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Quality and shelf-life prediction of cauliflower using machine learning under vacuum and modified atmosphere packaging

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ABSTRACT

Ensuring the freshness and quality of cauliflower during storage and transportation is essential due to its high perishability. This study harnesses the power of machine learning to predict the quality and shelf-life of cauliflower under cost-effective vacuum and modified atmosphere packaging (MAP) techniques. By investigating key parameters such as total soluble solids (TSS), pH, weight loss, and color change, a significant impact on post-packaging quality was identified. To address the challenge of accurate color change measurement, an innovative method utilizing a bilateral filter for noise reduction and particle swarm optimization (PSO) with Markov random field (MRF) segmentation was developed. TSS, weight loss, and color change were identified as key parameters, and leveraging these parameters, artificial neural networks (ANN) were employed to create highly precise predictive models, achieving R-squared values of 0.952 for TSS, 0.992 for weight loss, and 0.981 for color change. This approach not only enhances the efficiency and sustainability of food production and distribution but also minimizes food waste and maximizes profitability for cauliflower in global markets through the use of cost-effective packaging solutions.

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1. INTRODUCTION

Cauliflower ranks among the most significant crops worldwide in terms of nutrition, valued for its versatility in culinary applications, including salads and various cooked dishes. Its health benefits, such as cancer resistance and detoxification properties, underscore its importance in modern diets [1], [2]. It is also a good source of vitamins B, C, E, and K, dietary fiber, folic acid, omega-3 fatty acids, proteins, phosphorus, potassium, iron, magnesium, and manganese [3], [4]. Consequently, cauliflower has great demand globally. A significant quantity of cauliflower is cultivated in Bangladesh, demonstrating its capacity to fulfill domestic needs and participate in profitable export markets [5]. However, cauliflower exhibits high perishability post-harvest due to its elevated respiration rate and propensity for water loss [6]–[8]. To mitigate these defects without compromising nutritional quality, various methods have been employed, including low-temperature storage [9], packaging [10], sanitization [11], anti-browning dipping treatments [12], and application of edible coatings [13]. For successful export, it is crucial to determine how long the quality of the products will be preserved under specific methods, meaning the shelf life and quality must be accurately assessed.

Accurate shelf-life prediction helps exporters meet the quality standards and regulations of importing countries, thereby avoiding rejections and financial losses. It ensures that the cauliflower maintains its nutritional value, appearance, and taste during transit. Additionally, it allows exporters to optimize packaging, storage, and transportation methods, reducing waste and increasing profitability. This also helps build trust with international buyers, who expect reliable and consistent quality in the produce they receive. Ultimately, accurate shelf-life prediction leads to increased revenue for the country and a stronger competitive position in the global market.

To maintain quality and extend shelf life during export, packaging is the most popular method. Among the various packaging techniques, modified atmosphere packaging (MAP) and vacuum packaging are the most commonly used. Vacuum packaging involves removing air from the package before sealing [14], while MAP manipulates the atmosphere inside the packaging [15]. In MAP, different gas ratios like nitrogen (N_2), oxygen (O_2), and carbon dioxide (CO_2) are commonly used to modify the atmosphere [16]–[18]. However, gas ratio-based MAP is costly [19]. Researchers have conducted studies to predict quality and shelf life under gas ratio-based MAP. Due to the high cost of gas ratio-based packaging, this research focused on chemical-based MAP packaging and vacuum packaging techniques to reduce costs and identify relevant factors to predict quality and shelf life. Understanding the factors that influence the degradation of cauliflower quality is essential for such predictions. Parameters such as color change, weight loss, pH, and total soluble solids (TSS) are evaluated to assess quality alterations. Among these, color change measurement is a critical factor. Traditional segmentation methods have been used to measure color change, but in cauliflower, small blank spaces within the florets can lead to inaccurate measurements when images are captured. To address this problem, this study proposed an optimized color change measurement system to improve accuracy. The key contributions of this research include: i) investigate cost-effective packaging techniques for cauliflower and acquire the packaged data; ii) identification of significant parameters for predicting cauliflower quality and shelf-life post-packaging, based on comprehensive testing after packaging; iii) development of a novel system for efficiently measuring color change in cauliflower post-packaging; and iv) accurately forecast the quality and shelf life of cauliflower.

The remainder of the paper is organized into several sections. Section 2 provides a review of the relevant literature, setting the foundation for the study. Section 3 details the methodology used in the research, while section 4 presents the results and engages in a discussion of the findings. Finally, section 5 concludes the paper by summarizing key insights and suggesting directions for future research.

2. LITERATURE REVIEW

Research focused on predicting the shelf life of packaged cauliflower is relatively uncommon in the scientific community. However, researchers have made significant strides in forecasting the shelf life of various perishable goods, such as fruits, vegetables, and fish. Some notable studies in this area include.

Mohammed *et al*. [20] emphasize the significance of maintaining the safety and quality of fresh fruits by utilizing advanced technologies like MAP. Their study introduces a cost-effective method employing tiny machine learning (TinyML) and multispectral sensors to predict the quality parameters and shelf life of packaged fresh dates under different conditions. The findings demonstrate a substantial increase in shelf life, particularly with vacuum and MAP1 packaging, with high prediction accuracy (R squared value, R^2=0.951). Through an optimal neural network model, various quality parameters such as pH, TSS, sugar content, moisture content (MC), and tannin content were efficiently predicted. These models offer robust tools for assessing fruit quality accurately, thereby benefiting producers and consumers in optimizing supply chain management and ensuring fresh fruit quality.

Albert-Weiss and Osman [21] focus on assessing agricultural product quality and ripeness using non-destructive testing techniques, specifically acoustic testing. They address challenges associated with employing deep learning (DL) methods like convolutional neural networks (CNNs) due to data inefficiency and a lack of annotated data. To tackle these challenges, the study introduces active learning as a framework, particularly relevant when labeled instances are scarce. They propose the k-determinantal point processes (k-DPP) method within the active learning framework, which aims to enhance exploration within the feature space by selecting a diverse subset k. This approach demonstrates efficiency, especially in scenarios with limited labeled samples, achieving an accuracy of 73.91% in grading 'Galia' muskmelons based on shelf life.

In a study led by Iorliam *et al.* [22], machine learning techniques, including support vector machine, naïve Bayes, decision tree, logistic regression, and k-nearest neighbor algorithms, are applied to predict the shelf life of Okra. The research aims to mitigate potential harm associated with consuming Okra beyond its shelf life. Various parameters such as weight loss, firmness, titrable acid, TSS, vitamin C/Ascorbic acid content, and pH are utilized as inputs for these machine-learning models. Notably, support vector machine, naïve Bayes, and decision tree algorithms achieve perfect predictions of Okra's shelf life, each with an accuracy of 100%. Logistic regression and k-nearest neighbor algorithms achieve slightly lower accuracies at 88.89 and 88.33%, respectively. The study concludes that machine learning techniques, particularly support vector machine, naïve Bayes, and decision tree, are effective in accurately predicting the shelf life of Okra.

Alden *et al.* [23] investigate the impact of MAP on cauliflower shelf life and quality. Their study analyzes four packaging methods over 30 days, demonstrating that MAP1 significantly extends shelf life beyond 30 days. Using artificial neural networks (ANN), a model with one hidden layer and 12 neurons accurately predicts cauliflower shelf life based on color changes, exhibiting high accuracy with a mean square error of 0.0095 and R squared value (R^2) of 0.990. Cauliflower packed with MAP1 demonstrates marketing capability for up to 50 days in terms of total color changes. Mechanical properties showed no significant differences among packaging methods on days 20, 25, and 30, while color changes and weight loss exhibited significant differences in these comparisons.

Fu *et al*. [24] investigate the shelf life of tricholoma matsutake (T. matsutake) from Tibet, focusing on MAP conditions in a cold chain to understand quality changes during T. matsutake's shelf life. Their study analyzes key quality indicators such as hardness, color, odor, pH, soluble solids content (SSC), and MC at specific environmental conditions. The sensory evaluation highlights odor sensitivity as a freshness indicator. Physiological changes in pH, SSC, and MC are categorized into three periods, reflecting cap spread, gradual changes, and complicated deterioration. The study establishes a back propagation (BP) neural network model to predict remaining shelf life based on quality indicators, optimizing through correlation analysis. This research is anticipated to benefit the transportation and preservation of T. matsutake, reducing losses in the postharvest chain.

The reviewed literature underscores the significance of predicting shelf life in the domain of perishable goods, particularly fruits, vegetables, and fish. Collectively, these studies contribute to the advancement of predictive models and preservation techniques. This ultimately enhancing food safety, quality, and supply chain management in the perishable goods industry.

3. METHODOLOGY

To accurately predict the quality and shelf-life of cauliflower under vacuum and MAP, a systematic approach involving multiple stages was employed. This comprehensive process is depicted in the flow diagram of Figure 1, which outlines each critical step in the methodology. Each stage is essential to ensure the precision and reliability of the predictive models.

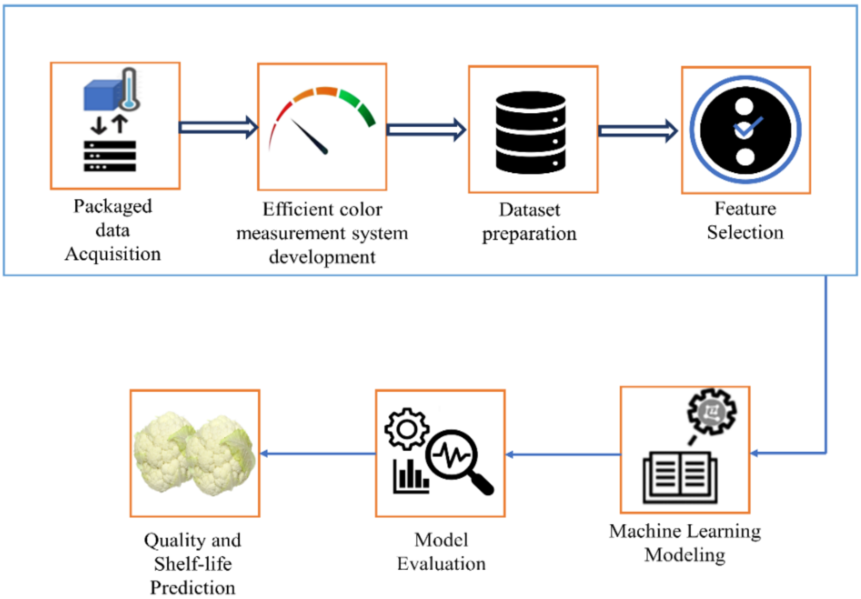


Figure 1. Workflow diagram of the system

3.1. Packaged data acquisition

The experimental approach was meticulously designed to investigate the influence of different packaging methods on the quality of cauliflower. Specifically, the focus was on two primary techniques:

vacuum packaging and MAP. As the primary objective of MAP is to alter the atmosphere within the packaging, a chemical-based approach was applied. $KMnO_4$, CaO, and activated carbon were used because $KMnO_4$ absorbs ethylene to slow ripening, CaO reduces moisture to prevent microbial growth, and activated carbon adsorbs unwanted gases and odors to maintain freshness. To evaluate the combination of chemicals, three different MAPs with varying chemical combinations were tested. MAP1 utilized CaO and activated carbon, MAP2 employed $KMnO_4$ and activated carbon, and MAP3 utilized $KMnO_4$, CaO, and activated carbon.

For the experiment, fresh cauliflower specimens were sourced from crop fields in Jashore, Bangladesh, with each specimen having an average weight of 650 grams. To ensure the integrity of the crop during collection and transportation, cauliflowers were harvested with their leaves enveloping the flower heads. The specimens were then randomly divided into four groups, with each group assigned to three MAP and vacuum packaging type to ensure unbiased distribution across experimental conditions. Baseline data, including initial pH, TSS, weight, and visual characteristics, were meticulously recorded using an imaging system. The imaging system was specifically designed and constructed using a wooden cube. A platform for placing the samples was positioned at the center of the bottom base, and to minimize light reflection, the interior surfaces of the box were painted black.

The cauliflower was then packaged in polyethylene pouches with sachets of chemicals. After that, all MAP-packaged cauliflower samples were stored in a refrigerated environment at 4±1 °C, while vacuum-packaged cauliflower was stored at room temperature. Over a period of seven days, various tests, including pH testing, TSS measurement, and weight loss assessment, were conducted in a chemical laboratory. Additionally, images of each sample were captured throughout the packaging period. The schematic representation of the data acquisition process is illustrated in Figure 2.

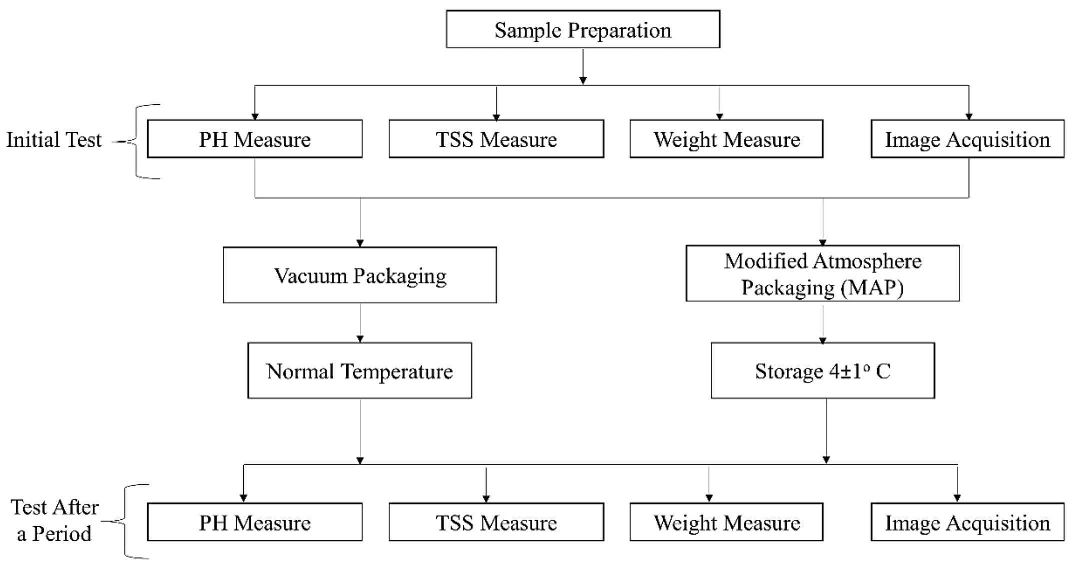


Figure 2. Diagram of the packaged data acquisition procedure

3.2. Color measurement system development

Measuring weight, TSS, and pH is relatively straightforward, but assessing color change poses a considerable challenge. However, precise color change measurement is crucial for evaluating the quality and shelf life of cauliflower florets, offering valuable insights into freshness and deterioration over time. To address this challenge, the efficient color change measurement system is introduced, meticulously crafted to accurately quantify color changes in cauliflower florets. The proposed color change measurement system is visually depicted in Figure 3.

At the core of this system, it incorporates red, green, blue (RGB) to CIELAB color space conversion to enhance color analysis. Converting RGB color values to the CIELAB color space ensures that color features are represented consistently and perceptually uniform, improving the accuracy of color change measurement. Utilizing the conversion equations defined by the International Commission on Illumination (CIE), the RGB color values of each pixel within the segmented regions are transformed to the corresponding CIELAB color values. The conversion equations are as present (1)-(3) respectively, where, X, Y, and Z are the tristimulus values of the RGB color and X_n, Y_n, and Z_n are the tristimulus values of the reference white point.

$$L^* = 116 \times f\left(\frac{Y}{Y_n}\right) - 16 \quad (1)$$

$$a^* = 500 \times \left[f\left(\frac{X}{X_n}\right) - f\left(\frac{Y}{Y_n}\right)\right] \quad (2)$$

$$b^* = 200 \times \left[f\left(\frac{Y}{Y_n}\right) - f\left(\frac{Z}{Z_n}\right)\right] \quad (3)$$

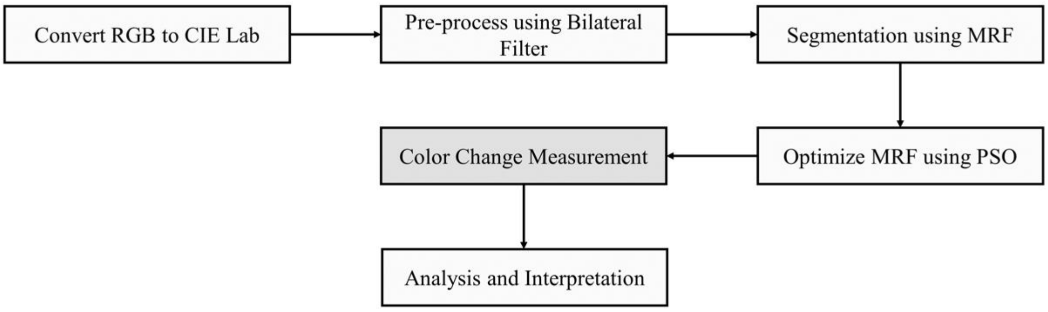


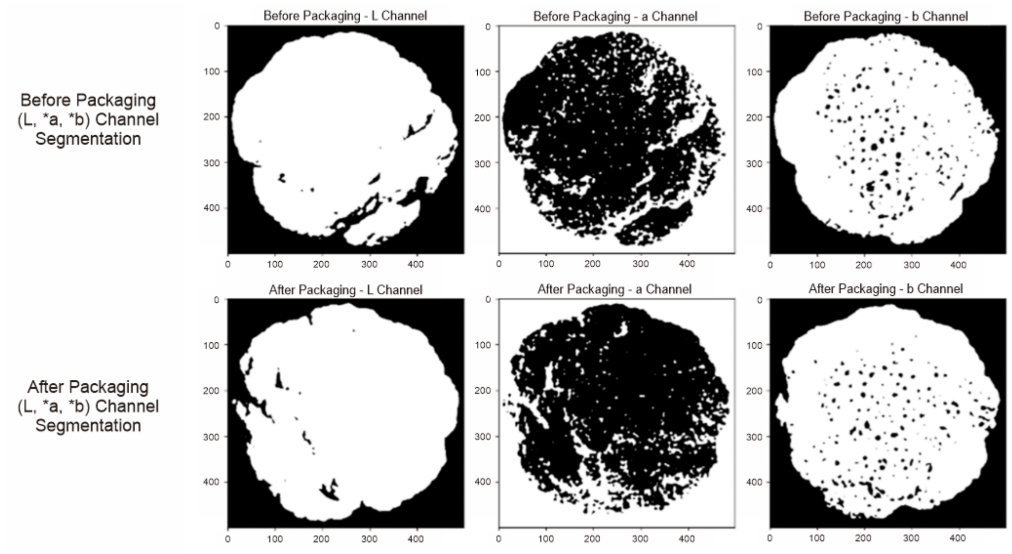
Figure 3. Flow diagram of proposed color change measurement system

After that the system lies the integration of advanced image processing techniques. A bilateral filter is applied during preprocessing to refine cauliflower floret images. This filter effectively reduces noise while preserving critical edges and details, ensuring that subsequent color change measurement is conducted on high-quality, noise-free images [25]. Following preprocessing, particle swarm optimization (PSO) coupled with Markov random field (MRF) segmentation is employed to optimize the segmentation process. The process begins with MRF segmentation, where the MRF model assigns labels to pixels based on their intensities and spatial relationships, ensuring coherent and context-aware segmentation. However, the effectiveness of MRF heavily depends on the choice of parameters, such as the weights of the spatial and intensity terms, which are optimized using PSO. A swarm of particles represents potential solutions, each particle corresponding to a set of MRF parameters. These particles explore the parameter space, updating their positions iteratively based on their own best-found solution and the best solution found by the swarm. This iterative process continues until the particles converge towards the optimal set of parameters. Figure 4 shows segmentation results of L, a, b channel, Figure 4(a) presents the segmentation results using MRF, while Figure 4(b) illustrates the optimized MRF segmentation outcomes. By comparing these figures, we can clearly observe the improvements introduced by our proposed system, highlighting its effectiveness in achieving more accurate segmentation results.

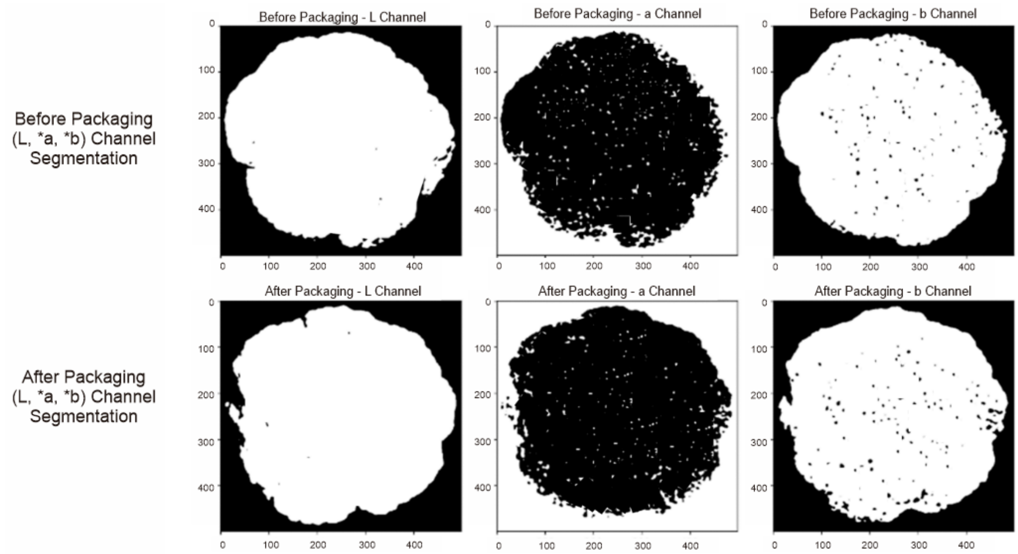
Finally, to assess the total color change across the cauliflower florets, the system calculates the delta E (ΔE) metric, a widely recognized standard for quantifying color differences across diverse industries, including food quality and packaging. This metric accurately captures the perceptual differences between the colors of images before and after packaging, as represented in the CIELAB color space. By evaluating the three components (L, a, and b), ΔE provides a thorough measurement of color change, reflecting any variations due to the effects of storage conditions over time. The formula for ΔE is detailed in (4), enabling a reliable and objective assessment of quality retention in packaged cauliflower.

$$\Delta E = \sqrt{(\Delta L)^2 + (\Delta a)^2 + (\Delta b)^2} \quad (4)$$

In (4), the change in lightness is represented by (ΔL), while (Δa), and (Δb), correspond to shifts in the green-red and blue-yellow color channels, respectively. By integrating these three components, the ΔE metric provides a reliable and holistic measure of the overall color change. This allows us to detect even subtle shifts in color, which are crucial for assessing the freshness and quality of the cauliflower florets throughout storage.



(a)



(b)

Figure 4. Segmentation results of L, a, b channel using (a) MRF and (b) optimized MRF segmentation

3.3. Dataset preparation

Before conducting the experiments, meticulous preparation of the dataset was essential to ensure the accuracy and reliability of the results. The dataset consisted of measurements obtained from various tests conducted on cauliflower samples over a series of periods post-packaging. Specifically, the dataset included measurements of weight loss, pH, TSS, and color change for each cauliflower sample at regular intervals. To facilitate uniformity and consistency in data collection, standardized protocols were followed for conducting each test, including sample preparation, measurement procedures, and recording methodologies. Stringent quality control measures were implemented to mitigate potential sources of error and ensure the integrity of the dataset.

3.4. Feature selection

To assess the significance of various parameters, including TSS, color change, weight loss, and pH, analysis of variance (ANOVA) was employed. ANOVA is a statistical technique that determines whether there are statistically significant differences between the means of three or more groups [26]. The results of the ANOVA tests are summarized in Table 1, where both the F-value and p-value were considered in selecting key predictors. Variables with p-values under 0.05 were deemed statistically significant, and higher F-values indicated a stronger variance among group means, underscoring the importance of the respective parameter.

The findings in Table 1 reveal that TSS, color change, and weight loss are statistically significant predictors of cauliflower quality and shelf life, as indicated by their p-values falling under the significance threshold of 0.05. Furthermore, their relatively high F-values 18.63, 22.48, and 20.36, respectively highlight the substantial differences in group means, reinforcing the relevance of these features for predictive modeling. Consequently, TSS, color change, and weight loss were selected as features for developing the predictive models. In contrast, pH did not meet the criteria for statistical significance, with a p-value of 0.349 and a low F-value of 1.46, suggesting minimal variance across group means. This result indicates that pH contributes minimally to forecasting cauliflower quality and shelf life in this study, leading to its exclusion from the final predictive model.

Table 1. Results of ANOVA for feature selection

Variable	F-value	p-value
TSS	18.63	0.025
Color Change	22.48	0.009
Weight Loss	20.36	0.017
pH	1.46	0.349

3.5. Machine learning modeling and model evaluation

To predict the quality and shelf life, it is necessary to know the weight loss, color change, and TSS on a specific day. Machine learning techniques are employed to predict the weight loss, color change, and TSS of cauliflower as dependent variables, with the number of days post-packaging as the independent variable. This approach allows for tracking the dynamic changes in weight loss, color change, and TSS over time. The predicted weight loss, color change, and TSS are compared with a threshold value, and based on this, the quality and shelf life of cauliflower under specific packaging conditions are predicted.

For prediction, two machine learning algorithms, ANN and linear regression, are employed. Linear regression models are utilized to establish relationships between the independent variable (days post-packaging) and the dependent variables (weight loss, color change, and TSS). Additionally, ANN is used to capture nonlinear dependencies and intricate patterns within the data, aiming to enhance the accuracy of predictions. The performance of these two algorithms is evaluated using the R-squared value, providing valuable insights into the accuracy and reliability of the models in predicting weight loss, color change, and TSS over time. By comparing the results of these two approaches, insights are developed into which algorithm performs better in forecasting cauliflower quality and shelf life, thereby informing decision-making in food production and distribution processes.

3.6. Quality and shelf-life prediction

Using the predicted values for weight loss, color change, and TSS, cauliflower quality and shelf life are estimated by comparing these values with established quality thresholds. These thresholds act as essential benchmarks, offering insights into the cauliflower's quality and expected longevity under specific packaging conditions. The experiment established that a maximum acceptable total color change of approximately 3 units is set for cauliflower meant for market; exceeding this threshold signals a noticeable decline in visual appeal and overall quality, making the cauliflower unsuitable for sale. Similarly, a weight loss under 15% is considered essential to maintain the cauliflower’s freshness and texture, as excessive weight loss indicates dehydration and significant moisture loss.

Moreover, TSS levels up to 7.2 are regarded as ideal for cauliflower, enhancing its taste and overall consumer appeal. Higher TSS levels generally correlate with better quality, which is crucial for both consumer satisfaction and market value. By aligning the predicted weight loss, color change, and TSS values with these predefined thresholds, accurate forecasts about the quality and remaining shelf life of cauliflower can be made. Cauliflower meeting the threshold criteria is classified as high quality with the potential for a longer shelf life. Conversely, when any of these limits are exceeded, the cauliflower's quality is likely to deteriorate more rapidly, requiring a shorter shelf-life estimate. This approach ensures that only cauliflower of optimal quality reaches the market, aligning with quality assurance standards.

4. RESULT AND DISCUSSION

This study investigated the prediction of cauliflower quality and shelf life using machine learning under vacuum and MAP. While previous research has explored the impact of various packaging methods on perishable goods such as fruits and fish, it has not thoroughly addressed the influence of cost-effective vacuum and chemical-based MAP on cauliflower. This gap is significant due to the high perishability and economic importance of cauliflower.

Our findings reveal that in chemical-based MAP and vacuum packaging systems weight loss, color change, and TSS have a great impact on quality and shelf. The proposed method significantly enhances the accuracy of predicting key quality parameters, including weight loss, color change, and TSS. The novel color change measurement system, which integrates bilateral filtering with PSO and MRF segmentation, achieved an intersection over union (IoU) score of 0.96 plays a great role in the prediction of key quality parameters. This performance surpasses that of alternative segmentation techniques, as shown in Table 2, which compares the IoU scores of different methods.

Table 2. Comparison of segmentation methods (IoU scores)

Segmentation method	IoU score
Proposed method	0.96
K-means clustering	0.87
Watershed transformation	0.81
Region growing	0.92

The IoU score for the proposed method is notably higher than those of K-means clustering, watershed transformation, and region growing, demonstrating superior accuracy in delineating cauliflower florets and measuring subtle color changes. A higher IoU score indicates better segmentation accuracy and consistency [27], suggesting that the proposed method achieves a more precise segmentation of individual florets, leading to improved measurement of color changes. Using this proposed color change measurement method in conjunction with machine learning modeling, the ANN models demonstrated high predictive accuracy across various packaging methods, with R-squared values of 0.981 for color change. The ANN also acquired the R squared value 0.992 for weight loss, and 0.952 for TSS. These results, detailed in Table 3, compare the R-squared values for linear regression and ANN models under different packaging conditions, further highlighting the robustness of the ANN approach in predicting quality metrics for cauliflower.

Table 3. Prediction result of different parameters for different packaging

Parameters	Packaging	Linear regression	ANN
Color	MAP1	0.926	0.978
	MAP2	0.912	0.970
	MAP3	0.931	0.981
	Vacuum	0.940	0.962
Weight loss	MAP1	0.944	0.983
	MAP2	0.961	0.990
	MAP3	0.962	0.985
	Vacuum	0.982	0.992
TSS	MAP1	0.893	0.911
	MAP2	0.886	0.934
	MAP3	0.904	0.946
	Vacuum	0.923	0.952

The study's results show that ANN models consistently outperform linear regression models in predicting cauliflower quality parameters. For color change, the ANN model achieved R-squared values ranging from 0.96 to 0.98 across different packaging methods. For weight loss, the ANN model reached R-squared values of up to 0.99, and for TSS, the R-squared values were between 0.91 and 0.95. To contextualize these results, the result is compared with findings from other relevant studies, as summarized in Table 4. Comparing the study's results with previous research shows that the approach with more precise color change measurement using ANN models achieved higher accuracy.

Table 4. Comparison of cauliflower quality and shelf-life prediction methods

Study	Packaging method	R-squared values
Current study	MAP (Chemical based) and Vacuum	0.992
Mohammed *et al*. [20]	MAP (Gas mixture) and Vacuum	0.951
Alden *et al*. [23]	MAP (Gas mixture)	0.990

However, the methods and results may not generalize across all cauliflower varieties or other perishable vegetables. Further research is needed to confirm the applicability of these techniques in various real-world conditions, such as differing storage and transportation environments. Future studies could focus on adapting the technology for commercial use on a larger scale and optimizing the machine-learning models by incorporating diverse data sets and environmental variables.

5. CONCLUSION

Through rigorous experimentation and analysis, the significance of features such as weight loss, color change, and TSS in predicting cauliflower quality over time in chemical (MAP) and vacuum packaging has been demonstrated. The novel color change measurement system, integrating advanced segmentation techniques and color space conversion, provides an accurate and efficient assessment of color changes in cauliflower florets. Additionally, machine learning algorithms, including linear regression and ANN, exhibit promising performance in predicting key quality indicators. These findings have implications for optimizing packaging strategies, minimizing food waste, and ensuring the delivery of high-quality cauliflower to consumers. Future research could focus on refining predictive models, exploring additional features, and validating results across different storage conditions and cauliflower varieties.

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