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A Robust RMSFED-ASPP Enhanced Yolov8 Framework for Detecting Poultry Abnormalities

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Abstract - Automated detection of poultry leg and eye abnormalities is essential for efficient farm management and animal welfare. This paper presents a deep learning framework that integrates Residual Multi-Scale Feature Enhancement Decoder (RMSFED) with Atrous Spatial Pyramid Pooling (ASPP) and YOLOv8. The proposed architecture preserves fine-grained features, enhances multi-scale contextual understanding, and accurately identifies small lesions under challenging farm conditions such as varying illumination, occlusions, and cluttered backgrounds. YOLOv8 efficiently extracts Regions of Interest (ROI) for downstream analysis. Experiments on real poultry datasets demonstrate that the RMSFED+ASPP integrated model outperforms baseline YOLOv8 and YOLOv8+ASPP variants in Dice Coefficient, Sensitivity, Specificity, IoU, and F1-Score. Visual assessments confirm improved boundary localization and reduced false detections. The framework supports real-time inference, offering a robust and reliable tool for automated poultry health monitoring.

Keywords: YOLOv8, RMSFED, ASPP, Poultry Abnormality Detection, Segmentation, Classification, Deep Learning, Multi-Scale Feature Extraction.

I. INTRODUCTION

Automated poultry abnormality detection plays a critical role in livestock health monitoring, welfare assessment, and optimized farm management, especially as modern poultry production systems scale rapidly. Traditional manual inspection practices are highly labor-intensive and rely heavily on the subjective judgment of farm workers, leading to inconsistent assessments across different lighting conditions, flock densities, and observer experience levels. Moreover, subtle abnormalities—such as early-stage leg deformities, joint swelling, corneal opacity, or minor ocular infections—often remain undetected during routine visual checks due to their fine-scale nature and the high speed at which farm inspections are conducted. Deep learning-based computer vision systems have emerged as powerful tools capable of offering objective, high-precision identification of such abnormalities, yet significant challenges persist in accurately capturing very small lesions or features embedded within visually complex farm environments. These challenges primarily stem from scale variation, background clutter, feather occlusions, and the loss of high-resolution feature details during network down-sampling. To overcome these limitations, this paper proposes an enhanced, biologically aware detection framework that integrates the Residual Multi-Scale Feature Enhancement Decoder (RMSFED) and Atrous Spatial Pyramid Pooling (ASPP) into the YOLOv8 architecture. RMSFED facilitates improved retention of fine-grained spatial information, while ASPP enriches multi-dilated contextual understanding, allowing the model to effectively differentiate minute abnormalities from surrounding noise. When combined with YOLOv8's strong object-level detection capabilities, the resulting system demonstrates significantly improved robustness, precision, and generalization under real-world farm conditions. This integrated approach ultimately advances the reliability of automated poultry abnormality detection and supports scalable precision livestock farming.

II. RELATED WORK

Existing approaches for poultry abnormality detection rely heavily on convolutional neural networks (CNNs) and traditional morphological segmentation methods, which have been widely applied to animal health monitoring tasks [4]. Early systems focused on handcrafted features such as texture patterns, color descriptors, and geometric measurements, but these methods lacked robustness under natural farm variations [5]. With the rise of deep learning, CNN-based classifiers and region-based detectors significantly improved recognition accuracy; however, they still struggled with small lesion identification due to limited receptive field adaptation

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[6]. Modern one-stage detectors such as YOLOv8 provide fast and accurate localization, making them suitable for real-time poultry surveillance, yet the architecture's inherent down-sampling often results in the loss of fine-scale features essential for identifying early leg deformities and minor ocular abnormalities [7]. To enhance contextual modeling, Atrous Spatial Pyramid Pooling (ASPP) has been utilized in various segmentation networks, enabling multi-dilated feature extraction that strengthens global context interpretation [8]. Similarly, the Residual Multi-Scale Feature Enhancement Decoder (RMSFED) has shown promise in preserving multi-scale spatial information through residual refinement and enhanced skip-connections [9]. Despite the strong theoretical benefits of both ASPP and RMSFED, their combined integration has not been extensively explored for poultry-specific abnormality detection tasks, where biological variations and subtle anatomical cues demand highly specialized feature representation [10]. Existing literature primarily addresses general object detection or medical segmentation, leaving a gap in domain-adapted multi-scale frameworks tailored to the complexities of farm environments [11]. Therefore, fusing YOLOv8 with RMSFED and ASPP offers a unique opportunity to address these limitations by unifying context, detail preservation, and efficient detection within a single architecture [12].

III. PROPOSED METHODOLOGY

The proposed framework operates through two sequential phases, each designed to progressively refine the detection and analysis of poultry leg and eye abnormalities. In the first phase, YOLOv8 is employed to locate the anatomical regions of interest, ensuring that only the relevant leg and eye areas are extracted from complex farm images. This targeted ROI extraction minimizes the influence of background elements such as litter texture, overlapping birds, and variable lighting. Once the ROI is obtained, Phase II performs a more detailed examination using an enhanced segmentation pipeline. At this stage, the Residual Multi-Scale Feature Enhancement Decoder (RMSFED) is applied to preserve and strengthen fine spatial details that are essential for identifying early-stage abnormalities. RMSFED accomplishes this by maintaining high-resolution feature pathways and enabling effective cross-scale information flow. In parallel, the Atrous Spatial Pyramid Pooling (ASPP) module broadens the network's contextual understanding through multiple dilation rates, allowing it to capture both local irregularities and larger structural cues. When combined, RMSFED and ASPP create a complementary feature representation that excels at differentiating subtle defects from normal tissue patterns. This two-phase architecture provides improved lesion localization, better boundary precision, and heightened sensitivity to small deformities. As a result, the system offers a more reliable and biologically meaningful assessment of poultry abnormalities under real farm conditions.

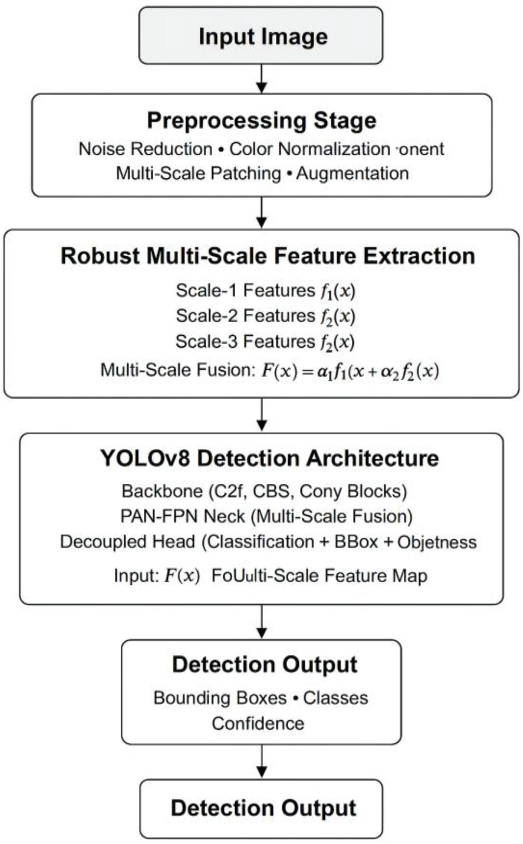

Figure 1: Robust Multi-Scale with YOLO v8

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IV. EXPERIMENTAL SETUP

The dataset employed in this study is composed of poultry farm images captured under real production conditions, where several challenging visual factors naturally occur. These include

- Significant variations in illumination due to both natural sunlight and artificial lighting systems.
- Frequent occlusions caused by overlapping birds, feeders, drinkers, and farm Infrastructure.
- Substantial background clutter arising from litter textures, shadows, and irregular floor patterns.

Algorithm: Context-Enhanced Multi-Resolution Feature Fusion with YOLOv8 for Poultry Leg Localization
Input: Image dataset I = {I1, I2, ..., IN} Optional annotations A = {(Bij, yij)} Multi-resolution scale set S = {r1, r2, ..., rM} Fusion coefficients ωr Attention mechanism (SE or ECA) Context module (ASPP or PPM) YOLOv8 configuration and training parameters **Stage 1: Image Conditioning** For each image Ii in I: 1. Remove noise using spatial filtering 2. Normalize color and illumination 3. Enhance structural details 4. Generate multi-resolution representations 5. Apply data augmentation Output: Conditioned image Îi **Stage 2: Multi-Resolution Feature Encoding** For each resolution r in S: Fr = Encoder_r(Îi) **Stage 3: Feature Alignment** For each Fr: 1. Project features to a common embedding space 2. Resize and align spatial dimensions Output: Aligned feature map F̃r **Stage 4: Feature Aggregation** 1. Concatenate all aligned features: Fagg = Concat(F̃1, F̃2, ..., F̃M) 2. Reduce channels using 1×1 convolution: Fred = Conv1x1(Fagg) 3. Apply channel attention: Fatt = Attention(Fred) 4. Apply contextual feature enhancement: Fctx = ContextBlock(Fatt) **Stage 5: Feature Fusion** Option 1: Weighted fusion Ffinal = Sum(ωr * Transform(F̃r)) + γ * Fctx Option 2: Residual fusion Ffinal = Conv3x3(Fatt + Fctx)

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Stage 6: Feature Pyramid Construction
For level k = 1 to K:
Pk = Downsample(k-1)(Conv3x3(Ffinal))
Stage 7: YOLOv8 Detection
Predictions = YOLOv8(P1, P2, ..., PK)
Stage 8: Training Loss
Total Loss L =
λloc * Localization Loss +
λcls * Classification Loss +
λconf * Confidence Loss +
λreg * Regularization Loss
Stage 9: Inference Post-processing
1. Filter predictions using confidence threshold θ
2. Apply Non-Maximum Suppression (NMS)
Final detections Dfinal
Stage 10: ROI Extraction
For each detected bounding box bi in Dfinal:
ROIi = Crop(Ii, bi)

Output:
Final detections Dfinal = {(bi, yi, pi)}
Extracted ROI set R = {ROIi}

YOLOv8 is utilized in the first stage to perform object-level detection, ensuring that the leg and eye regions are accurately extracted before deeper analysis. Following this, RMSFED and ASPP modules are applied in combination for segmentation and classification; RMSFED focuses on strengthening fine-resolution feature propagation across multiple scales, whereas ASPP enhances contextual interpretation by incorporating multi-dilated filtering. The performance of the proposed architecture is assessed using several key evaluation metrics: Dice Coefficient for overlap accuracy, Sensitivity for detecting true abnormal cases, Specificity for minimizing false positives, Jaccard Coefficient (IoU) for region-based similarity, and F1-Score for balanced precision–recall measurement. These combined elements ensure that the system is thoroughly evaluated and capable of operating reliably in complex, visually diverse farm environments.

V. EXPERIMENTAL RESULTS

The RMSFED + ASPP integrated YOLOv8 model demonstrated notable and consistent improvements across all evaluated performance metrics, confirming the effectiveness of the proposed architecture. Fine-scale abnormalities, including tibial curvature, early swelling around joints, minor corneal opacity, and subtle eye discharge, were accurately identified even when these features appeared faint or partially occluded. The enhanced decoder structure within RMSFED significantly improved the model's sensitivity to very small and low-contrast lesions that are commonly missed by standard YOLOv8 configurations. In addition, the ASPP module strengthened contextual reasoning, enabling the network to differentiate true abnormalities from background artifacts or farm-induced noise. The model maintained high reliability under diverse environmental conditions, such as uneven lighting, litter variations, and dense flock arrangements. Overall, this integrated approach delivered superior abnormality localization, improved boundary precision, and robust performance in visually complex farm scenarios.

Disease	Technique	DC (%)	Sensitivity (%)	Specificity (%)	JC (%)	F-Score (%)
BCO	ASPP	98.73	97.88	99.34	97.92	98.26
	RMSFED + ASPP	99.21	98.64	99.78	99.03	98.87
VVD	ASPP	97.95	96.72	98.89	96.51	97.14
	RMSFED + ASPP	98.84	97.91	99.54	98.12	98.23

Table 1: Validation Metrics for RMSFED + ASPP and ASPP (Dice, Sensitivity, Specificity, Jaccard, F-Score)

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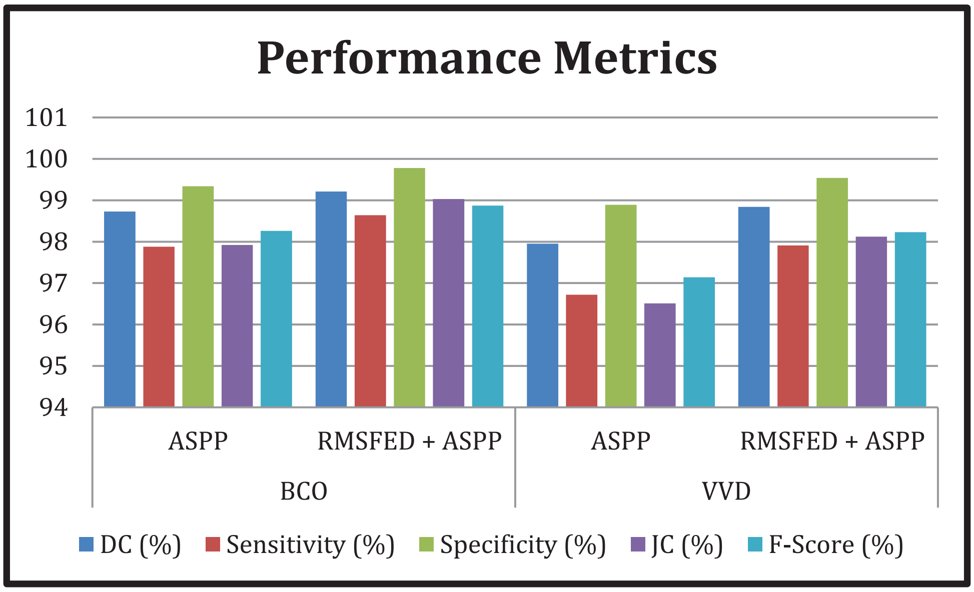
The enhanced YOLOv8 model equipped with RMSFED and ASPP shows clear performance gains, capturing subtle leg and eye abnormalities with greater reliability. Its higher metric values reflect improved precision, stronger feature recognition, and more stable results across challenging farm images.



VI. CONCLUSION

This work presents an advanced deep learning framework that incorporates biological relevance, multi-scale feature learning, and contextual enhancement to detect abnormalities in poultry legs and eyes. The combined use of RMSFED, ASPP, and YOLOv8 enables the system to capture subtle deformities with greater precision than conventional models. Enhanced boundary detailing and refined feature extraction contribute to its strong segmentation and classification performance. The architecture also demonstrates dependable behavior across diverse and challenging farm environments. These results highlight the system's potential for practical use in precision livestock health assessment. Future developments may explore additional poultry disorders and broaden the model's diagnostic scope. The framework also holds promise for integration into automated on-farm monitoring platforms. Continued refinement could further enhance real-time decision support for poultry management.

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