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Beef Freshness Classification Using CNN with DCT and GLCM Feature Extraction

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Abstract

The increasing global demand for beef, which has risen by 13.9% over the past decade, underscores the growing importance of ensuring meat quality and freshness in the food industry. Conventional methods for assessing beef freshness rely on manual visual inspection, which is time-consuming, subjective, and often inaccurate. To address these limitations, this study proposes a hybrid approach that integrates the Discrete Cosine Transform (DCT), Gray Level Co-occurrence Matrix (GLCM), and Convolutional Neural Network (CNN) techniques for automated beef freshness classification. A dataset of fresh and spoiled beef images was used, followed by a series of preprocessing steps, feature extraction using DCT and GLCM, and classification through a CNN-based model. The integration of frequency-domain and texture-based features enhances the model's ability to capture discriminative visual patterns associated with meat freshness. Experimental results demonstrate that the proposed model achieves an overall classification accuracy of 93%, with F1-scores of 0.94 for fresh meat and 0.93 for spoiled meat. These findings indicate that the DCT, GLCM, and CNN framework provides an efficient and reliable alternative to traditional inspection methods. The proposed approach contributes to the advancement of computer vision applications in food quality assessment, promoting improved automation, objectivity, and quality control across the meat supply chain.

1. Introduction

Global demand for beef has continued to rise steadily, with consumption in Organisation for Economic Co-operation and Development (OECD) countries increasing by 13.9% over the past decade[1]. As a major source of protein and essential nutrients[2], fresh beef plays an important role in global food security and nutrition. However, because beef is a perishable product, it requires appropriate handling, processing, and storage to maintain its freshness, sensory quality, and safety. Failure to monitor freshness accurately not only affects consumer satisfaction but also contributes to food waste, financial losses, and inefficiencies in the meat supply chain[3]. Traditionally, the assessment of beef freshness has been conducted through manual inspection based on sensory attributes such as color, odor, and texture[4]. Although this approach is widely practiced, it is highly dependent on human perception, which can lead to inconsistent and inaccurate evaluations. Therefore, there is a growing need for automated and objective methods that can evaluate meat freshness more reliably and efficiently.

Recent advances in artificial intelligence (AI) and computer vision have created new opportunities for automating food quality assessment. Among the AI techniques developed in recent years, Convolutional Neural Networks (CNNs)[5], [6] have demonstrated exceptional performance in image classification and pattern recognition due to their ability to automatically extract hierarchical features from raw images[7]. CNNs have been successfully applied to various domains, including medical imaging, agricultural analysis, and material inspection. However, their application to meat freshness classification still faces several challenges. When processing high-resolution or texture-rich images, CNNs may capture redundant spatial information or fail to detect subtle differences in texture and color that are essential for distinguishing fresh from spoiled meat[8], [9]. These limitations suggest that CNN-based models could benefit from additional feature extraction techniques that complement their ability to capture spatial features while enhancing texture sensitivity.

To overcome these challenges, this study proposes a hybrid method that integrates the Discrete Cosine Transform (DCT)[10] and the Gray Level Co-occurrence Matrix (GLCM)[11] with a CNN-based classifier[12]. The DCT is a frequency-domain transformation technique that converts an image from the spatial domain into the frequency domain, emphasizing low-frequency components that represent the most important structural information while suppressing high-frequency noise[13]. In parallel, the GLCM technique focuses on texture characterization by analyzing the spatial relationships between pixel pairs at specific distances and orientations. It produces statistical descriptors such as contrast, correlation, and homogeneity, which effectively represent texture variations associated with the freshness or spoilage of meat[14]. The integration of DCT and GLCM provides a complementary balance between global frequency information and local texture patterns, resulting in a richer and more discriminative feature representation compared to using CNNs alone.

Several previous studies have demonstrated the individual effectiveness of these techniques in different domains[15]. DCT-based approaches have successfully improved classification accuracy in medical imaging tasks, such as brain tumor detection[16], while GLCM-based texture features have been effective in identifying plant species and detecting surface defects[11]. Furthermore, hybrid methods combining DCT and GLCM have been applied in facial recognition and texture-sensitive industrial inspection, showing better robustness against noise and illumination variation[17]. Despite their success in other fields, the joint application of DCT and GLCM within deep learning frameworks for meat freshness detection remains underexplored. This gap highlights the potential of combining classical feature extraction methods with modern neural architectures to enhance performance in food quality assessment.

Based on these considerations, this research aims to develop a hybrid DCT, GLCM, and CNN framework for automated beef freshness classification. The primary objective is to improve classification accuracy and robustness while maintaining computational efficiency. The proposed method applies DCT and GLCM to extract frequency and texture features before feeding them into a CNN for feature fusion and classification. Experimental results show that the proposed model achieves an accuracy of 93%, with F1-scores of 0.94 and 0.93 for fresh and spoiled meat, respectively. These results indicate a significant improvement compared to standard CNN-based approaches. This study contributes to the advancement of intelligent food inspection systems by providing an effective and scalable solution for meat freshness evaluation, supporting quality control, food safety assurance, and sustainability across the meat industry supply chain.

While the proposed framework focuses on enhancing model accuracy through hybrid feature integration, it is also essential to contextualize this research within the broader landscape of existing studies that have explored similar techniques in computer vision and food quality inspection.

2. Related Work

The development of computer vision techniques for food quality assessment has been widely explored in recent years, particularly in detecting freshness, contamination, and surface defects. Several approaches rely solely on deep learning architectures such as Convolutional Neural Networks (CNNs), which automatically learn visual representations from raw images. For example, Zhang et al. (2020) applied CNNs to classify poultry freshness, achieving high accuracy under controlled lighting conditions but decreased performance when illumination varied[4]. Similarly, Azeez et al. (2024) proposed a computationally efficient transfer learning pipeline using pre-trained CNN architectures such as ResNet50 and EfficientNetB0 for detecting defects in oil palm fresh fruit bunches[18]. Their study demonstrated that end-to-end deep learning models can effectively capture maturity and defect features under controlled conditions, but their accuracy tends to decrease when texture complexity and lighting variation increase. This finding reinforces that CNN-based approaches achieve strong baseline performance, yet their robustness still relies heavily on the uniformity and consistency of the dataset.

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To overcome such limitations, classical feature extraction methods like the Discrete Cosine Transform (DCT) and Gray Level Co-occurrence Matrix (GLCM) have been employed to enhance texture and frequency representation. DCT has been shown to compress redundant spatial information while preserving essential structure, making it effective for medical imaging, defect detection, and other texture-dominant tasks[19]. On the other hand, GLCM-based features have been widely adopted in plant leaf disease identification and agricultural inspection for their ability to quantify micro-texture and spatial relationships between pixels. These methods provide complementary advantages that CNNs alone may overlook, particularly under varying lighting and color saturation conditions.
Hybrid strategies that integrate handcrafted features with deep learning have gained increasing attention in the last five years. For instance, DCT-based preprocessing has been combined with CNNs to improve robustness against illumination changes in facial recognition, while GLCM descriptors fused with CNN embeddings have enhanced defect classification in industrial images. Recent works show that fusing frequency-domain and texture features with deep representations yields higher accuracy and more stable performance than single-domain inputs[20], [21]. However, most existing works focused on non-food datasets or simple binary defects, leaving meat freshness classification relatively underexplored in this hybrid context.
Given these findings, the present study builds upon prior research by integrating DCT and GLCM with CNN to develop a hybrid model tailored for beef freshness classification. Unlike previous works that used either handcrafted or deep features independently, this research emphasizes feature fusion to achieve a balanced trade-off between generalization and interpretability. Furthermore, it evaluates different parameter settings (e.g., DCT coefficient thresholds and GLCM distances) to determine their impact on classification accuracy, thereby contributing novel insights into hybrid feature optimization for food quality analysis.

3. Methodology

This study aims to enhance the accuracy and robustness of beef freshness classification through the integration of three complementary computational techniques: Discrete Cosine Transform (DCT), Gray Level Co-occurrence Matrix (GLCM), and Convolutional Neural Network (CNN). The combination of these methods allows the model to capture both global frequency features and local texture patterns, providing a more comprehensive representation of visual characteristics that distinguish fresh from spoiled meat.

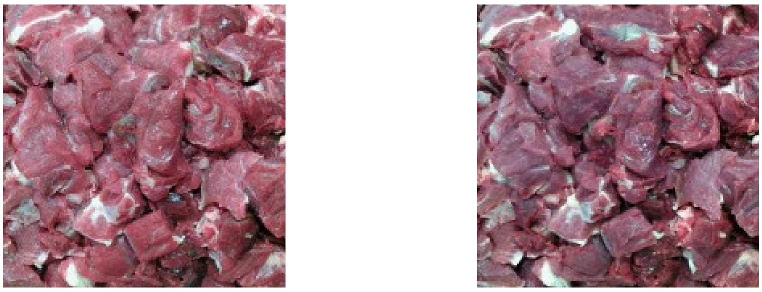
The overall workflow of the proposed approach consists of six main stages: (1) data collection, (2) image preprocessing, (3) feature extraction, (4) dataset partitioning, (5) model construction and training, and (6) model evaluation. Each stage plays a specific role in ensuring that the system operates efficiently and produces consistent classification results. Data collection establishes the foundation for representativeness and class balance. Preprocessing standardizes input quality and reduces unwanted variations. Feature extraction employs DCT and GLCM to capture frequency- and texture-based attributes that may not be learned effectively by CNNs alone. The partitioning stage ensures that training, validation, and testing are performed on non-overlapping data subsets to avoid overfitting. Model construction integrates handcrafted and deep features into a unified learning framework, while the evaluation stage quantitatively and visually assesses classification performance using multiple metrics.

This structured design ensures that each component of the workflow contributes systematically to the accuracy, stability, and interpretability of the proposed DCT, GLCM, and CNN model, thereby supporting its potential application in automated meat freshness inspection.

3.1 Data Collection

The dataset used in this study was obtained from the publicly available Kaggle platform, containing images of both fresh and rotten beef[22]. Each category comprised 948 samples with an original resolution of 1280 × 720 pixels. These images were carefully reviewed to ensure representativeness and visual clarity. A cropping process was then applied to focus solely on the relevant portion of the meat surface, excluding any background or irrelevant visual noise such as cutting boards or packaging. This step also reduced file size and computational overhead during model training. Figure 1 illustrates an example of the dataset before and after cropping, showing how this preprocessing step improved visual consistency and focus[23].

(a)



(b)

Fig. 1 *Example of image dataset before (a); and after cropping (b)*

3.2 Data Processing

Image preprocessing was performed to enhance quality, reduce noise, and standardize dimensions across the dataset. Each image was first cropped to a 400 × 400-pixel region of interest to maintain spatial uniformity while retaining essential features. Subsequently, all images were converted into grayscale using the OpenCV (Open Source Computer Vision)[24] library to minimize the effect of color variation and focus the analysis on texture and intensity patterns. The grayscale images were then resized to 224 × 224 pixels, which aligns with the standard input size required by most CNN architectures, thus ensuring compatibility and efficient model training[25].

3.3 Feature Extraction

Feature extraction is conducted using the DCT and GLCM methods, each of which offers advantages in processing different image characteristic[26]. In the feature extraction process using the DCT, the DCT is applied to each image to transform it from the spatial domain to the frequency domain. This method isolates low-frequency components[27], [28] which typically contain important information, while eliminating high-frequency components that often contain noise.

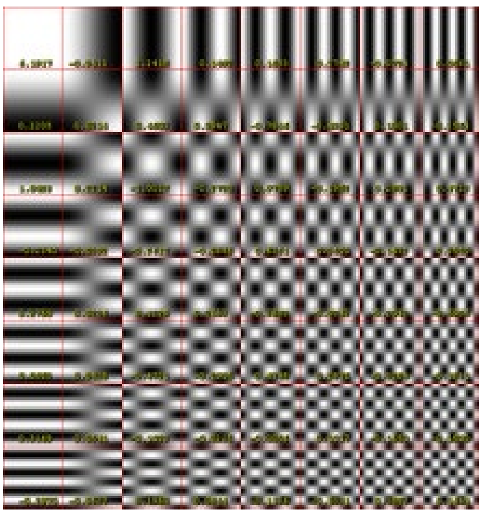


Fig. 2 *Frequency domain of DCT*

The image (Figure 2) shows DCT basis functions, each block representing a combination of horizontal and vertical frequencies. The top-left block captures low frequencies (smooth areas), while the bottom-right shows high frequencies (fine textures or noise). This structure explains why formats like JPEG retain low-frequency data for efficient compression[28].

GLCM extracts texture by measuring how often pixel pairs occur at specific distances and angles[29]. In this study, GLCM used distances of 1 and 2, extracting features like ASM, contrast, correlation, and entropy. These features were normalized for consistent analysis[30].

3.4 Data Division

After feature extraction, the dataset was divided into three subsets using a stratified split to preserve class proportions: 80% for training, 10% for validation, and 10% for testing. This partitioning ensures that the model learns effectively from sufficient data while being evaluated on unseen samples. The stratified approach also prevents bias toward any particular class, which is critical for maintaining balanced performance. The random seed for data splitting was fixed to ensure reproducibility of the results[31].

3.5 Model Creation and Training

The hybrid classification model was constructed by combining a CNN feature extractor with handcrafted features from DCT and GLCM. The CNN component processes raw images through convolutional and pooling layers to automatically learn deep spatial features, while the handcrafted features are fed into a separate Multi-Layer Perceptron (MLP) branch[32]. The outputs from both branches were concatenated into a single feature vector using the Keras functional API[33], forming a dual-input, single-output architecture. The final dense layer uses a sigmoid activation function for binary classification (fresh or spoiled)[34].

The model was trained using the Adam optimizer with an initial learning rate of 0.0001, batch size of 32, and binary cross-entropy loss function. Early stopping was implemented to prevent overfitting by monitoring the validation loss with a patience of 10 epochs. All experiments were conducted on a workstation equipped with an NVIDIA GPU (8 GB VRAM), Intel i7 CPU, and 16 GB RAM, using Python 3.10, TensorFlow 2.15, and scikit-learn 1.5. The training process was repeated with three learning rate variations (0.01, 0.001, and 0.0001) to determine the most stable configuration.

3.6 Model Evaluation

The trained model's performance was evaluated using both quantitative and visual metrics. A confusion matrix was employed to analyze classification performance by comparing predicted and actual labels, providing insight into the distribution of true and false predictions[35]. Furthermore, precision, recall, and F1-score were computed for each class to measure the model's discriminative ability. These metrics collectively provided a comprehensive understanding of how effectively the hybrid DCT, GLCM, and CNN architecture differentiated between fresh and spoiled beef samples[36].

3.7 Experimental Setup and Reproducibility

All experiments were conducted on a workstation equipped with an NVIDIA GPU (≥8 GB VRAM), an Intel/AMD multi-core CPU, and 16 GB RAM. The software stack comprised Python 3.10, TensorFlow/Keras 2.15, scikit-image 0.22, scikit-learn 1.5, OpenCV 4.9, NumPy 2.x, and cuDNN/CUDA compatible with the above framework versions. To ensure reproducibility, we fixed the random seed across NumPy and TensorFlow, disabled non-deterministic cuDNN kernels where feasible, and reported results on the held-out test set only after model selection on the validation set.

Unless otherwise stated, models were trained using Adam optimizer[37] ($\beta 1=0.9$, $\beta 2=0.999$) with cross-entropy loss, batch size 32, and early stopping on validation loss with patience of 10 epochs. Learning rates were swept over {0.01, 0.001, 0.0001}; the best configuration for the final model was 0.0001 with a DCT threshold of 25% and GLCM distance of 1. We applied standardization to handcrafted features and normalized image intensities to [0,1]. To avoid information leakage between datasets, all preprocessing and feature extraction procedures were carried out independently within each of the stratified training, validation, and testing subsets. This approach ensures that no information from the validation or testing data influenced the training process[38].

4. Results and Discussion

4.1 Results

This study integrates Discrete Cosine Transform (DCT) and Gray Level Co-occurrence Matrix (GLCM) feature extraction with a Convolutional Neural Network (CNN) to enhance the accuracy of beef freshness classification.

The experiments were conducted through several configurations to evaluate the contribution of each parameter, including different GLCM distances (1 and 2), DCT coefficient removal thresholds (25%, 50%, and 75%), and learning rates (0.01, 0.001, and 0.0001).

The DCT method was used to extract key structural and textural patterns from the beef images by converting spatial data into the frequency domain. This transformation allowed the model to focus on the low-frequency regions that generally represent essential color gradients and surface consistency. Meanwhile, the GLCM method complemented this by capturing the fine-grained texture relationships between pixel pairs. These two approaches, when combined, were expected to produce features that are more robust against lighting variations and color distortions, two major challenges in visual meat classification.

i. Training CNN-DCT Models (8×8 Block, GLCM Distance 1)

Table 1 *CNN training results with DCT 8×8 and GLCM distance 1*

Learning Rate	Accuracy	Loss	Training Time (s)	Test Time (s)
0.01	46.05%	0.732	19104	43.374
0.001	48.95%	0.736	18324	82.590
0.0001	49.21%	0.492	20004	48.836

In the first experiment (Table 1), using a DCT block size of 8×8 and a GLCM distance of 1, the CNN achieved a moderate accuracy of 49.21% at a learning rate of 0.0001. Although the performance was relatively low, this result served as a baseline, indicating that the CNN alone with standard DCT encoding still struggled to generalize under varying illumination and texture conditions. The loss value of 0.492 suggested that the network was learning, but not yet optimally converging.

ii. Training CNN-DCT Models (8×8 Block, GLCM Distance 2)

Table 2 *CNN training results with DCT 8×8 and GLCM distance 2*

Learning Rate	Accuracy	Loss	Training Time (s)	Test Time (s)
0.01	51.05%	0.729	19764	82.499
0.001	83.42%	0.400	18324	51.688
0.0001	48.68%	0.723	21864	142.259

The CNN model with DCT Block 8×8 and GLCM Distance 2 (Table 2) achieved 83.42% accuracy at a 0.001 learning rate, showing strong performance. A loss of 0.400 indicates effective learning. Training took 18,324 seconds, slightly faster than previous models, with a test time of 51.688 seconds. These results show the value of tuning GLCM distance and learning rate for optimal CNN performance.

When the GLCM distance was increased from 1 to 2, the model accuracy improved to 83.42% at a learning rate of 0.001. This shows that slightly increasing the distance between pixel pairs helps the GLCM capture broader textural patterns, especially those associated with muscle fiber direction and fat marbling. However, further increasing the distance or removing too many DCT coefficients led to reduced precision, indicating that there is an optimal spatial relationship for feature extraction in this context.

iii. Training CNN-DCT Models (25% Threshold, GLCM Distance 1)

Table 3 *CNN results (25% threshold, GLCM distance 1)*

Learning Rate	Accuracy	Loss	Training Time (s)	Test Time (s)
0.01	86.05%	0.208	20664	52.188
0.001	77.00%	0.445	20004	82.152
0.0001	93.00%	0.211	20304	82.160

A significant performance jump occurred when a 25% DCT threshold was applied in combination with a GLCM distance of 1 (Table 3). In this configuration, the model achieved 93% accuracy with a loss value of 0.211, demonstrating that most of the important low-frequency components had been preserved, while redundant high-frequency noise was effectively filtered out. This result confirmed that discarding a small proportion of high-frequency components could help the CNN focus on the most discriminative features rather than being distracted by visual noise such as reflections or uneven lighting.

iv. Training CNN-DCT Models (25% Threshold, GLCM Distance 2)

Table 4 *CNN results (25% threshold, GLCM distance 2)*

Learning Rate	Accuracy	Loss	Training Time (s)	Test Time (s)
0.01	83.16%	0.408	18324	82.030
0.001	83.95%	0.555	19404	55.922
0.0001	80.00%	0.436	19464	82.042

In Table 4, increasing the GLCM distance to 2 under the same DCT threshold produced slightly lower accuracy (83.95%), indicating that a smaller spatial offset (distance = 1) provides more precise textural context for beef freshness classification. Larger distances may overlook subtle surface variations critical to identifying freshness, such as moisture levels and color gradients. Therefore, the distance of 1 was found to be more suitable for capturing micro-texture differences that define freshness attributes.

After training, the performance of the optimal model (DCT threshold 25%, GLCM distance 1, learning rate 0.0001) was further evaluated using a confusion matrix and a classification report. The confusion matrix revealed 174 true positives, 181 true negatives, and a small number of false predictions (16 false positives and 9 false negatives). This pattern indicates that the model had strong discrimination power between fresh and spoiled meat categories, with relatively few misclassifications.

```
12/12 [==============================] - 49s 4s/step
              precision    recall  f1-score   support

           1       0.95      0.92      0.93       190
           2       0.92      0.95      0.94       190

    accuracy                           0.93       380
   macro avg       0.93      0.93      0.93       380
weighted avg       0.93      0.93      0.93       380
```

Fig. 3 *Classification report results*

The detailed classification report confirmed this observation (Fig 3), showing a precision of 95% for fresh meat and 92% for rotten meat, while recall values were 92% and 95% respectively. The balance between precision and recall resulted in F1-scores of 0.94 and 0.93, which reflects stable performance across both classes. The macro and weighted averages being identical at 0.93 further demonstrated that the model-maintained consistency without bias toward any particular class.

Overall, the experimental results reveal that the combination of frequency-domain and texture-domain features enables the CNN to learn more discriminative representations of beef freshness. The hybrid feature set helps the model generalize better under variations in lighting, surface texture, and color saturation — conditions often encountered in real-world meat inspection environments.

4.2 Discussion

The experimental findings confirm that integrating DCT and GLCM with CNN provides significant improvements over using CNN alone. The DCT effectively compresses visual information by emphasizing the low-frequency regions that carry the essential color and structural details of beef tissue. This helps the network avoid overfitting to irrelevant visual noise. Meanwhile, the GLCM contributes valuable statistical texture descriptors that enhance the CNN's ability to distinguish fine-grained surface differences between fresh and spoiled meat, such as slight discoloration or drying on the surface.

The 25% DCT threshold emerged as the most effective configuration. Removing only a quarter of the high-frequency coefficients allowed the system to retain sufficient spatial details while discarding unnecessary information that often increases variance and computational complexity. This finding aligns with earlier works, which noted that moderate DCT compression improves classification accuracy by focusing learning on salient visual features.

On the other hand, the experiments revealed that GLCM distance plays a crucial role in determining how texture is perceived. A smaller distance (d=1) captured local variations in pixel intensity that correspond to subtle freshness indicators, such as microstructural uniformity and moisture distribution. Larger distances (d=2) tended to generalize these relationships, leading to lower sensitivity in detecting early spoilage signs. This observation is consistent with findings by Chen et al. (2022), who reported that short-distance GLCM parameters better capture local degradation textures in food imaging.

The CNN architecture itself benefited from the feature fusion process. By combining the handcrafted statistical features from DCT and GLCM with CNN's automated feature learning, the model leveraged both domain-specific knowledge and data-driven patterns. This synergy significantly reduced overfitting and improved generalization. Moreover, the relatively low loss values and balanced confusion matrix indicate that the hybrid network successfully learned to differentiate classes with minimal bias.

Practically, this hybrid model demonstrates the potential to be applied in automated meat inspection systems, providing fast and reliable quality assessments without manual observation. Compared to conventional chemical or sensor-based freshness tests, this vision-based approach offers a more scalable and non-invasive solution that can be deployed in retail, slaughterhouse, or supply-chain monitoring environments.

5. Conclusion

This study proposed an integrated approach for beef freshness classification by combining Discrete Cosine Transform (DCT), Gray Level Co-occurrence Matrix (GLCM), and Convolutional Neural Network (CNN) techniques. The experimental results demonstrated that this hybrid method significantly improved classification performance compared to using CNN alone, achieving an accuracy of 93% and balanced F1-scores of 0.94 for fresh meat and 0.93 for rotten meat. The DCT component effectively extracted low-frequency features representing essential color and structure information, while the GLCM method captured fine texture patterns related to surface moisture and tissue degradation. When fused with CNN's deep feature representations, these complementary characteristics enhanced the model's robustness and generalization ability.

Beyond its quantitative performance, this research highlights the potential of combining frequency-domain and texture-domain analysis to support computer vision applications in food quality monitoring. The results show that moderate DCT compression (25% coefficient reduction) and short-distance GLCM configurations (distance = 1) yield optimal trade-offs between accuracy and computational efficiency. These findings offer a valuable contribution to the development of non-invasive, image-based freshness detection systems, which can reduce human subjectivity, minimize food waste, and strengthen traceability in the meat supply chain.

Nevertheless, this work represents a foundational step rather than a complete solution. The model's performance should be further validated on larger and more diverse datasets, encompassing different lighting conditions, camera types, and intermediate freshness levels. Future extensions could also explore lightweight neural architectures or explainable AI techniques to improve real-time applicability and interpretability.

In conclusion, the integration of DCT, GLCM, and CNN provides a promising pathway toward intelligent food inspection systems. By bridging classical image processing with modern deep learning, this approach demonstrates how hybrid computational models can enhance accuracy, efficiency, and transparency in the agri-food sector, supporting broader goals of food safety, sustainability, and digital transformation in the global meat industry.

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Conflict of Interest

The manuscript has not been published elsewhere and is not under consideration by other journals. All authors have approved the review, agree with its submission and declare no conflict of interest on the manuscript.

Author Contribution

Adhi Kusnadi ***led the research design, supervision, and manuscript development;*** *Fenina Tobing* ***handled experiments, CNN implementation, and feature extraction;*** *Rangga Winantyo* ***managed data collection and***

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model evaluation; *Monica Haryanto and Muhammad Tanveer* ***supported technical setup, literature review, and contributed to the discussion****. All authors approved the final manuscript.*

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