SYSTEMIZATION OF REQUIREMENTS FOR OPERATIONAL QUALITY CONTROL SYSTEMS OF MEAT PRODUCTS

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Abstract. This paper presents a study on organizing requirements for automated meat quality control systems. It identifies key quality indicators – color, texture, marbling, and gloss and analyzes the technical and functional parameters essential for practical assessment. The research highlights integrating computer vision, image processing, and machine learning algorithms to enhance objectivity, accuracy, and evaluation speed. The proposed approach aims to reduce human influence, enable real-time monitoring, and offer scalable solutions suitable for large-scale producers and small enterprises.

Key words: meat quality control, classification algorithms, computer vision, machine learning, image analysis, texture assessment, marbling evaluation, automated quality systems.

1. Introduction

Quality control of meat products is a crucial aspect of the modern food industry, driven by high safety standards and the need to assess product quality characteristics objectively. As consumer demand for safe and high-quality food products continues to rise, the importance of effective control methods becomes increasingly significant. However, traditional assessment methods, such as organoleptic, physicochemical, and microbiological analyses [1], have significant drawbacks – they are labor-intensive, costly, and heavily reliant on human factors. This underscores the necessity for developing innovative approaches that enable more precise and rapid assessment of meat quality.

The primary goal of this research is to identify meat's key quality characteristics and establish control system requirements. Evaluating parameters directly influencing product quality, such as color, texture, marbling, and gloss, is crucial. Additionally, it is essential to explore the fundamental characteristics of quality control systems, ensuring analysis accuracy and speed, minimizing subjective errors, and integrating collected data into contemporary quality control information systems.

Classification algorithms play a pivotal role in the development of highly accurate models that evaluate meat parameters with minimal error [2]. Such an approach not only enhances control efficiency but also increases consumer trust and reduces the risk of distributing substandard products. By streamlining control system requirements, we can establish precise evaluation criteria and significantly elevate the effectiveness of meat product quality monitoring processes.

2. Drawbacks

Traditional methods for assessing meat quality – sensory evaluations, physicochemical tests, and microbiological analyses – have several limitations. These approaches are often resource-intensive, requiring considerable time, labor, and expertise. Additionally, they can be subjective and inconsistent due to human involvement [3], making them unsuitable for real-time application in modern, high-throughput production environments. While machine learning and image-based technologies offer promising alternatives, their effectiveness depends heavily on the accurate selection of input features. If irrelevant or inadequately defined characteristics are used, the models may generate unreliable results and lead to incorrect quality classifications. Therefore, the success of automated systems relies on identifying and utilizing the most informative and representative parameters to ensure high accuracy and robust decision-making.

3. Goal

The goal of this research is to define key meat quality indicators and requirements for automated control systems to improve assessment accuracy and efficiency.

4. Core characteristics of meat quality control systems

An effective meat quality control system must satisfy several essential criteria to ensure its practical application, accuracy, and scalability. These characteristics include:

- Processing Speed. Rapid analysis is crucial for timely detection of quality deviations. Real-time evaluation prevents substandard products from reaching consumers and is especially vital in high-volume production lines. Modern technologies facilitate fast, automated assessment without interrupting workflow.
- Accuracy. Precision in measurement is fundamental for maintaining product standards. Minimizing errors through digital technologies – such as spectral analysis, computerized evaluation, and machine learning algorithms – ensures reliable quality assessments and enhances food safety.

- Technology Accessibility. Control systems should be adaptable to both large-scale enterprises and smaller operations. Scalability and ease of integration into existing production environments make the technology accessible across various sectors of the meat industry.
- User-Friendliness. Intuitive interfaces and automated analysis tools are essential to reduce operator error. User-centric designs, including mobile applications and web-based platforms, allow personnel to access and interpret quality data efficiently.
- Adaptability and Customization. Control systems should support configuration for different meat types (e. g., beef, pork, poultry) and specific product requirements. Flexible parameter settings allow businesses to tailor the system to their operational and regulatory needs.
- Regulatory Compliance. The system should ensure conformity with local and international food safety and quality standards (e. g., HACCP [4], ISO 22000 [5], USDA [6]), helping businesses avoid penalties and meet export requirements.

These foundational characteristics form the basis of a robust, automated meat quality control system capable of delivering consistent, real-time results while minimizing human involvement and subjectivity.

5. Key meat product characteristics for quality assessment

Key classification features such as color, texture, and marbling were selected for quick and precise evaluation to ensure an effective meat quality control system. These features integrate seamlessly into algorithms for consistent quality control.

Color, one of the most apparent indicators for visually assessing freshness and quality, is crucial in meat product classification. Bright red or pink coloring usually indicates freshness due to the presence of muscle pigments like myoglobin and hemoglobin. Changes in color, such as browning due to myoglobin oxidation, indicate chemical or physical alterations [7]. Surface gloss also signifies freshness, with a natural moist sheen indicating high moisture levels. Loss of gloss suggests moisture depletion, potentially due to extended storage or improper transportation conditions. Through image analysis, machine learning models can accurately distinguish fresh from spoiled meat, providing rapid, real-time freshness assessments that reduce subjectivity.

Texture profoundly affects meat quality, influencing consumer satisfaction significantly through tenderness. Texture properties are determined by connective tissue quantity, muscle fiber arrangement, and intramuscular fat levels [8]. Excessive connective tissue may toughen the meat, reducing consumer appeal. Muscle fiber alignment affects meat graininess, while elasticity impacts meat resilience during cooking and consumption.

Marbling, integral to texture, involves intramuscular fat evenly distributed between muscle fibers, enhancing meat flavor by retaining moisture during cooking and increasing juiciness [9]. High marbling correlates with premium meat quality characterized by rich flavor and tenderness. Marbling assessments typically employ USDA [10] and Japanese BMS scales [11], effectively categorizing meat quality. These systems provide clear grading criteria that can be used for algorithm training and automated quality control. used to assess meat quality. Two widely accepted systems are used internationally to classify the degree of marbling: the USDA standard and the Japanese BMS (Beef Marbling Standard) scale. A detailed description of these grading systems is presented in Table 1 for USDA and Table 2 for BMS [10, 11].

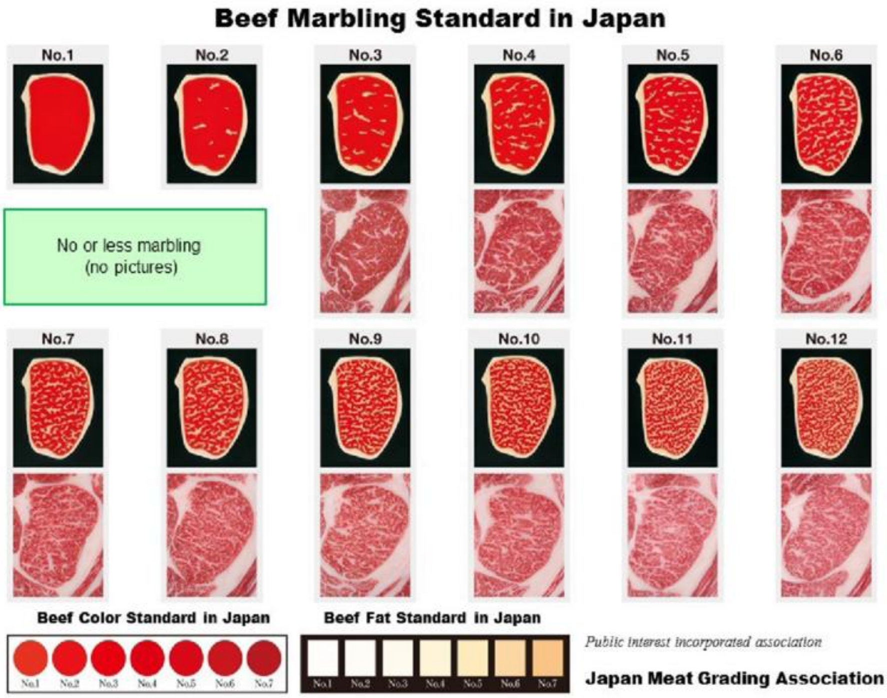
Table 1. Marbling grade according to USDA standard

Marbling Grade	Description
Prime	Highest degree of marbling; high juiciness and tenderness
Choice	Medium degree of marbling; moderate juiciness and tenderness
Select	Low degree of marbling; leaner meat, less juicy

Table 2. Marbling grade according to japanese BMS scale

BMS Score	Marbling grade	Description
8–12	Very high	Premium quality, exceptionally tender and juicy meat
5–7	High	High level of tenderness and juiciness
3–4	Medium	Moderate level of tenderness and fat content
1–2	Low	Low fat content, less tender meat

The Figure illustrates the Japanese Beef Marbling Standard, which visually classifies beef based on the degree of intramuscular fat distribution. The scale ranges from No. 1 (minimal marbling) to No. 12 (extremely high marbling), with each level represented by both a schematic cross-section and a real meat sample. The marbling becomes progressively denser and more evenly distributed as the grade increases. The lower part of the figure also presents Japanese standards for beef muscle color and fat color, both of which are important indicators in comprehensive meat quality evaluation.



Beef marbling standard in Japan (BMS)

These grading systems are essential for calibrating automated analysis models and for ensuring consistency with international quality standards. Integrating such classifications into machine learning algorithms improves the objectivity of marbling evaluation and enhances the decision-making process in meat quality control systems.

6. Technical features of meat quality control systems

Acquiring high-quality images under standardized conditions is key to effective automated meat quality control systems. It also involves developing diverse, well-annotated datasets for training classification models. Utilizing high-resolution cameras, such as Full HD and 4K systems, allows for the detailed capture of features in meat products, including marbling and muscle fiber orientation [2].

Lighting conditions during image capture are another critical factor. Inconsistent or inappropriate illumination can skew the perceived color of meat, leading to erroneous freshness or quality assessments. Uniform, shadow-free lighting helps maintain consistency in color measurements across all samples. Moreover, capturing images from multiple angles and under various conditions can improve robustness [2]. By taking photographs of meat cuts from different viewpoints (and even at different times of the day or with slight lighting changes), the system can learn to recognize quality features regardless of orientation or external variability.

Equally important is constructing comprehensive datasets containing images of various meat types – beef, pork, lamb, and poultry. Since each exhibits distinct color hues, muscle fiber structures, and marbling patterns, incorporating all these categories ensures the system can be adapted for multi-species use, aligning with the requirement that quality control systems be configurable for different meat types. In addition, within each meat category, the images should span the spectrum of quality outcomes (for example, fresh vs. spoiled meat or various marbling grades). This comprehensive approach guards against biases and equips the classification model to handle the full range of products encountered in operational settings. All images must be accurately labeled with relevant quality indicators as ground truth. Depending on the application, labels might include categorical freshness levels (“fresh”, “semi-fresh”, “spoiled”), marbling scores, color-based grades, defect presence, or tenderness class.

Image processing algorithms are central to converting raw visual data into objective meat quality indicators. Deep learning techniques, especially convolutional neural networks (CNNs) [12], offer high accuracy in classifying key attributes such as marbling, texture, color, and muscle structure. Unlike traditional methods, CNNs learn hierarchical features directly from labeled images, making them more robust to lighting, angle, and meat type variations.

For detailed analysis, segmentation algorithms like U-Net enable pixel-level identification of distinct regions–such as fat, muscle, and defects–allowing precise quantification of quality features like intramuscular fat distribution [13]. This segmentation is crucial for tasks such as marbling assessment and defect detection. Combined with well-structured datasets and preprocessing [13], these models ensure reliable, high-throughput, and repeatable evaluations in automated meat quality control systems.

Processing extensive data volumes is essential for seamless system operation. Powerful computing platforms and optimized algorithms facilitate rapid analysis of large datasets from cameras and sensors. Artificial intelligence and machine learning methods automate real-time result processing and anomaly detection, significantly boosting control speed and efficiency.

7. Conclusions

Ensuring meat product quality is essential due to increasing consumer demands for safety and high standards in food products. This research has systematically identified crucial meat quality indicators such as color, texture, marbling, and gloss, which directly influence consumer perception and product freshness. The study defined essential characteristics for automated quality control systems, highlighting processing speed, accuracy, technology accessibility, user-friendliness, adaptability, and regulatory compliance. The integration of these characteristics into automated systems facilitates consistent, objective assessments, significantly outperforming traditional subjective methods. Furthermore, advanced techniques such as machine learning and computer vision require precise feature selection and standardized imaging conditions to maximize their effectiveness and reliability. By addressing these elements, the proposed approach not only enhances assessment accuracy and efficiency but also ensures scalability across diverse operational scales–from small enterprises to large production environments. Continuous advancements and improvements in automated technologies further promise enhanced monitoring capabilities, reduced operational costs, and increased consumer trust and satisfaction.

Conflict of interest

The authors state that there are no financial or other potential conflicts regarding this work.

Gratitude

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References

[1] I. F. Ovchynnikova, S. O. Dubinina, T. M. Letuta, M. O. Naumenko, and A. A. Dubinina, *Methods for determining the falsification of goods*. Kyiv: Pub. dim “Professional”, 2010 [Online]. Available: https://library.nlu.edu.ua/POLN_TEXT/CUL/24-Metodi%20viznachennya%20falsif%20tovariv-Dubinina.pdf

[2] Y. Shi et al., “A review on meat quality evaluation methods based on non-destructive computer vision and artificial intelligence technologies”, Food Sci. Animal Resour., vol. 41, No. 4, pp. 563–588, Jul. 2021. Accessed: Apr. 2, 2025 [Online]. Available: https://doi.org/10.5851/kosfa.2021.e25

[3] K. O. Honikel, “Assessment of meat quality”, in Animal Biotechnology and the Quality of Meat Production. Elsevier, 1991, pp. 107–125. Accessed: Apr. 2, 2025 [Online]. Available: https://doi.org/10.1016/b978-0-444-88930-0.50013-4

[4] “HACCP principles & application guidelines.” U.S. Food & Drug. Accessed: Apr. 2, 2025 [Online]. Available: https://www.fda.gov/food/hazard-analysis-critical-control-point-haccp/haccp-principles-application-guidelines

[5] “Food safety”, in Iso 22000. United Nations, 2007, pp. 11–16. Accessed: Apr. 2, 2025 [Online]. Available: https://doi.org/10.18356/adf67d38-en

[6] “U.S. Department of agriculture.” Accessed: Apr. 2, 2025 [Online]. Available: https://www.usda.gov/

[7] C. Ruedt, M. Gibis, and J. Weiss, “Meat color and iridescence: Origin, analysis, and approaches to modulation”, Comprehensive Rev. Food Sci. Food Saf., Jun. 2023. Accessed: Apr. 2, 2025 [Online]. Available: https://doi.org/10.1111/1541-4337.13191

[8] R. Warner et al., “Meat tenderness: Advances in biology, biochemistry, molecular mechanisms and new technologies”, Meat Sci., p. 108657, Aug. 2021. Accessed: Apr. 2, 2025 [Online]. Available: https://doi.org/10.1016/j.meatsci.2021.108657

[9] W. Cheng, J.-H. Cheng, D.-W. Sun, and H. Pu, “Marbling analysis for evaluating meat quality: Methods and techniques”, Comprehensive Rev. Food Sci. Food Saf., vol. 14, No. 5, pp. 523–535, Aug. 2015. Accessed: Apr. 2, 2025. [Online]. Available: https://doi.org/10.1111/1541-4337.12149

[10] “Carcass beef grades and standards | agricultural marketing service”. Home / Agricultural Marketing Service. Accessed: Apr. 2, 2025 [Online]. Available: https://www.ams.usda.gov/grades-standards/carcass-beef-grades-and-standards

[11] T. Gotoh, T. Nishimura, K. Kuchida, and H. Mannen, “The Japanese Wagyu beef industry: Current situation and future prospects – A review”, Asian-Australas. J. Animal Sci., vol. 31, No. 7, pp. 933–950, Jul. 2018. Accessed: Apr. 2, 2025 [Online]. Available: https://doi.org/10.5713/ajas.18.0333

[12] L. Chen, S. Li, Q. Bai, J. Yang, S. Jiang, and Y. Miao, “Review of image classification algorithms based on convolutional neural networks”, Remote Sens., vol. 13, No. 22, p. 4712, Nov. 2021. Accessed: Apr. 3, 2025 [Online]. Available: https://doi.org/10.3390/rs13224712

[13] N. Siddique, S. Paheding, C. P. Elkin, and V. Devabhaktuni, “U-Net and its variants for medical image segmentation: A review of theory and applications”, IEEE Access, vol. 9, pp. 82031–82057, 2021. Accessed: Apr. 3, 2025 [Online]. Available: https://doi.org/10.1109/access.2021.3086020

[14] K. Maharana, S. Mondal, and B. Nemade, “A review: Data pre-processing and data augmentation techniques”, Global Transitions Proc., Apr. 2022. Accessed: Apr. 3, 2025 [Online]. Available: https://doi.org/10.1016/j.gltp.2022.04.020