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AUTOMATED POULTRY QUALITY ASSURANCE SYSTEM FOR PRECISE INSPECTION AND SORTING

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Abstract— This study introduces an automated poultry quality assurance system to address inefficiencies and inconsistencies in traditional inspection methods. Manual inspection processes are labour-intensive, prone to errors, and unsuitable for high-throughput poultry production environments. The proposed system uses real-time image capture via smartphone cameras and YOLOv8 object detection technique used to identify defects such as blood clots and feathers on chicken (Cobb 500) carcasses. Defective chickens

Pneumatic, Arduino, YOLOv8	are automatically sorted using an Arduino-controlled pneumatic system integrated into the production line. The system's dataset was prepared through careful annotation and augmentation to enhance detection accuracy. YOLOv8 was trained over 150 epochs, achieving reliable defect classification, with results indicating high precision in separating defective products from quality chickens. The integration of image processing, real-time video analysis, and automated sorting mechanisms significantly reduced human involvement and increased operational efficiency. Limitations, such as false positives in complex scenarios and insufficient dataset diversity, highlight areas for improvement. Future research will focus on optimizing the detection model, expanding the dataset, and improving pneumatic actuation for better sorting accuracy. This work offers a scalable, cost-effective solution for poultry quality assurance, ensuring consistency and reducing wastage. Its implementation in processing plants advances automation and sets a benchmark for integrating computer vision and hardware systems. The developed system achieved an average accuracy of 95.33% in detecting quality chickens and 81.35% in identifying defects across five trials, demonstrating its effectiveness and reliability in sorting.

I. Introduction

The poultry industry plays a critical role in the global food supply chain, with quality assurance being essential for consumer safety and maintaining market standards. Traditional methods of poultry inspection rely heavily on manual labour, making them time-consuming, inconsistent, and prone to human error. These limitations are further exacerbated by the increasing demand for high-throughput processing in modern poultry plants, where consistent and reliable defect detection is crucial.

The primary challenge lies in identifying defects such as blood clots and feathers on chicken carcasses, which diminish product quality and marketability. Current manual inspection systems struggle to maintain efficiency and accuracy under industrial-scale production. This research addresses these challenges by proposing an automated solution that integrates computer vision and hardware for real-time defect detection and sorting.

The main objective of this study is to develop an automated poultry quality assurance system capable of detecting and classifying defects in real-time using YOLOv8 object detection. Smartphone cameras are utilized for image acquisition, while an Arduino-controlled pneumatic system handles defect sorting. This system aims to reduce reliance on manual inspection, enhance efficiency, and improve overall product quality in the poultry processing industry.

The proposed solution not only demonstrates the potential of computer vision and automation in industrial applications but also offers a scalable and cost-effective alternative to traditional methods. The study's findings highlight the importance of integrating modern technologies to achieve higher productivity and consistency in quality assurance processes.

II. Literature Review

Advancements in imaging technologies and machine vision systems have revolutionized quality assurance in the food and meat industries, offering efficient, reliable, and non-destructive alternatives to traditional methods.

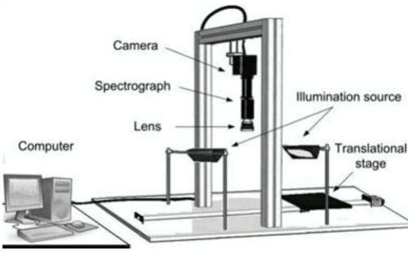


Figure 1: Components of a Push Broom Hyperspectral Imaging System

[1] introduced Hyperspectral Imaging (HSI) as a transformative tool for non-destructive meat quality evaluation. HSI combines imaging and spectroscopy as in Figure 1, enabling comprehensive analysis of quality attributes such as tenderness, fat content, and contamination. This technology excels in maintaining spatial and spectral data for each pixel, making it suitable for detecting surface contaminants in poultry and assessing freshness in fish. While HSI achieves high accuracy in quality assessments, challenges such as high costs, complex calibration, and data processing limit its large-scale adoption. Advances in hardware and machine learning are progressively addressing these barriers, making HSI a potential in-line quality assessment tool in meat processing.

[2] emphasized the application of machine vision systems for automated quality inspection of food products, highlighting their speed, accuracy, and non-destructive nature. Combining imaging, optics, and digital algorithms, these systems can detect surface defects, ensure color uniformity, and grade products based on size and texture. In poultry processing, structured lighting with high-resolution cameras allows real-time detection of defects like blood clots and feathers on flying carcasses. Automation not only reduces labor requirements but also ensures compliance with stringent quality standards, aligning with the increasing consumer demand for high-quality food products.

[3] proposed a neural network-based image processing system for meat quality grading, focusing on marbling scores. The system extracts feature such

as fat distribution and muscle size from binarized monochromatic images and employs regression analysis to provide reliable and objective evaluations. The experimental results demonstrated strong agreement with professional graders, highlighting the potential of neural networks to improve consistency in quality assessments while reducing human subjectivity.

[4] presented a low-cost, contactless approach to chicken meat quality estimation using smartphone cameras and color correction techniques. The proposed system integrates a pre-defined color card for rectifying chromatic aberrations in captured images, which are then analyzed using multivariate regression and hierarchical clustering. This method effectively classifies chicken into quality grades and adapts to real-world conditions with variable lighting and environmental factors. Unlike traditional laboratory-based methods, this approach is affordable and practical for commercial use, further emphasizing the role of computer vision in enhancing quality control processes.

[5] used deep learning for object detection and it gained traction in waste management due to its potential to improve recycling efficiency. YOLOv8, a state-of-the-art model, offers real-time object detection capabilities with high precision and adaptability to various contexts. Previous studies have demonstrated YOLO's utility in identifying recyclable materials, leveraging datasets like WaRP and TACO for training robust models. Techniques such as data augmentation and hyperparameter tuning enhance performance in diverse and challenging conditions. Despite advancements, limitations remain in accurately detecting objects amidst cluttered backgrounds and under varying lighting, underscoring the need for optimized datasets and real-world testing environments.

Recent advancements in object detection models have significantly improved the efficiency of quality control systems in poultry processing.

For example, [6] applied YOLOv5 with transfer learning to detect poultry carcass defects in real-time with high precision. [7] demonstrated a vision-based grading system using YOLOv7 and EfficientDet, achieving consistent results under variable lighting. Other studies focused on feather detection [8], scalable real-time frameworks [9], and AI-driven smart poultry monitoring [10], showcasing the increasing role of deep learning in meat and poultry industries. These studies validate the selection of YOLOv8 in the proposed system due to its performance, speed, and adaptability.

These studies collectively highlight the transformative potential of imaging and machine vision technologies in automating quality assurance. While each approach addresses specific challenges in meat processing, the integration of advanced algorithms, cost-effective designs, and robust image processing techniques provides a foundation for developing scalable and efficient solutions. Further research could focus on integrating these technologies into real-time processing lines, improving dataset diversity, and enhancing user experience through advanced notification systems.

III. Research Objectives

This project focuses on developing an automated quality assurance system that operates independently from the production line to improve the efficiency and accuracy of the poultry industry. By utilizing advanced image processing and computer vision techniques, the system aims to streamline the quality-checking process, ensuring consistent and reliable results.

The system is designed to identify defects such as blood clots and feathers on poultry. Once defective poultry is detected, it is automatically removed from the shackles. Additionally, the system incorporates a counting feature to keep track of the processed poultry, enhancing overall operational efficiency while maintaining high standards of quality control.

IV. Research Methodology

The proposed system integrates real-time image capture, computer vision analysis, signal transmission, hardware actuation, automated sorting, and a web application for monitoring and reporting. As shown in Figure 2, the process begins with continuous video streaming from a camera positioned along the conveyor belt, enabling prompt analysis with minimal delay. Captured video frames are analysed using YOLO object detection algorithms, which identify defects such as blood clots and feathers. Each chicken is classified as either "Quality" or "Defective" based on predefined criteria.

Upon detection of a defect, the Python-based detection system sends a classification signal to the Arduino microcontroller via serial communication, ensuring seamless interaction between the software and hardware components. The Arduino then activates a solenoid valve that controls a double-acting pneumatic cylinder. The solenoid valve directs compressed air into the cylinder, enabling rapid mechanical movement to extend or retract it for sorting purposes. The pneumatic cylinder is the core of the sorting mechanism, directing defective chickens into a separate bin when activated, ensuring efficient segregation and reducing human intervention.

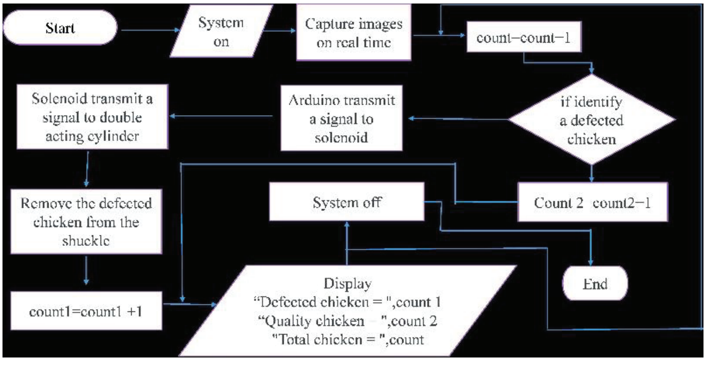


Figure 2: The Flow Diagram of the System

Additionally, a web application was developed to provide real-time system data as shown in Figure 3, including the date and time of operation, sorting duration, and the number of quality and defective chickens processed. This application offers continuous monitoring and a user-friendly interface, allowing for effective performance analysis and improving the overall quality assurance process. This integrated approach ensures efficient, automated sorting, reducing human error and enhancing production line efficiency.

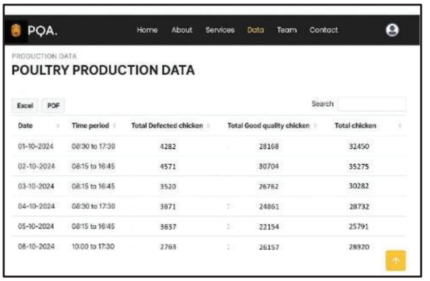


Figure 3: Production Data

A. Software Tools and Platforms

Four distinct software are employed in this project, each serving a unique purpose to ensure the project's successful operation. Table 1 provides a compilation of the software utilized in this project along with their respective functions.

Table 1: List of Software Used

Software	Version/Platform	Functions and Role in the Project
Arduino (Integrated Development Environment)	Version 2.0	Programming and uploading Arduino code for controlling pneumatic cylinders
Roboflow	Web-based	Annotating and augmenting the dataset for detecting "Chicken" and "Defect" labels
Google Colab	Cloud-based	Training YOLOv8 models using GPU acceleration and managing large datasets
Visual Studio Code	Desktop (Integrated Development Environment)	Developing and debugging Python scripts and managing Arduino communication

B. Hardware Components and Integration

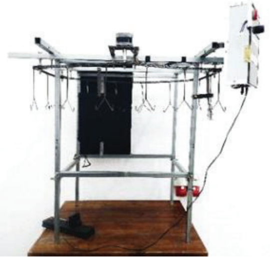
The development of the proposed project involves the utilization of various types of electronic components. Each of these components serves a distinct function, collectively contributing to the seamless operation of the project. Table 2 lists the components used in this project.

Table 2: List of Hardware Used

Material/Component	Function
Arduino Mega Board	Acts as the main microcontroller to control various inputs and outputs in the system
DRV8825 Stepper Motor Driver	Controls the stepper motor by providing precise current for accurate rotational movement
24V 5A SMPS	Supplies regulated DC power to components like stepper motors and solenoid valves
Pneumatic Cylinder	Creates linear motion using compressed air to lift, press, or position objects
5/2 Solenoid Valve	Controls the airflow to extend or retract the pneumatic cylinder using compressed air
Pneumatic PU Tube	Transports compressed air to the pneumatic components like cylinders and valves
Box Bar	Provides a structural frame for mounting and holding various components securely
Mild Steel Flat Bar	Offers support and reinforcement for structural stability
Hex Head Nuts and Bolts	Fastens and joins different materials securely
Fabric Cotton-Polyester Black	Serves as a non-reflective background screen for video recording
Flexible Phone Holder	Holds mobile phones for recording video at desired angles and positions
LED Flood Light Flasher	Provides bright illumination for clear video capturing
NEMA 23 Stepper Motor	Provides precise rotational motion for moving mechanical components
Honda Sprocket Cam and Chain	Ensures synchronized motion in the camshaft timing system for proper operation
Aluminum Composite Panels (ACP)	Used as durable, lightweight material for structural and aesthetic purposes

C. Prototype Development

This project's prototype encompasses both software and hardware components. To validate the functionality of the automated chicken quality checking system and evaluate the feasibility of the concept, a small-scale system as shown in Figure 4 is designed before implementing the overall system.



(a)

(b)

Figure 4: Prototype Design

D. System Framework

The proposed system integrates computer vision, hardware control, and monitoring components into a unified automated quality assurance platform. As shown in Figure 5, video is captured using cameras mounted over the poultry conveyor. These video streams are processed using a YOLOv8 object detection algorithm in a Python environment. When a defect is detected, a classification signal is sent to an Arduino Mega via serial communication. The Arduino triggers a solenoid valve to actuate a pneumatic cylinder that pushes the defective chicken into a separate reject line. Meanwhile, the system also logs production statistics to a web application that displays live data, such as defect counts and timestamps. This real-time feedback loop enhances accuracy, efficiency, and traceability in poultry quality assessment.

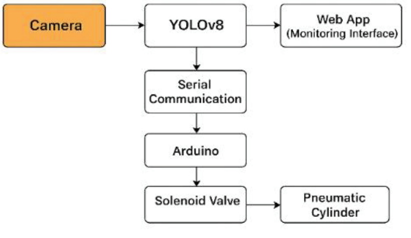


Figure 5: System Framework

V. Results and Discussion

The developed automated poultry quality assurance system was evaluated using YOLOv8, trained for 150 epochs. The system effectively detected defects such as blood clots and feathers, achieving reasonable accuracy, though manual inspections outperformed it in precision for intricate cases.

During real-time testing on the poultry conveyor system, lighting and environmental conditions played a significant role in detection accuracy. The system was tested under indoor fluorescent lighting with additional LED floodlights to enhance image clarity. However, variations in light intensity, reflections from the metallic conveyor, and shadows caused by hanging chickens occasionally introduced noise and misclassifications. Specifically, small blood clots or loose feathers were harder to detect in underlit or overexposed areas of the frame.

To minimize these effects, a black cotton-polyester non-reflective background was used to improve contrast, and LED lights were positioned at a fixed angle to reduce glare. Despite these efforts, the model still showed reduced performance in some real-time conditions, highlighting the need for better lighting control or adaptive exposure settings. Future system iterations may include auto-exposure camera modules, real-time histogram balancing, or additional light diffusers to stabilize image quality.

A. Performance Metrics

The confusion matrix in Figure 6 reveals that the model achieves high accuracy in distinguishing between ‘Chicken’ and ‘Defect’.

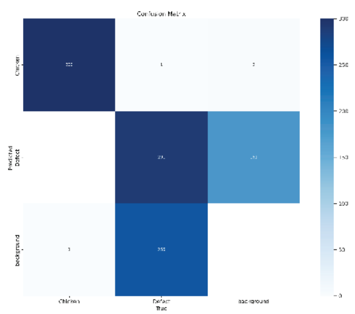


Figure 6: Confusion Matrix

However, some defect samples were misclassified as background. This typically occurred when defects were partially visible or blurred due to motion or lighting inconsistencies. While the model achieved a precision of

98.4% and recall of 96.6% for the 'Chicken' class, it achieved slightly lower values for the 'Defect' class which 83.1% precision and 73.5% recall that indicating a need for better representation of diverse defect types in the dataset.

Training performance graphs in Figure 7 show that all loss values consistently decrease, with smooth convergence by epoch 150. The mAP@0.5 surpasses 90%, demonstrating the model's effective bounding box prediction. Meanwhile, mAP@0.5:0.95 reaches 62%, which is reasonable for a two-class object detection problem, especially considering the subtle and variable appearance of poultry defects. These metrics support the model's robustness in detecting quality issues in real-time production environments.

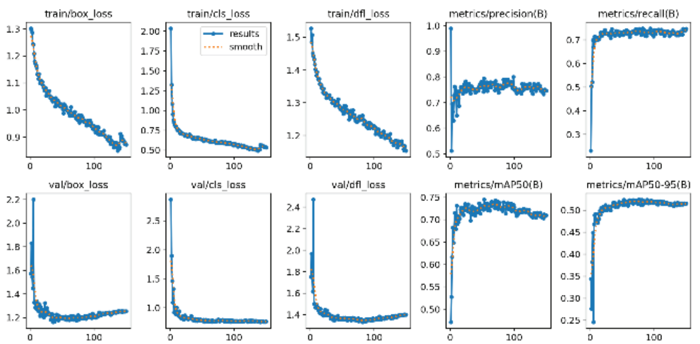


Figure 7: Training and Validation Metrics

B. Data Analysis

Table 3: Testing Data

	Trials	1	2	3	4	5	Average %
Manual Results	Sample Chicken	43	30	40	45	25	
	Quality Chicken	36	21	35	38	21	
	Defected Chicken	7	9	5	7	4	
System Results	Quality Chicken	38	22	35	40	22	
	Defected Chicken	5	8	5	5	3	
System Accuracy	Quality (%)	91.43	95.24	100	94.74	95.24	95.33
	Defect (%)	71.43	88.89	100	71.43	75	81.35

The testing data of 5 trials are tabulated in Table 3. High accuracy in identifying quality chickens, with an average accuracy of 95.33% across all trials, demonstrating consistent performance in detecting quality chickens. Greater deviation in defect detection with an average accuracy of 81.35%, and notable discrepancies like in trial 2, where the system identified fewer defects than the manual result, highlighting challenges in defect detection accuracy.

C. Research Challenges

The system faced several challenges, including insufficient training data to represent the wide range of defect variations. Besides, poor camera resolution and inconsistent lighting conditions affected the clarity and consistency of captured images. The high speed of the conveyor belt limited both the image capture quality and the available processing time, making real-time defect detection more difficult.

D. Recommendations for Improvement

In order to further improve the reliability and accuracy, several recommendations are proposed. To enhance the overall performance of the system, it is recommended to expand and diversify the training dataset to improve model robustness, upgrade the camera resolution and maintain consistent lighting to ensure higher-quality image capture, optimize the conveyor belt speed to achieve clearer images during operation, and regularly update as well as fine-tune the detection model to sustain accuracy over time.

VI. Conclusion

This research developed an automatic quality assurance system that integrates object detection and hardware regulation to improve the assessment and categorization of poultry products. The developed approach is highly assured of accuracy by detecting blood clots and feathers using the YOLO based model. On processing real-time video input captured with a smartphone camera, the system is connected to an Arduino for a solenoid valve to implement the sorting control.

While this system has demonstrated functional operation, there are still some changes that need to be made in terms of adjustments, particularly in pneumatic tuning. regarding the solenoid valve and optimization of the object detection model under different conditions of operation. Further research will concentrate on these issues, smoothing out the web interface for real-time observation, and providing easier integration of hardware and software components. This research, in general, lays the foundation that may lead to an automated solution fast and efficient with much potential for practical applications in poultry.

VII. Acknowledgement

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