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Multi-Criteria Rotary System for Quality Control and Classification of Eggs into Categories

Jakhfer Alikhanov [1], Aidar Moldazhanov [1], Akmaral Kulmakhambetova [1], Dmitriy Zinchenko [1], Tsvetelina Georgieva [2], Eleonora Nedelcheva [2] and Plamen Daskalov [2,*]

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Abstract

This article presents methods and hardware for multi-criteria non-destructive determination of chicken egg quality parameters, implemented using a multifunctional rotary system. Unlike traditional single-criteria sorting, which relies primarily on weight, the proposed approach utilizes a combination of physical and geometric parameters, including weight, linear dimensions, cross-sectional area and perimeter, volume, density, and shape. The experimental framework for the study was formed by measuring the parameters of 750 chicken eggs, covering the entire range of product categories and morphological variations. Geometric parameters were determined using machine vision methods, weight was determined using a strain gauge, and derived parameters were calculated using formalized models. A multi-criteria evaluation algorithm based on fuzzy set theory was used to make the classification decision, accounting for overlapping feature ranges and regulatory differences between EU and EAEU standards. The results of statistical and correlation analysis showed that egg density is an independent diagnostic parameter, weakly correlated with weight and geometric characteristics, justifying its inclusion in the quality model. A comparison of manual and automatic classification revealed systematic biases in boundary categories during single-criteria sorting and demonstrated the advantages of a multi-criteria approach. The obtained results confirm the effectiveness of the developed methods and hardware for automated egg quality control in industrial poultry farming.

Keywords: egg quality; machine vision; multi-criteria classification; fuzzy logic; rotary installation

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1. Introduction

In today's developing agro-industrial complex, ensuring consistent food quality is of strategic importance. Chicken eggs, one of the most widely produced and biologically complex livestock products, place special demands on quality control systems, as they combine high nutritional value, sensitivity to external influences, and significant variability in physical and biological parameters.

Unlike most agricultural products, eggs are a natural, multi-layered system comprising the shell, membranes, white, yolk, and air cell, each of which can be a source of deviations from the norm. Egg quality is influenced by numerous factors: bird breed, feeding conditions, age, microclimate, as well as the harvesting, transportation, and storage processes. Therefore, a definitive assessment of egg quality cannot be reduced to a single indicator and requires consideration of a combination of characteristics reflecting both the external and internal state of the egg. Traditional industrial egg grading practices, focused primarily on weight classification, are increasingly viewed as inadequate. While egg weight does correlate with its commercial grade, it does not reflect the condition of the shell, the presence of microdamage, contamination, shape defects, or signs of deterioration in freshness. This is why, in recent years, scientific research has seen a steady shift toward the concept

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of multi-criteria quality assessment, which involves the use of a set of measurable parameters that provide a more complete picture of the egg’s condition.

Harnsoongnoen et al. [1] demonstrated that determining egg density using a combination of machine vision for volume assessment and strain gauge measurements of egg mass allows for a more objective assessment of egg freshness compared to traditional methods. This result demonstrates the fundamental importance of integrating various physical parameters within a single measurement system. Similarly, a study by Pacure Angelia et al. [2] confirmed the feasibility of automated egg classification into categories based on image analysis, demonstrating the high information content of geometric and visual features in quality assessment.

At the same time, review studies [3] emphasize that existing automated methods still do not provide sufficient control, as most focus either on appearance or individual physical parameters, without comprehensively considering the relationships between them.

Despite the widespread use of single-criteria sorting methods, primarily by mass, their use in modern conditions is associated with a number of fundamental limitations. The weight of an egg does not reflect the presence of microcracks, shell defects, contamination, or the internal condition, which can significantly affect the safety and shelf life of the product.

Modern research convincingly demonstrates that shell microdamage is a key cause of quality loss and reduced marketability of eggs. For example, Botta et al. [4] demonstrated the feasibility of automated shell crack detection using deep convolutional neural networks, highlighting the fundamental inadequacy of human visual inspection and simple threshold algorithms.

Acoustic diagnostic methods presented in the study [5] also confirm that shell defects can manifest themselves in physical signals not detected by standard weighing or visual means. This further emphasizes that a single-criterion approach is unable to adequately describe the actual condition of an object.

The development of hyperspectral inspection methods [6] has made it possible to explain microdefects and internal inhomogeneities through the analysis of reflected spectra; however, the high cost of equipment and computational complexity of such systems significantly limit their implementation in mass-scale industrial sorting lines. In this context, the search for more accessible yet comprehensive solutions based on a combination of classic optoelectronic tools and intelligent data processing is becoming increasingly important.

Furthermore, single-criteria methods are unstable in areas of class overlap, where eggs of different categories have similar weights or sizes. This leads to classification errors at category boundaries and reduces the reproducibility of sorting results. Thus, the transition to multi-criteria analysis is becoming not just desirable, but a necessary condition for increasing the reliability of quality control.

Modern egg quality control systems are based on the synergy of optoelectronic, digital, and intelligent technologies. Each of these components performs its own function, but maximum effectiveness is achieved when integrated into a single hardware and software system.

Optoelectronic tools provide primary information about the object being tested. In the work of Yang et al. [7] It has been shown that computer vision systems are capable of not only classifying eggs into categories, but also detecting surface defects under real-world production conditions, ensuring high repeatability and stability of results. This indicates that visual features can be effectively used as one of the key elements of a multi-criteria quality assessment system.

The development of digital measurement tools has enabled a transition from local measurements to the integration of various types of data. For example, research by Jiang et al. [8] demonstrated the feasibility of monitoring egg weight during transportation using computer vision, opening up prospects for the creation of contactless and distributed measurement systems in which visual and weight data are combined into a single information loop.

Intelligent data processing methods act as a link between physical measurements and decision making. The use of statistical classification and dimensionality reduction methods, such as principal component analysis, linear discriminant analysis, and nearest neighbor algorithms, allows for increased diagnostic robustness and feature interpretability [9]. At the same time, deep learning is developing, focusing on the automatic extraction of features and classification of defects and quality categories.

Edge computing is becoming especially important, allowing for image analysis and decision making to be transferred directly to the sorting line. In the work of Hadjisavvas et al. [10] It has been demonstrated that such systems are capable of operating in real time with limited computing resources, which is critical for the industrial implementation of intelligent control systems.

Modern review studies [11,12] emphasize that the further development of egg quality control technologies is associated not so much with the improvement of individual sensors, but with the creation of multimodal systems that combine visual, geometric, weight, and spectral features in a single architecture. Such systems are considered the basis for the transition to a new generation of intelligent sorting.

The aim of this work is to substantiate multi-criteria non-destructive quality control and classification of chicken eggs based on the combined determination of mass, geometric parameters, density, and fuzzy logic algorithms, as well as to experimentally validate and evaluate the effectiveness of a rotary automated system for classifying eggs into categories.

2. Materials and Methods

This study aims to develop and experimentally verify methods and hardware for multi-criteria, non-destructive determination of hen egg quality indicators. The methodology simultaneously integrates physical, geometric and derived parameters of the egg, based on traditional single-criteria weight-based sorting.

The biological nature of eggs as a test object determines the high variability of their characteristics, even within a single weight category. Eggs of the same weight can vary significantly in shape, density, shell thickness, air cell condition, and internal structure. This makes it obvious that there is a need to build a control system that is capable of interpreting not individual parameters, but their totality, and also taking into account uncertainty and overlapping ranges of attributes (features).

Based on this, the study implements the concept of generating a digital egg quality profile, which is a vector of interconnected features reflecting the egg's condition as a physical object. This profile is used as the basis for subsequent intelligent interpretation and sorting.

The experimental sample consisted of 750 chicken eggs obtained from a single industrial poultry farm (Kazakhstan) specializing in egg production. All eggs were obtained from hens of the cross "..." industrial-type hens aged 32–45 weeks, which corresponds to the period of stable egg production. The experiment included eggs selected from the current batch after initial sorting at the farm.

The eggs were no more than three days old at the time of the measurements. Prior to the experiment, the eggs were stored at a temperature of +4 to +6 °C and a relative humidity of 75–80% in a refrigerated warehouse. The study included table eggs that met current regulatory requirements. (EU Regulation No 589/2008; ГОСТ 31654–2012).

Hatching eggs were not considered in this study.

The sample was designed to cover:

- a full range of mass-produced product categories;
- eggs with varying morphologies (normal, elongated, flattened);
- samples with variations in density;
- eggs with acceptable geometric deviations within standard values.

This approach ensured the representativeness of the sample and the correctness of the statistical analyses, including the assessment of the relationships between the parameters and the completeness of the experimental basis of the multi-criteria quality assessment system, as well as the possibility of statistically valid comparison of the differences between different egg categories.

Each study object was described by a set of measured and calculated characteristics, forming a single record in the experimental database. The tabular data structure allowed for the following: statistical processing,

- correlation analysis,
- distribution analysis,
- reproducibility assessment,
- parameter dynamics study.

Each egg in the experimental sample was described by a multidimensional feature vector:

$$Q_i = \{m_i, D_i, d_i, S_i, P_i, I_{fi}, K_{fi}, V_i, \rho_i, C_i\}, i = 1, \dots, 750$$

where Q_i—a feature vector the i-th egg, forming a multidimensional feature space.

The vector components have the following physical values and units of measurement:

m_i—egg mass, g
D_i,d_i—large and small diameters, mm
S_i—longitudinal cross-sectional area, mm^2
P_i—perimeter of the longitudinal section contour, mm
I_{fi}—form index, %
K_{fi}—form factor, dimensionless
V_i—estimated volume, sm^3
ϱ_i—density,g/sm^3
C_i—categorical solution of the system (egg category according to the selected standard).

This formalized representation made it possible to move from the analysis of individual measurements to the study of parameters as a single information space, in which each object of study is represented by a point in a 10-dimensional feature space, which allows the use of methods of statistical analysis and multi-criteria classification.[13]

The classification of chicken eggs during experimental studies was carried out taking into account the requirements of current international and interstate regulatory documents. The provisions of European Union standards were used in the study (EU Regulation No 589/2008) and the Eurasian Economic Union—EAEU (ГОСТ 31654–2012, ТР ТС 021/2011), which regulate the division of eggs into commodity categories by weight.

According to the EU standard, eggs are classified into four categories: K_S, K_M, K_L, and K_XL, while EAEU regulations use a different grading system with five categories, including categories 3, 2, 1, “selected,” and “premium.” Significant differences in the weight ranges lead to ambiguity in the classification of eggs when switching between standards. [13–16]

Figure 1 shows the layout of the developed multifunctional rotary system for individual non-destructive testing and automatic classification of chicken eggs. The design integrates mechanical, measurement, computing, and actuator subsystems within a single process cycle.

The drum rotor is driven by an industrial-grade DC planetary gear motor (12–24 V). Manufacturer: Ningbo Zhongda Leader Intelligent Transmission Co., Ltd., Ningbo, Zhejiang Province, People’s Republic of China.

The geared motor provides high torque at low rotation speed and enables discrete, step-by-step drum positioning. A planetary gear reduces backlash and improves the angular accuracy of the measuring cells. The electric drive is synchronized with the system’s measuring cycle, ensuring consistent, repeatable process operations.

To coordinate the actuators, a programmable logic controller “ОВЕН ПЛК110-24.Р-М”, manufactured by ООО «ОВЕН», Moscow, Russian Federation, was used. The controller is designed for industrial automation and performs:

- control of the rotary drum electric drive;
- processing of position sensor signals;
- generation of control pulses for electromagnetic actuators;
- synchronization of mechanical and computational processes.

The use of an industrial PLC ensures the system's stable operation and the repeatability of the control algorithm in continuous mode.

The optical module is a Logitech HD Webcam C270 webcam, manufactured by Logitech International S.A., Lausanne, Switzerland (factory assembly in China).

Key Features:

- Maximum resolution: 1280 × 720 pixels;
- Frame rate: up to 30 fps;
- Connection interface: USB 2.0;
- Built-in CMOS sensor.

The camera captures images of the egg's longitudinal cross-section. The resulting digital data is used to calculate the linear dimensions (D, d), area (S), perimeter (P), and derived morphological parameters.

The computing core is a single-board computer Raspberry Pi 4 Model B (4 GB RAM), manufactured by the Raspberry Pi Foundation, Cambridge, UK (production assembly—China).

Specifications:

- Broadcom BCM2711 processor (1.5 GHz, ARM Cortex-A72);
- RAM—4 GB;
- Operating system—Raspberry Pi OS;
- Software environment—Python 3.x, OpenCV library.

This module processes images, calculates geometric parameters and egg mass, implements a fuzzy classification algorithm, and transmits control signals to actuators.

To measure the mass, a 1 kg beam strain gauge load cell (Strain Gauge Load Cell, 1 kg) manufactured by Shenzhen Eeworld Electronic Co., Ltd., Shenzhen, Guangdong Province, People's Republic of China, was used.

The sensor signal is amplified and digitized by a 24-bit analog-to-digital converter HX711, manufactured by Avia Semiconductor Co., Ltd., Wuhan, Hubei Province, People's Republic of China.

Main characteristics of the measuring channel:

- Measurement range: 0–1 kg;
- Resolution: up to 0.01 g;
- Bridge circuit: full strain gauge bridge;
- Digital data transfer interface.

The actuator used is an industrial-grade linear electromagnetic solenoid (12 V DC), manufactured by Dongguan Hongfa Electromechanical Equipment Co., Ltd., Dongguan, Guangdong Province, People's Republic of China.

The solenoid is activated by a PLC control signal and provides mechanical movement of the guide element, causing the egg to be ejected into the corresponding sorting channel.

The mechanical part is based on a rotary design, in which eggs are placed in carriages of a rotating drum and sequentially pass through the feeding, mass and geometric measurement, and removal zones. This arrangement ensures strict coordination of physical and computational processes, as well as high repeatability of measurement conditions.

The 10-cell rotary drum is made of a structural polymer material and machined in a laboratory setting (Almaty, Republic of Kazakhstan). Each cell is designed to maintain a fixed longitudinal position of the egg and prevent its rotation during measurement, eliminating orientation variations during optical analysis and improving the reproducibility of geometric parameters.

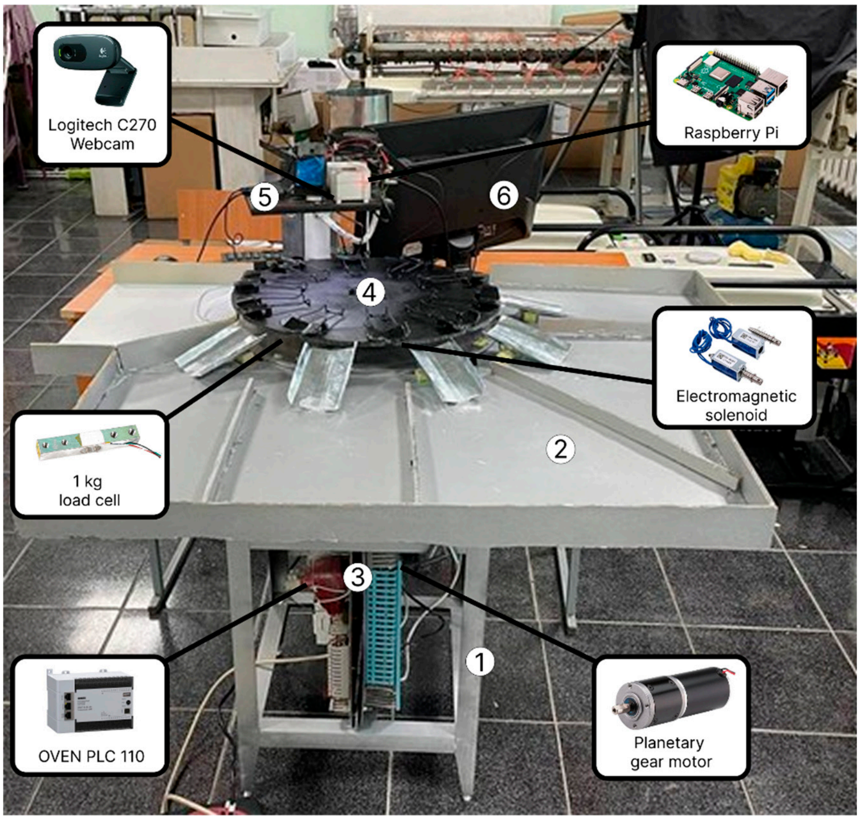

Figure 1. General view of the multifunctional unit. 1—unit frame, 2—base table with compartments for categories, 3—electric drive with control system, 4—drum with carriages and strain gauge module, 5—machine vision module, 6—monitor for interface display.

The number of cells (10) was chosen deliberately and is determined by the logic of the process cycle and the structure of the classification algorithm. The functional distribution of positions by the angular pitch of the drum is implemented as follows:

1. Feed cell—the operator loads eggs into the system.

2. Weighing cell—mass measurement using a strain gauge.

3. Optical inspection cell—image capture under the camera and calculation of linear dimensions, area, perimeter, and derived morphological parameters.

4–7. Sorting positions for product categories: S, M, L, XL (according to the selected regulatory standard).

8–9. The "Defective/Non-Standard" category is formed based on a combination of morphophysical deviations. This item can be programmatically divided into two independent subcategories:

– defective by shape (deviations If and Kf);

– defective by density (ϱ outside the permissible ranges).

10. Reserve cell—designed to expand the functionality of the algorithm (for example, the introduction of an additional diagnostic parameter or an alternative normative scale).

The drum's step-by-step rotation is synchronized with the weighing, optical analysis, volume and density calculation, and classification decision generation cycles. This distribution of positions ensures the technological cycle is completed within a single rotation and allows for parallel processing of each egg without overlapping measurement operations. The duration of determining quality indicators and classifying the category of one egg is 1 s.

The rational configuration of ten cells ensures a balance between the technological compactness of the design and the functional flexibility of the multi-criteria classification algorithm.

Quality indicators were determined, and the eggs were automatically classified using a multifunctional rotary unit operating on a step-by-step principle of cyclical movement of objects. The

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main actuator of the system is a rotary drum, consisting of ten evenly spaced cells for individual egg placement. The drum moves discretely, at a fixed angle, ensuring the sequential delivery of each egg to the measuring and sorting zones. The stepping principle ensures stable egg positioning, synchronized measuring operations, and repeatable control conditions within a full drum rotation.

Eggs were fed into the system manually by the operator, one at a time. Before analysis, each egg was placed in a free cell of the rotor drum with its longitudinal axis oriented horizontally. Once the cell was full, the system automatically initiated a step-by-step rotation cycle of the drum.

The carriage design ensured a stable, fixed position of the egg during the measurement process, preventing its displacement and rotation as it passed through the weighing and optical-electronic control zones. The next egg was reintroduced after the drum moved to the next position.

During operation, each egg is assigned a serial number upon entering the drum cell, which is stored in the control system throughout the entire analysis cycle. As the drum rotates, the egg passes through a weighing zone equipped with a strain gauge and an optoelectronic control zone, where digital images are captured and geometric parameters (major and minor diameters, cross-sectional area and perimeter), as well as derived shape parameters, are calculated. Based on the measured weight and geometric characteristics, the egg's volume and density are calculated. Once the measurements and data are processed, the system assigns a quality category to the egg. When the drum reaches the appropriate position, the release mechanism is triggered by a control signal.

The egg release mechanism is implemented as an actuator unit, ensuring controlled release of eggs from the drum cell within a specified trajectory zone. The machine's worktable is equipped with receiving cells and guide channels corresponding to various product categories and defective groups. Depending on the classification decision, the egg is automatically dropped into the appropriate receiving area, after which the cycle repeats for the next item. This process design ensures continuous operation, accurate sorting, and adaptability to various regulatory standards.

The "Defective/Non-Standard" category is determined automatically by a combination of morphophysical criteria and is not determined solely by egg weight. Unlike manual sorting, which relies primarily on weight, the multi-criteria algorithm takes into account the following rejection conditions:

1. Density deviation outside the standard range determined by the experimental distribution and established membership functions (low density, indicating an enlarged air cell).
2. Morphological deviations, identified by the values of the shape index If and shape coefficient Kf, that fall outside the acceptable ranges for product categories.
3. Combined parameter deviations, in which the egg complies with the mass category but exhibits simultaneous deviations in density and shape, leading to a decrease in the final degree of membership in any product category below the established decision threshold. [17,18]

The egg mass was recorded using the strain gauge principle. Under the force of gravity, the egg exerts a load on the sensing element, causing a change in the resistance of the strain gauge circuit. This signal is converted into digital form and transmitted to the system's computing core.

The mass measurement was carried out directly as part of the transport system, which is fundamentally important for ensuring the reproducibility of measurement conditions and the possibility of scaling the system to an industrial level.

The egg's geometric parameters were determined using digital images obtained from a camera mounted above the installation's work area. The viewing geometry, lighting parameters, and background were fixed, ensuring stable shooting conditions and metric comparability of the images. The vision module is shown in Figure 2.

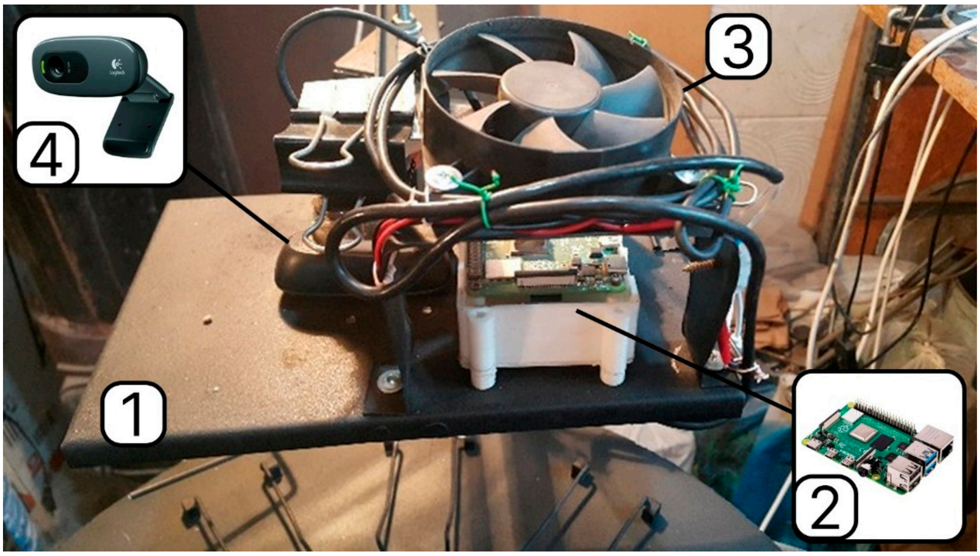

Figure 2. Machine vision module: 1—platform base, 2—single-board computer, 3—cooling system, 4—webcam.

The images were subjected to sequential processing, including:

- noise filtering,
- binarization,
- morphological processing,
- contour detection,
- shape approximation.

Based on the contour analysis, linear dimensions (major and minor diameters), cross-sectional area, and perimeter were calculated and used to generate quantitative shape metrics. Figure 3 shows an example of egg image capture and contour capture.

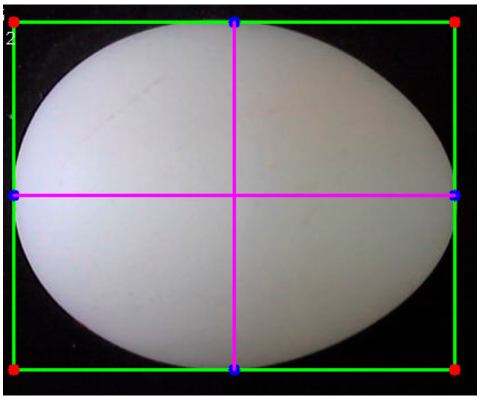

Figure 3. Capturing an egg image using the program.

After segmenting the image, a binary egg mask was created, from which the outer contour was extracted. Based on this contour, the main geometric parameters were calculated.

Linear dimensions were determined using the bounding box of the contour:

$$D_i = x_{max} - x_{min}, d_i = y_{max} - y_{min}$$

where x_{min}, x_{max}, y_{min}, y_{max}—The minimum and maximum coordinates of the contour pixels along the image axes. To convert from pixels to metric units, a scaling factor k (mm/px) was used, determined by calibration:

$$D_i^{(mm)} = k \cdot D_i^{(px)}, d_i^{(mm)} = k \cdot d_i^{(px)}$$

The area Si was defined as the area of the binary mask region:

$$S_i^{(mm^2)} = k^2 \cdot S_i^{(px)}$$

where $S_i^{(px)}$—the number of pixels inside the mask.

The perimeter Pi was calculated as the length of the contour:

$$P_i^{(mm)} = k \cdot P_i^{(px)} \quad (1)$$

where $P_i^{(px)}$

- the perimeter in pixels obtained by summing the distances between adjacent points of the contour.

The shape index was calculated using the standard ratio:

$$I_{fi} = \frac{d_i}{D_i} \cdot 100\%$$

where:

D$_i$—major diameter, mm.;

d$_i$—minor diameter, mm.

This indicator characterizes the degree of egg elongation and is widely used in quality control practices. Ifi values allow for the detection of deviations from the standard shape and are used in assessing commercial and hatching qualities.

However, the shape index only takes into account the ratio of two linear dimensions and does not reflect the features of the actual egg contour, including asymmetry, local deformations, and surface irregularities.

To increase the morphological sensitivity of the analysis, the shape coefficient K$_{fi}$ was additionally used, calculated based on the ratio of the perimeter to the longitudinal cross-sectional area:

$$K_{fi} = \frac{P_i^2}{S_i}$$

where:

P$_i$—perimeter of the longitudinal section contour, mm;

S$_i$—is the area of the longitudinal section, mm^2.

The K$_f$ index is based on the geometric relationship between area and perimeter and reflects the degree to which an object's shape deviates from a compact figure. For geometrically more regular shapes, the Kf value is minimal, while with increasing elongation, asymmetry, or the presence of contour irregularities, the index increases.

Thus, the shape index I$_{fi}$ describes the global geometric proportion, while the shape coefficient K$_f$ additionally takes into account the characteristics of the curvature distribution and the complexity of the contour.

The combined use of these two indicators allows for:

- increasing the system's sensitivity to morphological deviations;
- identifying eggs with standard weight but geometric defects;
- reducing the likelihood of classifying non-standard eggs into commodity categories;
- improving the stability of classification in the boundary zones of mass categories.

Correlation analysis showed that the index and the form coefficient demonstrate a high relationship (r = 0.84), but are not completely identical parameters, which confirms their additional diagnostic contribution to the multi-criteria model.

The inclusion of morphological indicators in the feature space allowed to increase the accuracy of automatic classification compared to a single-criteria approach based solely on mass.

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To move from external characteristics to the physical parameters of the internal state, the study used calculations of the egg's volume and density.

The egg's volume, Vi, was determined by approximating its shape with a body of revolution close to an ellipsoid. The measured values of the major and minor diameters of the longitudinal cross-section were used.

The volume of the ellipsoid is calculated using the formula:

$$V_i = \frac{\pi}{6} D_i d_i^2$$

where:

D_i—major diameter, mm.;

di—minor diameter, mm;

V_i—volume, mm^3.

Based on previous studies, an empirical formula was obtained for calculating the volume of an egg through the area of the longitudinal section and the minor diameter, which takes into account the deviation of the egg shape from the ellipsoid, which was used when calculating the volume on this installation. [19].

$$V_i = 0{,}641\ S_i\ d_i$$

where:

0,641—correction factor obtained empirically;

Si—longitudinal cross-sectional area of the egg, mm^2;

d_i—minor diameter, mm.

To transition to the SI system, the volume was converted to cubic centimeters:

$$V_i^{(sm^3)} = \frac{V_i^{(mm^3)}}{1000}$$

The egg density was calculated using the standard physical ratio:

$$\rho_i = \frac{m_i}{V_i}$$

where:

m_i—mass of eggs, g;

V_i—volume, sm^3;

ϱ_i—density, g/sm^3.

Density is considered as an integral physical indicator reflecting the ratio of mass and volume of the egg and indirectly characterizing the state of the internal structure, including the size of the air chamber and the distribution of protein and yolk.

Correlation analysis (Table 2) showed that the correlation coefficients of density with mass and geometric parameters are in the range of $|r| \leq 0.29$, indicating a weak statistical relationship between this parameter and the weight-geometric group of features. While mass demonstrates a high correlation with volume and linear dimensions (r=0.88–0.94), density forms a separate cluster of features.

This means that density provides additional diagnostic information that doesn't duplicate weight and geometric characteristics.

The practical significance of this fact is evident in boundary weight categories. Eggs with similar weights can have different volumes due to shape variations, leading to differences in density. Within a single-criteria sorting system, such eggs are assigned to the same category, whereas a multi-criteria model allows for the identification of hidden morphophysical differences and the adjustment of the classification decision.

An experimental comparison of manual and automatic sorting (Table 3) showed a redistribution of objects into borderline categories and identification of a group of substandard eggs. This confirms the need to use additional parameters, including density, to increase the sensitivity of the system.

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Thus, including density in the feature space expands the diagnostic capabilities of the system, increases the stability of classification in areas with overlapping mass intervals, and reduces the probability of misclassification of eggs into categories.

The overlapping ranges of mass categories, as well as differences in regulatory requirements between the European Union and the Eurasian Economic Union (EAEU), create fundamental uncertainty in the unambiguous classification of chicken eggs based on strict threshold values. Given the biological variability of the samples and the heterogeneity of experimental data, the use of deterministic criteria leads to a decrease in the stability of classification decisions, especially in the boundary zones of product categories.

In this study, a Mamdani Fuzzy Inference System (MFI) was implemented to make classification decisions. This system handles overlapping parameter ranges and formalizes measurement uncertainty.[20]

The classification algorithm includes the following sequential steps:

1. Measurement and calculation of input parameters:
   mass m_i (г),
   volume V_i (см^3),
   density ϱ_i (г/см^3),
   shape index I_{fi} (%).
2. Normalization of input data, taking into account the ranges of the experimental sample.
3. Determining the degrees of membership of input parameters to the corresponding fuzzy terms.
4. Applying a fuzzy rule base.
5. Aggregating output results.
6. Defuzzification of the output variable using the center of gravity method.
7. Assigning a quality category to the egg.

Each diagnostic parameter was treated as a linguistic variable described by a system of fuzzy terms.

For mass, the following terms were used:
Small (S), Medium (M), Large (L), and Extra Large (XL).
For density:
Low, Normal, High.
For shape index:
Elongated, Normal, Round.
For volume:
Low, Medium, High.

Membership functions were defined by triangular and trapezoidal functions, ensuring smooth overlap of the standard intervals. In general, a trapezoidal membership function is defined:

$$\mu(x) = \begin{cases} 0, & x \le a \\ \frac{x-a}{b-a}, & a < x \le b \\ 1, & b < x \le c \\ \frac{d-x}{d-c}, & c < x \le d \\ 0, & x > d \end{cases}$$

Parameters a, b, c, and d were determined based on the normative category boundaries for the EU standard and the distribution of experimental data. Membership functions of the mass parameters are m in Figure 4, and density ϱ in Figure 5.

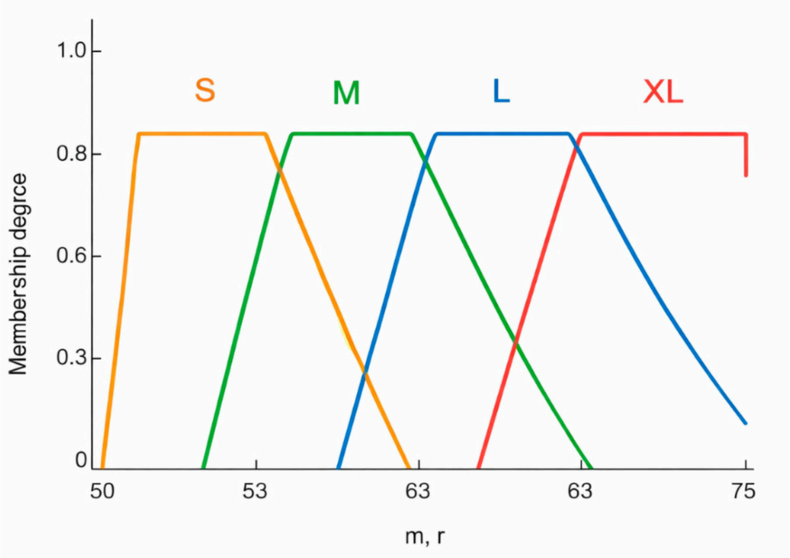

Figure 4. Membership functions of the mass parameter m.

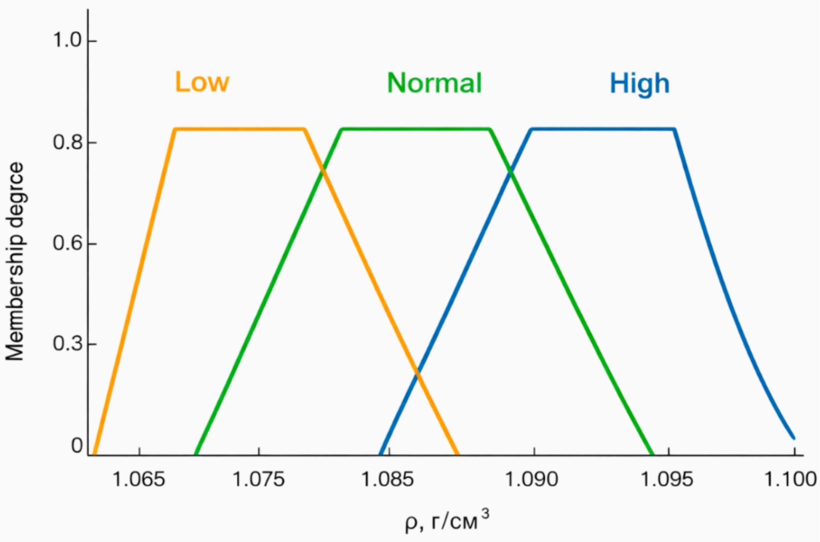

Figure 5. Membership functions of the density parameter ϱ.

For the mass parameter, overlapping trapezoidal membership functions are defined, corresponding to the S, M, L, and XL categories according to the EU standard. The overlap of adjacent functions ensures a smooth transition between boundary intervals and eliminates sudden changes in the classification decision with minor mass changes.

For the density parameter, membership functions for the terms Low, Normal, and High are specified. The function boundaries are determined based on the experimental data distribution (Table 1) and take into account the range of 1.067–1.098 g/cm^3. The overlap of the functions reflects the biological variability of eggs and measurement uncertainty.

Membership functions were defined as triangular and trapezoidal dependencies and were determined by parameters a, b, c, and d, which formed regions of zero, partial, and full membership. This assignment ensures:

- classification stability in areas of category overlap;
- algorithm adaptation to various standard scales (EU and EAEU);
- reduction in the impact of measurement error on the final solution:

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The presented graphs illustrate the operating principle of the fuzzy model and demonstrate the mechanism for transitioning from a rigid threshold classification to a multi-criteria system with a smooth gradation of membership degrees.

The classification decision was formed based on a set of rules of the form, for example:

IF (m is Large) AND (ϱ is Normal) THEN Category = L
IF (m is Medium) AND (ϱ is Low) THEN Category = M
IF (m is Large) AND (I_f is Elongated) THEN Category = Non-standard
IF (ϱ is Low) THEN Category = Reject

The rule base was developed taking into account regulatory requirements and experimentally identified patterns. A total of 24 rules were used.

To obtain a clear classification solution, the center of gravity method was used:

$$C = \frac{\int x\mu(x)dx}{\int \mu(x)dx}$$

The resulting value was compared with the corresponding range of quality categories.

Unlike a rigid threshold classification, the fuzzy model allows for the overlap of mass intervals and the biological variability of objects to be taken into account. Correlation analysis revealed that density forms a separate cluster of features weakly correlated with mass ($|r| \le 0.29$), confirming the need to integrate multiple parameters into a single model.

An experimental comparison with manual sorting demonstrated a redistribution of eggs within the boundary categories and the identification of a group of non-standard products, confirming the increased sensitivity of the system when using a multi-criteria fuzzy approach.

Standard methods of mathematical statistics were used to quantitatively characterize the accuracy and reproducibility of the system.

Absolute and relative errors:

$$\delta_{abs} = |x_{meas} - x_{ref}|$$

$$\delta_{rel} = \frac{|x_{meas} - x_{ref}|}{x_{ref}} \cdot 100\%$$

where:

x_{meas}—The measured value of a parameter (mass, diameter, area, etc.) obtained by an automated system;

x_{ref}—the reference value of the parameter, determined using control standard measuring instruments.

The following were used as reference values:

- verified control weights—to check the weighing channel;
- caliper measurements (accuracy ±0.02 mm)—to check linear dimensions;
- control geometric templates—to verify the scale factor.

The average values of absolute and relative error were determined for the entire experimental sample.

For each parameter, the following values were determined:

- mean,
- median,
- standard deviation σ,
- coefficient of variation Cv,
- 95% confidence intervals.

The obtained values were used:

- to assess the metrological correctness of the system;
- to confirm the admissibility of using the calculated parameters in multi-criteria classification;
- to analyze the impact of measurement errors on the stability of the fuzzy model.

The Pearson correlation coefficient was used to identify relationships between parameters:

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$$r_{xy} = \frac{\sum_{i=1}^{750}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{750}(x_i - \bar{x})^2 \sum_{i=1}^{750}(y_i - \bar{y})^2}}$$

This made it possible to quantitatively justify the need for a multi-criteria approach.

Error calculations revealed that measurement errors do not exceed regulatory limits and do not have a statistically significant impact on the distribution of eggs across quality categories.

Thus, the use of absolute and relative error formulas provided quantitative confirmation of the accuracy of the developed system.

Unlike deterministic classification based on hard thresholds, fuzzy logic allows for the interpretation of an object’s category membership as a degree value rather than a binary decision. Within fuzzy set theory, each parameter is described by a membership function, which takes values between 0 and 1, reflecting a gradual transition between categories.

This approach is necessary due to the overlapping standard weight ranges and the biological variability of eggs. At the extremes, weight, volume, and density values can correspond to several categories simultaneously. When using strict thresholds, even a minor measurement error leads to a sudden change in the classification decision. This reduces the stability of sorting and increases the likelihood of systematic errors.

A fuzzy model eliminates this problem by:

- defining overlapping membership functions for each category;
- using inference rules that take into account a set of parameters;
- aggregating membership degrees instead of binary cutoff.

Thus, an object can simultaneously have partial membership in several classes, and the final decision is formed based on the combined contribution of all diagnostic features.

Experimental confirmation of the feasibility of using fuzzy logic was obtained through a comparative analysis of manual and automatic classification. In the boundary categories (K_S/K_M and K_L/K_XL), a redistribution of objects and the identification of a group of non-standard products were detected, indicating a higher sensitivity of the multi-criteria model compared to single-criteria sorting by weight.

Integration of EU and EAEU standard requirements within a single fuzzy system is achieved by customizing the parameters of the membership functions without changing the algorithm structure. This allows the model to be adapted to various regulatory scales without revising the mathematical basis of the classification. Therefore, the use of fuzzy logic is not a formal complication of the model, but rather a methodologically sound tool for improving the robustness, reproducibility, and adaptability of automated egg grading in the face of category overlap and measurement uncertainty.

3. Results

The experimental database was compiled from measurements of 750 chicken eggs. All samples were obtained from a single industrial poultry farm specializing in table egg production, minimizing the impact of interfarm technological differences (feeding, housing conditions, microclimate).

The eggs were obtained from hens of the industrial Alatau cross at 30–45 weeks of age, corresponding to the period of stable productivity and standardized product quality.

Experimental samples were collected over three consecutive production days from ongoing daily collection lots. Egg age at the time of initial measurement was no more than 72 h after laying.

Before the study, the eggs were stored in a refrigerated warehouse at a temperature of +4 to +6 °C and a relative humidity of 75–80%, which meets regulatory requirements for storing table eggs.

The study included only table eggs. Hatching eggs (intended for hatching young) were not considered in this study. References to hatching categories in the text refer to generally accepted classifications based on morphological parameters; however, the actual experimental sample was formed from commercial eggs.

The sample was designed to cover the entire range of commercial mass categories (S, M, L, XL according to EU standards). The distribution of eggs by category ensured representativeness of the boundary intervals where problems with single-criterion sorting are most pronounced.

This sampling approach ensured:

- uniformity of production conditions;
- controlled age of samples;
- comparability of measurement results;
- statistical representativeness in the analysis of a multi-criteria model.

Within the multi-criteria approach, each egg was described by a set of the following parameters:

- mass m (g);
- major and minor diameters D,d (mm);
- longitudinal cross-sectional area S (mm^2);
- contour perimeter P (mm);
- shape index I_f (%);
- shape factor K_f;
- calculated volume V (cm^3);
- density ϱ (g/cm^3).

Thus, the classification was based not on a single parameter (mass), but on nine quantitative characteristics that form a multidimensional feature space.

Statistical analysis (Table 1) showed that mass exhibited the greatest variability (Cv = 8.1%), while density had the lowest coefficient of variation (Cv = 0.65%), demonstrating its high stability as an integral physical indicator.

Table 1. General statistical characteristics of the experimental sample.

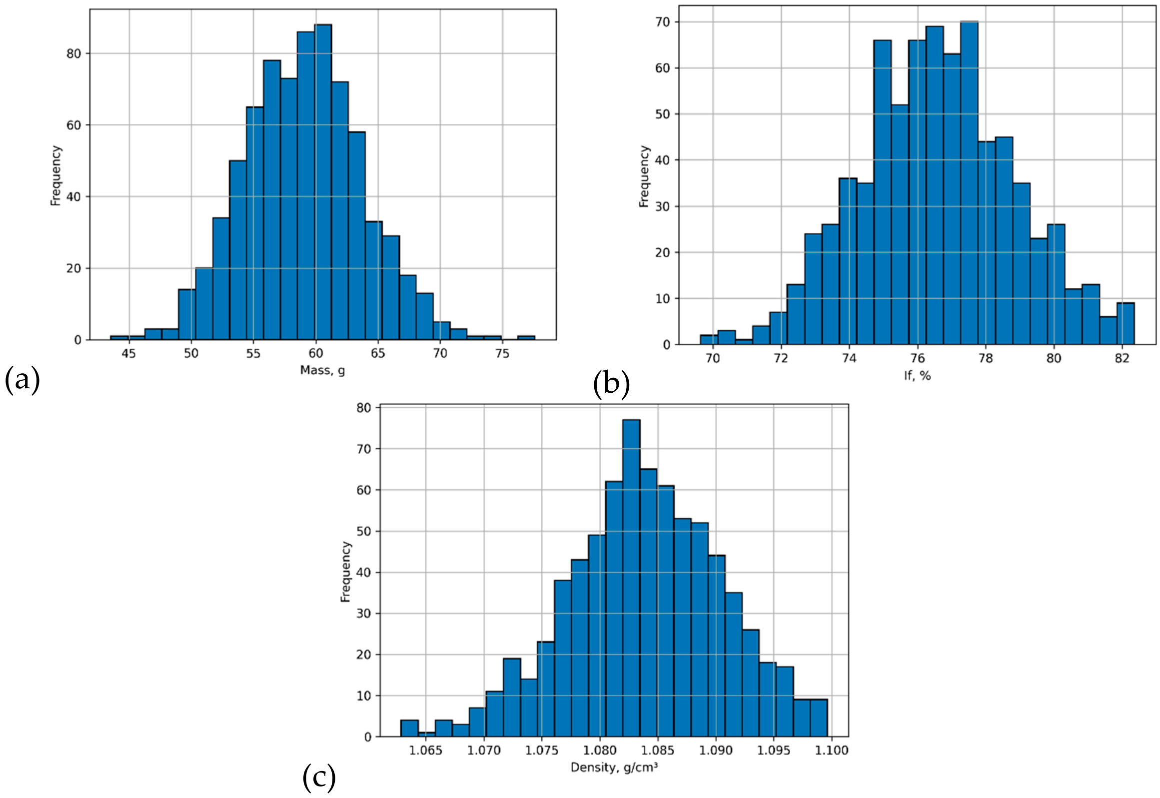
Parameter	**Designation**	**Minimum**	**Maximum**	**Mean**	**Standard deviation,σ**	**Cv, %**	**Method of obtaining**
mass (g)	m	42,3	78.6	59.1	4.8	8.1	Strain gauge
Major diameter (mm)	D	53.1	61.4	56.9	1.6	2.8	Machine vision
Minor diameter, mm	d	41.2	44.5	42.9	0.7	1.6	Machine vision
Cross-sectional area, mm^2	S	1750	2250	1985	135	6.8	Machine vision
Perimeter, mm	P	155	186	169	5.9	3.6	Machine vision
Shape index, %	If	70.1	82.4	76.3	2.3	3.0	Calculated
Shape factor	Kf	13.7	15.6	14.5	0.8	3.9	Calculated
Volume, sm^3	V	49.2	57.8	54.5	2.1	3.9	Calculated
Density, g/sm^3	ϱ	1.067	1.098	1.084	0.007	0.65	Calculated
Analysis time, sec	t	0.7	1.2	0.9	0.15	16.7	Hardware
Category	C	S	XL	-	-	-	Fuzzy logic

It should be noted that the “Quality Category” (C) parameter is not a measurable physical quantity and, unlike the other parameters in the table, is the result of a classification algorithm.

In this study, the category is formed based on a multi-criteria fuzzy model integrating the values of mass, volume, density, and morphological parameters.

Therefore, the table does not provide a numerical range; rather, it presents the full spectrum of categorical decisions produced by the algorithm.

Since parameter C is a discrete output variable of the system, the mean, standard deviation, and coefficient of variation are not calculated for it. The histograms presented in Figure 6 reflect the distribution of the key diagnostic parameters of the experimental sample: mass, shape index, and density. Their inclusion in the study is due to the need for statistical justification of the representativeness of the sample and confirmation of the informativeness of the features used within the multicriteria model.



(a) (b)

(c)

Figure 6. Histograms of distribution of the main parameters: (a) egg weight; (b) shape index If; (c).

The weight distribution (Figure 6a) demonstrates a close to normal pattern with a concentration of values in the range of 55–65 g, which corresponds to the predominant product categories M and L. The presence of distribution tails in the zones of minimum and maximum values confirms the coverage of the boundary weight intervals in which errors in single-criterion sorting by fixed thresholds are most likely.

The shape index distribution (Figure 6b) is characterized by moderate variability and reflects the presence of morphological differences with comparable linear dimensions. This confirms the feasibility of including morphological parameters in the quality assessment system, since geometric deviations can be present even with standard weight.

The density histogram (Figure 6c) exhibits significantly lower variation than weight, consistent with the minimal coefficient of variation (Cv = 0.65%). However, the observed asymmetry in the lower range of values indicates the presence of eggs with lower density, which is associated with an increase in the air cell volume. This fact confirms the diagnostic independence of density as a physical parameter that weakly correlates with weight and geometric characteristics ($|r| \leq 0{,}29$, Table 2).

The presented histograms are used to:

- confirm the statistical correctness of the experimental sample;
- visually assess the overlap of mass intervals;
- substantiate the independence of density as a diagnostic feature;
- demonstrate the need to use a multicriteria approach instead of a rigid threshold classification.

The presence of overlapping distribution zones further confirms the limitations of single-criterion mass sorting and explains the feasibility of using a fuzzy model for robust classification decisions in boundary ranges.

Table 2. Correlation Matrix.

Parameter	m	D	d	S	P	V	ϱ	If	Kf
m (mass)	1.00	0.88	0.82	0.86	0.84	0.94	–0.21	–0.18	–0.23
D (major diameter)	0.88	1.00	0.79	0.91	0.89	0.91	–0.18	–0.42	–0.37
d (minor diameter)	0.82	0.79	1.00	0.86	0.83	0.86	–0.23	–0.51	–0.44
S (Cross-sectional area)	0.86	0.91	0.86	1.00	0.95	0.93	–0.26	–0.35	–0.31
P (perimeter)	0.84	0.89	0.83	0.95	1.00	0.90	–0.24	–0.33	–0.29
V (volume)	0.94	0.91	0.86	0.93	0.90	1.00	–0.29	–0.22	–0.27
ϱ (density)	–0.21	–0.18	–0.23	–0.26	–0.24	–0.29	1.00	0.08	0.11
If (shape index)	–0.18	–0.42	–0.51	–0.35	–0.33	–0.22	0.08	1.00	0.84
Kf (shape factor)	–0.23	–0.37	–0.44	–0.31	–0.29	–0.27	0.11	0.84	1.00

Correlation analysis (Table 2) showed that egg weight is closely related to geometric parameters and volume (r = 0.88–0.94), confirming the physical basis of the weight criterion. However, density exhibits a weak correlation with weight and size (|r| ≤ 0.29), indicating its independent diagnostic nature and confirming the appropriateness of including this parameter in a multi-criteria quality assessment model.

The high correlation between the shape index and the shape coefficient (r = 0.84) indicates the consistency of morphological indicators, while their negative correlation with linear dimensions reflects the influence of the egg geometry on its aerodynamic and mechanical stability.

It should be noted that the parameters S, P, V and Kf, which demonstrated high information content in the correlation analysis, are not determined manually in principle and are available only when using the developed hardware, which emphasizes the role of the multifunctional rotary unit not only as an automation tool, but also as a tool for expanding the diagnostic capabilities of the egg quality control system.

The correlation map (Figure 7) clearly confirms the presence of two clusters of parameters: weight-geometric (m, V) and physical (ϱ), which experimentally substantiates the feasibility of using a multi-criteria model for assessing egg quality.

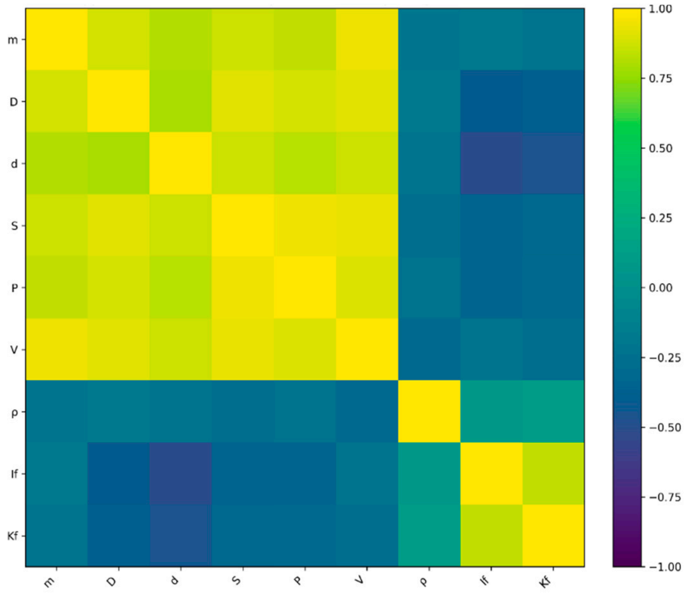


Figure 7. Correlation map of key egg quality parameters.

The selection of a regulatory classification standard is made during the system configuration stage and is determined by the requirements of the operating enterprise or the target market for the product. The automatic sorting system does not perform simultaneous classification according to EU and EAEU standards. At any given time, the algorithm operates within the framework of one selected regulatory scale.

Technically, the standard is selected by configuring the parameters of the membership functions and category boundary intervals during the software initialization phase. The structure of the multicriteria model, the composition of the diagnostic parameters, and the fuzzy inference logic remain unchanged; only the normative category boundaries and the corresponding rules are modified.

It should be noted that the algorithm is universal in architecture and adaptable across the regulatory scale. Switching between standards does not require hardware modifications or revisions to the mathematical model, but is accomplished by selecting the appropriate configuration profile.

Comparison of classification results using the alternative standard was used solely for analytical purposes to assess category redistribution and identify differences between the standard systems. The results of the comparative analysis of manual and automatic classification are presented in Table 3.

Table 3. Comparison of Manual and Automatic Classification.

Category (EC)	Mass, g	Manual sorting, pcs	Rotary installation, pcs	Abs. deviation, pcs	Rel. deviation, %
K_S	< 53	267	235	32	11.9
K_M	53–63	249	260	11	4.4
K_L	63–73	199	195	4	2.0
K_XL	> 73	35	30	5	14.3
Defective/non-standard	–	0	30	30	–
Total	–	750	750	–	–

To accurately compare the results, it is necessary to refine the manual grading algorithm. In the study, manual classification was performed by a poultry farm operator in accordance with EU standards using a weight criterion. The procedure included the following steps:

1. Weighing eggs on an electronic scale.
2. Determining the category using established weight ranges (K_S <53 g; K_M 53–63 g; K_L 63–73 g; K_XL >73 g).
3. Visual inspection of the shell for obvious defects.
4. The manual grading capacity was 900 eggs per hour.

Geometric parameters (shape index, shape coefficient, area, perimeter), as well as egg density, were not manually measured. Therefore, manual sorting is primarily single-criteria (mass) with elements of subjective visual assessment.

The automated system used in the experiment was configured to operate according to EU standards. The automated sorting capacity was 3,600 eggs per hour.

A comparison of the results of manual and automatic classification (Table 3) reveals a redistribution of eggs between the marginal categories. The largest discrepancies are observed in the K_S and K_XL categories, where the relative deviation was 11.9% and 14.3%, respectively. Furthermore, the automated system classified 30 eggs (4% of the sample) in the “Defective/Non-Standard” category, which was absent from manual sorting.

It is important to emphasize that the conclusion regarding the superiority of automatic classification is based not only on the difference in the number of categories, but also on the structure of the diagnostic parameters used. Correlation analysis (Table 2) showed that density forms an independent diagnostic cluster ($|r| \le 0.29$), which is not taken into account during manual sorting.

Thus, the automatic system utilizes an expanded feature space, including morphophysical characteristics, which allows it to identify objects with standard mass but deviations in internal or geometric parameters.

Therefore, the differences between manual and automatic classification are not due to the inaccuracy of one system or the other, but to the difference in methodological approach: a single-criterion threshold model versus a multi-criterion model with fuzzy inference. The results demonstrate that the multi-criteria algorithm provides a more detailed lot structure by identifying boundary and non-standard items, which, during manual sorting, are distributed within product classes.

Within the fuzzy model, an object was classified as "Defective/Non-Standard" if the maximum aggregated degree of belonging to commodity classes was below the established threshold value of $\mu<0.5$. Thirty eggs (4% of the sample), classified by the automated system into this category, had standard weight, but demonstrated deviations in morphological or physical parameters that were not detected by traditional weight sorting.

It should be emphasized that this category is not regulated by the EU standard as a separate product class; however, its identification increases the diagnostic sensitivity of the system and allows for the exclusion of potentially non-standard products from batches.

The classification decision algorithm is based on a Mamdani-type fuzzy inference system, in which the input parameters are mass m, volume V, density ϱ, shape index I_f , and shape factor K_f.

For each parameter, membership functions for the corresponding product categories are defined. The final degree of an object's membership in a category is calculated based on the aggregation of fuzzy logic rules. The final decision is made based on the maximum value of the aggregated membership function. If the maximum degree of membership in any product category does not exceed the established threshold of $\mu<0.5$, the egg is classified as "Defective/Non-Standard."

The numerical results of applying the algorithm to a sample of 750 eggs showed the following:

- redistribution of 32 eggs (11.9%) from the K_S category;
- redistribution of 11 eggs (4,4%) from the K_M category;
- redistribution of 4 eggs (2,0%) from the K_L category;
- redistribution of 5 eggs (14,3%) from the K_XL category;
- allocation of 30 eggs (4% of the sample) to the category "Defective/non-standard".

Correlation analysis (Table 2) showed that density exhibits a weak relationship with mass and volume ($|r| \leq 0.29$), confirming its independent diagnostic value. However, mass and volume are highly correlated ($r = 0.94$), indicating partial duplication of information in the weight-geometric cluster.

Thus, adding the density parameter expands the dimensionality of the feature space and allows for the identification of objects with standard weight but internal structure deviations. This is confirmed by the fact that 30 eggs with acceptable weight were excluded from the product categories by the automated system.

Therefore, the proposed algorithm enables a transition from single-criteria weight sorting to physically and morphologically validated multi-criteria classification. The differences between manual and automatic sorting are not due to measurement error, but to the expansion of the set of diagnostic features and the use of a fuzzy decision-making mechanism that takes into account the uncertainty and biological variability of objects.

4. Conclusions

1. This work involved developing and experimentally testing a rotary automated system for individual non-destructive quality control and sorting of chicken eggs into categories. This system provides a complete measurement and classification cycle in an average of 0.9 s (range 0.7–1.2 s). The drum is divided into 10 functionally distributed cells and enables sequential passage through the feeding, weighing, optical analysis, and sorting zones within a single cycle.

Operational tests on a sample of 750 eggs confirmed the stability of object positioning, synchronization of measurement operations, and reproducibility of results, which ensures the technological completeness and industrial applicability of the proposed architecture.

2. A single hardware and software cycle for determining mass (42.3–78.6 g; average 59.1 g; σ = 4.8 g; Cv = 8.1%), linear dimensions (D = 53.1–61.4 mm; d = 41.2–44.5 mm), longitudinal sectional area (1750–2250 mm^2) and perimeter (155–186 mm) was implemented, followed by calculation of volume (49.2–57.8 cm^3) and density (1.067–1.098 g/cm^3; average 1.084 g/cm^3; σ = 0.007; Cv = 0.65%). Correlation analysis revealed a high correlation between the parameters of the weight-geometric block (m–V: r = 0.94; m–D: r = 0.88; m–S: r = 0.86), confirming the physical basis of the weight criterion. At the same time, density demonstrated a weak correlation with mass and size ($|r| \leq 0.29$), which statistically substantiates its independent diagnostic significance and the need for inclusion in the multi-criteria quality assessment model.

3. A controlled sample of 750 table eggs was generated, covering the entire range of EU product categories S–XL. The weight distribution was close to normal, with a maximum concentration of values in the 55–65 g range, while maintaining the boundary intervals where single-criterion sorting errors are most likely. The presence of distribution tails and overlapping parameter ranges confirmed the representativeness of the sample and allowed for an accurate assessment of the stability of the classification model under conditions of biological variability. The analysis revealed the presence of two diagnostic clusters: weight-geometric (m, V, D, d, S, P) and physical (ϱ). Density forms a separate independent cluster ($|r| \leq 0.29$), while mass and volume are closely correlated (r = 0.94), indicating partial duplication of information within the weight block. The high correlation between the shape index and the shape coefficient (r = 0.84) confirms the consistency of the morphological indicators with their additional information content. The minimal variability of density (Cv = 0.65%) indicates its diagnostic stability as an integral physical quality indicator.

4. A Mamdani-type fuzzy inference system was implemented, comprising 24 rules and using the parameters m, V, ϱ, If, and Kf. The use of overlapping membership functions ensured classification stability in the intersection zones of mass intervals. Using the threshold condition $\mu < 0.5$, the system classified 30 eggs (4% of the sample) as "Defective/Non-Standard," despite their weight being within the standard range. This experimentally confirms the model's expanded diagnostic capabilities compared to strict threshold sorting.

5. The comparison revealed a redistribution of eggs within the border categories: 32 eggs (11.9%) in the K_S category, 11 eggs (4.4%) in the K_M category, 4 eggs (2.0%) in the K_L category, and 5 eggs (14.3%) in the K_XL category. The automated system additionally identified 30 non-standard items, which were distributed within the product classes during manual sorting. The differences are not due to measurement error, but to the expansion of the feature space and the use of a fuzzy decision-making algorithm. This demonstrates the transition from formal single-criteria weight sorting to physically and morphologically based multi-criteria quality diagnostics.

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Data Availability Statement: The raw/processed data required to reproduce these findings cannot be shared at this time, as the data also form part of an ongoing study. However, the data can be provided to readers when kindly requested.

Conflicts of Interest: The authors have no conflicts of interest to declare.

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