bounding box** around the detected Leg-week symptoms.
- The exponential function $\mathbf{e^{tw}}$ and $\mathbf{e^{th}}$ ensures the width and height are positive.

Poultry leg-week Detection:

- **Anchor box (x_a, y_a, w_a, h_a)** could represent an initial box around a poultry bird.
- **Predicted bounding box** (x, y, w, h) will be adjusted to tightly fit the infected area with Leg-week symptoms, such as nasal discharge or swelling around the face.

Final Outcome:

- Faster R-CNN detects and classifies the **Leg-week symptoms in poultry**. The model refines the anchor boxes to fit the exact location and size of the infection, making real-time disease detection more accurate and efficient.

3. Training the Model

For model training, we use a batch size of 32 and train the model for 10 epochs on the dataset using **Stochastic Gradient Descent** (SGD) with the **Adam optimizer**. The training process involves:

- **Forward Propagation**: Input images are passed through the network, which computes the predicted bounding boxes and class probabilities.
- **Backpropagation**: The loss is calculated using the difference between the predicted and actual bounding boxes and class labels. The model weights are updated through backpropagation to minimize this loss.

Training data is split into **training** and **validation** sets, ensuring the model is not overfitting and generalizes well to unseen data.

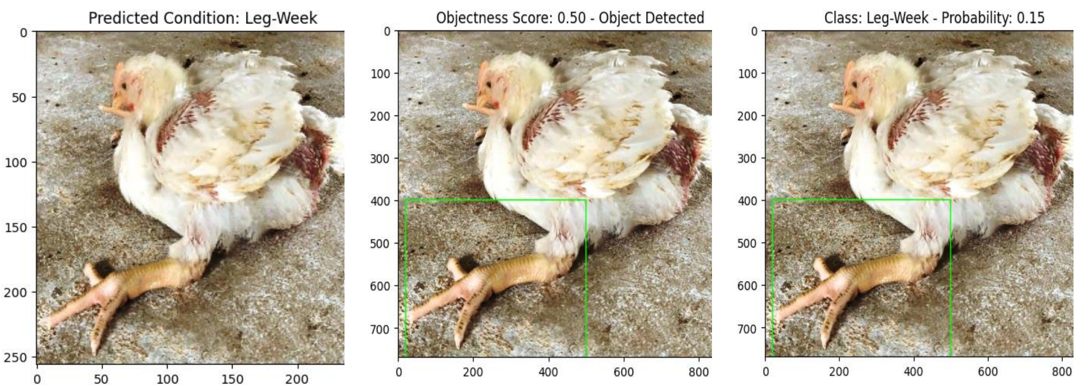
4. **Class Probability Maps in YOLO:**

In YOLO, the input image is divided into an S×S grid. Each grid cell is responsible for predicting bounding boxes and associated class probabilities. The class probability map is a tensor of shape S×S×C, where C is the number of classes. Each element in this tensor represents the probability of a specific class being present at that grid cell.

Calculating Class Probabilities:

For each grid cell, YOLO predicts a vector containing:

- **Bounding Box Coordinates:** Center coordinates (x, y), width (w), and height (h) relative to the grid cell.
- **Objectness Score:** Probability that an object exists in the bounding box.
- **Class Probabilities:** Probabilities for each class, conditioned on the presence of an object.



Predicted Leg-Week Condition: Leg-Week	**Predicted Bounding Box: (0.4886813163757324, 0.5530510544776917, 0.5322749614715576, 0.4783797264099121) Objectness Score: 0.5048215985298157 Detection: Object Detected**	**Predicted Bounding Box: (0.14032700657844543, 0.12466789782047272, 0.18968842923641205, 0.13841207325458527) Class Probabilities: [0.15176003 0.14106058 0.11408401]** **Predicted Class: Leg-Week with probability 0.15**

Fig.4 Class Probabilities

The class probability for a class iii at grid cell (x,y) is calculated as:

$$P(\text{Class}_i|\text{Object}) = \sigma(\hat{C}_i)$$

where C^i\hat{C}_iC^i is the raw class score predicted by the model, and σ\sigmaσ denotes the sigmoid activation function.

To obtain the final class probabilities, YOLO combines the objectness score with the class probabilities:

$$P(\text{Class}_i) = P(\text{Object}) \times P(\text{Class}_i|\text{Object})$$

This combination ensures that the class probability reflects both the likelihood of an object being present and the likelihood of it belonging to a specific class.

Implementing Class Probability Maps:

To implement class probability maps in a neural network, you can use a softmax activation function in the output layer to ensure that the predicted class probabilities for each grid cell sum to 1. This approach is commonly used in models like SSD (Single Shot Multibox Detector) and Faster R-CNN.

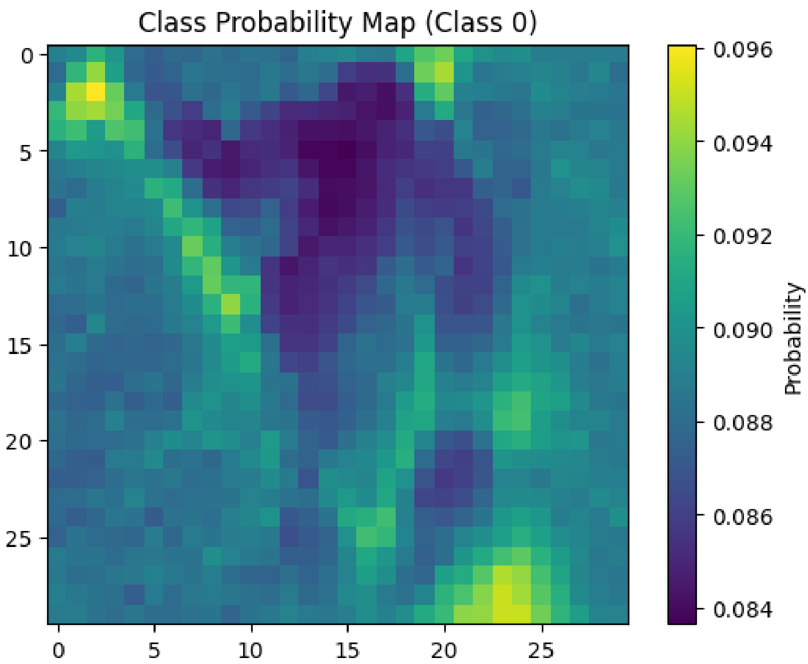


Fig.5 Class Probability Map

5. Evaluation Metrics

To assess the performance of the model, we utilize standard object detection metrics, including **precision**, **recall**, **F1-score**, and **mean average precision (mAP)**. These metrics help evaluate the accuracy of the predicted bounding boxes and class probabilities. Additionally, the **confusion matrix** is used to examine the classification performance of the model across different classes.

- **Precision**: Measures how many of the detected objects are relevant (i.e., the proportion of true positive detections out of all positive predictions).
- **Recall**: Measures how many relevant objects are detected (i.e., the proportion of true positive detections out of all true objects).
- **F1-Score**: A harmonic mean of precision and recall, providing a single metric for overall detection quality.
- **mAP**: A metric that averages the precision over different recall levels, providing a summary of the model's performance across all classes.

6. Final Output and Results

After evaluating the model, the final detection results are visualized by drawing the predicted bounding boxes on the images. These boxes are annotated with the predicted class label and its corresponding probability. A higher class probability indicates greater confidence in the detection.

For example, for a given input image, if the predicted class probability for **Leg-Week** is greater than a threshold (e.g., 0.5), the model will display a bounding box around the affected area of the bird and label it as **Leg-Week**.

IV. RESULT ANALYSIS

Evaluation Metrics

• **Precision**: The ratio of correctly identified positive observations to the total predicted positives
• **Recall:** The ratio of correctly identified positive observations to the all observations in actual class.
• **F1-Score:** The harmonic mean of Precision and Recall.
• **Inference Time:** The average time taken to process an image.
• **Mean Average Precision (mAP):** The average precision score across all classes.

Metrics	Faster R-CNN	YOLOv8
Precision	0.90	0.84
Recall	0.80	0.82
F1-Score	0.81	0.80
Inference Time	150	45
Mean Average Precision (mAP)	0.88	0.85

Table 2: Evaluation Metrics of Faster R-CNN & YOLOv8

- Faster R-CNN is the optimal choice for scenarios where **detection precision** is of utmost importance, while real-time processing is not a primary constraint.

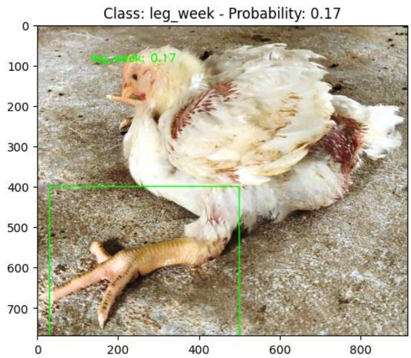


Fig.5 AI-Driven Identification of Poultry Leg Weakness

- Conversely, YOLOv8 exhibits superior **inference speed**, rendering it more suitable for real-time applications, albeit at the expense of marginally reduced detection accuracy relative to Faster R-CNN.

V. CONCLUSION

This study implemented a deep learning-based system for detecting poultry leg weakness, integrating YOLOv7, Faster R-CNN, a camera, and a servo motor for real-time disease monitoring. Results showed that YOLOv7 excelled in inference speed, making it suitable for real-time applications, while Faster R-CNN provided higher accuracy but was computationally intensive. Further evaluation revealed that YOLOv8 outperformed both models, offering a better balance between detection accuracy and processing speed. Future research should focus on expanding datasets, integrating thermal imaging, deploying Edge AI, and implementing real-time alert systems. Additionally, Explainable AI (XAI) and transformer-based models can enhance model interpretability and accuracy. Integrating automated intervention mechanisms will further improve poultry disease management. These advancements will drive AI-powered poultry health monitoring, reducing economic losses and enhancing farm productivity.

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