EfficientNet B0-Based RLDA for Beef and Pork Image Classification

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Abstract. This study employs a novel approach to enhance the classification of beef and pork images using EfficientNet B0 as a feature extractor and Regularized Linear Discriminant Analysis (RLDA) for analysis. The integration of EfficientNet B0 and RLDA significantly improves beef recognition performance. In rigorous 5-fold cross-validation, the approach achieves an impressive 98.75% accuracy for 128x128 pixel images and 99% for 256x256 pixel datasets. Additionally, a 90% training data and 10% testing data split results in an accuracy rate of 100% for 128x128 pixel images and a perfect 100% accuracy for the 256x256 pixel dataset. These results signify a substantial advancement in beef quality assessment and classification, particularly in varying lighting conditions. EfficientNet B0 is a practical feature extractor, allowing the model to capture critical characteristics of beef images. RLDA, a regularized approach, further refines the classification process, improving the model's accuracy and robustness. This research offers promising implications for applications in beef quality assessment, focusing on accuracy and adaptability across diverse environmental conditions.

Keywords: Transfer Learning, Beef Classification, EfficientNet, Image Analysis, Feature Extraction.

1 Introduction

The meat industry has witnessed a continuous surge in beef prices [1], attributed to the persistent growth in meat consumption and population density[2]. The increasing of beef price has impacted the meat market and led to revenue losses among meat sellers [3]. To minimize these losses, some sellers have adopted questionable practices, such as blending pork with beef, further complicating the challenge of authenticating meat products [4]. An essential aspect in this context is the visual resemblance between pork and beef, especially concerning color and texture [5]–[7], which has significant implications for customer protection and halal dietary requirements.

Machine learning has emerged as a pivotal solution to address these challenges. Various techniques, such as Gray-Level Co-Occurrence Matrix (GLCM) [8], [9],

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Local Binary Pattern (LBP) [10], Histogram of Oriented Gradients (HOG) [11], and pre-trained Convolutional Neural Networks (CNNs) [10], [12], [13], hyperspectral imaging also has proven instrumental in classifying between various meat types [14]. These technologies have proven invaluable in overcoming the limitations posed by the visual similarities between beef and pork. Additionally, image recognition systems, including Fuzzy C-Means (FCM) [15], [16] and Probabilistic Neural Networks (PNN) [8], [17], have excelled in discerning various aspects of beef and pork cuts [18], with PNN demonstrating remarkable efficiency in the classification of images with distinct textures [19]. Deep learning, focusing on CNNs [20], has significantly improved the accuracy of meat classification [21], in addition the classification on feature extraction based on the Fusion of CNN and Bi-LSTM [22].

This study investigates into evaluating the potential of EfficientNet B0's deep feature extraction method for distinguishing between beef and pork, and the evaluation is underpinned by the Regularized Linear Discriminant Analysis (RLDA) technique [23] leveraging an existing dataset [8]. The principal objective of this research is to enhance and refine feature extraction methodologies, ultimately leading to more accurate and effective meat classification.

This article is organized as follows: Section 2 provides a detailed overview of the methodology, encompassing the essential components of EfficientNet B0 and RLDA. Section 3 unveils the empirical results obtained and discusses their implications. Finally, in Section 4, we conclude by summarizing the outcomes and highlighting the significance of our approach.

2 Research Method

This research encompassed several stages, including dataset collection, pre-processing, EfficientNet B0 feature extraction, 5-fold cross-validation for vector data classification, data splitting using RLDA, and performance evaluation, as illustrated in Fig. 1.

Fig. 1. Flowchart of the proposed method for beef and pork classification.

2.1 Dataset and Image Pre-processing

The dataset consists of 400 high-quality images of beef and pork cuts captured with a Canon DSLR camera from four angles (0°, 45°, 90°, and 135°) at a consistent 20 cm distance to minimize background interference [8]. These unaltered meat samples (Fig. 2) were photographed under controlled lighting conditions, offering a comprehensive representation of each cut, with "0" denoting beef and "1" denoting pork.

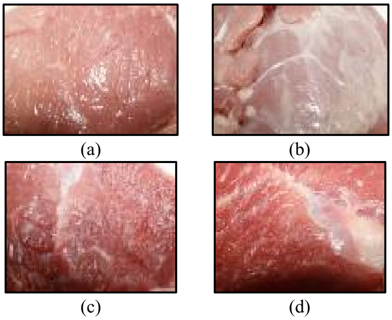


Fig. 2. Example images of beef and pork cuts: (a, b) pork meat, and (c, d) beef meat.

Based on the dataset, we performed image pre-processing to standardize image sizes. This involved resizing the images to 32x32 pixels for initial assessment and then to 256x256 and 128x128 pixels for testing, as recommended by [8] for improved classification accuracy. In addition, we pre-trained the image features extracted from EfficientNet B0 based the imagenet dataset [24], [25].

2.2 Feature Extraction Using EfficientNet B0 Model

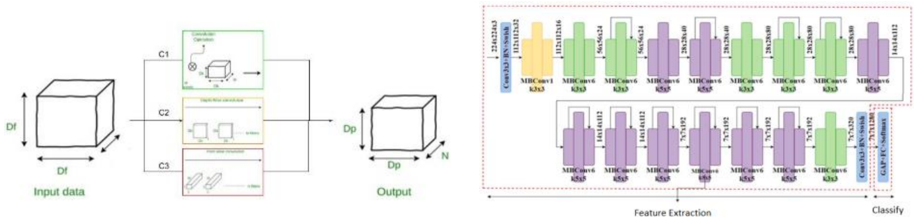
This research applied transfer learning with EfficientNet B0, a pre-trained CNN model [26], adapting it for classifying smaller datasets by modifying activation and output layers. This efficient approach is favored due to its performance and parameter optimization, as depicted in Fig. 3. (a) [27]. EfficientNet B0 excels with its depthwise and point-wise convolution [25], reducing computational complexity [24]. It optimizes,

$$\text{resolution } (r(i) = \gamma * r(i-1)) \tag{1}$$

$$\text{width}(w(i) = \alpha * w(i-1) \tag{2}$$

$$\text{and depth } (d(i) = \beta * d(i-1)) \tag{3}$$

using scaling coefficients α, β, and γ. The model's output, represented as a vector after global average pooling and dropout layers, serves as training and testing data, delivering high accuracy, efficiency, and reduced FLOPS [28], [29], exemplified in Fig. 3. (b).



(a) (b)

Fig. 3. (a) Various Convolutional Techniques: Standard (C1), Depth-wise (C2), and Point-wise (C3) convolutions, alongside (b) EfficientNet B0 Architecture for Feature Extraction

2.3 Classification using Regularized Linear Discriminant Analysis (RLDA)

RLDA (Regularized Linear Discriminant Analysis) is applied in this study for classification, enhancement class differentiation by incorporating ridge parameters [23], [30]. The process involves:
Calculating probabilities of classes $\prod_0$ and $\prod_1$,

$$\text{class averages } (\overline{x_i} = \frac{1}{n_i}\sum_{x_l \in Si} x_l) \tag{4}$$

$$\text{covariance matrices for each class: } C_i = \frac{1}{n_i - 1}\sum_{x_l \in Si}(x_l - \overline{x_i})(x_l - \overline{x_i})^T \tag{5}$$

$$\text{non-singular polarized covariance matrices : } C = \frac{(n0-1)C0+(n1-1)C1}{n0+n1-2}) \tag{6}$$

$$\text{a discriminant function } (W(\overline{x_0}; \overline{x_1}; C; x) = (x - \frac{\overline{x_0}+\overline{x_1}}{2})\mathrm{H}(\overline{x_0} - \overline{x_1})) \tag{7}$$

where

$$\mathrm{H} = (\mathrm{I_p} + \beta \mathrm{C})^{-1} \tag{8}$$

with $\mathrm{I_p}$ is the p-dimensional identity matrix, and β is the ridge parameter. The β Value > 0, and the best ridge parameter in this research is $\beta = 10^{-3}$.

and to determine class labels [23]:

$$\varphi_n^{RLDA}(x) = \begin{cases} 1, \ if \ \ W(\overline{x_0}; \overline{x_1}; C; x) \ \leq 0 \\ 0, \ if \ \ W(\overline{x_0}; \overline{x_1}; C; x) \ \geq 0 \end{cases} \tag{9}$$

The model's performance is evaluated using ROC, accuracy, precision, and recall as performance metrics. This comprehensive evaluation ensures robust classification results, mainly when dealing with imbalanced datasets.

3 Result and Discussion

This section presents a detailed analysis of our experiments using EfficientNet B0 and RLDA to classify meat images. The experiments cover four test scenarios with 400 images each and involve pre-processing, ridge parameter optimization, and performance metric evaluation.

3.1 Data Pre-processing and Ridge Parameter Selection

First, we uniformly resized all images to a dimension of 32x32 pixels, followed by feature extraction using the EfficientNet B0 architecture pre-trained on the ImageNet dataset. We choose this image size because small image resolution is less amount of features so it can enforce the performance of machine learning to distinguish each of classes. By that condition, tuning the ridge parameter is very important to improve the machine learning so we also focused on optimizing the ridge parameter (β) for RLDA classification. To achieve this, we employed 5-fold cross-validation to evaluate different values of β (10^{-2} to 10^{-9}) as seen in the Figure 4. After through this experiment, we selected the ridge parameter $\beta = 10^{-3}$ as the most optimal choice for our subsequent tests. As seen in the Figure 4, the brown line of *Avg. Score* represent the average from score summary of Accuracy, F1-Score, Recall, RoC, and Precission.

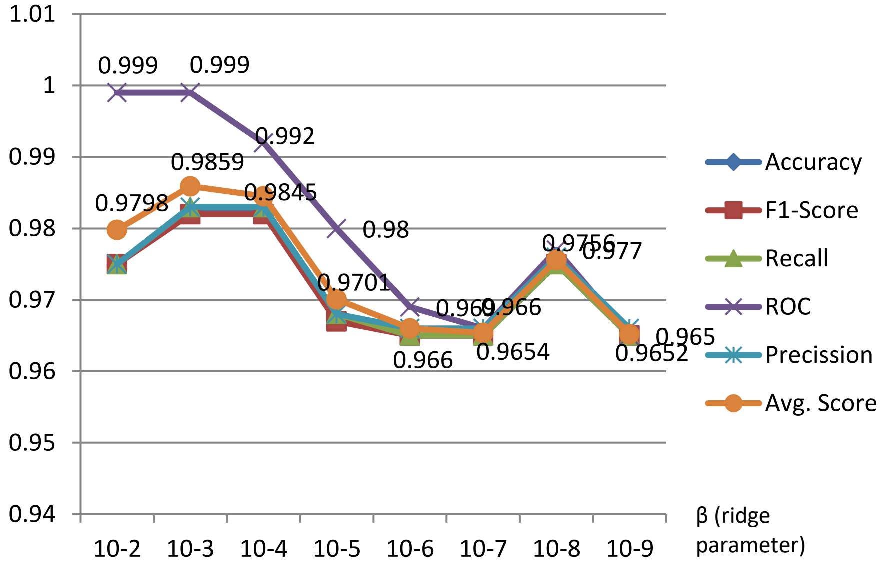


Fig. 4. Performance graph depicting the optimal ridge parameter ($\beta=10^{-3}$) determined through 5-fold cross-validation.

This study conducted tests across four scenarios. First, images were resized to 128x128 and processed using the pre-trained EfficientNet B0 architecture with the ImageNet dataset. The feature vectors obtained were classified using Regularized Linear Discriminant Analysis (RLDA) with a ridge parameter 10^{-3} via 5-fold cross-validation. In the second scenario, the same 128x128 image size and EfficientNet B0 pre-processing were used, but this time, the data was split into 90% for training and

10% for testing. In the third scenario, the image size was resized into 256x256, and the EfficientNet B0 pre-processing and RLDA classification with a ridge parameter of 10^{-3} were applied via 5-fold cross-validation. Finally, in the fourth scenario, the 256x256 images were processed as in scenario three, with a 90% training and 10% testing data split. Evaluation metrics for each scenario included a confusion matrix, accuracy, recall, precision, RoC, and F1-Score.

3.2 Performance Evaluation Metrics

The four test scenarios highlighted the superior performance of EfficientNet B0 + RLDA over the previous method [8], as shown in Table 2. In the first scenario, with 400 meat images at 128x128 pixels, RLDA achieved an impressive 98.75% accuracy, 98.8% recall, and 98.8% precision. Likewise, with different data distributions, the second scenario delivered a remarkable 100% accuracy, surpassing prior research [8].

Table 1. Result of the four test scenarios.

No	Image (pixels)	Testing	GLCM+PNN [8]	Proposed Method (EfficientNet B0+RLDA)				
			Accuracy (%)	Accuracy (%)	F1-Score (%)	Recall (%)	ROC (%)	Precision (%)
1	128x128	5-Fold	93	**98.75**	98.7	98.8	99.5	98.8
2	128x128	Split 9:1	94	**100**	100	100	100	100
3	256x256	5-Fold	87	**99**	99	99	99.7	99
4	256x256	Split 9:1	97	**100**	100	100	100	100

In the third scenario, classifying 256x256-pixel meat images with RLDA achieved 99% accuracy. Remarkably, the fourth scenario using the same dataset reached a flawless 100% accuracy, underscoring the efficacy of EfficientNet B0 + RLDA. The results in Table 2 firmly establish EfficientNet B0 + RLDA as superior to the traditional GLCM + PNN method [8], indicating the potential of deep feature extraction combined with supervised learning for real-world applications.

The performance of our proposed method have surpassed the previous research with same dataset[8]. But there are still some limitations of our research especially the accuracy on 5 fold classification still under 100%. This research also did not use pre-processing to grab the red color intensity in every images or maybe histogram equalization for emerging more features in each of images before extracted by CNN Model then classified by machine learning. The dataset in this research comprise balanced classes. But there are still some white flash such light reflection in meat images. We assume those noise become potential impact to the performance of our proposed method in the feature extraction step. Therefore, this condition led to under 100% accuracy of several testing scenarios.

The previous research [5] using HSV (Hue, Saturation, and Value) color feature extraction and texture extraction such as LOOPS (Local Optimal-oriented pattern) succeeded in increasing the accuracy of pork and beef image classification. According to [5] research, augmenting the training images with rotation does not increase accuracy. Previous studies using GLCM [8][9]only focused on feature extraction in the form of texture of meat images, so the accuracy was less than optimal. Another study using HSV color feature extraction and LBP texture features produced 90% accuracy in image classification of beef, pork and wildboar [11]. Research using a combination of PCA (Principal Component Analysis) +HSV feature extraction with the PNN classifier produces 100% accuracy in recognizing mixed beef and pork [17]. However, from those previous studies, the inappropriate choice of texture and color feature extraction methods cannot optimally increase accuracy in classification. By considering constraints on texture features and color features, we chose to use a feature extractor from a deep learning model trained on high diversity images such as the imageNet dataset. In this way, hidden and undetected features in terms of color, texture and other aspects can be recognized to maximize information in classification in our research dataset.

Our performance results are quite stable for 5 cross validations reaching accuracy above 98%, and in the 90:10 test our accuracy reaches a maximum of 100% for resolutions of 128x128 and 256x256. The previous research [5] with the same number of datasets but different images, its accuracy obtained was 99.16% when testing 70:30, and achieved 100% accuracy when testing 80:20 and 90:10. This is very possible because the image was taken at a distance of 15 cm [5], while the distance we took the meat image was further, namely 20 cm. Therefore, differences in meat image datasets, distance from which meat images were taken, image noise such as reflections of camera LED light, types of feature extraction methods are certain aspects that greatly influence the accuracy results of image classification.

4 Conclusion

This study illuminates the constraints of traditional feature extraction methods in challenging conditions, emphasizing the need for supplementary features. We achieved remarkable accuracy using the EfficientNet B0 architecture with transfer learning, with 98.75% for 128x128-pixel and 99% for 256x256-pixel images (5-fold cross-validation). Data splitting yielded 100% for 128x128-pixel and 100% accuracy for 256x256-pixel images. These results surpass previous research and offer valuable insights for minor dataset investigations. The study underscores the potential of transfer learning for further improvements, significantly contributing to image classification and analysis. The Challenge for Future research is how the method can be developed to classify more robustly towards the mixed cuts of pork and beef, also to recognize mixed of beef and pork paste.

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