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YOLOX-BASED MONITORING FOR HUMANE POULTRY SLAUGHTER

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Abstract

Using deep-learning and image-recognition techniques, we built a smart, safe, and humane poultry-slaughter system that raises production efficiency while safeguarding animal welfare. The system centres on a YOLOX object-detection network that classifies each Red-Feather chicken on the processing line as either stunning or unstunning in real time. A total of 1 683 manually labelled images were collected. Of these, 1 268 were reserved for model development and 419 for final testing. The development set was divided into 1 011 training images and 253 validation images, giving roughly an 80 / 20 split. Every training image was resized to 960 × 540 pixels and randomly given one of seven basic augmentations—colour jitter, horizontal flip, scale, rotation, translation, Gaussian blur, or Gaussian noise—to increase data diversity and improve model robustness.

After training, YOLOX reached 95.32 % average precision (AP) for the unstunning class and 96.42 % AP for the stunning class; its mean AP (mAP) was 95.87 %. In live-video trials the model processed images at 29 fps, comfortably meeting the 25 fps requirement of the production line, and raised an alert whenever a bird remained unstunning, thereby helping staff take immediate corrective action.

We also compared our results with a YOLOv4 model trained on the same data under identical settings. YOLOv4 produced 93.74 % AP for unstunning birds and 94.81 % AP for stunning birds, yielding an mAP of 94.28 % and an inference speed of 23.45 fps. Although these figures confirm that YOLOv4 is effective, YOLOX delivered both higher precision and faster throughput.

Because of its superior accuracy and speed, YOLOX was selected for field deployment. The proposed system continuously analyses live video, flags any conscious birds, and alerts operators, thereby supporting efficient production while maintaining strict welfare standards.

Keywords: poultry slaughter, animal welfare, YOLOX, YOLOv4

INTRODUCTION

In recent years, computer vision has been widely applied to monitoring the status of animals and plants, such as assessing poultry health and evaluating whether plant growth is normal. These technologies not only increase monitoring efficiency in agriculture and animal husbandry but also enable timely detection of abnormalities,

allowing appropriate interventions.
In 2020, Ye et al. proposed an algorithm derived from Fast R-CNN to improve both the accuracy and efficiency of assessing broiler stunning status. The method classifies birds into three categories—under-stunned, adequately stunned, and over-stunned—and employs multi-layer residual modules based on the principles of residual networks to extract fine-grained features. The model achieved an accuracy of 98.6% and a throughput of up to 40,000 broilers per hour.
Also in 2020, Geffen et al. designed a system for detecting and counting caged laying hens. Conducted in an 87-m-long poultry house with 18–30 hens per cage, the study mounted cameras on the feeder to acquire images and used Fast R-CNN for detection and recognition. With ~2,000 images used for validation, the system reached an accuracy of 89.6%.
In 2022, Chang et al. adopted the YOLOv4 object detection model to identify five predefined anatomical parts of broilers and construct a skeletal representation, from which angles between backbone joint vectors were computed. Using a time-series long short-term memory (LSTM) network, the system recognized six dynamic behaviors to detect postural patterns associated with poultry diseases.
In 2023, Saenong et al. combined Faster R-CNN with a MobileNet-V3 backbone to recognize reproductive behaviors of caged Muscovy ducks and examined how image preprocessing (e.g., augmentation and blurring) affects model performance. Without preprocessing, accuracies for mating, non-mating, and egg-laying behaviors were 82%, 74%, and 88%, respectively; after preprocessing, these increased to 86%, 80%, and 94%, indicating that preprocessing of training images can improve algorithmic accuracy.

MATERIALS AND METHODS

SYSTEM ARCHITECTURE AND EQUIPMENT USED

The slaughter setup used in this study was installed at the Animal Industry Research Institute of National Chung Hsing University. The site is equipped with a wireless router and a workstation that serve as the hub for image acquisition and data storage. In the processing line, Red-Feather chickens are transported to the bleeding area immediately after electrical stunning, where operators perform a neck incision. Exsanguination continues during subsequent conveyance until vital signs cease.
Cameras are mounted at the water-bath stunner and the bleeding station to facilitate automated recognition of stunning and bleeding status. After bleeding, the birds are transferred to a defeathering machine, where feathers are removed using hot water and high-speed rotary action to produce the market-ready appearance; viscera are then manually removed by plant personnel.
The line begins at the shackling station, where operators hang both legs of each bird onto the conveyor shackles to initiate automated transport. The birds then pass through the water-bath stunner, where voltage and current are applied for electrical stunning. A dedicated control panel in this area allows adjustment of stunning parameters. The overall layout of the facility and equipment is shown in Figure 1.

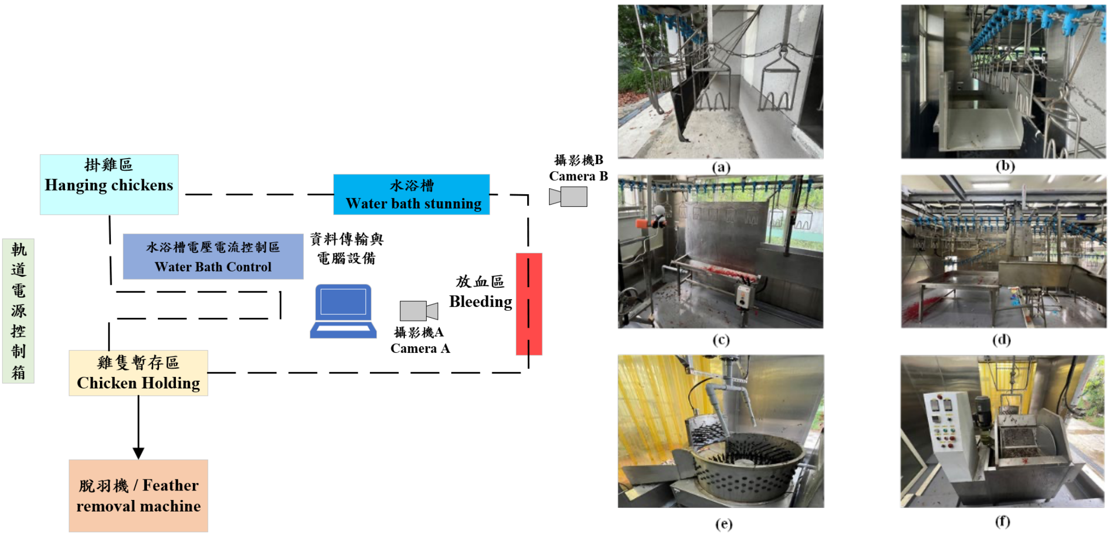

Figure 1. (A) Study-site layout; (B) Slaughter-line equipment at the Animal Industry Research Institute, National Chung Hsing University.

Construction of the Training Dataset for the Image Recognition Model

A total of 1,683 annotated images were collected for this study, of which 1,264 were used for training and validation and the remaining 419 for testing. The 1,264 images were randomly split at an approximately 80:20 ratio, yielding 1,011 training images and 253 validation images. During training, all training images underwent data augmentation; each image was randomly subjected to seven operations—color jittering, horizontal flipping, random scaling, random rotation, random translation, Gaussian blurring, and Gaussian noise—before being resized to 960 × 540 × 3 as model input.
We adopted transfer learning to train the models and compared YOLOv4 and YOLOX for recognizing electrical stunning status in Red-Feather hens. Both models were initialized with pretrained weights provided by MathWorks for MATLAB, which reduced time spent on tuning initial parameters and the number of training iterations. Although transfer learning can in some cases yield slightly lower accuracy than training from scratch, its efficiency makes it a widely preferred approach in contemporary deep learning and neural network research.

RESULTS & DISCUSSION

Model Performance Evaluation

In addition to comparing YOLOX and YOLOv4, we examined the impact of data augmentation on training outcomes. With augmentation, YOLOv4 achieved an AP of 93.74% for stunned Red-Feather chickens and 94.81% for unstunned birds. Similarly, YOLOX reached 95.32% AP for unstunned and 96.42% AP for stunned birds. These results indicate that data augmentation substantially improves recognition accuracy, thereby enhancing the reliability and stability of the models for electrical-stunning status detection in Red-Feather chickens.

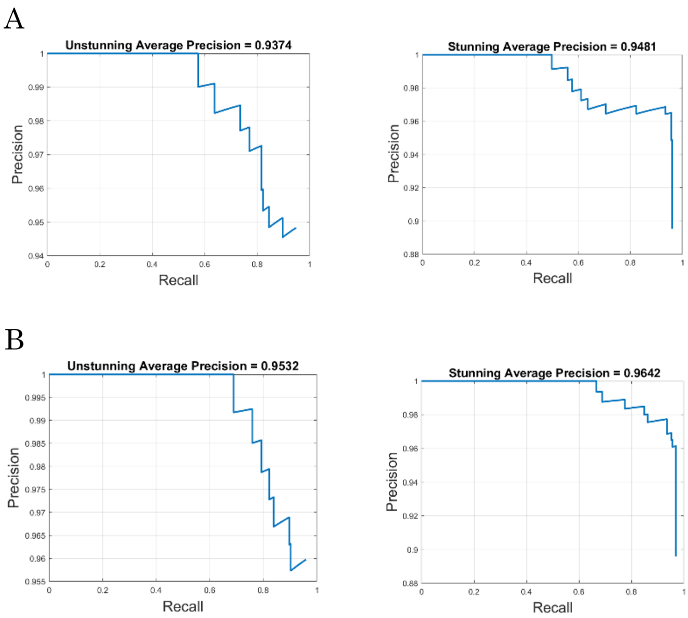

Figure 2. Average precision (AP) after data augmentation: (A) YOLOv4; (B) YOLOX

To assess deployability on a slaughterhouse conveyor, we measured inference throughput on three 10-min in-plant videos in MATLAB. YOLOv4 sustained 23.45 FPS, whereas YOLOX reached 29.00 FPS, indicating a clear speed advantage while maintaining recognition accuracy. Accordingly, YOLOX better meets the high-throughput requirements for real-time stunning-status monitoring.

A B

Figure 3. YOLOX-based stunning-status detection in Red-Feather chickens: (A) unstunning; (B) stunning

Table 1. Comparison of YOLOv4 and YOLOX for stunning-status detection in Red-Feather chickens.

Parameter name	YOLOv4	YOLOX
Training time	346 minute	277 minute
Unstunning Average Precision	93.74%	95.32%
Stunning Average Precision	94,81%	96.42%
mAP	94.28%	95.87%
Processing Speed	23.45 FPS	29 FPS

CONCLUSIONS

Based on the results summarized in Table 1, YOLOX outperforms YOLOv4 across all evaluation metrics. First, YOLOX required only 277 minutes of training, compared with

346 minutes for YOLOv4. For class-wise average precision (AP), YOLOX achieved 95.32% for unstunned Red-Feather hens and 96.42% for stunned hens, whereas YOLOv4 reached 93.74% and 94.81%, respectively. The overall mAP was 95.87% for YOLOX versus 94.28% for YOLOv4. In terms of runtime, YOLOX sustained 29 frames per second (FPS) while YOLOv4 operated at 23.45 FPS, indicating a clear advantage in throughput. Taken together, YOLOX delivers superior training efficiency, recognition accuracy, and processing speed.

For deployment, the system will be implemented on the slaughter line, where camera streams are transmitted to a workstation for real-time inference. When a Red-Feather hen does not meet the stunning criterion, the system issues an on-screen alert to notify operators, thereby supporting animal-welfare compliance during processing. Future work includes on-site trials and integration of a GUI-based monitoring platform to visualize detections, provide real-time alerts, and query historical data to facilitate operational management and process adjustment.

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