Computer Vision And Artificial Intelligence For The Verification Of Standard Operating Procedures In Beef Carcasses In The Meat Industry

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***Abstract* — The adoption of technologies based on Artificial Intelligence (AI) and Computer Vision has significantly expanded the possibilities for automation and quality control in the meatpacking industry. This study presents the development and application of an intelligent system for the automated verification of Standard Operating Procedures (SOPs) in beef carcasses, specifically targeting the visual assessment of compliance regarding the presence of the Matambrinho muscle cut post-slaughter. The methodology involves the use of computer vision models trained to recognize specific visual patterns required by quality standards, enabling rapid and accurate detection of non-conformities that directly impact profitability and economic losses. The system was validated in a controlled environment using real images of beef carcasses, demonstrating satisfactory accuracy in identifying deviations from the SOP. Automated verification contributes to process standardization, reduction of human errors, increased traceability, and greater efficiency across the beef production chain. The results indicate that integrating AI into SOP monitoring is a promising strategy to raise quality standards, detect potential non-compliant practices, and reduce operational losses in the meat industry.**

Keywords— Computational Intelligence; Convolutional Neural Networks; Quality

I. Introduction

The Brazilian meatpacking sector is widely recognized for its economic relevance, standing out in the global beef production and export market [1]. However, to maintain competitiveness and meet regulatory, sanitary, and quality requirements in international markets, it is essential to ensure carcass compliance through the execution of Standard Operating Procedures (SOPs), which aim to standardize operations and reduce variability in industrial processes.

SOPs consist of detailed technical descriptions of the steps required to perform specific tasks, serving as a foundation for achieving uniform results and minimizing deviations in the production process. Their proper implementation directly contributes to maintaining quality and operational efficiency in slaughter lines [2].

Nonetheless, the verification of these procedures is still predominantly carried out by human operators, making it susceptible to issues such as fatigue, subjective judgment, and lack of consistency. These limitations can lead to rework, economic losses, and compromised product traceability.

With advancements in Artificial Intelligence (AI) and Computer Vision, there is growing interest in automated solutions capable of replacing or supporting operational decisions in industrial environments [3]. While successful applications of these technologies already exist in carcass classification and quality grading within large Brazilian meat processors as well as in research related to genetic prediction and disease detection [4][5][6] there remains a lack of studies focused specifically on the automated verification of critical SOP stages. These stages are essential to ensuring final carcass compliance and standardizing cuts, which helps prevent economic losses for the industry.

In this context, the present study aims to develop an intelligent system based on AI and Computer Vision for the automated verification of visual conformity of the Matambrinho beef cut in bovine carcasses. This proposal seeks to reduce human errors, standardize quality control, enable digital traceability, and increase efficiency in the beef production chain.

II. THEORETICAL FRAMEWORK

A. *Artificial Intelligence and Computer Vision*

Artificial Intelligence (AI) is a rapidly evolving field focused on developing systems capable of performing tasks that typically require human cognitive abilities, such as pattern recognition, decision-making, and learning from data [7]. In general terms, AI refers to the creation of algorithms and computational architectures capable of solving complex problems, overcoming human limitations or those of conventional algorithmic methods, and providing faster and more adaptive responses to real-world challenges [8][9].

The range of techniques within AI is broad, encompassing symbolic approaches that use explicit reasoning rules, connectionist paradigms such as deep neural networks, as well as evolutionary and probabilistic models. The tasks covered include search, reasoning, decision-making, perception, natural language processing, and machine learning [9]. This methodological diversity supports applications from precision medicine to agribusiness, attracting interest from researchers, investors, and companies, and driving investment in data-driven solutions [10].

A particularly relevant subfield is computer vision, defined as the ability of a computational system to extract, interpret, and act on information contained in digital images [11]. From a computational perspective, an image is composed of a matrix of pixels whose values represent color and intensity. Computer vision algorithms analyze these matrices to identify meaningful patterns, translating visual information into data that supports decision-making [12].

Computer vision systems analyze images by interpreting the pixel matrix that represents the color and intensity of each point in a scene. By extracting relevant visual features and converting them into structured, quantifiable data, these systems enable the automation of complex tasks such as carcass assessment, quality classification, and anomaly detection in meat processing environments. Their effectiveness depends on factors such as dataset size and quality, model architecture, and parameter tuning. Studies have shown that large, well-annotated datasets enhance learning efficiency and model stability, resulting in more accurate and robust performance in industrial applications [13][14].

B. *Convolutional Neural Networks (CNNs) for Visual Classification*

Convolutional Neural Networks (CNNs) are a class of artificial neural networks, also known as deep learning algorithms, designed specifically for computer vision tasks such as image classification. The classification process consists of assigning an input image to a specific class or estimating the probability that the image belongs to a given class [15].

A key advantage of CNNs is their architectural flexibility. Additional components such as extra convolutional layers, normalization operations, attention mechanisms, or shortcut connections can be integrated to improve accuracy and optimize the training process. These enhancements support applications such as image classification and object detection [16].

The effectiveness of CNNs lies in their ability to learn hierarchical feature representations directly from data, offering a powerful alternative to traditional handcrafted feature extraction methods. However, this capability comes at a cost: CNNs typically require large, labeled image datasets to successfully learn relevant patterns [17]. Convolutional architectures are typically composed of three main stages: convolutional layers that detect local patterns; pooling layers that reduce dimensionality and aggregate information; and fully connected layers that convert activations into final predictions [17].

The early stages comprising convolution and pooling pairs are computationally demanding due to the exhaustive scanning of filters over all image pixels [18]. In the final stage, an activation function such as Softmax is applied to the output layer, and a loss function is used to calculate prediction errors, which are then backpropagated to update the network's weights [19].

The integration of CNNs with computer vision techniques enables applications once considered futuristic, such as high-precision facial recognition, autonomous driving, self-service retail systems, and intelligent medical diagnostics [20]. These applications require not only a robust convolutional model, but also a complete pipeline for image acquisition, preprocessing, and annotation to ensure the quality of input data and the overall reliability of the system.

C. *Applications of AI and Computer Vision*

Computer vision has become a strategic technology, with applications in areas such as autonomous vehicles, automated product inspection, and augmented reality systems, among others [21]. In recent years, its use has expanded into fields such as agriculture, security, healthcare, and industrial automation [22], reflecting both technological advancements and improved real-time image processing capabilities.

In the meatpacking industry, for instance, visual inspections performed by human operators often suffer from standardization issues, low repeatability, and susceptibility to subjective or environmental factors, which compromise the uniformity of quality criteria [23]. This limitation has driven the adoption of automated systems that leverage computer vision to ensure more objective, faster, and cost-effective inspections.

Among the technologies supporting these solutions, artificial neural networks (ANNs) stand out, especially in the agricultural sector. Studies have shown that ANNs perform well in estimating genetic values. One such study [24] compared multilayer perceptron networks with the BLUP (Best Linear Unbiased Predictor) method, highlighting the feasibility of ANNs as an efficient alternative. Complementarily, [25] applied neurais networks in univariate and bivariate predictions of post-weaning weight in beef cattle, reinforcing the potential of these tools to support decision-making in the field.

Regarding food quality control, [26] emphasized that computer vision combined with machine learning techniques offers a promising alternative for routine inspections, simulating human judgment through automated image analysis. Studies such as [27] have demonstrated successful applications in production lines, both for detecting foreign objects and for monitoring the visual conformity of products. In swine production, [28] proposed an image segmentation-based system to estimate body weight, optimizing the assessment of feed quality. More recently, [29] applied deep neural networks to classify beef cuts based on visual characteristics, confirming the robustness of these models in industrial settings.

Thus, it is evident that computer vision has played an increasingly important role in modernizing the agri-food industry, offering precise, scalable, and adaptable solutions for tasks that previously relied exclusively on human interpretation.

D. *Standard Operating Procedure (SOP) and Quality Assessment in Beef Carcasses*

The assurance of quality and safety of animal-origin foods requires the adoption of standardized practices that ensure compliance with sanitary requirements and national and international regulations. In this context, Standard Operating Procedures (SOPs) are fundamental quality tools, as they establish formal and systematic instructions for performing critical activities in industrial processing, aiming for uniformity, traceability, process control, and cost reduction [30].

Quality assessment in beef carcasses is one of the critical points addressed in SOPs, as it aims to ensure that the final product meets sanitary and commercial standards by identifying possible contaminations, lesions, effective removal of unwanted parts, morphological alterations, or other nonconformities that may compromise the integrity of the food or even cause significant losses to the industry or producer. This assessment is performed visually by trained evaluators who follow technical criteria to classify and identify the quality standards of the carcasses.

Despite its relevance, traditional visual inspection is subject to subjectivity and variation between evaluators, which undermines repeatability and increases the risk of operational errors. Factors such as fatigue, poor lighting, and high slaughter line speed can also negatively impact inspection accuracy [23].

For this reason, recent research has sought to automate or technically support carcass evaluation through the use of advanced technologies such as sensors, cameras, and artificial intelligence algorithms, as a way to reinforce SOPs and minimize human and operational errors. These solutions can contribute to a more rigorous assessment after slaughter. A practical example is the detection of failures during the operation process at slaughter, such as in the case of the “Matambrinho” meat cut, where part of the cut may be removed, resulting in economic losses for producers and industries. Integrating these technologies enhances quality control by improving efficiency and traceability, while also supporting the industry's competitiveness in response to growing consumer market demands [31].

In this context, the adoption of tools based on computational intelligence is configured as an essential strategy for improving industrial evaluation processes. By promoting greater precision, standardization, and reliability in carcass evaluation, these technologies directly contribute to strengthening quality control systems, as well as driving innovation and competitiveness in the meatpacking industry.

III. METHODOLOGY

An autonomous image capture system for beef carcasses was installed in a slaughterhouse using high-resolution cameras and lenses, resulting in the construction of a dataset comprising 5,633 images. The images were automatically captured immediately after the animal slaughter procedure, at the exact moment the half-carcasses were weighed on a scale mounted on an overhead rail. One Standard Operating Procedure (SOP) was evaluated: Matambrinho. The captured images were annotated by trained professionals into two classes: class 0 – compliant SOP and class 1 – non-compliant SOP.

After annotation, a model was trained using the YOLOv8 architecture [32] responsible for detection, followed by bounding box cropping and binary classification (compliant or non-compliant) through a separate model employing the ResNet50 architecture [33], which is well-established in the literature.

A total of 4,482 images (~80% of the captured images) were used for training the AI models (AI MOD), and 1,151 images (~20% of the captured images) were used for validation to evaluate the AI model’s performance. Following the training, the model’s performance was assessed on the validation set using metrics such as precision, recall, F1-score, and confusion matrix to understand the classification capability (accuracy).

Subsequently, final testing was performed using a separate test dataset to verify the model’s robustness and generalization, enabling deployment in a real production environment the slaughter line and operational procedures of the beef carcass processing plant to validate the performance and practical feasibility of the proposed solution.

The performance and feasibility assessment were based on 711 test images captured during a single day of slaughter, which were processed and used as input for the detection and classification models in the production environment. Afterward, annotation (ground truth determination) and comparison with model predictions were conducted.

IV. RESULTS AND DISCUSSION

This section presents and discusses the main results obtained by the detection and classification models for the Matambrinho meat cut class. Evaluation metrics such as Intersection over Union (IoU), Precision, Recall, F1-score, and the Confusion Matrix were used.

A. *Detection Stage*

Analyzing Fig. 1, it is evident that the model exhibited excellent performance for the evaluated class, with the following quantitative metric values: Intersection over Union (IoU): 0.989; Precision: 0.999; Recall: 1.000; F1-score: 0.999.

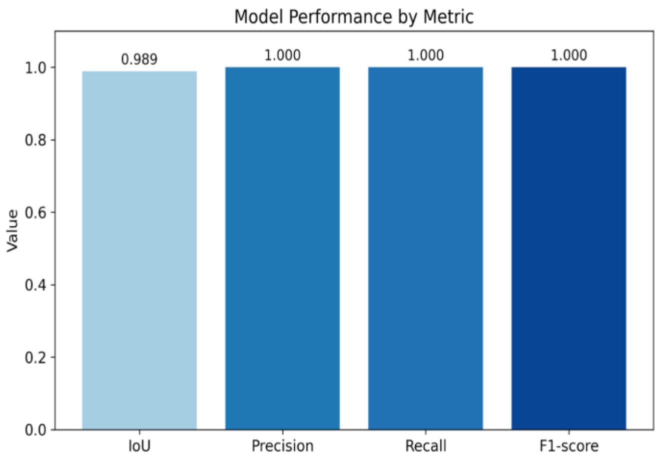

Fig. 1. Detection model performance metrics

The high Intersection over Union (IoU) value of 0.989 indicates that the predicted and ground truth bounding boxes exhibit an almost perfect overlap, demonstrating that the model detects the region of interest with high fidelity. A Precision of 1.000 suggests that all positive predictions truly belong to the Matambrinho class, with zero false positives. Similarly, a Recall of 1.000 reveals that no false negatives were predicted, meaning the model successfully identified all actual occurrences of the class. Finally, the F1-score, which is the harmonic means of precision and recall, confirms the excellent balance between these two metrics.

B. *Confusion Matrix*

The confusion matrix (Fig. 2) indicates that out of a total of 711 samples, the model correctly detected all 711, committing no errors. Additionally, there were no instances of background samples being incorrectly classified as Matambrinho. There were no cases where Matambrinho was predicted as background, i.e., no false negatives occurred, as previously reflected by the recall value of 100%.

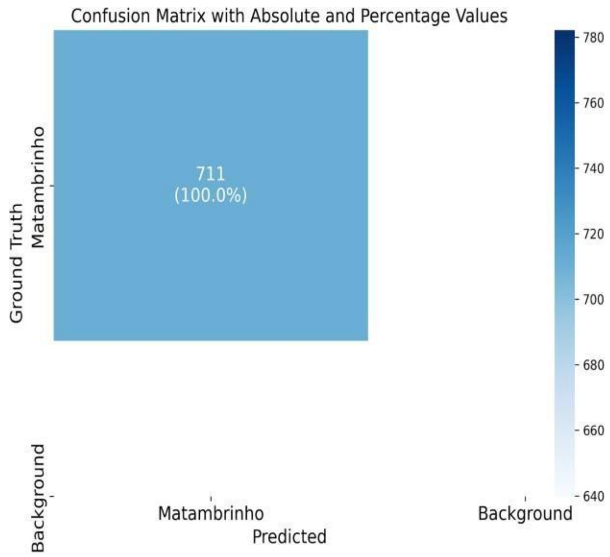

Fig. 2. Confusion matrix displaying absolute and percentage values for the detection task.

These results demonstrate that a highly effective and reliable model was developed for identifying the Matambrinho meat cut region. The absence of false negatives ensures complete coverage of the target class, while the minimal false positive rate (1 out of 712) highlights the model's robustness and low risk of incorrect detections. This performance can be attributed to the quality and quantity of the annotated datasets used for training and validation, the suitability of the YOLOv8 architecture, and the proper tuning of hyperparameters. Studies indicate that larger datasets tend to improve learning rates, accelerate processing, and contribute to greater stability of the loss function throughout network training [34].

For practical applications, especially in industrial or automated evaluation environments, such a level of performance is highly desirable, given the reduced need for manual correction, which in turn increases confidence in the automated system. According to [35], the adoption of automated visual inspection has expanded significantly in the food sector, driven by advantages such as lower operational costs, greater consistency in results, faster processing, and high accuracy in detecting nonconformities.

C. *Classification Stage*

Analyzing the results presented in Fig. 3, it is observed that the classification model achieved a highly satisfactory performance in distinguishing between the Adequate and Inadequate classes for the region detected as belonging to the Matambrinho category. The quantitative metrics yielded the following values: Precision: 1.000; Recall: 0.962; F1-score: 0.981; Accuracy: 0.966.

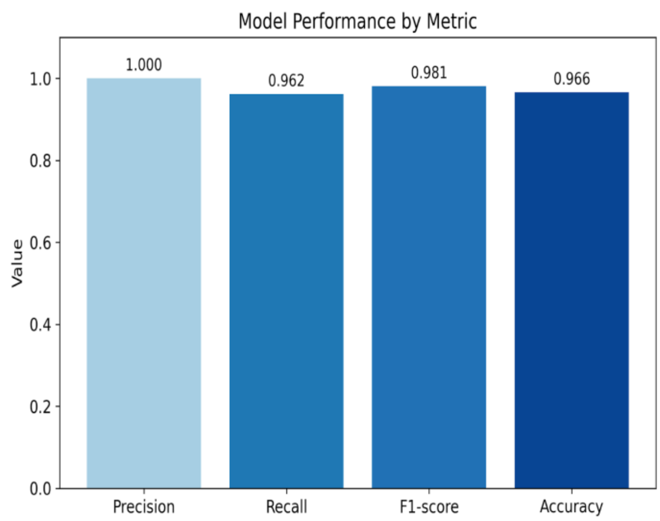

Fig. 3. Quantitative performance metrics of the classification model.

A precision of 100% indicates that all samples classified as Inadequate by the model were indeed correctly predicted, meaning there were no false positive occurrences. The recall of 0.962 shows that the model was able to identify the vast majority of truly Inadequate samples, with very few Inadequate instances misclassified as Adequate. The F1-score, which harmonically combines precision and recall, confirms the robustness of the performance with a high value of 98.1%. Furthermore, accurate reinforces this capability, showing that 96.6% of all images were correctly classified.

The confusion matrix, shown in Fig. 4, complements this analysis by visually presenting the distribution of correct and incorrect classifications, revealing a promising model performance in the context of automated evaluation of the presence of the Matambrinho meat cut on beef carcasses. Out of a total of 711 samples, the model correctly classified 613 "Inadequate" examples as "Inadequate" and 74 "Adequate" examples as "Adequate."

The high number of classifications as "Inadequate" (a total of 637 occurrences, compared to only 74 samples of "Adequate") is directly related to the operational culture adopted by the slaughterhouse and its workers, who tend not to perform this practice routinely. This established behavior in daily operations contributed to a significant class imbalance in the test dataset, impacting the data representativeness.

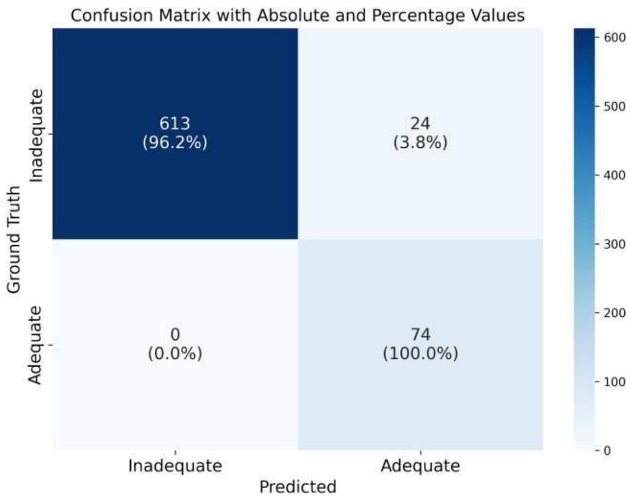

Fig. 4. Confusion matrix displays absolute percentage values for the classification task.

The high accuracy rate in detecting "Inadequate" samples indicates that the system is effective in identifying failures in the operational process at slaughter that may result in partial or total removal of this muscle. Although technically simple, this type of operational error can lead to significant economic losses for both the slaughterhouse and the producer, since carcass yield parameters are directly associated with the producer's economic returns [36].

A total of 24 false negative errors were recorded, meaning that "Inadequate" samples were misclassified by the model as "Adequate." No false positives were observed, which supports the maximum precision percentage reported.

The results demonstrate that the model exhibits high reliability in identifying "Inadequate" samples, which is particularly important in scenarios where accurate classification of operational failures can positively influence quality-related decision-making. The absence of false positives reinforces the tool's reliability as a decision-support system. This is critical in an industrial environment, where misclassifications can lead to unnecessary reclassification, rework, or improper discarding, ultimately compromising productivity and increasing operational costs.

This performance can be attributed to a combination of factors, including the quality of the image annotations in the dataset, the choice of the ResNet50 neural network architecture, and the effective tuning of hyperparameters. Among the various convolutional neural network architectures evaluated, ResNet stood out by achieving the highest accuracy reaching 93.4% in its application, as reported in [37].

From an operational efficiency standpoint, the deployment of a model with this performance profile particularly in automated inspections or industrial processes ensures a reliable system, fostering efficiency and confidence in automated decision-making. Moreover, considering that the Matambrinho meat cut adds value to the final product, can be used as a criterion for producer bonuses, and is commercially valuable within the industry, the use of automated systems contributes to fairer and more transparent decisions, strengthening commercial relationships and promoting continuous process improvement.

D. Visual Demonstration of Results

To further support the effectiveness of the proposed model in a practical context, representative images were selected to visually demonstrate the detection of the Matambrinho beef cut in bovine carcasses.

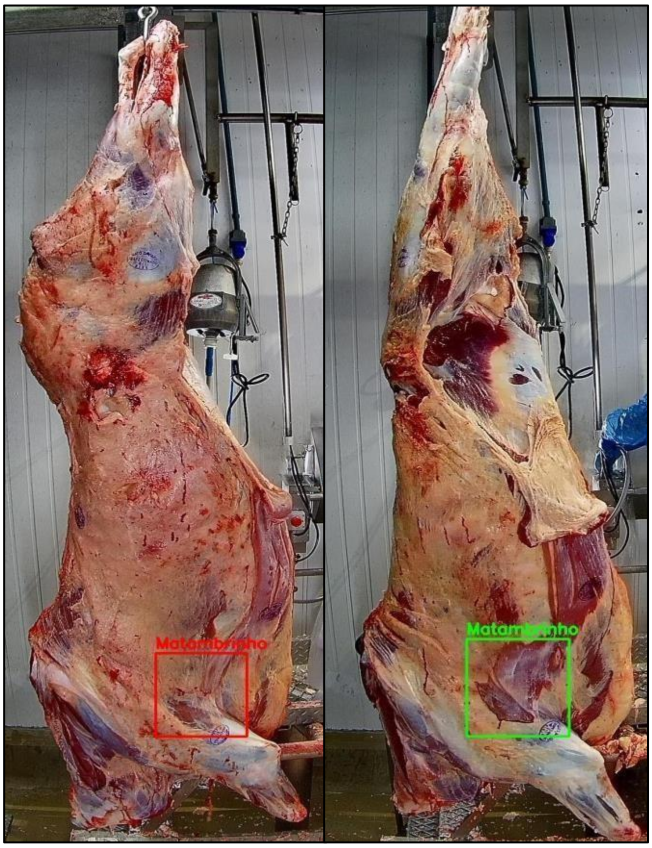

Fig. 5. Detection of the Matambrinho cut: *Inadequate* case (left, red bounding box) and *Adequate* case (right, green bounding box), identified by the YOLOv8-based model.

These images provide qualitative evidence of the model's ability to accurately identify the region of interest, even under real production line conditions. The bounding boxes generated by the detection algorithm show consistent alignment with the annotations provided by trained specialists, indicating robustness and anatomical fidelity in locating the cut. This visual demonstration complements the quantitative results previously presented, highlighting the potential of the proposed solution for industrial application particularly in strengthening traceability, standardization, and decision-making support in carcass conformity assessments.

V. CONCLUSION

This study demonstrates the potential of computer vision technologies for automating the evaluation of beef carcasses, with a specific focus on verifying the presence of the Matambrinho meat cut. The high accuracy, combined with the absence of false positives, reinforces the reliability of the developed model, making it a promising tool to support decision-making in industrial environments. It directly contributes to reducing economic losses while enhancing traceability, standardization, and compliance with Standard Operating Procedures (SOPs).

Furthermore, the results indicate that the proposed approach can be extended to the evaluation of other SOPs and different cuts or regions of the carcass, broadening its impact on improving compliance, operational efficiency, and quality control in meat processing plants. Integrating artificial intelligence models into carcass evaluation processes significantly contributes to reducing losses, standardizing operations, and enhancing traceability, thereby supporting the modernization of the meat production chain.

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