Science in Information Technology Letters
Vol. 4., No. 2, November 2023, pp. 65-74
ISSN 2722-4139
http://pubs2.ascee.org/index.php/sitech

Vision-based chicken meat freshness recognition system using RGB color moment features and support vector machine

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ARTICLE INFO

Article history
Received October 11, 2023
Revised November 6, 2023
Accepted November 23, 2023

Keywords
Support vector machine
RGB color moment features
Chicken meat freshness

ABSTRACT

Chicken meat is a highly sought-after food product among various segments of the general population, known for its high nutritional value and easy accessibility. Presently, meat identification is primarily conducted manually, relying on visual inspection or tactile assessment of the meat's color and texture. However, this approach presents several limitations, particularly when consumers lack the discernment to differentiate the quality of chicken meat freshness. This research aims to identify the freshness level of chicken meat using the Support Vector Machine method, employing the extraction of RGB color moment features to determine the freshness of the meat. The feature extraction process involves calculating the percentage of intensity values for R (Red), G (Green), and B (Blue) in each chicken meat image. Based on the image processing results, the percentage of intensity values, particularly in the R and B parameters, can be used as determining factors. The study involves software testing using fresh and non-fresh chicken meat. The developed system can identify the freshness level of fresh chicken meat with an accuracy rate of 71.6% using the linear kernel SVM and 60.5% using the RBF kernel SVM. This research represents a significant step toward the automation of chicken meat freshness assessment, potentially reducing food waste and enhancing food safety in the food industry. Further research and development could improve the system's accuracy and expand its applications in various food quality control settings.

1. Introduction

Meat consumption is a fundamental component of human diets, providing essential nutrients and proteins [1] that contribute significantly to overall health [2]. However, ensuring the quality and safety of meat products is of paramount importance, with the freshness of meat playing a critical role in influencing taste, nutritional value, and potential health risks [3]. In recent years, the detection and assurance of meat freshness have gained increased attention [4], marked by significant advancements in meat freshness recognition [5].

The significance of meat freshness recognition extends beyond consumer satisfaction [6], [7], encompassing crucial aspects such as food safety [8], reduction of food wastage [9], [10], and efficient supply chain management [11], [12]. Timely detection of deteriorating meat quality prevents the sale of unsafe or substandard products [13], thereby safeguarding public health and reducing economic losses within the industry [14], [15]. Additionally, effective freshness recognition contributes to a reduction in food wastage [16], addressing the global issue of food loss [17], [18]. Moreover, it facilitates informed decision-making in supply chain management, optimizing inventory and logistics.

The field of meat freshness recognition draws from a range of scientific disciplines, including computer vision, spectroscopy, and machine learning [19]–[21]. Computer vision techniques are utilized to extract valuable information from meat images, such as color and texture, serving as indicators of freshness [22], [23]. Spectroscopic methods offer insights into meat quality by examining the interaction between light and meat samples [24]–[26]. Machine learning algorithms are employed to develop models capable of distinguishing fresh from non-fresh meat based on various features and patterns [27]–[29].

Challenges in meat freshness recognition include the accessibility of tools and features. Spectroscopic methods, while effective, often require specialized equipment and precise calibration, making them less practical for real-world applications. In contrast, computer vision and machine learning approaches provide cost-effective and practical solutions. Features related to microbial contamination [30] and odor are difficult to obtain due to their specialized nature, necessitating expertise in microbiology and specialized equipment like e-noses [31]. Color [32], [33] and texture features [31], on the other hand, are readily accessible from meat images, making them practical choices for meat freshness recognition.

This study distinguishes itself by focusing on the recognition of chicken meat freshness, one of the most widely consumed meat types in Indonesia. While previous research predominantly concentrated on beef freshness recognition [34], [35], this research brings a fresh perspective by targeting chicken meat. Furthermore, while earlier studies, such as [36], utilized chicken meat for freshness recognition, they relied on computationally intensive deep learning techniques, specifically convolutional neural networks. In contrast, this research adopts a more computationally efficient approach by employing the Support Vector Machine (SVM).

This research elaborates on two SVM kernels: the linear kernel and the Radial Basis Function (RBF) kernel, facilitating a comparative performance analysis and assisting in selecting the classifier with the best performance. The proposed system categorizes meat freshness into two classes: fresh and non-fresh. Before entering the classifier stage, chicken meat images undergo feature extraction using the RGB color moment method, resulting in nine features derived from the mean, standard deviation, and skewness of each RGB layer. The system's performance evaluation is conducted comprehensively using various metrics. These include an accuracy score, which measures the system's overall correctness in classifying meat freshness, a confusion matrix providing detailed information on true positives, true negatives, false positives, and false negatives, and precision, recall, and F1-Score, all of which collectively offer a thorough evaluation of the system's performance.

2. Method

In this section, we delve into the technical aspects of the research methodology, offering a comprehensive understanding of the processes involved in developing the vision-based chicken meat freshness recognition system

2.1. Support Vector Machine (SVM) Classification

Support Vector Machine (SVM), a powerful machine learning algorithm, is the cornerstone of our chicken meat freshness recognition system. SVM was originally developed by Boser, Guyon, and Vapnik in 1992, drawing from decades of prior computational learning theory. SVM's fundamental concept involves finding an optimal hyperplane to separate two classes in the input space [37]. This is illustrated in Fig. 1. The best hyperplane, in this context, is one that maximizes the margin, the distance between the hyperplane and the nearest data points from each class [38]. These closest data points are referred to as support vectors. The search for these support vectors is accomplished by incorporating a soft margin approach, introducing slack variables ε_i where ε_i > 0. Overall, the support vector search is guided by (1).

$$min_w = \tau(w) = \frac{1}{2\|w\|^2} + C\sum_{i=1}^{l}\varepsilon_i \quad (1)$$

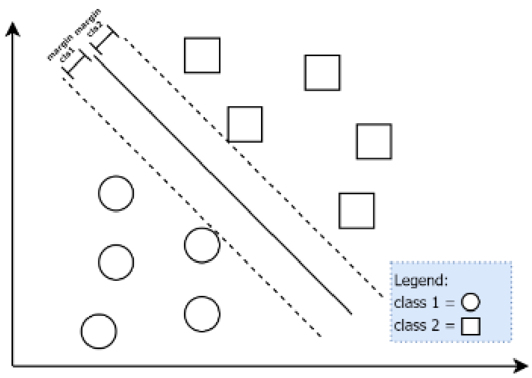


Fig. 1. Illustration of SVM classification based on hyperplane for two classes

Here, 'w' represents the weight vector defining the hyperplane, 'C' is a parameter controlling the trade-off between margin and classification errors, and 'ε' is the slack variable measuring the extent to which each data point violates the constraints or experiences classification errors.

The introduction of slack variables ε renders SVM more tolerant to challenging, non-linearly separable data [39]. The 'C' value, a hyperparameter, is fine-tuned according to the specific problem requirements to control the trade-off between margin and classification errors. A higher 'C' value encourages SVM to minimize classification errors at the expense of a narrower margin, while a lower 'C' value prioritizes a wider margin with greater error tolerance.

2.2. RGB Color Moment Features

RGB color moment analysis is a critical component of our methodology for extracting color information from the chicken meat images. In this context, color moments refer to high-order statistics computed based on the Red (R), Green (G), and Blue (B) color components of each pixel in the image [40]. RGB color moment features encompass calculations of various moments, including zero-order moments (mean color), first-order moments (color centroid), second-order moments (color variance), and so on. Our research focuses on zero-order moments, specifically the mean color. The zero-order moment, denoted as 'M_00,' is the first and simplest moment in the sequence of RGB color moment features. It represents the center of mass of the color distribution within an image. The computation of the zero-order moment is depicted in (2), where 'I(x, y)' denotes the color intensity value at pixel (x, y) in the image.

$$M_{00} = \sum\sum I(x, y) \tag{2}$$

Zero-order moments are versatile and find applications in various image processing tasks, including image segmentation, object recognition, and texture analysis. The 'M_00' values are crucial features for classifying images based on color and identifying objects of specific colors.

Table 1 provides an illustrative example of color moment features extracted from chicken meat images. Each image yields a set of nine features: the first three values derive from the mean of each RGB layer. The remaining six values are obtained from the standard deviation and skewness of each RGB layer within the image. Furthermore, each image is categorized into one of two classes: 'Not Fresh' or 'Fresh.

Table 1. Example of color moment features extracted from chicken meat images

Image Sample	Mean			Standard Deviation			Skewness			Class
	R	*G*	*B*	*R*	*G*	*B*	*R*	*G*	*B*	
	98.2	38	30.1	13	18.7	16.3	17.5	25.5	24.2	Not Fresh
	145.6	79.4	53.1	11.6	17	18.1	12.7	19.9	21.5	Fresh

2.3. Data Collection and Dataset Description

The source of data utilized in this research is secondary, consisting of image data of chicken meat. Specifically, the data comprises images of fresh and non-fresh chicken meat. The dataset used in this study is a publicly available dataset named the "free-range chicken meat dataset," obtainable from Kaggle. This dataset is categorized into two classes: fresh and non-fresh chicken meat. The research leverages a total of 200 data samples, evenly divided into 100 images of fresh chicken meat and 100 images of non-fresh chicken meat. Several representative data samples are showcased in Fig. 2, providing insight into the image dataset's characteristics.

(a) (b)

Fig. 2. Examples of chicken meat images

2.4. Research Design and Implementation

The research methodology follows a systematic approach illustrated in Fig. 3. It commences with problem identification, necessitating the formulation of a research title, problem statement, problem constraints, and research objectives [41]. This phase also involves a comprehensive literature review to harness relevant theories that aid in problem resolution.

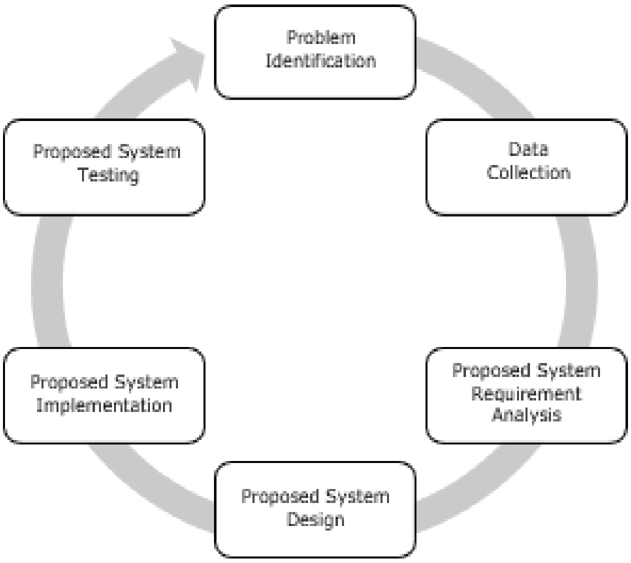


Fig. 3. Illustration of steps of research design and implementation approach

An essential step in the research methodology is the analysis of system requirements. This phase involves translating user needs into detailed system specifications, enabling the identification of challenges within the existing system. By discerning potential issues, the research paves the way for the development of a more robust system.

Following requirement analysis, the research progresses to the system design phase. In this stage, the system's workflow, process flow, and user interface design are conceptualized. The design is instrumental in conveying the sequence of processes and operations, ensuring a coherent approach to system development. Subsequently, the designed system is implemented using Python programming language, with Visual Studio Code as the text editor. This phase results in a functional system capable of classifying chicken meat as fresh or non-fresh based on the extracted features.

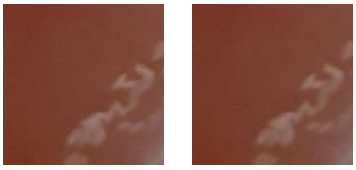
System testing is a critical phase in the research, as it validates the system's performance. The Support Vector Machine (SVM) classification method, employing both the Linear Support Vector Classification (LinearSVC) and the Radial Basis Function (RBF) kernels, is tested extensively. The testing process assesses the accuracy of the classification results using a confusion matrix, which provides a comprehensive comparison between the system's classifications and the true class labels of the input data. Through rigorous testing, the system's ability to accurately categorize chicken meat freshness is validated.

3. Results and Discussion

In this section, we delve into the detailed results and discuss the implications of the preprocessing, system implementation, and classification process. We also provide a comprehensive analysis of the findings.

3.1. Preprocessing Results

The preprocessing stage is vital to ensure that the input data is of the highest quality. In this study, preprocessing for chicken meat images entailed resizing each image to 256x256 pixels and converting the color channel from RGB to BGR. To better understand the effects of preprocessing, refer to Fig. 4.



(a) (b)

Fig. 4. Comparison of chicken meat images (a) before preprocessing and (b) after preprocessing

These preprocessing techniques were applied to a total of 200 data samples, categorizing them into two labels: 100 samples of fresh chicken meat and 100 samples of non-fresh chicken meat. The impact of preprocessing on these images is not just visual but also affects the quality of the features extracted from them. This step ensures that the dataset is in an optimal form for the subsequent classification.

3.2. Classification Results

In addition to creating the system interface for chicken meat freshness classification, this research focuses on the performance of the classification method. The study leverages Support Vector Machine (SVM) as the classifier, utilizing the extracted color moment features. SVM provides various kernels for classification, and two of the most common are the linear and Radial Basis Function (RBF) kernels. The evaluation process begins with the linear kernel and then transitions to the RBF kernel. Table 2 presents the results of these evaluations for chicken meat freshness classification.

Table 2. SVM Testing Results for Chicken Meat Freshness Classification

No	SVM Kernel	Accuracy
1	Linear Kernel	71.6%
2	RBF Kernel	60.5%

Table 2 highlights that the highest accuracy is achieved using the linear kernel SVM, registering an accuracy of 71.6%. However, accuracy alone doesn't provide a complete picture of the classifier's performance, especially in scenarios where class imbalances are prevalent. As a result, this study employs a confusion matrix to offer a more detailed performance evaluation. The confusion matrix for the linear kernel SVM is presented in Table 3.

Table 3. Confusion Matrix for Linear Kernel SVM

Actual	Fresh Chicken Meat	Not Fresh Chicken Meat
Predicted Fresh	10	30
Predicted Not Fresh	1	39

The confusion matrix serves as the basis for calculating other performance metrics such as precision, recall, and F1-Score. For the linear kernel SVM classifier in this study, these metrics are Precision: 80%, Recall: 60%, F1-Score: 68%. The same evaluations are conducted for the RBF kernel classifier. In this case, the precision, recall, and F1-Score are 91%, 25%, and 39%, respectively.

3.3. Discussion

The results and analyses presented in this section offer valuable insights into the performance and practicality of the system for chicken meat freshness classification. Let's delve deeper into these findings:

Effect of Preprocessing: Preprocessing is essential for ensuring that the dataset is in optimal condition. Resizing the images and changing the color channel are two crucial steps that contribute to the enhancement of the dataset. These steps not only impact the visual aspects of the images but also influence the quality of the features extracted. Preprocessing is a vital prerequisite for accurate classification.

Classification Performance: The evaluation of classification performance is a pivotal aspect of this research. Leveraging SVM with both linear and RBF kernels provides valuable insights into the strengths and weaknesses of each kernel type. While the linear kernel exhibits a higher overall accuracy, it is crucial to consider other performance metrics such as precision, recall, and F1-Score. These metrics give a more comprehensive view of the classifier's performance, especially in scenarios where class imbalances exist.

The findings from the confusion matrices and performance metrics reveal that the linear kernel SVM outperforms the RBF kernel in terms of accuracy, recall, and F1-Score. However, it's important to highlight that the RBF kernel demonstrates high precision, which could be advantageous in specific applications. The choice of kernel should align with the specific requirements of the classification task and the relative importance of precision and recall.

Future Directions: The results indicate the potential for further enhancements and optimization. Future research may focus on hybrid kernel approaches to harness the strengths of both linear and RBF kernels, aiming to achieve even more accurate classification results. Additionally, expanding the dataset and incorporating more advanced feature extraction methods may lead to improved performance and practical applications in quality control within the food industry.

4. Conclusion

In this research, a system for chicken meat freshness identification, using color moment features and Support Vector Machine (SVM), has demonstrated a commendable accuracy of 71.6% on a well-balanced dataset. The SVM model with a linear kernel and specific parameter settings contributed significantly to this success. It was observed that the linear kernel outperforms the Radial Basis Function (RBF) kernel, but the RBF kernel holds untapped potential. Future research directions include the use of heuristic parameter search for optimizing the RBF kernel, dataset expansion to enhance generalization, and exploration of various data splitting scenarios for robustness testing. This research serves as a foundational step towards a versatile system for chicken meat freshness classification, with promising applications in food quality control and assurance.

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