EggQuality-UFRPE: A Chicken Egg Dataset for Multidisciplinary Studies in Animal Science and Computing

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Abstract. *This paper presents EggQuality-UFRPE, a multidisciplinary dataset comprising 2,150 chicken egg instances with 29 features, collected through manual measurements using advanced instrumentation. It addresses the scarcity of open-access empirical data in animal science, supporting multidisciplinary research with computer disciplines, such as data science and machine learning. A descriptive analysis is included, reporting mean, median, dispersion metrics, missing data proportions, and Pearson correlation coefficients among features. These statistics reveal the dataset's internal consistency and support exploratory modeling. Despite limitations, such as a single hen strain, the dataset enables applications ranging from regression and predictive modeling to synthetic data generation and multimodal learning, promoting integration between computational and animal sciences.*

1. Introduction

The publishing of datasets has become an essential pillar for the advancement of scientific research across multiple disciplines. In recent years, there has been an exponential growth in the number of published datasets, especially those generated entirely through digital means. Studies with datasets from social media platforms such as Twitter [Kakimoto et al. 2024] and TikTok [Lima et al. 2023] can be easily found, as well as image datasets such as [Chang et al. 2019] and user-generated data [Silva et al. 2024]. These datasets are easily collected, processed, and shared, as they are inherently born-digital and do not require significant manual intervention.

Many scientific domains, such as biological sciences, animal science, and agricultural engineering, still face a critical scarcity of openly available datasets. Unlike in computer science, where data is often collected automatically through digital pipelines, these fields depend on complex, time-consuming, and costly physical data collection processes. Researchers must rely on manual measurements, laboratory equipment, and specialized machinery, and even when high-quality research is published in prestigious journals—whether from animal science [Wang et al. 2019], computer science [Sehirli and

Arslan 2022], or interdisciplinary venues [Coronel-Reyes et al. 2018]—it is rare for the associated datasets to be shared. The poultry industry, particularly in chicken egg studies, exemplifies this gap. Obtaining detailed morphological and quality-related data on eggs typically requires labor-intensive methods, including caliper measurements, gravimetric analysis, and advanced imaging techniques like Magnetic Resonance Imaging (MRI). Access to such resources remains limited geographically and financially, making publicly available, high-quality datasets on chicken eggs—especially those acquired through rigorous physical procedures—exceedingly rare [López Vargas et al. 2024].

In response to this pressing need, this dataset paper introduces and describes EggQuality-UFRPE, a valuable dataset focused on chicken eggs. The dataset was collected almost entirely through manual and physical procedures supported by advanced instrumentation. The complexity and resource-intensive nature of this data acquisition process make the dataset particularly rare and valuable for the research community. It is available in the Github Repository: https://github.com/InnovaZoo/EggQuality-UFRPE.

The primary motivation for creating this dataset stems from a broader research project aimed at applying computer vision and machine learning techniques to assess and predict chicken egg quality. This dataset represents the foundational step of that larger initiative, providing researchers with rich empirical data that can serve multiple purposes. Potential applications of this dataset span across disciplines, supporting work in animal science and artificial intelligence, including the validation of theoretical models related to egg measurements, conducting correlation and regression analyses, developing predictive models, estimating key variables, and even experimenting with the application of Large Language Models (LLMs) for feature extraction from egg images. The combination of empirical data with detailed physical measurements opens the door for multidisciplinary research that bridges the gap between computational techniques and animal sciences.

The remainder of this dataset paper is organized as follows. Session 2 briefly presents related works that used computational methods for analyzing or predicting in animal science. Section 3 presents the methodology and tools for data collection. Section 4 presents a detailed description of the dataset, with an initial general data analysis and a discussion regarding its usability and possible future works. Lastly, Section 5 wraps up the concluding remarks.

2. Related Works

The assessment of egg properties and quality using computational methods has been the subject of a limited number of studies in the scientific literature. Zhao et. al. [Zhao et al. 2010] investigated the classification of egg freshness using near-infrared (NIR) spectroscopy combined with various pattern recognition techniques. A total of 101 eggs were used, and NIR spectral data were collected from all samples. The classification of eggs as either fresh or non-fresh was performed using several methods, including Partial Least Squares Discriminant Analysis (PLS-DA), k-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), Support Vector Machines (SVM), and Support Vector Data Description (SVDD). The SVDD method yielded the highest classification accuracy, achieving a rate of 93.3%. Later, [Zhang et al. 2015] also assessed internal egg quality by using NIR spectral range and determined the Haugh Unit (HU) value. Their study involved a total of 645 eggs, which were stored for varying durations and divided into three distinct sets. The Successive Projections Algorithm combined with Support Vector Classification (SPA-SVC) was applied to classify egg freshness, obtaining a classification accuracy of 84.0%.

Soltani and Omid [Soltani and Omid 2015] investigated the possibility of non-destructive classification and quality inspection of eggs using the dielectric detection technique at the radio frequency. In total, 150 eggs were used with several machine learning (ML) methods for freshness detection and air cell height, including artificial neural networks (ANN), Bayesian networks (BNs), decision trees (DTs), and support vector machines (SVMs), and BNs presented the highest performance.

More recently, [Coronel-Reyes et al. 2018] applied artificial neural networks in a sample of 660 eggs to determine the egg storage time at room temperature; [Wang et al. 2019] studied measurement methods on the phenotype of 354 eggs; and [Sehirli and Arslan 2022] also used several machine learning models, such as DT, LDA, LR, NB, SVM, KNN, RF and ANN for the classification of egg quality and haugh unit based on 803 eggs in its 20 features. Lastly and very recently, [López Vargas et al. 2024] presented an approach for estimating morphometric measurements of chicken eggs based on tomographic images and computer vision, using 150 eggs.

The main commonality of these studies is the low number of samples (eggs) collected, varying between 101 and 803. Also, with the only exception of [López Vargas et al. 2024], the studies did not publish the used dataset, making it hard, if not impossible, to replicate the experiments, assess the results, or produce new studies based on them.

3. Data Collection

In order to collect egg features, the entire dataset was built by evaluating eggs from laying hens of the Dekalb White strain, reared at the Poultry Research Laboratory of the *Universidade Federal Rural de Pernambuco (UFRPE)*. These eggs come from a research project approved by the UFRPE Animal Ethics Committee (CEUA 6000110221).

The data collection was conducted on fresh eggs (0 days) and eggs stored at room temperature (26,42 ± 1,31°C) for 7, 14, 21, and 28 days. The entire dataset was built by the research team using a set of techniques. It is categorized according to the poultry literature, considering (a) quality features, such as yolk weight, height and color; (b) egg shape features, such as egg length, maximum egg width and shape index; and (c) other, such as storage time, destination and extra observations. Usually, the destination is defined by the storage time, but one of the objectives of the dataset is to allow the estimation of the storage time according to the other features. Table 1 shows the list of features, including their category, label (as in the dataset), description, type of collection, and tool used for collection.

The features can also be grouped into two groups according to their source. Primary features are extracted directly from the eggs or primary measurements, and computed features are calculated from the primary data.

Considering the primary features, some data, such as the Hen age and storage time, were already known. Other features were collected using non-destructive techniques, such as the egg length, the maximum egg width, and the egg diameter. Additionally, some features need destructive techniques, such as the shell-breaking force, shell weight, and shell thickness, as they require breaking the egg for measurement.

Table 1. List of features, including their category, label (as in the dataset), description, type of collection, and tool used for collection

Category	Label	Description	Collection	Tool
ID	N_OVO	Egg Number (ID)	Defined	
Quality features	IDADE_AVES	Hen Age (weeks)	Previous Knowledge	
	P_OVO	Egg Weight	Non-Destructive	Semi-analytical balance
	AL_ALB	Albumen Height (mm)	Destructive	Egg tester
	PH_ALB	Albumen pH	Destructive	pH meter
	P_ALB	Albumen Weight (g)	Calculated	
	%_ALB	Albumen Weight Percentage (%)	Calculated	
	P_GE	Yolk Weight (g)	Destructive	Semi-analytical balance
	C_GE	Yolk Color	Destructive	Egg tester
	%_GE	Yolk Weight Percentage (%)	Calculated	
	YH	Yolk Height (mm)	Destructive	Egg tester
	YD	Yolk Diameter (mm)	Destructive	Egg tester
	YI	Yolk Index	Destructive	Egg tester
	HU	Haugh Unit	Destructive	Egg tester
	RK	Haugh Unit Ranking	Destructive	Egg tester
	F_Q	Shell Breaking Force (kgf)	Destructive	Egg tester
	P_CA	Shell Weight (g)	Destructive	Semi-analytical balance
	E_CA	Shell Thickness (mm)	Destructive	Micrômeter
	%_CA	Shell Weight Percentage (%)	Calculated	
	OV	Candling - Translucency	Non-Destructive	Images' visual analyzis
	CL_PESO	Weight Class	Calculated	
Egg shape features	L	Egg Length (mm)	Non-Destructive	Digital caliper
	B	Maximum Egg Width (mm)	Non-Destructive	Digital caliper
	I_FOR	Shape Index	Calculated	
	CLA_I_FOR	Shape Index Classification	Calculated	
	VOL_OVO	Egg Volume (cm^3)	Calculated	
	S_OVO	Egg Surface Area (cm^2)	Calculated	
Other	TEMPO	Storage Time (days)	Previous Knowledge	
	DESTINACAO	Destination	Calculated	
	OBS	Extra observations		

For the data collection of primary features, special tools were used, such as a semi-analytical balance (L3102iH, Bel Engineering®, Milan, Italy), an egg tester (Egg tester det6500), a micrometer (547-360, Mitutoyo), a digital caliper (684132, Lee-Tools), and a pH meter (Akso pH Basic, Akso, São Leopoldo, Brazil). For example, egg length and width measurements were taken using the digital caliper. To determine the thickness of the shell, it was washed and then dried at room temperature (26,42 ± 1,31°C) for 48 h. The measurement was then determined by averaging the thickness of the basal, equatorial, and apical regions using a digital micrometer. The egg tester took most of the destructive features, and the pH meter measured the albumen pH. Lastly, three different researchers performed a visual assessment of the candling images for the translucency, and the discrepancies were resolved through a consensus meeting. Some of this equipment, owned by the research group and used in this collection, is shown in Figure 1.

Considering the computed features, they are calculated from the primary data. Table 2 presents the formulas used to determine the computed features. The first four computed features are straightforward. The weight of the albumen (P_ALB) is obtained by subtracting the weights of the yolk (P_GE) and the shell (P_CA) from the total egg weight (P_OVO). The percentages of albumen (%_ALB), shell (%_CA), and yolk (%_GE) are calculated by dividing each component's weight by the total egg weight (P_OVO). The remaining calculations are based on values reported in the literature. The weight classification (CL_PESO) is defined according to the Brazilian Ministry of Agriculture and Livestock[1], while the shape index (I_FOR) is presented by [K.E. Anderson et al. 2003], and the shape index classification (CLA_I_FOR) is provided by [Duman et al. 2016]. Lastly, for the egg volume (VOL_OVO) and surface area (S_OVO), we used the formulations presented in [Narushin 2005]. Table 2 presents the formulas used.

(a) Digital Caliper (b) Micrometer (c) Egg Tester

Figure 1. Measuring Equipment

Table 2: Calculations of computed features

Feature	*Calculation*
P_ALB	P_OVO - P_GE - P_CA
%_ALB	P_ALB / P_OVO
%_GE	P_GE / P_OVO
%_CA	P_CA / P_OVO
CL_PESO: JUMBO	P_OVO >= 68
CL_PESO: EXTRA	68 > P_OVO >= 58
CL_PESO: GRANDE	58 > P_OVO >= 48
CL_PESO: MÉDIO	48 > P_OVO >= 38
CL_PESO: OTHER	38 > P_OVO
I_FOR	B / L
CLA_I_FOR: PONTIAGUDO	I_FOR < 72
CLA_I_FOR: PADRÃO	72 <= I_FOR <= 76
CLA_I_FOR: REDONDO	76 < I_FOR
VOL_OVO	(0.6057 - 0.0018 * B) * L * (B ^ 2) / 1000
S_OVO	(3.155 - 0.0136 * L + 0.00155 * B) * L * B)/100

3. The EggQuality-UFRPE Dataset

The data collection was conducted on fresh eggs (0 days) and eggs stored at room temperature (26,42 ± 1,31°C) for 7, 14, 21, and 28 days. It was 400 fresh and 7-day eggs each, 430 14-day eggs, 460 21-day and 28-day eggs each, totaling 2150 instances. The dataset is composed of 29 features, not considering the egg ID (N_OVO), as presented in Table 1. Twenty four features are numeric, four are categorical (RK, CL_PESO, CLA_I_FOR, DESTINACAO), and one is descriptive (OBS).

[1] MAPA (Ministério da Agricultura, Pecuária e Abastecimento). 2024. Portaria SDA/MAPA nº 1.179, de 5 de setembro de 2024. Diário Oficial da União, Brasília, DF. Disponível em: https://www.gov.br/agricultura/pt-br/assuntos/defesa-agropecuaria/suasa/regulamentos-tecnicos-de-identidade-e-qualidade-de-produtos-de-origem-animal-1/PORTARIASDA_MAPAN1.179DE5deSETEMBRODE2024PORTARIAOVO.pdf

Missing data in the dataset can be attributed to several factors. Primarily, the inherent fragility of eggs plays a significant role. Some eggs were accidentally damaged or lost during handling, making data collection impossible. Furthermore, certain eggs exhibited physical or internal anomalies—such as dirt, cracks, or, in one case, the presence of double yolks—which compromised measurement accuracy. Additionally, occasional malfunctions in the data acquisition equipment may have contributed to the loss of information. Given these challenges, particularly those related to the delicate nature of the samples, the missing value rate of 5.5% can be considered low and indicative of careful handling and effective data collection protocols. Records containing missing data were retained in the database, with empty values.

In addition to the percentage of missing data for each column, Table 3 provides basic descriptive statistics, including mean, median, dispersion (relative standard deviation – RSD), minimum, and maximum values for all numeric features, offering a general overview of the dataset.

Table 3: Statistics for numeric features, including mean, median, dispersion, minimum and maximum values, and the percentage of missing data

Feature	Mean	Median	Dispersion	Min.	Max.	Missing	Missing(%)
IDADE_AVES	62.45	53.00	0.30	25.00	85	0	0%
P_OVO	62.15	62.30	0.09	44.50	87.2	4	0%
AL_ALB	5.05	4.50	0.37	2.50	10.6	81	4%
PH_ALB	9.34	9.30	0.15	6.40	57.2	40	2%
P_ALB	38.09	37.74	0.13	19.19	58.814	244	11%
%_ALB	61.12	61.03	0.06	31.01	75.179	244	11%
P_GE	17.94	17.92	0.10	10.45	33.976	234	11%
C_GE	6.06	6.00	0.13	1.00	10	79	4%
%_GE	28.97	29.00	0.10	16.02	54.889	234	11%
YH	13.60	13.50	0.23	3.40	20.8	81	4%
YD	46.58	46.00	0.15	5.10	112.1	124	6%
YI	0.30	0.30	0.28	0.03	0.618	124	6%
HU	65.48	63.90	0.24	26.40	101.7	81	4%
F_Q	4.31	4.38	0.27	0.58	7.98	10	0%
P_CA	6.15	6.17	0.11	2.24	9.712	20	1%
E_CA	0.41	0.40	0.46	0.26	5.45	10	0%
%_CA	9.95	9.94	0.11	3.70	16.461	21	1%
OV	2.14	2.00	0.42	1.00	4	4	0%
L	58.22	58.29	0.04	50.33	73.32	3	0%
B	44.43	44.49	0.03	38.55	50.36	3	0%
I_FOR	76.38	76.46	0.03	64.03	93.41	3	0%
VOL_OVO	60.55	60.70	0.09	43.15	91.019	3	0%
S_OVO	62.86	63.08	0.06	0.00	80.197	1	0%
TEMPO	14.59	14.00	0.68	0.00	28	0	0%

Lastly, Figure 2 provides a correlation map of the features. In the figure, strong blue indicates a high positive correlation, and strong red indicates a high negative correlation. To support a better understanding, Table 4 lists the 20 strongest correlations, all of them with their absolute value $p >= |0.67|$.

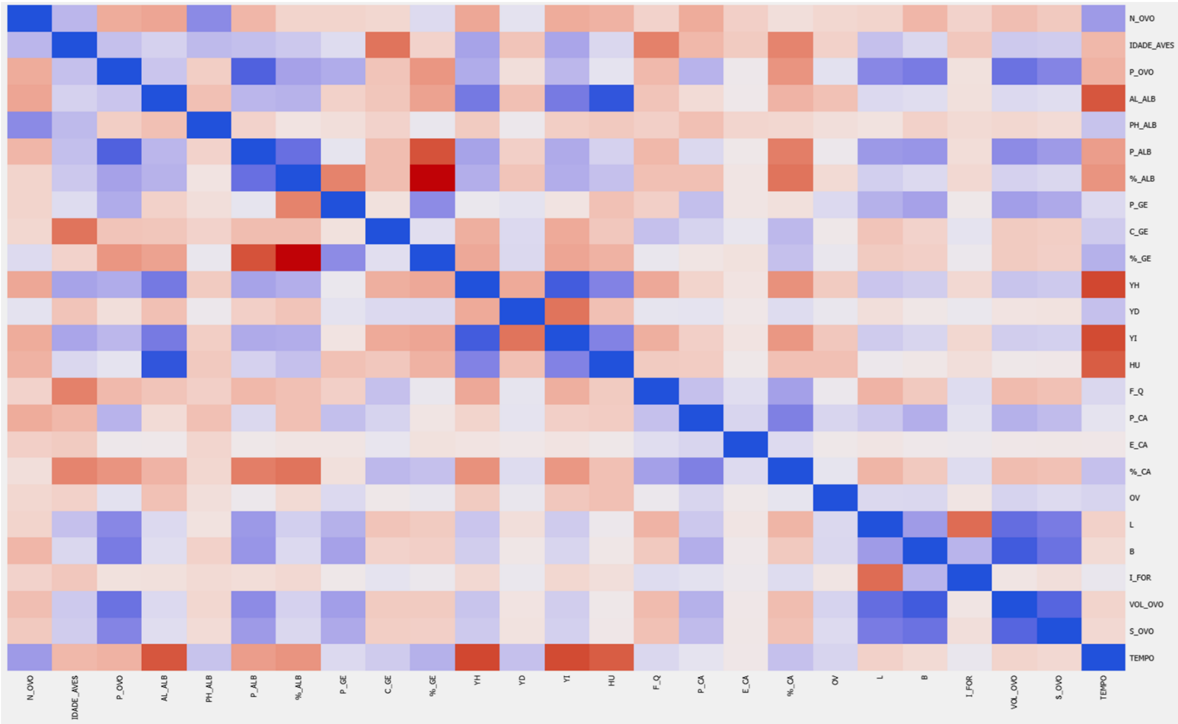

Figure 2: Features' Correlations. Bold colors mean high correlation

Table 4: The 20 strongest correlations between features

	p	Feature 1	Feature 2		*p*	Feature 1	Feature 2
1	0.968	AL_ALB	HU	11	-0.769	TEMPO	YH
2	-0.945	%_ALB	%_GE	12	-0.751	TEMPO	YI
3	0.924	B	VOL_OVO	13	0.728	AL_ALB	YH
4	0.917	YH	YI	14	0.719	AL_ALB	YI
5	0.879	P_ALB	P_OVO	15	-0.718	%_GE	P_ALB
6	0.858	S_OVO	VOL_OVO	16	0.715	L	S_OVO
7	0.803	L	VOL_OVO	17	0.712	B	P_OVO
8	0.793	%_ALB	P_ALB	18	-0.707	AL_ALB	TEMPO
9	0.778	B	S_OVO	19	0.683	%_CA	P_CA
10	0.775	P_OVO	VOL_OVO	20	-0.676	HU	TEMPO

4. Discussion

The primary objective of creating this dataset is its use as "ground data" in a multidisciplinary project entitled "Prediction of Chicken Egg Quality Using Candling, Depth Sensing, Computed Tomography, Computer Vision, and Machine Learning". This dataset is the first part of the project that, by adding images of different sources (such as Computed Tomography, Candling, and Depth Sensing), aims to create and compare diverse ways of predicting and estimating egg characteristics and quality using computational techniques, such as Computer Vision and Machine Learning.

One of the project's initial results is presented in [López Vargas et al. 2024]. The study used an initial sample of this dataset, with data from 150 eggs, and the only features used were the egg's length, width, shell thickness, and the calculated volume. Then, the eggs were submitted to computed tomography, and the sample of data was used to train and validate the computer vision models designed to estimate the eggs' morphometric measurements.

This dataset is relevant to animal and computer science, especially for multidisciplinary research. Due to the need for costly manual and physical procedures supported by advanced instrumentation for collecting data, allied to a lack of open datasets of this nature, this dataset is a step in the direction of supporting researchers in both areas to improve their projects. A direct example of data scarcity is the study defining the formula for calculating the egg's volume. In 2005, [Narushin 2005] used a sample of only 90 fresh eggs, and it became a world reference. Thus, by exploring the EggQuality-UFRPE, with 2150 instances, both previous research data can be validated or improved, and new conclusions can be drawn. For computer scientists, who usually work with digitally created data, a new set of work can be done, including data science for knowledge discovery and machine learning models for predicting and estimating features in the absence of the resources for manually collecting them. We can exemplify the conduct of correlation and regression analyses, developing predictive models, estimating key variables, and even experimenting with the application of Large Language Models (LLMs) for feature extraction or estimation. The combination of empirical data with detailed physical measurements opens the door for multidisciplinary research that bridges the gap between computational techniques and animal sciences.

While the dataset offers considerable potential for various analyses, it also presents limitations. First, the eggs were from one unique strain, which impacts the generalization for future studies. Also, the eggs were stored at room temperature in Recife, a warm and humid city (26,42 ± 1,31°C). Moreover, even when strictly following established protocols in the field, manual procedures are inherently susceptible to errors, such as the accidental breakage of eggs during handling. Finally, the research community must exercise great caution when using these data and making strong claims, as the measurements pertain to living organisms, which are influenced by thousands of variables beyond those captured in this dataset.

5. Concluding Remarks

The EggQuality-UFRPE dataset, containing 29 features across 2,150 instances of chicken eggs aged from 0 to 28 days, and originating from hens aged between 25 and 85 weeks, represents a valuable contribution to both animal science and computer science. Collected through rigorous manual and instrumental procedures, the dataset offers high-quality empirical data rarely found in open-access formats. In addition to the dataset itself, available in the Github Repository https://github.com/InnovaZoo/EggQuality-UFRPE, this work presents a comprehensive descriptive analysis, including the mean, median, dispersion, range metrics, proportions of missing data, and Pearson correlation coefficients among features, enabling an initial understanding of the dataset's internal structure and consistency.

This resource opens multidisciplinary opportunities by addressing the notable scarcity of openly available poultry-related datasets. Despite limitations, such as using a single hen strain, temperature-specific storage conditions, and potential manual measurement errors, it is a robust foundation for validating current models and developing predictive tools using computer vision and machine learning techniques.

Future work may expand the dataset by including eggs from different genetic strains and environmental conditions to enhance generalizability. Further integration of image-based data, such as computed tomography, candling, and depth sensing, will support multimodal learning approaches. Additionally, this dataset may be used for the development of synthetic data generation techniques and for evaluating the applicability of large language models in feature extraction and annotation tasks, promoting cross-disciplinary innovation.

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