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A comprehensive comparative analysis of chicken meat classification techniques through machine learning models

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ABSTRACT

This study develops a digital image processing technique to distinguish between fresh and rotten chicken. Chicken freshness has a significant impact on public health and industry sustainability. This study uses a multi-stage approach including data acquisition, preprocessing, feature extraction, and classification. A total of 1,000 chicken images were obtained, consisting of 800 images for training and 200 images for testing, with a proportion of 80:20. Feature extraction was performed using a combination of the HSI (Hue, Saturation, Intensity) color model to capture the color characteristics of chicken, and Local Binary Pattern (LBP) to extract texture information. Classification was performed using the K-Nearest Neighbor (KNN) algorithm with various K values and distance metrics. The experimental results show that the combination of color and texture features provides higher accuracy than using either feature alone. The best model using HSI and LBP feature extraction with K = 1 and K = 3 in the Euclidean distance metric, achieved the highest accuracy of 95.4%. With a promising level of accuracy, this method can be applied in automated inspections in the poultry supply chain, improving food safety, and helping consumers make better purchasing decisions. However, the main challenge in this study is the variation in lighting during image capture, which causes the fresh and rotten chicken feature values to overlap, thus hindering perfect classification.

1. Introduction

In the culinary field, chicken is a versatile and favored choice, with broiler chickens the most popular. This type of chicken, known for its high protein [1], fat [2], mineral [3], carbohydrate, and abundant vitamin content, has become deeply integrated into society, attracting interest from people across various socioeconomic backgrounds. Its nutritional advantages [4] and affordability compared to beef, goat, and buffalo meat have further increased its appeal [5]. According to a report by the Food and Agriculture Organization (FAO), global chicken meat consumption has increased by more than 20% over the past decade, making it one of the most consumed sources of animal protein [6]. However, this rise has also raised concerns about food safety. According to a report by the European Food Safety Authority and the European Centre for Disease Prevention and Control, from 2004 to 2015, the highest cases of Salmonella infections originated from chicken meat and its processed products [7]. However, this remarkable information conceals an urgent issue. The increasing demand for chicken has led to the emergence of a black market in which unscrupulous sellers distribute low-quality products [6]. Consumers face challenges in distinguishing between pure and contaminated food, leaving them in a difficult situation in which spoiled chicken coexists with fresh chicken [7]. Poultry, eggs, and dairy products, in particular, are common carriers of Salmonella [8], a harmful bacterium widely feared for its ability to cause severe gastrointestinal symptoms such as cramping, diarrhea, and fever [9]. These illicit activities not only deceive the public but also heighten the risk of foodborne illness, posing serious public health concerns [10].

Analyzing the color range of chicken and pH readings, which serve as indicators of its overall health, can determine its freshness [11]. Meat quality heavily depends on the fundamental structure of chicken skin [12]. At first glance, fresh and spoiled chicken may appear similar, necessitating a detailed examination by an expert [13]. However, not everyone can distinguish fresh from spoiled chicken using this method. Researchers have identified this as a problem. Due to the long duration and complexity of the procedures, implementation is difficult. Moreover, it can incur high costs and produce unpredictable results. The incompatibility of this approach with large-scale production exacerbates the problem, making it essential to find a more effective solution [5]. Revolutionary advances in research have led to the development of cutting-edge systems that leverage digital image processing to address these critical issues [14]. By precisely distinguishing between fresh and spoiled chicken through a combination of advanced approaches, this innovative method aims to transform the poultry market.

At the core of this research is the application of advanced digital image processing techniques to analyze the intricate characteristics of chicken meat [15]. This technology relies on extracting complex feature values from image data, forming the basis for sophisticated machine learning algorithms to evolve, enabling an exceptional learning process. The primary focus of this approach is on widely used feature extraction methods, which are praised for their effectiveness in identifying an object's fundamental characteristics [16], [17]. This approach uncovers the true freshness of chicken meat by carefully combining color and texture analysis [18]. This study employs the HSI (Hue, Saturation, and Intensity) [19] approach to extract color data and the LBP (Local Binary Pattern) method [20] to reveal hidden texture information. This meticulous integration ensures a comprehensive understanding of the chicken's condition.

This innovation progresses as feature extraction seamlessly integrates with the KNN (K-Nearest Neighbors) algorithm [21], establishing a mutually beneficial relationship [22] that enables precise classification [23]. The entire process is divided into four key stages: initial image acquisition, careful preprocessing, including resizing and cropping the image, feature extraction with three different scenarios (standalone HSI feature extraction, standalone LBP feature extraction, and a novel fusion of both methods) [24], [25]. This combination offers immense potential, enabling the discovery of details that are unattainable with individual approaches [26]. The success of this system heavily relies on the final categorization stage, which involves various distance calculation methods [27]. This phase is crucial, serving as evidence of the KNN approach's rigor, ultimately aiming for the highest accuracy level [28]. This research is centered on a firm commitment to achieving accuracy.

The expected results align to improve classification accuracy and serve as a guiding principle for seamlessly integrating this technique into real-world systems. This idea aims to empower many by providing a tool that expands beyond the scientific domain. In its implementation, producers can reduce manual inspection costs and enhance production efficiency. Additionally, this system can assist supermarkets, restaurants, and slaughterhouses in ensuring the quality and safety of the poultry products they sell, thereby increasing consumer confidence in poultry. Essentially, this advanced technique will enable users to determine chicken freshness with absolute certainty, eliminating uncertainties that have persisted until now.

2. Research Method

This phase clarifies the study's structured order. The scientific process involves several unique stages: data collection, preprocessing, feature extraction, classification, and evaluation.

2.1. Data Collection

The primary goal of image clarity capture is to produce high-quality image files depicting fresh and spoiled chicken. The dataset was carefully curated through in-person visits to slaughterhouses, where we collected a variety of poultry meat samples with meticulous attention to detail. Fresh chicken images were captured immediately after slaughter and cleaning. In contrast, spoiled chicken images were collected after being stored for 24 to 48 hours at room temperature to simulate market conditions, as shown in Fig. 1.

Fig. 1. Image of Fresh Chicken (Left) and Rotten Chicken (Right)

To ensure consistency in data collection, images were captured outdoors. Natural lighting was utilized for lighting conditions. This project was approached with a contemporary perspective, using a 12-megapixel smartphone camera to capture images from multiple angles, covering a variety of poultry cuts, including whole chicken, breast fillets, thighs, and wings. This approach ensured that the dataset was diverse and reflective of real-world market conditions. The dataset comprises 1000 photographs. The research data was partitioned into training and testing sets in an 80:20 ratio. We established an equilibrium by using 800 photographs for training, with 400 showing chicken flesh in an appropriate freshness state and another 400 showing chicken meat in an improper freshness state.

The system testing was conducted on the remaining 200 photographs. There are 100 photographs of fresh chicken flesh, as well as 100 images of decaying chicken meat. This demonstrates the researchers' dedication to meticulously examining each individual pixel to classify chicken flesh as either fresh or non-fresh.

2.2. Preprocessing

Following data acquisition, a crucial step in the subsequent study is pre-processing, which aims to establish an optimal path for analysis. Fig 2 provides a clear visualization of the many elements involved in picture data preparation. In other words, the original image is modified. Cropping reduced the original picture resolution of 1712x1961 pixels to 500x500 pixels. This intentional decrease in size is not only a reduction, but rather seeks to match the resolution of the image, a crucial step in gathering uniform datasets.

Cropping is a proficient technique that supports the process. The image is trimmed to enhance clarity and eliminate unnecessary borders, exposing the fundamental core. The central portion of the poultry remains is kept, while the other halves are discarded. This presentation demonstrates the creativity of digital editing through a meticulously altered image, carefully cropped and balanced to capture its true essence.

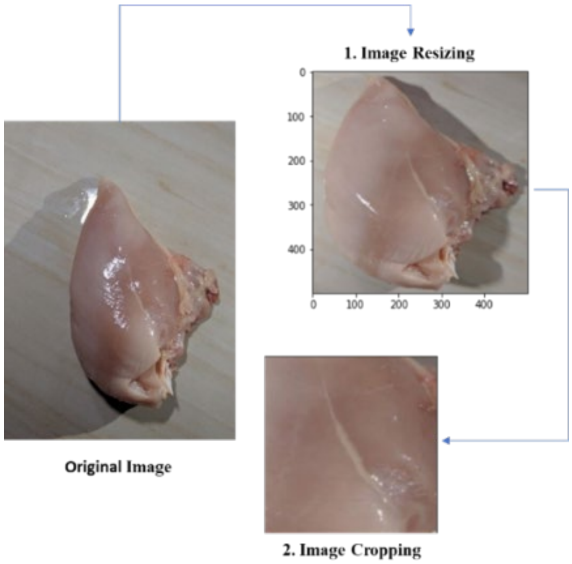

Fig. 2. Preprocessing Stages of Image Data

2.3. Feature Extraction and Classification

The intricate domain of image analysis includes feature extraction, a crucial component of recognition [6]. The complex procedure begins with the sorting phase, in which the gathered characteristics serve as crucial elements for distinguishing one object from another. What makes this process so fascinating is the dynamic transformation of colors and forms over time. Each one exhibits a distinct facet of the object's character. The color scheme and pattern combination appear to provide valuable insights about the situation [29]. The HSI color feature extraction approach meticulously isolates the hue, saturation, and intensity components, considering them as the fundamental color elements [30]. The HSI color feature defines color in terms of Hue (H), Saturation (S), and Intensity (I). Hue describes the basic color and is determined by the dominant wavelength in a light's spectral distribution. Saturation represents the attribute of color that describes its purity (pure color). Intensity or brightness of a color is a parameter that describes its lightness or darkness [31].

The selection of the HSI color model in this study is based on several advantages, including its resistance to lighting variations, where the HSI model is more stable than RGB under uneven lighting conditions, and ease of interpretation, as Hue represents the basic color, Saturation indicates the level of color purity, and Intensity describes brightness [32]. This facilitates the visual differentiation between fresh and spoiled chicken. Previous studies have shown that HSI-based color features can improve image recognition accuracy compared to RGB, as they better reflect human color perception [31].

Furthermore, we use texture to determine the composition of objects in an image. The image feature extraction process employs Local Binary Patterns (LBP), a method for extracting texture features from an image. LBP is a grayscale texture analysis measure that quantifies local contrast in an image. It transforms an image into an array of integer labels that describe its small-scale appearance [33]. These labels or statistics are typically represented as a histogram, which is then used for further image analysis. The process involves collecting feature values such as mean, variance, and entropy, which provide insights into the complex and diverse nature of image textures. Next, we use texture to determine the object's composition in a picture. The process of extracting image features using LBP involves computing mean, variance, and entropy [32]. These components offer insight into the intricate and diverse nature of an image's texture. The image recognition process reaches its peak when the picture's color and texture characteristics merge [34]. This research demonstrates a sophisticated technique for extracting complex features, in which each feature provides a distinct representation of the object's identity.

Fig. 3 depicts the methodology with the simplicity and detail of a masterpiece. The extremely complex comparison process serves as a signal, prompting us to consider the consistency of features and their intricate combination. It serves as an elucidation, giving the previously stagnant image vitality.

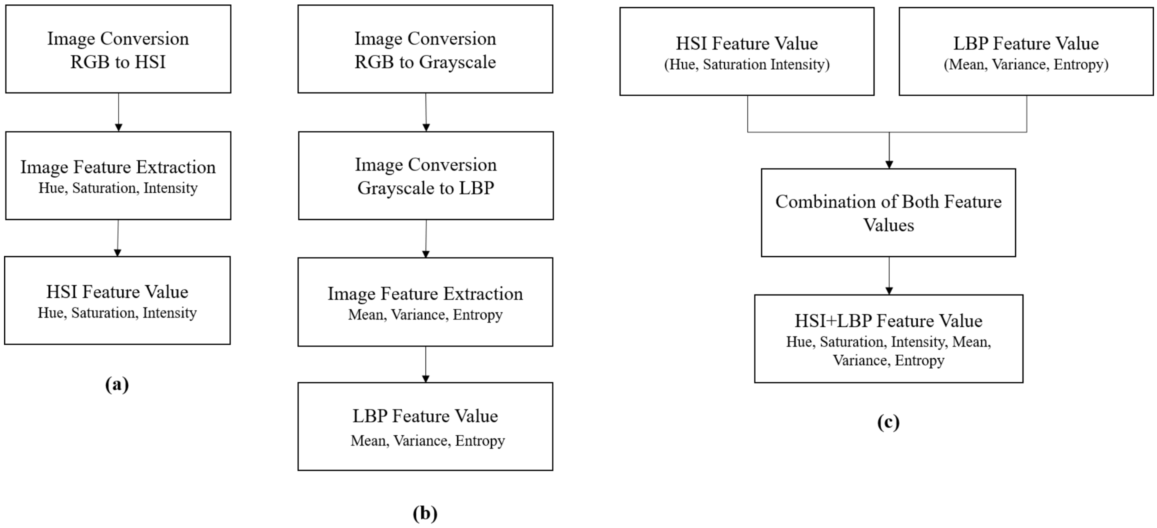

Fig. 3. Stages of Feature Extraction comparison: *(a) HSI, (b) LBP, and (c)* combination of HSI and LBP feature extraction

We identify the extraction of color features as a significant step in uncovering important visual attributes in photos, building on prior research that examined the categorization of fresh and spoiled chicken flesh using Convolutional Neural Networks (CNNs) [35]. This technique entails examining the color composition of the chicken meat photos, which consist of pixels with different color intensities [36]. Based on previous research [8], [37], We utilize the HSI (Hue, Saturation, Intensity) color feature to define color characteristics. Prior to feature extraction, a crucial step is to transform the photos from the RGB color space to the HSI color space [38]. The conversion is necessary because it enables the calculation of the HSI value for each pixel, which requires prior knowledge of its RGB values [39]. Fig. 4 provides a detailed depiction of the conversion process, illustrating the sequential steps required to convert from RGB to the HSI representation. This conversion is important because it enables the extraction of color features, which in turn enhances the categorization of fresh and rotten chicken flesh.

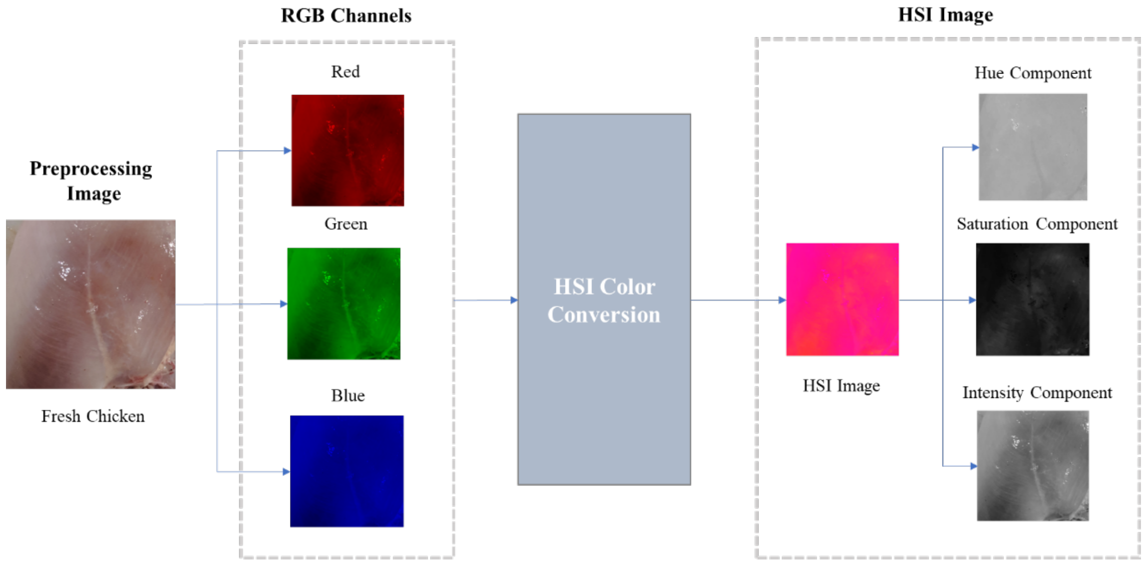

Fig. 4. Image Conversion Stages from RGB to HIS

Fig. 4 clearly depicts the complex process of transforming an RGB image into the HSI color space. This transformation is crucial because it enables a detailed comprehension of color characteristics [40] that are necessary for extracting the features. We rigorously extract features from the preprocessed picture, converted to the HSI color space, to identify essential hue, saturation, and intensity values. This stage is crucial in collecting the tiny visual clues that are present in the photos of fresh and rotting chicken flesh [41]. Fig. 5 provides a detailed reference for exploring the complexities of the feature extraction approach specifically designed for photos of fresh and rotting chicken flesh.

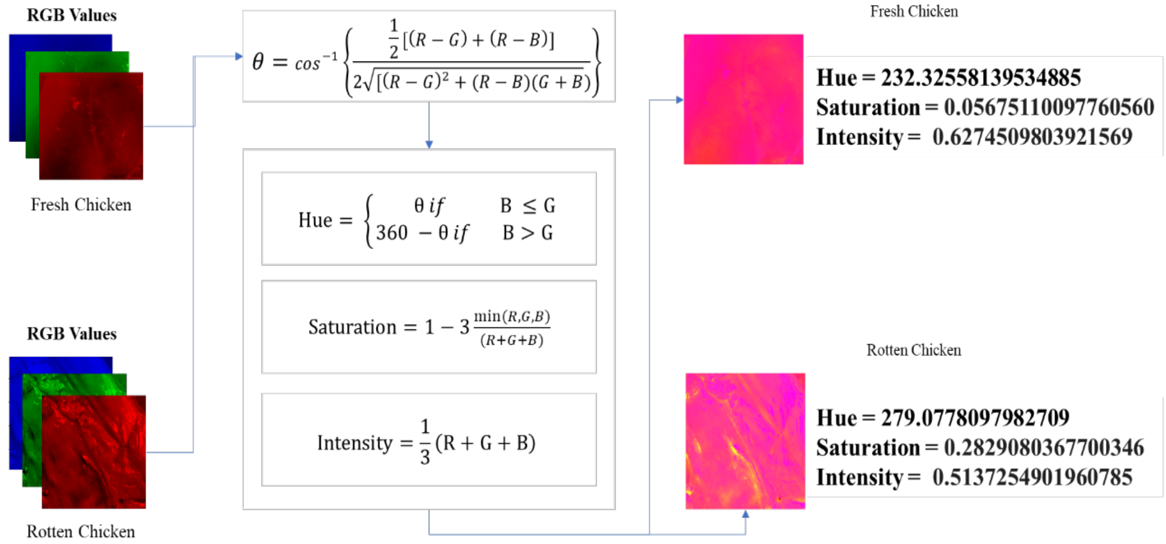

Fig. 5. Images of Fresh and Rotten Chicken with HSI Feature Extraction Value

Hue, a primary element of HSI colour characteristics, represents the fundamental nature of primary colours and is determined by the predominant wavelength in the distribution of light wavelengths. Saturation is a crucial factor that determines the intensity of a pure colour, representing the vividness or dullness of hues. The third component, intensity or brightness, defines the degree of lightness or darkness of colours, ranging from vivid tints to muted tones. These precise definitions provide insight into the complex characteristics of colour attributes and emphasize their importance in the feature-extraction procedure for distinguishing between fresh and spoiled chicken flesh.

On the other hand, in 1996, Ojala *et al.* [6] introduced the Local Binary Pattern (LBP) as a visual descriptor for detecting surface structural features. In recent years, there has been a notable focus on texture feature extraction, particularly the LBP method, which has been widely compared with other techniques in computer vision [42]. The LBP algorithm has shown exceptional performance in a wide range of fields, with particular success in face detection and identification studies [9], [11], [12]. The procedure usually starts by converting the initial image to grayscale. We then use the LBP operator with parameters P and R, where P denotes the number of surrounding pixels considered in the calculation and R denotes the distance between the center point and the neighboring pixels [43]. The careful and thorough method highlights the algorithm's effectiveness in extracting key texture features for tasks such as image analysis and classification.

After performing the first stages of converting the picture to grayscale and applying the Local Binary Pattern (LBP) operator, the image is subjected to additional processing. This involves breaking the image into several blocks or local areas depending on the descriptor and circular neighborhood operator, as explained in earlier research [13], [44]. The rotation-variation arrangement is specifically used, incorporating three distinct radii (R) and accounting for 24 adjacent pixels (P). This setup guarantees the strength and resilience needed to capture texture characteristics across a wide range of spatial scales. The computation of LBP is performed using the uniform LBP technique [45], leveraging utilities provided by the image library to enable rapid execution. Fig. 6 clearly depicts the consecutive stages required to convert an RGB image into its matching LBP representation, providing a detailed explanation of the transformation process.

Fig. 6 illustrates the image transformation process in image preprocessing and feature extraction. It shows the transfer of the picture from its original RGB format to grayscale and then to Local Binary Pattern (LBP). The purpose of this conversion procedure is to optimize future studies by simplifying image representation by assigning a single value, referred to as the gray value, to each pixel. Subsequently, the grayscale matrix is obtained, enabling the thresholding procedure to identify the most suitable threshold values [14]. Afterwards, the process of converting binary values into decimal numbers occurs, a crucial step repeated until all pixels in the picture are successfully converted into LBP images. The core of LBP feature extraction involves acquiring fundamental feature values, such as mean, variance, and entropy, which are vital for later analysis and classification tasks. Fig. 7 provides further clarification of the complex process of LBP feature extraction, enhancing our understanding of this crucial step in image processing.

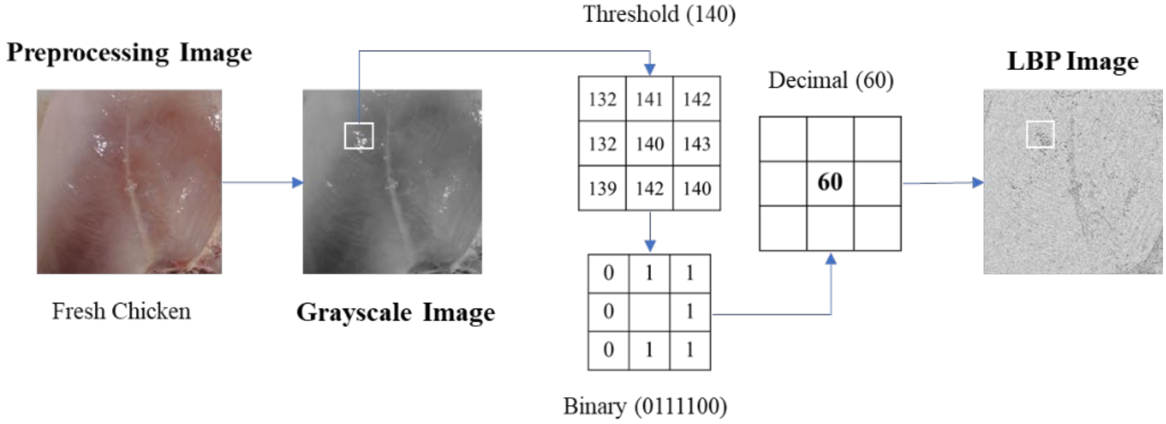

Fig. 6. Image Conversion from RGB to LBP in Stages

In image analysis, the mean is a fundamental measure that represents the average value of the pixels in a picture. The mean of an image's intensity distribution is calculated by dividing the sum of pixel values by the total number of pixels. This measure represents the central tendency of the distribution. Variance provides information about the range of grayscale values in an image, indicating how dispersed the pixel intensity values are [15]. Entropy is a metric that gauges the complexity of a picture by measuring its unpredictability or chaos. Photographs with complex textures or varied patterns often exhibit high entropy, indicating a lack of consistency in pixel distribution [16]. In Fig. 7, the notation P(i,j) represents the grayscale level of an individual picture pixel at the row location (i,j) [15]. These measurements are critical for describing picture characteristics and for further analysis and classification activities.

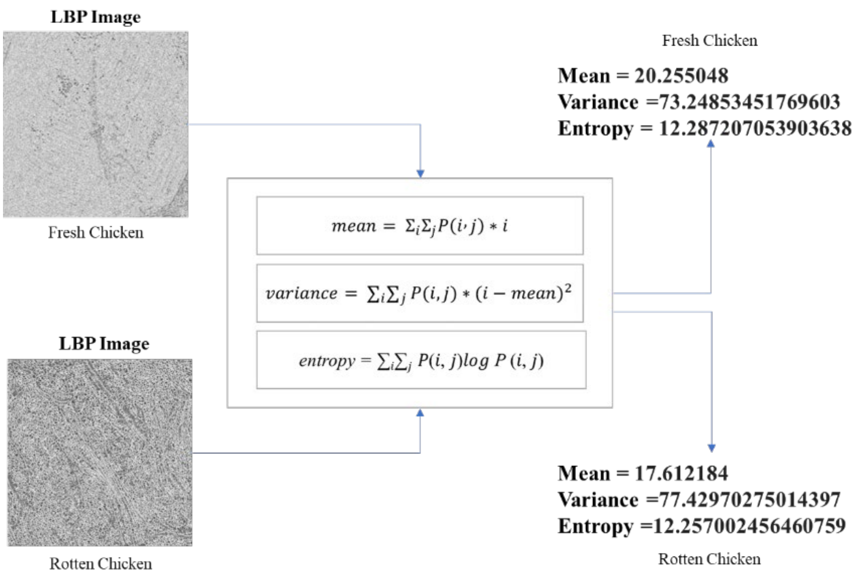

Fig. 7. Extraction of LBP Image Features from Fresh and Rotten Chicken

During the post-feature extraction step, the processed picture data is classified using a well-known approach in the field of Machine Learning, namely the K-Nearest Neighbor (KNN) algorithm [46]. KNN is a widely used classification approach that uses the training data to identify the nearest neighbors to the target item [47]. The first phase of this technique involves calculating the distance between feature values in the test and training datasets. This procedure is governed by the value of K. Afterwards, these distances are carefully organized to get the closest neighbor that has both the smallest distance and the highest similarity in feature values. This neighbor, along with similar neighbors, is categorized by assigning a label to the data item based on the majority class of its closest neighbors [19]. KNN uses proximity to infer class membership, demonstrating its effectiveness as a reliable classification tool through an iterative process [48].

This study focuses on the classification challenge of differentiating between two separate categories: fresh chicken and spoiled chicken. To optimize the performance of the K-Nearest Neighbor (KNN) method, a range of K values, namely K = 1, 3, 5, and 7, is thoroughly investigated. This comparison aims to identify the K value that provides the best accuracy in classifying fresh and rotten chicken [49]. In addition, many distance computation formulae are used to determine the distances between feature vectors, such as Euclidean, Minkowski, Manhattan, and Chebyshev [50]. This comprehensive methodology allows for a full assessment of the algorithm's efficacy across different settings. The study aims to determine the optimal combination of K parameters and distance calculation models [37] that yields the maximum classification accuracy [19] by systematically adjusting both. Through a thorough comparison study, we gain valuable insights into how KNN parameters and distance metrics interact. This analysis improves classification performance in distinguishing between fresh and rotten chicken flesh.

3. Results and Discussion

This section examines the experimental results for implementing the k-Nearest Neighbors (KNN) method, in which multiple values of K and various distance metrics (Euclidean, Manhattan, Chebyshev, and Minkowski) were investigated. The topic focuses on the utilization of cross-validation using HSI (Hyperspectral Imaging) and LBP (Local Binary Patterns) features. Table 1 presents the model's categorization results for the testing data in each scenario.

Table 1. Results of Accuracy Testing on Each Scenario Model

Cross Validation	KNN (K)	Euclidean	Manhattan	Chebyshev	Minkowski
HSI Feature	1	0.921	0.9119	0.9199	0.921
	3	0.9205	0.916	0.9195	0.9205
	5	0.9183	0.9153	0.9176	0.9183
	7	0.9162	0.9153	0.9148	0.9163
	9	0.9140	0.916	0.9122	0.9140
LBP Feature	1	0.944	0.9389	0.9289	0.944
	3	0.9450	0.9435	0.9285	0.9450
	5	0.9437	0.943	0.9317	0.9437
	7	0.9415	0.9425	0.9339	0.9415
	9	0.9414	0.943	0.9358	0.9414
HSI and LBP Feature	1	0.954	0.9490	0.9450	0.954
	3	0.9505	0.9505	0.9465	0.9505
	5	0.9507	0.9500	0.9477	0.9507
	7	0.952	0.9518	0.9493	0.952
	9	0.9522	0.9526	0.9502	0.9522

3.1. Cross-Validation Performance with HSI Feature

The initial technique examined is the Histogram of Spectral Indices (HSI) for assessing chicken freshness. Fig. 8 displays the performance outcomes for several values of parameter K and distance measurements.

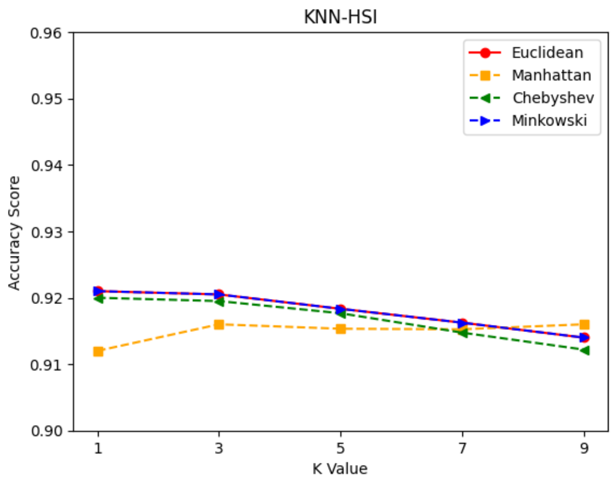

Fig. 8. Performance of the HSI Method

Fig 8 methodically examines the performance of the KNN algorithm using HSI characteristics. It explores many values of k, especially k=1, 3, 5, 7, and 9. We are examining Euclidean distance, Manhattan distance, Chebyshev distance, and Minkowski distance as the metrics. Both the Euclidean and Manhattan distance metrics yield an impressive accuracy of 0.921 when k = 1. In contrast, the Manhattan distance measure attains its highest accuracy, 0.9153, when k is 5. When k equals 1, the Chebyshev distance measure achieves its maximum accuracy of 0.9199. The performance gradually decreases as k increases for the Euclidean, Chebyshev, and Minkowski metrics. In contrast, the KNN algorithm's performance shows consistent improvement as k increases, especially with the Manhattan distance measure.

3.2. Cross-Validation Performance with LBP Feature

The analysis includes Local Binary Pattern (LBP) characteristics, revealing notable performance patterns. The accuracy of Euclidean, Manhattan, and Minkowski distances consistently improves as the K values decrease. The Chebyshev distance has a distinct pattern, with the greatest level of accuracy seen when K=3. The Local Binary Patterns (LBP) features exhibit strong and consistent performance across various distance metrics.

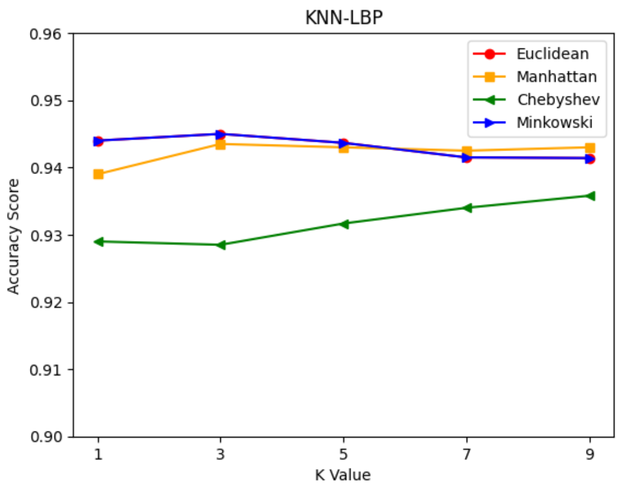

Fig. 9. Performance of the LBP Method

During cross-validation testing using LBP (Local Binary Pattern) Features, the performance of the k-Nearest Neighbors (KNN) method varies across different k values (1, 3, 5, 7, 9) and distance metrics (Euclidean, Manhattan, Chebyshev, Minkowski). For k=1, the Euclidean and Minkowski metrics obtained the best accuracy of 0.944, whilst the Manhattan metric yielded a slightly lower accuracy of 0.939. Although there were some little variations, the KNN algorithm demonstrated consistent performance. The Chebyshev and Minkowski metrics yield highly accurate findings, particularly when the k values are low.

3.3. Cross-Validation Performance with HSI & LBP Combination

Fig. 10 shows how the K-Nearest Neighbors (KNN) method can be used with data from both hyperspectral imaging (HSI) and local binary pattern (LBP) in science experiments.

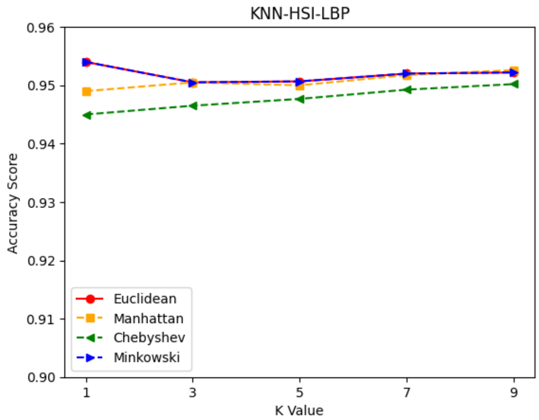

Fig. 10. Performance of the LBP and HSI Combination

The performance of the LBP and HSI combination is shown in Fig. 10, which illustrates how well the K-Nearest Neighbors (KNN) algorithm performs when features from hyperspectral imaging (HSI) and local binary patterns (LBP) are combined. The investigated factors encompass the number of neighbors (k) and various distance metrics (Euclidean, Manhattan, Chebyshev, and Minkowski). The Euclidean and Minkowski distance metrics consistently outperform other metrics across a variety of k values. This indicates that both metrics are suitable for capturing relationships within the hybrid feature set. These metrics achieve the highest accuracy at k=1. Additionally, the Manhattan metric also demonstrates competitive performance, with accuracy values approaching those of Euclidean and Minkowski. Meanwhile, the Chebyshev metric exhibits slightly lower accuracy than other metrics, particularly at larger values of k.

In addition to evaluating model performance based on accuracy, analysis was also carried out on Precision, Recall, and F1-score. These metrics provide an overview of the model's ability to classify fresh and rotten chicken and compare the KNN and SVM models to assess their effectiveness in identifying chicken categories from the processed images.

Table 2 presents a comparison of the performance of the KNN and SVM models for classifying fresh and rotten chicken using the HSI + LBP feature extraction method. The KNN model with parameter K = 1 has perfect precision (1.00), while the recall and F1-score values are at 0.99. Meanwhile, the SVM model achieved a Precision of 0.99, a Recall of 0.99, and an F1-score of 0.99, indicating high performance but slightly lower than KNN in terms of precision. These results indicate that KNN is superior in identifying fresh and rotten chicken categories with fewer classification errors than SVM.

Table 2. Comparison evaluation of KNN and SVM models based on Precision, Recall, and F1-score.

Model	Precision	Recall	F1-scores
KNN (HSI+LBP, K=1)	1.00	0.99	0.99
SVM (HSI+LBP)	0.99	0.99	0.99

Table 3 presents a comprehensive comparison of study results from different authors using different methods and years. Each row in the table represents a distinct study, including the authors' names, the year of the research, the technique used, and the achieved matching accuracy level. In 2017, Asmara *et al.* [51] conducted a study employing an RGB histogram and a Support Vector Machine (SVM) classifier. They achieved an accuracy rate of 58.33%. In 2018, Asmara *et al.* [52] used GLCM and HOG features with an SVM classifier, achieving an accuracy of 98%. Calvin *et al.* [53] used a convolutional neural network (CNN) to achieve an accuracy of 92.9%. In 2022, Gracia *et al.* [54] utilized the VGG16 architecture of a Convolutional Neural Network, achieving a precision rate of 94.11%. In 2022, Anraeni *et al.* [55] completed a study using HSI and LBP characteristics in combination with a KNN classifier . The results showed an accuracy rate of 95.40%. Additionally, Anraeni *et al.* [56] conducted a study using Convolutional Neural Networks (CNNs) to classify chicken freshness, achieving an accuracy of 94%. This table presents a thorough comparison of the performance of several techniques in reaching classification accuracy in different research investigations.

Table 3. Comparison of Study Findings Obtained by Diverse Authors Using Different Approaches Throughout Different Years

Authors	Research Year	Method	Accuracy
Asmara *et al.* [51]	2017	Chicken Meat Freshness Identification Using The Histogram Color Feature	58.33%
Asmara *et al.* [52]	2018	Chicken Meat Freshness Identification using Colors and Textures Feature	98%
Calvin *et al.* [53]	2020	Classification of Chicken Meat Freshness Using Convolutional Neural Network Algorithms	92.9%
Gracia *et al.* [54]	2022	Chicken Meat Freshness Classification Based on VGG16 Architecture	94.11%
Anraeni *et al.* [55]	2022	Ripeness Identification of Chayote Fruits Using HSI And LBP Feature Extraction With KNN Classification	95.40%
Anraeni *et al.* [56]	2024	Innovative CNN Approach for Reliable Chickenmeat Classification in the Poultry Industry	94%

3.4. Discussion of Results

In the results discussion phase, we analyzed various feature extraction methods for the K-Nearest Neighbors (KNN) algorithm, including hyperspectral imaging (HSI) and local binary pattern (LBP), as well as their combination, to gain valuable insights into the algorithm's behavior under various conditions. This discussion focused on analyzing classification accuracy for varying values of k and distance metrics, including Euclidean, Manhattan, Chebyshev, and Minkowski.

The HSI feature extraction method yields consistent KNN classification results across varying k and distance metrics. Notably, at k=1, the Euclidean and Minkowski metrics achieve the highest accuracy, indicating their effectiveness in capturing intrinsic relationships within the HSI feature set. However, accuracy declines gradually as k increases, highlighting the influence of neighboring data points on the decision-making process. Similarly, KNN classification outcomes using the LBP feature extraction method show similar patterns in accuracy across varying values of k and distance metrics. At k=1, the Euclidean and Minkowski metrics again achieve the highest accuracy, indicating their suitability for capturing patterns within the LBP feature set. The consistent decline in accuracy with increasing k underscores the importance of selecting an optimal number of neighbors for effective classification. The Euclidean and Minkowski metrics consistently perform well across different values of k when combining both HSI and LBP features in KNN classification. The highest accuracy is consistently achieved at k=1, emphasizing the importance of considering only the nearest neighbor when combining these diverse features. This implies a synergistic effect between HSI and LBP features in enhancing the algorithm's performance.

From a mathematical perspective, the improvement in classification accuracy achieved by feature extraction can be explained by class separation in feature space. HSI feature extraction helps differentiate data based on color differences between fresh and rotten chicken, as reflected in changes in Hue values due to hemoglobin degradation and oxidation. Meanwhile, LBP captures texture differences caused by structural changes on the surface of rotting chicken, resulting in a more distinct feature distribution between the two classes.

The combination of these two features expands the decision margin between fresh and rotten chicken in the feature space, enhancing class separability and reducing classification errors in KNN. As a result, the model can identify classes more accurately, as the distinction between data groups becomes more significant. KNN with HSI feature, KNN with LBP feature, and KNN with HSI and LBP feature, it is apparent that the combined HSI and LBP features generally yield higher accuracy across various values of k. This suggests that integrating both feature sets enhances the algorithm's ability to discriminate and classify patterns effectively.

The research results indicate that the choice of feature extraction method significantly impacts the performance of the KNN algorithm. The combination of HSI and LBP features proves particularly effective in achieving high accuracy, highlighting the complementary nature of these two methods. These findings underscore the importance of thoughtful feature and parameter selection to optimize the performance of the KNN algorithm across diverse scenarios.

3.5. Failure Analysis

Although the method used has demonstrated high accuracy, some classification errors still require analysis. First, the dataset used in this study is limited to specific experimental conditions, so generalizing the results to a broader dataset requires further testing. Second, environmental variations, such as changes in lighting and image capture conditions, may affect the algorithm's performance. Therefore, implementing the model in real-world scenarios must consider these factors and may require data augmentation strategies or model adaptation.

4. Conclusion

This study compared three different situations: KNN with an HSI feature, KNN with an LBP feature, and KNN with a combination of HSI and LBP features. The results showed that the combined approach, which uses both spectral and textural information, outperforms the individual feature extraction methods. The amalgamation of HSI and LBP features yields a more comprehensive representation of chicken freshness, improving classification accuracy. These findings hold practical implications for the food industry, particularly in quality control and inspection processes. The integrated approach that uses both spectral and textural features provides a robust method for accurately distinguishing between fresh and spoiled chicken, thereby contributing to improved food safety and quality assurance. While this study provides valuable insights, it is important to acknowledge certain limitations. Further research could explore additional feature-extraction methods, refine parameter tuning, and expand the dataset to improve the generalizability of the findings. Additionally, investigating the applicability of the proposed approach to diverse poultry types and storage conditions would contribute to a more comprehensive understanding of its effectiveness. To enhance system performance, future research can integrate more advanced machine learning techniques, such as Convolutional Neural Networks (CNN). CNN excels at recognizing more complex visual patterns and can improve resilience against lighting variations and texture changes in rotten chicken. Additionally, to address current limitations, deep learning-based approaches can be employed with data augmentation techniques and improved image quality through better preprocessing methods. For example, lighting normalization and adaptive histogram equalization can be applied to minimize the impact of lighting variations. In terms of implementation, this model has significant potential for real-time applications in the food industry. By leveraging more efficient hardware, such as industrial cameras and edge computing, the model can be deployed on production lines to automatically detect chicken quality. This system can assist in meat quality inspection in poultry processing plants, supermarkets, and restaurants, thereby enhancing food safety and operational efficiency. In summary, the research outcomes underscore the effectiveness of integrating HSI and LBP features in enhancing KNN's ability to discriminate between fresh and spoiled chicken. This study lays the groundwork for continued exploration and refinement of machine learning techniques for food quality assessment in the poultry industry.

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Declarations

Author contribution. The authors contributed to this paper by collaboratively designing the study, developing and implementing the digital image processing techniques, conducting the data analysis, and drafting and revising the manuscript to ensure the accuracy and clarity of the findings.

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