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Automated Egg Sorting System Using TCS34725 Color Sensor and Arduino Microcontroller

Riyan Irawan[1]*, Irsyadi Yani[2], Agung Mataram[3]
[1]irawanriyan354@gmail.com, [2]irsyadiyani@ft.unsri.ac.id, [3]amataram@unsri.ac.id
Universitas Sriwijaya Sumatera Selatan

*Corresponding Author: Riyan Irawan
E-mail: irawanriyan354@gmail.com

ABSTRACT

This study presents the design and performance evaluation of a low-cost automated egg sorting system utilizing a TCS34725 color sensor and Arduino Uno microcontroller for small-scale poultry operations. The system classifies chicken and duck eggs based on real-time RGB value measurements integrated with servo motor actuators and conveyor mechanisms for automated separation. Experimental testing was conducted on 12 samples comprising 6 chicken eggs and 6 duck eggs under variable ambient lighting conditions. The TCS34725 sensor successfully differentiated eggshell colors based on RGB value variations, with chicken eggs exhibiting higher values due to lighter coloration compared to darker duck eggs. System performance achieved classification accuracy ranging from 90% to 95%, with a mean sorting time of 4 to 8 seconds per egg and an operational cost of approximately Rp2–3 per egg. Primary classification errors were attributed to misaligned egg positioning and ambient lighting variations. Despite these limitations, the system demonstrated reliable automated operation suitable for resource-constrained agricultural contexts. The findings validate the feasibility of employing low-cost RGB sensors as viable alternatives to expensive industrial vision systems for species-based egg classification. This research contributes practical insights for implementing affordable automation technologies in small to medium-scale poultry farms, supporting the broader adoption of smart farming practices in developing agricultural economies.

Keywords: *Arduino Microcontroller, Egg Sorting Automation, Poultry Technology, Smart Farming, TCS34725 Sensor*

INTRODUCTION

The global transition toward Industry 4.0 has fundamentally transformed agricultural practices through the adoption of automated systems, robotics, and smart sensing technologies (Costa et al., 2023; Pletsch et al., 2025). This paradigm shift aims to address critical challenges in food production, including labor shortages, operational efficiency, and product quality consistency (Javaid et al., 2022). Within the poultry sector, egg production represents a significant component of agricultural economies worldwide, with global production exceeding 86 million metric tons annually (FAOSTAT, 2025; Gautron et al., 2022). However, the traditional manual sorting processes employed in many facilities, particularly in small to medium-scale operations, remain labor-intensive and susceptible to human error, resulting in inconsistent grading and economic losses (Nasiri et al., 2020). The implementation of automated sorting systems has therefore emerged as a strategic priority for modernizing poultry production chains.

Egg quality assessment and classification traditionally rely on multiple parameters, including size, weight, shape, shell integrity, and color (Kumar et al., 2022). Among these characteristics, shell color serves as a primary indicator for species identification and market segmentation, as consumer preferences vary significantly across different regions and cultural contexts (Amfo et al., 2024; Idrus et al., 2023). Chicken eggs typically exhibit light brown to white coloration, whereas duck eggs display distinctive blue-green to dark brown hues due to variations in pigment deposition during shell formation. The biological basis of these color differences stems from the presence of protoporphyrin and biliverdin pigments, which are deposited in species-specific patterns during the egg formation process in the shell gland (Cheng & Ning, 2023; Hodges et al., 2020). Protoporphyrin pigments are responsible for brown coloration in chicken eggs, while biliverdin contributes to the blue-green appearance characteristic of duck eggs (Lu et al., 2021). These pigments are synthesized in the uterine epithelium and deposited onto the calcified shell surface during the final stages of egg formation (Wang et al., 2023). Accurate differentiation based on shell color therefore provides a reliable and non-invasive method for automated species classification in mixed production environments.

Computer vision and optical sensing technologies have demonstrated considerable potential for automating agricultural grading processes. Recent advances in sensor miniaturization and cost reduction have made these technologies increasingly accessible to small-scale producers. Low-cost RGB color sensors, such as the TCS34725, offer practical alternatives to expensive industrial camera systems while maintaining adequate precision for classification tasks (Tagarakis et al., 2021). The TCS34725 is a digital color sensor equipped with RGB photodiode arrays, an integrated infrared blocking filter, and a high-performance analog-to-digital converter (ADC) (Keresteš & Pohanka, 2024). This sensor operates by measuring light intensity across red, green, and blue spectral channels, producing quantitative RGB values that represent the color characteristics of illuminated objects. The infrared filter minimizes interference from ambient infrared radiation, thereby enhancing color measurement accuracy under varying lighting conditions. The sensor communicates via an I2C interface, facilitating seamless integration with microcontroller platforms. These sensors employ photodiode arrays with integrated infrared filters and analog-to-digital converters to quantify color intensity across red, green, and blue spectral channels (Yuliza et al., 2025). Krishna (2025) believed when combined with microcontroller-based processing units, such sensors enable real-time decision-making capabilities suitable for automated sorting applications.

The Arduino Uno microcontroller, based on the ATmega328P processor, serves as an effective control platform for low-cost automation applications. This microcontroller features 14 digital input/output pins, 6 analog input channels, a 16 MHz crystal oscillator, and 32 KB of flash memory for program storage. Its open-source architecture and extensive community support make it particularly suitable for prototyping and small-scale industrial implementations. In automated sorting systems, the Arduino Uno functions as the central processing unit, receiving RGB data from color sensors, executing classification algorithms, and generating control signals for actuator mechanisms (Rahman et al., 2025). The integration of servo and DC motor actuators facilitates the physical separation of classified items, thereby completing the automation chain from detection to sorting. Servo motors provide precise angular positioning for directional control, while DC motors enable continuous rotational motion for conveyor belt systems. Together, these components form a complete egg sorting system comprising object detection sensors, a microcontroller as the data processing center, and actuators responsible for executing egg transfer according to shell color identification results.

Several studies have explored automated egg grading and sorting systems using various technological approaches. Delgado et al. (2014) developed a machine vision system for egg quality classification that achieved accuracy rates exceeding 94% under controlled laboratory conditions. Similarly, Alikhanov et al. (2019) implemented RGB-based geometric analysis for egg weight estimation, reporting accuracy levels between 90% and 95%. More recently, Chang et al. (2020) demonstrated the effectiveness of automated color sorting mechanisms in industrial settings, while deep learning-based grading systems have achieved classification accuracies of 94.8% with R^2 values of 96.0% for combined egg classification and weight prediction (Yang et al., 2023). Additionally, convolutional neural network approaches have been successfully applied to eggshell crack detection, achieving accuracies above 98% (Deng et al., 2010). Research by Nasiri et al. (2020) further validated the application of machine learning algorithms for multi-parameter egg quality assessment, demonstrating the feasibility of automated grading across multiple quality dimensions simultaneously.

Despite these technological advances, existing systems predominantly operate under controlled lighting conditions and utilize expensive industrial camera equipment, rendering them economically impractical for small to medium-scale producers. Furthermore, the majority of previous research has focused on single-species classification or quality assessment rather than inter-species differentiation based on shell color. The application of low-cost RGB sensors, specifically the TCS34725, for distinguishing between chicken and duck eggs remains underexplored in the scientific literature. This represents a significant gap, particularly given the operational constraints faced by small-scale poultry farms in developing regions where cost-effective automation solutions are urgently needed.

This study addresses these limitations by designing and evaluating an automated egg sorting robot that employs a TCS34725 color sensor integrated with an Arduino Uno microcontroller and automated actuator mechanisms for real-time classification and separation based on shell color. The primary objective is to develop a low-cost, reliable sorting system capable of operating effectively in variable ambient lighting conditions without requiring expensive infrastructure. The novelty of this research lies in three key contributions: first, the application of a low-cost RGB sensor for inter-species egg differentiation, demonstrating its viability as an alternative to expensive vision systems; second, the development of a robust classification algorithm optimized for microcontroller implementation that maintains high accuracy despite computational constraints; and third, the comprehensive evaluation of system performance under real-world operational conditions, including analysis of sorting speed, accuracy, and per-unit operational costs. The findings of this research are expected to provide practical insights for implementing affordable automation technologies in small-scale agricultural operations, thereby contributing to the broader adoption of smart farming practices in resource-constrained environments.

RESEARCH METHODOLOGY

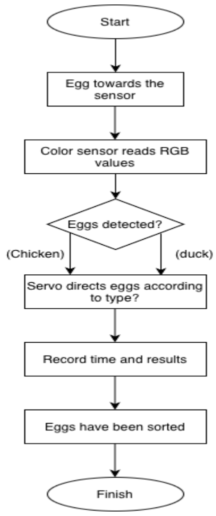

Figure 1 Flowchart
Source: Author's Database (2025)

This study employed a quantitative approach with an experimental method to evaluate the performance of the egg sorting system based on three primary parameters: classification accuracy, sorting time, and system reliability. The experimental setup comprised an Arduino Uno as the main controller, a TCS34725 color sensor for shell color detection, a servo motor as the sorting actuator, a DC motor with conveyor belt for egg transportation, and a 5V–12V power supply system. Figure 1 illustrates the operational flowchart of the sorting process.

Table 1 Component Specifications

Component	Specification	Function
Arduino Uno	ATmega328p, 5v	Main controller
TCS34725 Color Sensor	RGB photodiode	Egg shell color reading
Servo Motor	0-180	Direct the eggs according to detection result
DC Motor + conveyor	12v	Move the egg
Battery	5v & 12v	Power microcontroller and conveyor
Chicken and Duck eggs	6+6	Object

Source: Author's Database (2025)

System Architecture and Actuator Mechanism

In the egg sorting system, actuators functioned as execution elements that moved mechanical components according to microcontroller instructions. The MG996R servo motor served as the primary actuator that determined egg output direction following the color classification process. This servo motor operated based on TCS34725 sensor readings: when an egg was identified as a chicken egg, the servo rotated to a In the egg sorting system, actuators functioned as execution elements that moved mechanical components according to microcontroller instructions. The MG996R servo motor served as the primary actuator that determined egg output direction following the color classification process. This servo motor operated based on TCS34725 sensor readings: when an egg was identified as a chicken egg, the servo rotated to a predetermined position (0°) to direct the egg toward the first sorting lane; conversely, when classified as a duck egg, the servo moved to an alternative position (90° or 180°) to direct the egg toward the second lane. With high torque capacity and precise rotation angle control ranging from 0° to 180°, the MG996R enabled rapid, stable, and powerful object transfer movements that repositioned eggs without generating excessive vibrations that could cause shell cracks.

The DC motor served as the primary driver of the conveyor belt that transported eggs to the sensor detection area. This motor was controlled through a relay module, which functioned as an electronic switch to manage voltage currents higher than those directly manageable by the Arduino Uno. The relay enabled the microcontroller to regulate conveyor operational speed effectively, ensuring eggs moved at a steady velocity sufficient to obtain accurate sensor readings. This combination of DC motor and relay ensured consistent egg flow at an appropriate pace, allowing the sensor to accurately capture shell color data before the servo initiated the separation process. The synergy between the DC motor/relay system as the egg transport driver and the MG996R servo as the sorting lane director created an automated, coordinated sorting mechanism suitable for low-cost applications.

Sensor Calibration Procedure

The TCS34725 sensor calibration process was conducted to ensure measurement accuracy on egg surfaces exhibiting different reflectance characteristics. First, the sensor was positioned at a distance of 1–2 cm from the shell surface to obtain stable reflected light intensity and minimize distortion caused by distance variations. Subsequently, white point calibration was performed using white paper as a reference for maximum LED illumination and photodiode response, enabling the system to consistently recognize peak light intensity conditions. Black point calibration was then executed using dark material to establish the minimum illumination value received by the sensor, thereby clearly defining the dynamic range of RGB readings. Following these calibrations, ambient lighting conditions were measured and compensated through an automatic adjustment mechanism implemented in the software, ensuring that environmental light fluctuations did not compromise signal stability.

System accuracy was quantitatively defined as the percentage of correctly classified eggs relative to the total number of tested samples. Accuracy was calculated using the formula: Accuracy = (N_correct / N_total) × 100%, where N_correct represented the number of classifications matching actual conditions and N_total denoted the total number of tested eggs. Beyond accuracy, system performance was further analyzed using a confusion matrix that separated classification errors into false positives and false negatives, yielding additional metrics including precision, recall, and F1-score.

Sorting time was defined as the total time interval required by the system to process one egg, measured from the moment of egg detection by the sensor until the egg was directed to the appropriate sorting lane. This duration encompassed several components: egg detection time, color sensor reading time, classification logic processing time by the microcontroller, servo motor response time, and conveyor travel time. Sorting time per egg was calculated from repeated measurements across all samples, then averaged to obtain the mean sorting time, accompanied by statistical measures of variation including range (minimum–maximum values) and standard deviation. Through this quantitative approach, system performance was objectively assessed in terms of both classification accuracy and sorting efficiency.

RESULT AND DISCUSSION

System Design and Implementation

This research encompassed three primary development phases: schematic design, robot assembly, and program code implementation. Figure 2 presents the schematic diagram illustrating the interconnection of all system components. The Arduino Uno R3 functioned as the main controller, managing the entire system operations including color sensor data acquisition, object detection, servo control, LCD data display, and DC motor power regulation via the relay module. The TCS34725 color sensor was employed to detect color differences between chicken and duck eggs, whereby chicken eggs typically exhibited lighter coloration while duck eggs displayed darker hues, resulting in distinct RGB value profiles. The proximity sensor detected egg presence in the detection zone without physical contact, outputting a logic signal upon egg detection. A 16×2 LCD module displayed egg type identification results, indicating whether the detected egg was classified as chicken or duck. The MG996R servo motor directed eggs to the appropriate sorting lane based on color sensor readings, while the relay module served as an electronic switch controlling the high-current conveyor motor. The DC motor drove the conveyor belt to transport eggs to the sorting area, and the entire system was powered by a dual-voltage power supply providing appropriate voltage levels to each robot component.

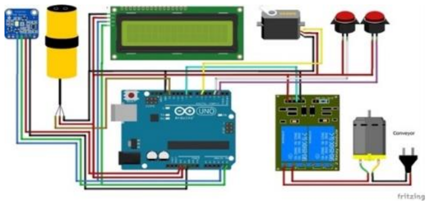

Figure 2 Schematic Design
Source: Author's Database (2025)

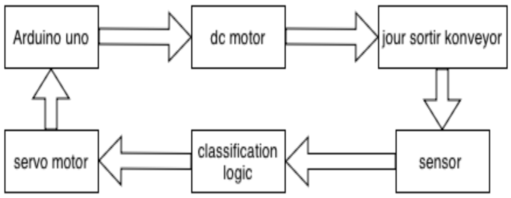

Figure 3 Diagram Block
Source: Author's Database (2025)

Figure 3 illustrates the workflow of the sorting system, commencing with the color sensor reading RGB values from egg surfaces and transmitting these data to the classification logic module. Classification results were subsequently processed by the Arduino Uno as the main controller to determine actuator actions. The Arduino controlled the servo motor to direct eggs toward the appropriate sorting lane while simultaneously regulating the DC motor through the relay to drive the conveyor. The conveyor transported eggs to the sorting area based on servo position commands. Through this operational flow, the complete process from color detection and decision-making to mechanical conveyor movement occurred in an integrated and automated manner.

The assembly phase of the egg sorting robot components was conducted by integrating all system elements sequentially to enable automatic and coordinated operation. The robot assembly process included wiring and integration of all components: connecting the relay module to the Arduino as an electronic switch, linking the DC motor to the relay for conveyor control, interfacing the proximity sensor to the relay for object detection, connecting the TCS34725 color sensor to the Arduino for egg color identification, attaching the servo motor to the Arduino as the egg directing actuator, and connecting the 5V and 12V power adapters as the primary power source and the 16×2 LCD to the Arduino for displaying detection results. The entire system was designed to operate automatically and in coordination according to logic signals processed by the microcontroller. The complete assembled robot configuration is presented in Figure 4.

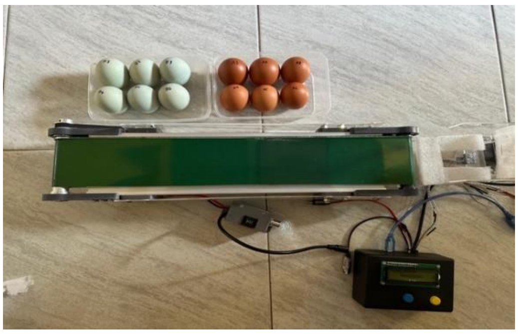

Figure 4 Overall Image of the Robot
Source: Author's Database (2025)

The subsequent development phase involved programming the robot to operate according to specified commands. The program contained instructions to acquire data from the TCS34725 color sensor and proximity sensor, subsequently classifying eggs based on predetermined parameters such as eggshell color differences. Data obtained from sensors were logically processed to determine actuator actions, including moving servo motors or positioning conveyors to specific locations for placing eggs in appropriate collection bins.

Furthermore, the program incorporated an auto-calibration function to adjust sensor readings to real-world environmental conditions, including light intensity variations and object color variations. This feature ensured that the system delivered more accurate and stable sorting results. The program code was developed using C++ language within the Arduino IDE environment.

System Performance Evaluation

Testing was conducted to evaluate overall system performance, including sensor reading accuracy, sorting speed, actuator response, and conveyor stability in transporting eggs from one position to another. The testing process utilized 12 egg samples, comprising 6 chicken eggs and 6 duck eggs. All components were verified for proper installation and integration. The robot was operated with egg samples exhibiting varying color characteristics. Color sensors detected differences in eggshell coloration, and sensor readings were transmitted to the microcontroller for analysis and comparison against predetermined threshold values. Classification results from the microcontroller were utilized to control actuators, specifically servo motors, to direct eggs into containers according to their category. Conveyor rotation speed was calibrated to ensure stable egg detection and separation processes without causing impact or damage to the eggs.

Tests utilizing 12 egg samples (6 chicken eggs and 6 duck eggs) demonstrated that the egg sorting robot accurately detected and sorted the majority of eggs by category. The system achieved an average success rate of approximately 90–95%, with two misclassification occurrences in 12 trials attributed to eggs being positioned at an angle as they passed the sensors, preventing light reflection from being captured correctly. Beyond accuracy assessment, the time required by the system to sort individual eggs was measured. The average sorting time per egg ranged from 4 to 8 seconds, encompassing sensor detection time, microcontroller data processing, conveyor movement, and servo actuator response to reposition the egg. This duration indicated that the system operated with sufficient efficiency and speed for small-scale automated sorting applications. The primary error factors identified during testing were incorrect egg positioning in front of sensors and the influence of ambient lighting conditions that were excessively bright or insufficiently dim.

Table 2 Chicken Egg Sorting Time

No	Ide Sample	Types Of Eggs	Conveyor Time(s)	Detection Time(s)	Actuator Time(s)
1	A1	chicken	3,36	4,12	2,99
2	A2	Chicken	3,05	4,08	2,61
3	A3	Chicken	3,35	3,25	2,56
4	A4	Chicken	3,53	4,67	2,21
5	A5	Chicken	4,26	3,88	2,38
6	A6	Chicken	3,91	4,03	2,21

Source: Author's Analysis (2025)

Table 3 Duck Egg Sorting Time

No	Ide Sample	Types Of Eggs	Conveyor Time(s)	Detection Time(s)	Actuator Time(s)
1	B1	Duck	3,80	3,70	2,50
2	B2	Duck	3,35	3,75	2,51
3	B3	Duck	4,05	3,88	2,86
4	B4	Duck	4,13	3,84	3,01
5	B5	Duck	3,75	3,18	3,18
6	B6	Duck	3,70	3,81	2,68

Source: Author's Analysis (2025)

The data presented in Tables 2 and 3 demonstrate that individual chicken and duck egg samples exhibited varying time measurements across conveyor time, detection time, and actuator time components. These variations were attributed to differences in weight among individual egg samples, which influenced sorting speed characteristics.

Table 4 Chicken Egg Test Results

Sample	Class	RGB	System Prediction	Status	Problem
Chicken 1	Chicken	(185,160,140)	Chicken	Correct	-
Chicken 2	Chicken	(178,155,130)	Chicken	Correct	-
Chicken 4	Chicken	(192,168,150)	Chicken	Correct	-
Chicken 4	Chicken	(188,163,142)	Duck	Incorrect	Too tilted (not enough bounce)
Chicken 5	Chicken	(181,157,135)	Chicken	Correct	-
Chicken 6	Chicken	(190,165,144)	Chicken	Correct	-

Source: Author's Analysis (2025)

As illustrated in Table 4, sample Chicken 4 was misclassified because the egg was positioned at an excessive angle during sensor reading. This condition prevented optimal light reflection capture, resulting in inaccurate RGB value measurements. Consequently, the system incorrectly identified the chicken egg as a duck egg. This error demonstrated that egg position during detection significantly influenced sensor reading accuracy.

Table 5 Duck Egg Test Results

Sample	Class	RGB	System Prediction	Status	Problem
Duck 1	Duck	(140,165,170)	Duck	Correct	-
Duck 2	Duck	(135,158,165)	Duck	Correct	-
Duck 3	Duck	(145,170,178)	Duck	Correct	-
Duck 4	Duck	(138,160,168)	Chicken	Incorrect	Ambient light is too bright
Duck 5	Duck	(142,166,172)	Duck	Correct	-
Duck 6	Duck	(137,162,169)	Duck	Correct	-

Source: Author's Analysis (2025)

In the case of sample Duck 4, a classification error occurred due to excessively bright ambient lighting, which distorted RGB value readings. This condition caused the duck egg to appear lighter than its actual coloration, leading the system to mistakenly classify it as a chicken egg. This finding indicated that ambient lighting conditions significantly affected sensor reading stability.

Error Analysis and System Improvement Strategies

Test results revealed two primary error sources in the system: incorrect egg positioning and ambient light interference. These issues required design-level solutions rather than mere causal explanations. From a mechanical perspective, egg position could be stabilized by incorporating an egg alignment guide featuring a curved or V-shaped holder in the sensor reading area, ensuring uniform egg orientation and preventing movement or rolling during conveyor operation. Additionally, implementing a sensor housing or mini-tube-shaped cover surrounding the TCS34725 would eliminate external light exposure, yielding more consistent color readings. From an algorithmic perspective, an explicit automatic calibration function should be implemented, for instance by periodically acquiring white balance and black level references or whenever changes in ambient light intensity were detected. This procedure would enable the system to readjust offset and gain values of RGB readings, ensuring that lighting variations no longer affected classification outcomes. Through this combination of mechanical and algorithmic improvements, the system could effectively mitigate major error sources and enhance classification accuracy stability under varying operational conditions.

The egg sorting system developed in this study achieved an average processing time of 4–8 seconds per egg with classification accuracy ranging from 90% to 95%. When compared with previous research, these performance metrics revealed both similarities and notable differences. The accuracy level obtained in this study aligns closely with the findings of Alikhanov et al. (2019), who reported accuracy rates of 90–95% for RGB-based geometric analysis in egg weight estimation. This consistency suggests that low-cost RGB sensors can achieve comparable accuracy to more sophisticated measurement systems when properly calibrated and implemented. However, the processing speed of the current system was substantially slower than that reported by Delgado et al. (2014), who achieved 2.5 seconds per unit with 99.2% accuracy, and Alikhanov et al. (2019), who demonstrated a capacity of 2–3 eggs per second. This performance gap can be attributed primarily to the mechanical and operational constraints inherent in the low-cost system architecture employed in this study.

The extended sorting time of 4–8 seconds per egg in the current system was predominantly influenced by several factors: the relatively slow conveyor speed necessary to maintain egg position stability during color reading, the dwell time required for eggs to remain stationary in the sensor area to stabilize RGB value acquisition, and the response latency of the MG996R servo motor in executing positional adjustments to the correct sorting lane. Furthermore, the color sampling process, which averaged 30 readings per egg to reduce signal noise, contributed additional processing time. These factors collectively explain the longer sorting duration compared to previous studies that utilized faster mechanical components, high-speed machine vision systems, or more stable and responsive industrial-grade conveyor systems. Despite these temporal limitations, the system demonstrated a cost-effectiveness advantage that addresses a critical gap identified in the literature regarding affordable automation solutions for small-scale operations.

The findings of this study extend the work of Chang et al. (2020), who demonstrated automated color sorting mechanisms in industrial settings with accuracy exceeding 94%. While Chang et al. focused on industrial-scale implementation with controlled environmental conditions, the current research validated the feasibility of achieving comparable accuracy levels using significantly lower-cost components in variable ambient lighting conditions. This represents an important advancement in democratizing automation technology for resource-constrained agricultural contexts. The misclassification rate of 5–10% observed in this study, primarily attributed to positioning errors and lighting variations, contrasts with the higher accuracy rates of 94.8% reported by deep learning-based grading systems (Yang et al., 2023). However, it is important to note that deep learning-based systems typically require substantially higher computational resources, extensive training datasets, and more expensive hardware infrastructure, which may be prohibitive for small-scale producers. The trade-off between system cost and classification accuracy thus represents a pragmatic consideration for technology adoption in developing agricultural economies.

Moreover, this study contributes to the growing body of literature on low-cost sensor applications in agricultural automation. While Deng et al. (2010) achieved accuracy rates exceeding 98% for eggshell crack detection using convolutional neural networks, their approach focused on a single quality parameter under controlled conditions. In contrast, the current research demonstrates that simple RGB-based classification can effectively differentiate between species categories in real-world operational environments. This finding has important implications for multi-parameter egg quality assessment systems, as suggested by Nasiri et al. (2020), who validated machine learning algorithms for comprehensive egg grading. The integration of low-cost color sensors with basic microcontroller processing represents a complementary approach that balances system complexity with practical implementation feasibility, particularly for applications where sophisticated AI infrastructure is unavailable or economically unviable.

CONCLUSION

Based on the experimental evaluation of 12 egg samples comprising 6 chicken eggs and 6 duck eggs, the conveyor-based egg sorting system utilizing a TCS34725 color sensor, Arduino microcontroller, servo motor, and automated conveyor demonstrated the capability to recognize and separate eggs automatically based on shell color differences. The TCS34725 sensor successfully detected variations in RGB values, wherein chicken eggs exhibited higher values due to their lighter coloration compared to darker duck eggs. The experimental results yielded a sorting accuracy of 90–95%, with primary classification errors attributed to misaligned egg positioning relative to the sensor and ambient lighting variations. The average sorting time per egg ranged from 4 to 8 seconds, encompassing the detection process, data processing, and actuator movement phases. Overall, the developed egg sorting robot operated automatically, efficiently, and with acceptable accuracy levels, demonstrating potential applicability for small to medium-scale egg sorting processes in the poultry sector.

The sample size of 12 eggs employed in this study constitutes a recognized limitation, as it does not adequately represent natural variation within the egg population. Small sample sizes tend to produce less stable accuracy estimates, whereby one or two misclassifications can result in significant percentage fluctuations. Consequently, the generalizability of the findings remains limited, and the results cannot be robustly extrapolated to broader operational conditions. To obtain more reliable performance estimates, future studies should involve larger and more diverse sample populations. Statistically, achieving a ±5% margin of error at a 95% confidence level for approximately 90% accuracy requires a minimum of 100 samples. Therefore, expanding the sample size represents a critical step toward strengthening the external validity and consistency of system performance metrics.

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