ABSTRACT

The cage-free poultry farming industry faces significant mortality monitoring challenges due to extreme flock density, severe visual occlusion between birds, and uneven lighting conditions inside the barn. Manual monitoring is inefficient and prone to human error, necessitating an automated detection system based on computer vision. This study implements the YOLOv11s architecture to detect two object classes, live chickens and dead chickens using a real-world image dataset extracted from CCTV recordings of an actual cage-free barn. The initial dataset of 1,191 images was augmented through flip, rotation, brightness, and exposure adjustments, expanding it to 2,025 images, then split at a 70:20:10 ratio for training, validation, and testing. Training was conducted on the Google Colab platform using an NVIDIA Tesla T4 GPU, with a configuration of 60 epochs, batch size of 8, learning rate of 0.001, image size of 960 x 540 pixels, and the AdamW optimizer. Model evaluation yielded an mAP@0.5 of 89.6%, precision of 84.4%, recall of 85.8%, and F1-Score of 85.0%, with a pure inference speed of 9.2 ms per frame. In a comparison across YOLO versions using identical datasets and hyperparameters, YOLOv11s achieved the fastest inference time compared to YOLOv10s (12.5 ms) and YOLOv9s (25.3 ms), making it the most optimal choice for real-time poultry barn monitoring. The model is also lightweight, with a file size of 18.30 MB, 9.4 million parameters, and a computational load of 21.6 GFLOPs. The results of this study are expected to serve as a foundation for developing automated early warning systems in large-scale poultry farms.

Keywords : YOLOv11, cage-free, object detection, deep learning, poultry mortality