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Tables 1 to 3 are available in the Supplementary Files section.

Integrating postharvest quality assessment and deep learning to identify the optimal harvest maturity stage of apricot fruit

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Abstract

Accurate determination of harvest maturity is essential for maintaining apricot fruit quality and maximizing postharvest storage potential. This study integrated postharvest quality assessment with deep learning to identify a favorable harvest maturity stage and develop a rapid, non-destructive image-based classification approach. Apricot fruits were harvested at five physiological maturity stages and stored at 6 °C for 35 days, during which firmness, weight loss, total soluble solids, titratable acidity, pH, and color attributes (L^* , C^* , h° , and ΔE) were evaluated at weekly intervals. Fruits harvested at Stage 3 exhibited the most favorable overall postharvest performance, characterized by greater firmness retention, lower weight loss, and comparatively greater stability in soluble solids, acidity, pH, and color attributes. To facilitate rapid recognition of the maturity stages, a lightweight dual-path convolutional neural network incorporating regular and dilated convolutional branches was developed using 1,032 RGB images acquired under natural orchard conditions. On the independent test dataset, the model achieved weighted precision, recall, and F1-score values of 0.81, 0.78, and 0.79, respectively, with most misclassifications occurring between adjacent maturity stages. These findings demonstrate the potential of integrating physiological quality assessment with deep learning to support rapid and non-destructive maturity-based harvest decisions in apricot. Further validation across cultivars, orchards, seasons, and field

imaging conditions is required to establish the robustness and practical applicability of the proposed approach.

Keywords: Apricot, Harvest maturity, Storage life, Deep learning, Image classification, Non-destructive quality assessment

Introduction

Apricot (*Prunus armeniaca* cv. *Zafarani*) is highly valued worldwide due to its rich nutritional profile and desirable organoleptic properties. Beyond fresh consumption, apricots also serve as an important raw material for processed products [1]. Fresh apricot production is concentrated from June to early summer, resulting in a temporary oversupply in the market. However, the fruit rapidly softens at ambient temperature, leading to accelerated losses in quality, flavor, and firmness, which ultimately contribute to extensive postharvest deterioration [2]. Owing to their fast ripening and soft texture, apricots are highly perishable and susceptible to mechanical damage and pathogenic contamination. To preserve firmness for postharvest handling, transportation, and marketing, the fruits are typically harvested at the pre-climacteric stage [3]. The ripeness stage at harvest is a key determinant of postharvest performance, as consumer acceptance is closely associated with sweetness, color, and juiciness. Furthermore, overall storage quality is strongly linked to the fruit's maturity stage at harvest [4].

Relying on human vision to estimate the apricot maturity stage at harvest is neither easy nor effective and involves uncertainty. To address this issue, a robust computer vision system embedded in an edge device could serve as a viable solution, enabling swift and accurate maturity-based apricot fruit image classification.

Traditional image processing methods have been employed in various studies to address fruit recognition or classification issues, as evidenced by several works [5-8]. These techniques have also been applied in studies aimed at classifying apricot fruit. For example, in a study on image-based apricot fruit classification, Khojastehnazhand et al., (2019) worked on maturity detection and volume estimation [9]. To this end, they collected apricot images under controlled lighting, followed by image cropping, noise filtering, fruit segmentation, RGB feature extraction, $L^*a^*b^*$ color feature extraction, and grayscale statistics. Similarly, Mirnezami et al., (2021) used image processing and machine learning approaches for apricot variety classification. Their method included RGB image acquisition, segmentation, and extraction of length, width, thickness, and

projected area to estimate some physical features by means of an ANFIS classifier and fuzzy C-means clustering [10].

Traditional image processing techniques rely on low-level feature extraction algorithms that may not yield fast or precise results. Additionally, these techniques are heavily dependent on imaging systems with suitable lighting setups and fixed camera-object distances, which may restrict the model's applicability for efficient apricot evaluation practices. This lack of robustness and adaptability is compounded by the difficulty in maintaining consistent performance across diverse settings in apricot orchards.

Recent advances in artificial intelligence have expanded opportunities for improving fruit monitoring tasks for pre- and postharvest decision-making in horticultural systems. Predictive modeling has been effectively implemented to estimate key physicochemical attributes of fruit. Artificial neural networks (ANNs), in particular, have demonstrated strong capability in modeling complex nonlinear relationships between measurable variables and quality parameters. Several studies have investigated the application of computational modeling and image-based techniques for evaluating apricot quality, maturity, and cultivar characteristics. Mozaffari et al., (2022) developed a non-destructive laser light backscattering imaging system combined with ANN, partial least squares regression (PLSR), and PCA-ANN models to predict apricot firmness and total soluble solids (TSS) during ripening [11]. The study demonstrated that ANN models outperformed conventional regression methods, achieving coefficients of determination of 0.974 for firmness and 0.963 for TSS, indicating the potential of machine learning to provide accurate, rapid, and non-destructive quality assessment of apricot fruit. More recently, comprehensive reviews have reinforced the importance of apricot nutritional composition by summarizing the relationships between mineral elements, phytochemicals, antioxidant compounds, sugars, and fruit quality. These studies indicate that potassium is the predominant mineral in apricot fruit, while calcium and magnesium contribute to cell wall stability and fruit texture. Although current apricot research has not yet integrated mineral nutrient composition directly into ANN-based prediction models, existing evidence suggests that combining nutrient information with machine learning and image processing techniques represents a promising direction for future research on non-destructive quality evaluation and postharvest management.

Deep learning, a cutting-edge AI technology based on revolutionized ANNs, can effectively address the challenges of sorting apricots based on maturity. By automatically integrating and

assessing various features such as texture, color, shape, edges, patterns, local features, deep features, activation maps, global features, and spatial features, and by automatically learning hierarchical features from raw pixel values, deep learning models can adeptly acquire discriminative representations for accurate image classification across diverse domains and applications without the need for manual feature engineering. This technique has garnered significant interest among scientists working in various agricultural domains [12-16]. Convolutional Neural Networks (CNNs), a sub-category of deep learning, have emerged as powerful tools for image processing tasks. They are capable of extracting high-level features regardless of imaging structures or environmental conditions, making them highly versatile. Among the various applications of CNNs, image classification, object detection, and image segmentation are the most significant. In the present study, the focus was on developing a CNN-based model for image classification purposes. A CNN is essentially an ANN, but its layers are designed specifically to extract features from input images. The initial layers are responsible for detecting basic features, and the complexity of features increases with deeper layers. The layers include various types, such as convolutional, pooling, dropout, batch normalization, and more [17, 18].

In parallel, deep learning has emerged as a transformative approach in precision horticulture, offering substantial improvements over traditional image-processing methods that are often unreliable under natural orchard conditions characterized by variable lighting, complex backgrounds, and occlusions [19, 20].

CNNs offer robust nonlinear feature-extraction capabilities and have been extensively applied in agricultural domains such as fruit detection, yield estimation, and plant classification [12, 18]. State-of-the-art CNN architectures—including Faster R-CNN, SSD, YOLOv3, and ResNet—have demonstrated high accuracy in detecting various fruit species under unstructured field environments [21-23]. However, many of these models are computationally demanding, which restricts their practical use for real-time deployment in orchards. More recent studies have highlighted the efficacy of lightweight CNNs for fast and accurate on-branch fruit recognition using RGB images, showing strong promise for integration into real-time precision horticulture systems [15].

Image classification using CNNs has been a central focus in numerous agricultural investigations. Examples include plant species classification [24], weed recognition [14], on-branch fruit

recognition [15], crop yield prediction [25], crop mapping [26], and land cover discrimination [27], among others. Several studies specifically addressing fruit sorting with CNNs have reported promising results. For instance, Nasiri et al., (2019) developed a VGG-16 model to classify date fruits according to maturity and health status, reaching an accuracy of 96.98% [28]. Ponce et al., (2019) employed an Inception-ResNetV2 model to classify seven olive varieties, achieving up to 95.91% accuracy [29]. Thuyet et al., (2020) presented a CNN-based garlic sorting and grading system that classified samples into good, bad, and scratched categories with accuracies of 95%, 68%, and 100%, respectively [30]. Fan et al., (2022) utilized a YOLOv4 network for defect detection on apples using NIR images captured under diffuse illumination, obtaining an average detection accuracy of 93.9% [31]. Seyed I Saedi & Rezaei, (2024) developed an exception deep learning classifier to discriminate olive fruit maturity, attaining accuracies between 86.93% and 93.46% [16]. Khosravi et al., (2021) introduced a deep CNN model for on-branch olive maturity classification, demonstrating robustness against environmental and imaging variations with an accuracy of 91.91% and an inference time of 12.46 ms, indicating suitability for online applications such as robotic interventions [13]. Lastly, S. I. Saedi et al., (2024) applied a lightweight CNN model for automatic sorting of olives by cultivar and maturity, achieving a total classification accuracy of 95.79% and a loss of 0.2214 [16].

Despite these significant advances, the application of CNN-based approaches to apricot ripening analysis remains relatively unexplored. Accurate, non-destructive, and real-time determination of apricot maturity is crucial for optimizing harvest timing, enhancing postharvest handling, and meeting market quality standards. Traditional image-processing methods have shown limited reliability for apricots due to their dependence on controlled lighting and fixed camera-object geometries. Developing CNN models tailored to apricot orchards holds the potential to provide reliable on-tree maturity detection under natural field conditions. Therefore, this study aims to bridge this gap by assessing the feasibility of CNN-based models for real-time, non-destructive evaluation of apricot ripening stages directly in orchard environments.

Materials and methods

This experiment was conducted in two phases. In the first phase, the postharvest shelf life of apricot fruit was evaluated based on five different harvest stages corresponding to physiological maturity.

In the second phase, a deep learning framework was employed to classify the different harvest stages using image processing of apricot fruits collected at the same five stages.

Experimental Procedure

Apricot fruits were sampled at five physiological maturity stages (Figure 1), corresponding to the maturity and ripeness stages described by Edwards (n.d.) from the University of California, Davis [32]. After harvest, the fruits were carefully transferred to the laboratory and subjected to surface disinfection before packaging. The disinfected fruits were then allowed to air-dry completely at room temperature before packaging. For each of the five harvest maturity stages, 150 fruits were randomly selected and assigned to three independent replicates. At each sampling time, 10 fruits were placed in each polyethylene container. Postharvest quality attributes were evaluated at five sampling times at 7-day intervals during storage. Thus, each harvest maturity stage comprised three replicates $\times$ five sampling times $\times$ 10 fruits, resulting in 150 fruits per harvest stage and a total of 750 fruits across the five harvest maturity stages. All samples were stored at 6 °C, and the selected quality attributes were measured at each sampling time throughout the storage period.

Quality Measurements

Weight Loss

The fruits were weighed at the beginning of the storage experiment (day 0) and again at the end of each sampling interval. Weight loss was expressed as a percentage of the initial fruit weight and calculated according to Eq 1:

$$\text{Weight loss (\%)} = \frac{W_0 - W_t}{W_0} \times 100 \quad (1)$$

where W_0 is the initial weight of the fruit sample measured at the beginning of storage and W_t is the weight of the same sample measured at the corresponding sampling time. Weight loss was therefore determined separately for each sampling time throughout storage.

Firmness

Fruit firmness was evaluated with a Lutron digital penetrometer fitted with a 0.8-cm probe. Two measurements were recorded from opposite equatorial positions on each fruit to account for spatial variability within the flesh.

Color Attributes

Surface color variations of apricot fruits were evaluated using the L^* , a^* , and b^* color coordinates. Measurements were taken from each replicate at two opposite points on the equatorial region of the fruit using a Chroma Meter CR-400 (Konica Minolta Sensing, Japan). The L^* values represent lightness, with higher positive values indicating greater brightness and lower values indicating darkness. The recorded a^* and b^* values were used to calculate chroma and hue angle, which reflects color intensity or saturation and the overall color tone of the fruit surface respectively, as well as the total color difference (ΔE^*) using Eq 2, Eq 3 and Eq 4.

$$C^* = \sqrt{(a^{*2} + b^{*2})} \quad (2)$$

$$h^\circ = \tan^{-1}(b^*/a^*) \quad (3)$$

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

Total Soluble Solids (TSS)

TSS content was determined with a calibrated ATAGO handheld refractometer. A small volume of fruit juice at ambient temperature was placed on the prism surface, and readings were expressed in °Brix.

pH Measurement

Fruit juice pH was recorded using a bench-top pH meter previously calibrated with standard buffers (pH 4.0 and 7.0). Measurements were taken at room temperature.

Titrateable Acidity (TA)

TA was quantified following standard acid–base titration procedures. A 10-mL aliquot of fruit extract was diluted with 40 mL of distilled water and titrated with 0.1 N NaOH to an endpoint of pH 8.2. Acidity values were calculated based on the dominant organic acids in apricot according to Eq 5.

$$TA (\%) = (V \times N \times mEqMA / Y) \times 100 \quad (5)$$

Where:

V = volume of NaOH (mL), N = normality of NaOH, Y = sample volume or weight (g), and $mEqMA = 67.05$ (Malic acid equivalent).

Deep Learning Model Development

Data preparation

To develop an image-based CNN model for classifying apricot fruits based on their maturity stages, images of *Zafarani* apricot fruits were captured at different stages of physiological maturity. The images were categorized into five classes based on storage life, corresponding to five distinct developmental stages of the apricot fruit. Image acquisition was conducted using a Samsung Galaxy A54 smartphone equipped with a 50-MP wide, 12-MP ultra-wide, and 5-MP macro camera during the period from June to July 2024. Figure 2 illustrates representative images of each developmental stage. A numerical label ranging from 1 to 5 was assigned to each harvesting stage to denote the corresponding class. All images were collected under natural orchard conditions, with no control over lighting conditions, camera-to-fruit distance, shooting angle, or other imaging parameters. The captured images were inspected, and unsuitable samples were removed. The total number of images for each class is also shown in Figure 2.

Based on Figure 2, a total of 1,032 images were utilized for model development and training. To ensure a consistent resolution, all images were resized to 256×256 pixels and normalized to the range of $[0,1]$. For the construction of the deep neural network, the dataset was randomly partitioned into training, validation, and test subsets. Specifically, 80% of the images were assigned to the training set, while the remaining 20% were reserved for testing. From the training subset, 20% was further allocated for validation. This resulted in 660 images for training, 165 images for validation, and 207 images for testing, ensuring a robust and balanced dataset for model development and evaluation.

Configuration of the CNN

To develop a model for classifying apricot fruits, our strategy involved creating a lightweight CNN model from scratch and comparing its performance, in terms of accuracy and loss, with that of several popular models. For the development of our user-defined model, we employed an

innovative dual-path CNN architecture. Each path independently performs feature extraction, and the resulting feature maps are merged, concatenated, and passed to the classifier layers. The two paths consist of conventional deep learning layers, including convolution, pooling, batch normalization, dropout, and dense layers. However, different types of convolution layers are used in the two paths: regular and dilated convolutions (Figure 3).

Dilated convolutions are employed because of their ability to extract more information and diverse features using a single filter without reducing the feature map resolution or increasing the computational burden. This is achieved by providing larger receptive fields [33, 34]. In addition, dilated convolutions have the potential to recover spatial information that may be lost during the pooling operation. This is accomplished by dilating the filter before performing the standard convolution operation. In a dilated convolution, convolution filters are applied while consecutively skipping certain pixels according to the specified dilation factor. For example, when the dilation factor is 2, one pixel is skipped between every two sampled pixels. In other words, the number of skipped pixels is $2 - 1 = 1$ (Figure 3). A dilation factor of 1 corresponds to a standard convolution, with no skipped pixels. The overall operation of dilated convolution can be expressed by Eq 6 [27].

$$y(p, q) = \sum_{i=1}^P \sum_{j=1}^Q x(p + d \times i, q + d \times j) w(i, j) \quad (6)$$

Where $x(p, q)$ and $y(p, q)$ represent the input and output (dilated) images, respectively. The filter $w(i, j)$ has dimensions of $P \times Q$, and d represents the dilation factor.

As depicted in Figure 3, utilizing a dilation factor will exponentially expand the receptive field. The figure demonstrates a 3×3 dilated convolution filter with a dilation factor of 2.

To develop the dual-path CNN, similar architectures with comparable characteristics were employed for both paths. The only difference between the two paths lies in the convolution layers, with Path 1 utilizing regular convolution (dilation = 1) and Path 2 employing dilated convolution (dilation = 2). The classification stage consists of a dense layer followed by a Softmax activation layer. To identify the optimal network architecture, several models were developed and evaluated by modifying the network depth and adjusting the positions of specific layers. Ultimately, the dual-path architecture shown in Figure 4 was selected.

Given that this study addresses a classification task, the categorical cross-entropy loss function was consistently employed. The training process was conducted using a batch size of 8, 80 epochs, and the Nadam optimizer. Table 1 presents the properties of this optimizer. Model performance was primarily evaluated using accuracy as the performance metric during training. The structure and properties of the proposed model are presented in detail in Figure 4 and Table 2.

Model Training

The training process followed the conventional procedure used in traditional neural networks. CNN training consists of two main stages: feed-forward and backpropagation. During the feed-forward stage, the network error is calculated by comparing the network output generated from the input image with the corresponding ground-truth label. In the backpropagation stage, the gradients of the network parameters are computed based on the calculated error, and the network weights are subsequently updated accordingly.

In this iterative process, input data are propagated through the network layers to produce an output, which is then compared with the desired output to compute the error. Based on this error, the network parameters are adjusted, and the input data are fed into the network again to recalculate the outputs and errors, followed by further parameter updates. This cycle is repeated multiple times, with each complete iteration over the training dataset referred to as an epoch. Various loss functions can be employed to quantify the network error, and the subsequent parameter updates constitute the optimization process, which aims to progressively minimize the loss by updating the network weights.

Evaluation of Image Classification Accuracy

One of the most commonly used approaches for assessing classification performance is based on the four fundamental concepts of true positive (TP), true negative (TN), false positive (FP), and false negative (FN), which are defined as follows:

1. True Positive (TP) refers to cases in which the classifier correctly predicts the positive class; that is, a positive sample is correctly identified.
2. True Negative (TN) refers to cases in which the classifier correctly predicts the negative class; that is, a negative sample is correctly identified.

3. False Negative (FN) refers to cases in which the classifier incorrectly predicts the negative class when the true class is positive; that is, a positive sample is mistakenly classified as negative.

4. False Positive (FP) refers to cases in which the classifier incorrectly predicts the positive class when the true class is negative; that is, a negative sample is mistakenly classified as positive.

These parameters are used to define three key metrics for assessing classification performance: precision, recall, and F1-score, each ranging from 0 to 1. The mathematical formulations of these performance metrics are provided below.

$$Precision = \left(\frac{TP}{TP + FP} \right) \quad (7)$$

$$Recall = \left(\frac{TP}{TP + FN} \right) \quad (8)$$

$$F1 - score = \left(2 \times \frac{Precision \times Recall}{Precision + Recall} \right) \quad (9)$$

Precision indicates the proportion of correctly predicted positive samples among all samples predicted as positive. A higher precision value reflects a lower ratio of incorrectly predicted samples to correctly predicted ones, and vice versa. Recall, also referred to as sensitivity or the true positive rate, measures the ability of the classification model to identify positive samples. In simple terms, recall indicates how many of the actual positive samples are correctly recognized by the classifier. A higher recall value implies a lower proportion of actual positive samples that are missed by the model. Finally, the F1-score represents the harmonic mean of precision and recall. By simultaneously considering both precision and recall, the F1-score provides a balanced evaluation of the classification model's performance. As a complementary metric, the F1-score offers an overall assessment of the classification model.

Based on these definitions, a classification report is used to present the classification results for each target class (five harvest stages), as reported in Table 3 (Results and Discussion section).

Another widely used tool for evaluating image classification performance is the confusion matrix. This matrix summarizes the model's predictions on the test dataset by comparing them with the corresponding ground-truth labels. It reports the numbers of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN) generated by the model for the test data. The confusion matrix enables the computation of various evaluation metrics, such as precision, recall,

and F1-score, and facilitates the analysis of the model's performance in terms of correct and incorrect classifications. Consequently, it provides a clear and comprehensive overview of the strengths and weaknesses of the model in distinguishing among the classes on which it was trained.

Statistical Analysis and Model Development

The first experiment was conducted as a factorial design with two factors—storage time and harvest stage—arranged in a completely randomized design (CRD) with three replications. The experimental data were analyzed using SAS software version 8.2 (SAS Institute Inc., Cary, NC, USA)., Duncan's multiple range test ($p < 0.05$) was applied for mean comparisons and graphical representations were generated using Microsoft Excel. The second experiment deals with deep learning techniques. In this process the model development and training were carried out using the Google Colaboratory cloud computing environment. The implementation was performed in Python, utilizing the Keras and TensorFlow libraries.

Results and Discussion

Firmness

Fruit firmness decreased significantly with increasing storage duration across all harvest maturity stages (Figure 5). The magnitude of firmness loss varied among harvest stages, indicating a significant influence of harvest maturity on postharvest firmness retention. The highest firmness value (22.48 N) was recorded in fruits harvested at Stage 1 immediately after harvest, whereas the lowest value (0.801 N) occurred in fruits harvested at Stage 5 after 35 days of cold storage. The percentage reduction in firmness across Stages 1–5 was 29.70%, 35.00%, 34.00%, 48.73%, and 55.92%, respectively. Notably, fruits harvested at Stage 3 exhibited comparatively greater firmness retention throughout the storage period, indicating a more favorable balance between maturity at harvest and subsequent softening.

The progressive decline in firmness during cold storage can be consistent with ripening-associated remodeling and degradation of cell-wall components, together with increased activity of cell-wall-modifying enzymes. The slower loss of firmness observed in Stage 3 fruit may indicate that these fruits were harvested within a physiological maturity window that provided a favorable balance between sufficient ripeness and resistance to postharvest softening. In contrast, fruit harvested at

the more advanced Stage 5 exhibited the greatest firmness loss, consistent with their more advanced ripening status at harvest.

Harvest maturity is therefore an important determinant of apricot storage potential. Feng et al. (2013) demonstrated that flesh firmness measured at harvest was a major predictor of final firmness after refrigerated storage, supporting the use of firmness as an indicator of storage potential in apricot [35]. Zarrin Bal et al. (2009) likewise showed that harvest maturity substantially affected the cold-storage performance of apricot cultivars, although the optimal maturity stage varied among cultivars [36]. Similarly, Ganji Moghadam and Shikh-eslami (2006) reported that harvest timing influenced the quantitative and qualitative characteristics and storage performance of 'Shahrودي' apricot [37].

Considering the combined firmness response across the storage period, Stage 3 appeared to provide the most favorable compromise between fruit maturity at harvest and retention of firmness during cold storage. This finding, together with the responses of other postharvest quality attributes evaluated in the present study, supports Stage 3 as a promising harvest window for extending apricot storage life.

Weight loss

The interaction between harvest stage and storage duration significantly affected fruit weight loss during cold storage ($P \leq 0.05$; Figure 6). Among the postharvest sampling dates, the lowest weight loss was observed after 7 days of storage, with values of 1.4% and 1.6% for fruits harvested at Stages 2 and 5, respectively; these values did not differ significantly. In contrast, fruits harvested at Stage 1 and stored for 35 days exhibited the highest weight loss (29.45%), which was significantly greater than that recorded for the other harvest stages at the same storage duration. Weight loss increased significantly with prolonged storage, and significant differences were also observed among harvest stages ($P \leq 0.05$). Notably, fruits harvested at Stage 3 showed relatively limited and statistically non-significant changes in weight loss during the first 28 days of storage, indicating comparatively greater weight retention during this period. By day 35, weight loss had increased; however, it remained the lowest compared with the other maturity stages. Weight loss during postharvest storage is primarily associated with water loss through transpiration, while respiratory metabolism contributes to a smaller fraction of total mass loss. The progressive increase in weight loss with storage duration observed in the present study is therefore consistent

with continued moisture loss from fruit tissues during cold storage. The greater cumulative weight loss observed in Stage 1 after prolonged storage may reflect differences in fruit physiological characteristics at harvest that affect water retention during subsequent storage. In contrast, although weight loss increased by day 35, Stage 3 exhibited the lowest changes in weight loss throughout the storage period, suggesting that this harvest stage may provide a more favorable balance between fruit maturity and resistance to postharvest moisture loss. The effect of harvest maturity observed in the present study is consistent with previous findings in apricot. Jing et al. (2018) reported differences in postharvest weight loss among apricot fruits harvested at different maturity stages, supporting the importance of harvest maturity in determining postharvest water-loss behavior [38]. Similarly, Ghasemnezhad et al. (2010) reported a progressive increase in apricot weight loss during cold storage, primarily associated with moisture loss. These findings collectively indicate that both harvest maturity and storage duration are important determinants of postharvest weight retention in apricot [39].

Titrateable Acidity

The interaction between harvest stage and storage duration significantly affected titrateable acidity (TA) of apricot fruit ($P < 0.05$; Figure 7). Although TA did not change significantly over storage within Stage 1, significant differences were observed among the harvest stage $\times$ storage duration combinations. The highest TA value (0.25%) was recorded in fruits harvested at Stage 1 both at harvest and after 35 days of storage, whereas the lowest value (0.027%) occurred in fruits harvested at Stage 5 after 35 days of storage. The percentage reduction in TA across Stages 1–5 was 11.69%, 16.51%, 20.84%, 32.38%, and 66.61%, respectively. The magnitude of TA loss therefore varied substantially among harvest stages, with Stage 3 showing a smaller reduction than Stages 4 and 5, indicating comparatively greater retention of titrateable acidity during storage.

The decline in TA during postharvest storage is closely associated with organic-acid metabolism and the utilization of organic acids as substrates for respiration and other ripening-related metabolic processes. The significant interaction between harvest stage and storage duration observed in the present study indicates that the extent of acidity loss depended on the maturity stage at harvest. Fruits harvested at the more advanced maturity stages exhibited greater reductions in TA, which may reflect their more advanced physiological status and the progression of ripening

during subsequent cold storage. In contrast, the relatively smaller reduction observed at Stage 3 suggests greater retention of titratable acidity during storage.

The observed maturity-dependent changes in TA are consistent with previous studies demonstrating that harvest maturity influences the postharvest quality and biochemical changes of apricot fruit. Jing et al. (2018), for example, reported that harvest maturity substantially affected apricot storage quality and physiological responses during cold storage [38]. Similarly, Ganji Moghadam and Shikh-eslami (2006) reported an effect of harvest time and shelf life on the quantitative and qualitative characteristics of ‘Shahrودي’ apricot [37]. Previous work on postharvest treatments has also demonstrated that TA can be retained during cold storage, although the magnitude of this effect depends on the treatment and storage conditions [40].

Overall, the comparatively lower loss of TA at Stage 3 indicates that this maturity stage may provide a favorable balance between physiological maturity at harvest and retention of acidity during cold storage. However, this interpretation should be considered together with the responses of firmness, weight loss, pH, TSS, and color attributes rather than being based on TA alone.

pH

Fruit pH was significantly affected by storage duration and varied among harvest maturity stages ($P < 0.05$; Figure 8). The pH values generally increased during cold storage, although the magnitude and pattern of change differed among harvest stages. More advanced harvest stages also exhibited higher initial pH values, indicating that maturity at harvest influenced the initial acid–base status of the fruit. A significant harvest stage $\times$ storage duration interaction was observed ($P < 0.05$), demonstrating that the trajectory of pH changes during storage depended on the maturity stage at harvest. The lowest pH value (4.5) was recorded in Stage 1 fruit after 7 days of storage, whereas the highest value (6.7) was observed in Stage 1 fruit after 28 days of storage.

The percentage changes in pH across Stages 1–5 were 9.79%, 10.32%, 6.54%, 9.26%, and 13.78%, respectively. Stage 3 exhibited the smallest change in pH during the 0–35-day storage period (6.54%), indicating comparatively greater pH stability during cold storage.

The increase in pH during storage, together with the decline in titratable acidity, may be associated with changes in organic-acid metabolism, including the utilization of organic acids as substrates for respiration and other ripening-related metabolic processes. The maturity-dependent differences observed in the present study suggest that the physiological stage at harvest influences the extent

of these biochemical changes during subsequent cold storage. The relatively small change in pH observed in Stage 3 fruit therefore indicates a slower alteration in acid–base status during storage and may contribute to its overall postharvest stability.

These findings are consistent with previous studies showing that fruit maturity is closely associated with changes in acidity and pH in apricot. Karabulut et al. (2018) reported that advancing maturity was associated with changes in physicochemical quality attributes, including pH and titratable acidity, in apricot fruit [41]. Similarly, Jing et al. (2018) demonstrated that harvest maturity significantly influenced the evolution of quality attributes during cold storage of apricot [38]. More recently, Gulsoy et al. (2026) reported that advancing fruit maturity was accompanied by an increase in pH and a decline in titratable acidity and organic acids [42]. Together, these findings support the interpretation that maturity-dependent changes in organic-acid metabolism contribute to the variation in pH observed during apricot maturation and subsequent storage.

Overall, the significant harvest stage $\times$ storage duration interaction demonstrates that pH changes during storage were strongly dependent on maturity at harvest. Among the five maturity stages, Stage 3 exhibited the smallest relative change in pH, supporting its favorable postharvest performance when considered together with firmness, weight loss, titratable acidity, TSS, and color attributes.

TSS

The interaction between harvest stage and storage duration significantly affected the total soluble solids (TSS) content of apricot fruit ($P < 0.05$; Figure 9). TSS generally increased during cold storage, with a more pronounced increase observed during the later stages of storage (21–35 days). The observed increase in TSS may reflect ripening-associated changes in carbohydrate metabolism, including the hydrolysis and mobilization of carbohydrate reserves and the accumulation of soluble sugars, together with changes in other soluble constituents.

The highest TSS value (19.33 °Brix) was recorded in fruits harvested at Stage 5 and stored for 35 days, whereas the lowest value (12.00 °Brix) was observed in Stage 1 fruit immediately after harvest. These results indicate that both harvest maturity and storage duration contributed to changes in soluble-solids concentration during postharvest storage.

The percentage changes in TSS during storage for Stages 1–5 were 41.66%, 13.79%, 4.16%, 15.62%, and 7.40%, respectively. Notably, fruits harvested at Stage 3 exhibited the smallest

relative change in TSS (4.16%) over the 0–35-day storage period, indicating comparatively greater compositional stability during storage. When considered together with the responses of firmness, weight loss, titratable acidity, and pH, this relatively small change in TSS further supports Stage 3 as a potentially favorable harvest stage for maintaining postharvest quality.

The increase in TSS during fruit ripening is not necessarily attributable solely to sugar accumulation. Changes in organic acids, soluble pectic substances, and other soluble components can also influence refractometric measurements of total soluble solids. Changes in carbohydrate metabolism, including alterations in enzymes involved in sucrose biosynthesis such as sucrose phosphate synthase (SPS), have been associated with soluble-sugar accumulation during fruit ripening (Chiacchierini et al., 2007). However, because enzyme activities and ethylene production were not measured in the present study, these mechanisms should be considered as possible physiological explanations rather than direct evidence from the current experiment.

The observed changes in TSS during storage are consistent with previous studies demonstrating that soluble solids and other physicochemical quality attributes of apricot fruit undergo significant changes during postharvest storage [43]

Overall, the significant interaction between harvest maturity and storage duration indicates that the evolution of soluble solids during storage depends on the physiological maturity of the fruit at harvest. The comparatively small variation in TSS observed in Stage 3, together with its performance for other quality attributes, supports this stage as a favorable harvest window for maintaining overall postharvest quality.

Lightness (L^*)

As illustrated in Figure 10, fruit lightness (L) varied according to both harvest stage and storage duration. During the first 14 days of storage, L values in fruits harvested at Stages 1 and 2 remained relatively stable, indicating limited changes in the optical properties of the fruit surface during the early storage period. This pattern was consistent with the retention of the green background color observed in the less advanced maturity stages

At Stage 3, particularly after 21 days of storage, L^* values increased, indicating greater lightness of the fruit surface. This change may be associated with the progression of ripening and accompanying alterations in surface pigmentation. In apricot, the transition from immature to more advanced maturity stages is accompanied by measurable changes in L^* and other color attributes,

supporting the use of L^* as an indicator of maturity-related color development [9]. However, because pigment concentrations, respiration rate, and ethylene production were not directly measured in the present study, these physiological mechanisms should be considered possible explanations rather than direct evidence.

Following the increase observed at Stage 3, L^* values declined at 35 days of storage, indicating a reduction in fruit surface lightness during prolonged storage. This late-storage decline may reflect advanced ripening and associated changes in surface pigmentation. Overall, the changes in L^* demonstrate that harvest maturity influenced the trajectory of fruit color development during cold storage. The relatively moderate changes observed at Stage 3, when considered together with the other quality attributes evaluated in this study, further support this stage as a favorable harvest window for maintaining postharvest quality.

Chroma (C^*)

The chroma index (C^*), which represents color saturation or intensity, showed relatively limited variation among harvest stages and storage durations during cold storage (Figure 11). The harvest stage $\times$ storage duration interaction was generally not significant for C^* , although some variation was observed at the advanced maturity stage. At Stage 3, C^* values remained relatively stable throughout storage, indicating comparatively limited changes in color saturation during this period. In contrast, greater fluctuations were observed in Stage 5 fruit, particularly during the later stages of storage.

During the first three weeks of storage, C values remained relatively stable, suggesting limited changes in fruit color saturation during the early-to-intermediate storage period. Subsequently, slight changes in C^* were observed during the fourth and fifth weeks, which may reflect the progression of ripening and associated changes in surface pigmentation. Such changes can be related to alterations in chlorophyll and carotenoid pigments during fruit maturation; however, pigment concentrations were not directly determined in the present study, and therefore these mechanisms should be considered as possible explanations rather than direct evidence.

The relatively stable C values observed in Stage 3 indicate greater stability of color saturation during storage. This finding is consistent with the general use of color parameters, including L , a^* , b^* , and C^* , as objective indicators of maturity and ripening progression in apricot fruit. Previous

research has demonstrated that color-related parameters can effectively discriminate among different maturity stages of apricot fruit [9].

Overall, the limited variation in C during storage, particularly in Stage 3 fruit, suggests that this maturity stage was associated with relatively stable color saturation. When considered together with the changes observed in L, firmness, weight loss, TA, pH, and TSS, the C* results provide additional evidence for the favorable postharvest performance of fruit harvested at Stage 3.

Hue Angle (h°)

The hue angle (h°), which represents the dominant color tone of apricot fruit surface, was significantly affected by harvest maturity stage and storage duration (Figure 12). Higher h° values observed during the earlier harvesting stages indicated the predominance of green coloration, reflecting a less advanced ripening status and greater retention of green pigments. As storage progressed, h° values gradually decreased, demonstrating progressive changes in fruit surface coloration associated with the advancement of ripening.

The reduction in h° became more evident during the intermediate and advanced harvesting stages, indicating a transition from green to yellowish coloration. In apricot fruit, this decline is generally associated with ripening-related pigment transformations, including chlorophyll degradation and the increased contribution of yellow carotenoid pigments. However, because pigment concentrations, chlorophyll content, and ethylene production were not directly quantified in the present study, these mechanisms should be interpreted as possible physiological explanations consistent with the observed color changes rather than direct measurements.

During the later harvesting stages (Stages 4 and 5), h° values continued to decline but at a lower rate, suggesting that the major color transition had already occurred and fruits were approaching a more advanced maturity condition. Conversely, fruits harvested at Stage 3 exhibited a more balanced color development pattern during storage, indicating an appropriate physiological maturity level that allowed continued ripening while maintaining postharvest quality.

Color parameters, including hue angle, are widely recognized as objective and non-destructive indicators for evaluating fruit maturity and quality changes during storage because they reflect complex biochemical and structural modifications occurring during ripening [5]. Similar reductions in h° during fruit maturation have been reported in apricot and other climacteric fruits,

where decreasing hue values were associated with the progression of color development and ripening processes [44, 45]. Considering the combined responses of firmness, weight loss, titratable acidity, pH, total soluble solids, and color attributes, Stage 3 represented the most favorable harvest maturity stage for maintaining apricot quality during cold storage. Therefore, h° can be considered a useful complementary parameter for maturity assessment and for supporting the identification of an optimal harvest window in apricot production systems.

Total Color Difference (ΔE)

The total color difference (ΔE), which represents the overall magnitude of color variation compared with the initial color state, was significantly affected by both harvest maturity stage and storage duration (Figure 13). A progressive increase in ΔE values was observed during cold storage, indicating continuous color transformation associated with fruit ripening and postharvest senescence.

The magnitude of color change differed among harvesting stages. Fruits harvested at the early maturity stages (Stages 1 and 2) exhibited the highest ΔE values after 35 days of storage, indicating greater instability of color attributes during storage. This response suggests that immature fruits undergo more pronounced color modifications after harvest, likely due to the continuation of ripening-related pigment transformations under storage conditions. In contrast, fruits harvested at later stages showed lower ΔE values, reflecting reduced variation from their initial color state and greater color stability.

The increase in ΔE during storage can be attributed to progressive changes in peel and flesh pigmentation, including alterations in chlorophyll-related green coloration and accumulation or redistribution of yellow pigments. In addition, prolonged storage may promote oxidative reactions that contribute to discoloration through phenolic oxidation and enzymatic browning processes. However, since pigment concentration and enzymatic browning activity were not directly measured in the present study, these mechanisms should be considered as possible explanations consistent with the observed color changes.

Color stability is an important quality attribute determining consumer acceptance and marketability of apricot fruit. Previous studies have demonstrated that changes in ΔE values provide a reliable indication of ripening-associated color evolution and postharvest quality deterioration in horticultural commodities [5, 44]

The lower ΔE variation observed in Stage 3 fruits, combined with their favorable retention of firmness, soluble solids, titratable acidity, and pH during storage, indicates that this harvesting stage provided an optimal balance between sufficient physiological maturity and storage stability. Fruits harvested before Stage 3 showed greater susceptibility to postharvest color alteration, whereas fruits harvested at more advanced stages may have limited storage potential due to accelerated ripening processes.

Therefore, ΔE , together with individual color parameters (L^* , C^* , and h°), can serve as a valuable non-destructive indicator for evaluating maturity progression and determining the optimal harvest window of apricot fruit. The identification of Stage 3 as the most suitable harvest stage also provides a biological basis for subsequent image-based maturity classification using deep learning approaches.

Deep Learning Model Performance

The training process of the deep learning model demonstrated a stable convergence pattern throughout the learning phase. As shown in Figure 14 (a), both the training and validation loss exhibited a generally decreasing trend with increasing epochs, indicating successful optimization of the network parameters. Although minor fluctuations were observed during training, the overall reduction in the loss values suggests that the model effectively learned the discriminative features associated with the different apricot developmental stages. Furthermore, the close agreement between the training and validation loss curves indicates that overfitting was effectively controlled and that the model maintained good generalization capability. The accuracy curves presented in Figure 14 (b) further confirm the effectiveness of the training process. Both the training and validation accuracies increased progressively with the number of epochs, eventually reaching a stable plateau. The similarity between the two curves demonstrates that the model achieved consistent performance on both the training and validation datasets, reflecting a robust learning process and good generalization ability.

The confusion matrix presented in Figure 15 provides a comprehensive view of the classification results and misclassification patterns. Each row and column correspond to a specific class, and the values represent the number of samples. Therefore, a well-performing classifier produces a confusion matrix with high values along the main diagonal and low values in the off-diagonal cells. As shown in Figure 15, the main diagonal of the confusion matrix contains substantially

higher values than the off-diagonal cells, indicating promising classification performance, with most samples correctly assigned to their respective developmental stages. This result confirms the strong discriminative capability of the proposed model.

To further examine the classification performance, the confusion matrix reveals the following misclassification patterns. For Stage 1, one sample was incorrectly classified as Stage 4 and eight samples were classified as Stage 5. Stage 2 exhibited the highest level of confusion, with sixteen samples being misclassified as Stage 3. This result is consistent with the relatively low recall value obtained for Stage 2 and suggests substantial visual similarity between these two developmental stages. For Stage 3, three samples were incorrectly assigned to Stage 2 and three samples to Stage 4, indicating overlap with both the preceding and subsequent maturity stages. In Stage 4, five samples were classified as Stage 1, two as Stage 3, and one as Stage 5. Finally, four samples belonging to Stage 5 were misclassified as Stage 1. Despite these errors, the confusion matrix reveals that misclassifications predominantly occurred between biologically adjacent developmental stages rather than between distinctly different stages. This behavior suggests that the model successfully captured the underlying progression of fruit maturation and that the classification errors mainly resulted from the gradual transition between maturity levels.

Practical Implications for Apricot Storage Management

The laboratory investigations conducted in the previous phase of this study demonstrated that fruits harvested at Stage 3 exhibited the most favorable storage performance and shelf-life characteristics. Therefore, accurate identification of this developmental stage is of considerable practical importance for optimizing postharvest management strategies.

The proposed deep learning model provides a rapid and non-destructive approach for determining the developmental stage of apricot fruits directly from RGB images. Under field conditions, images can be captured during fruit development and analyzed automatically by the trained model. When the model identifies a fruit as belonging to Stage 3, harvesting can be initiated and the fruits can be transferred to storage facilities with a high probability of achieving extended storage life. Conversely, fruits classified into other developmental stages may not exhibit the same storage potential and may require alternative harvest or marketing strategies.

Moreover, the developed framework can support growers, storage operators, and supply-chain managers in making objective and timely decisions regarding harvest scheduling and postharvest

handling. By integrating image-based maturity assessment with storage recommendations, the proposed approach contributes to reducing postharvest losses, improving fruit quality preservation, and enhancing the economic efficiency of apricot production systems.

Taken together, the responses of firmness, weight loss, TSS, TA, pH, and color attributes indicate that the postharvest behavior of apricot fruit was strongly dependent on the physiological maturity reached at harvest. Rather than exhibiting superiority in a single quality attribute, Stage 3 showed the most favorable overall balance between maturity advancement and preservation of postharvest quality. Earlier-harvested fruit retained characteristics of less advanced maturity but underwent greater changes during subsequent storage, whereas fruit harvested at later stages entered storage at a more advanced physiological state and consequently exhibited greater susceptibility to softening and quality deterioration. Thus, the superior performance of Stage 3 can be interpreted as the outcome of an intermediate physiological maturity window in which fruit had developed sufficiently for acceptable quality while retaining adequate capacity to withstand postharvest deterioration. This integrated response provides the biological basis for selecting Stage 3 as the target maturity class for the image-based classification developed in the second phase of the study. Importantly, the CNN was used to recognize the maturity stage identified as optimal by the postharvest quality assessment, rather than independently determining its optimality.

Conclusion

This study demonstrated that harvest maturity is a critical determinant of the postharvest quality and storage potential of apricot fruit and that its assessment can be effectively complemented by image-based deep learning. Among the five maturity stages evaluated, Stage 3 provided the most favorable balance between physiological maturity and quality retention during 35 days of cold storage, as reflected by the combined responses of firmness, weight loss, soluble solids, acidity, pH, and color attributes. Based on this physiologically defined maturity classification, a lightweight dual-path convolutional neural network was developed to recognize the five harvest stages from RGB images acquired under natural orchard conditions. The proposed model achieved a weighted precision of 0.81, recall of 0.78, and F1-score of 0.79 on the independent test dataset, with most misclassifications occurring between adjacent maturity stages. These findings demonstrate the potential of integrating postharvest physiological assessment with computer vision to provide a rapid and non-destructive approach for maturity-based harvest decision-making

in apricot. Further validation across cultivars, orchards, seasons, and variable field imaging conditions is required before deployment in practical commercial orchard systems.

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Authors' contributions

Sh.N. conducted the experiments, performed the postharvest treatments, and carried out the physicochemical analyses and related laboratory measurements. H.B. conceived and designed the research, managed and supervised the project execution, coordinated the experimental activities, performed the postharvest data analysis, wrote the manuscript, and served as the corresponding author. S.I.S. designed the deep learning framework, managed and analyzed the related data, contributed to data interpretation, and participated in manuscript preparation. All authors read and approved the final version of the manuscript.

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Data availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate

Not applicable. The present study involved harvested apricot fruit and did not involve human participants, human data, or experimental animals; therefore, ethical approval and consent to participate were not required.

Consent for publication

Not applicable. This manuscript does not contain any individual person's data, images, or other identifiable information requiring consent for publication.

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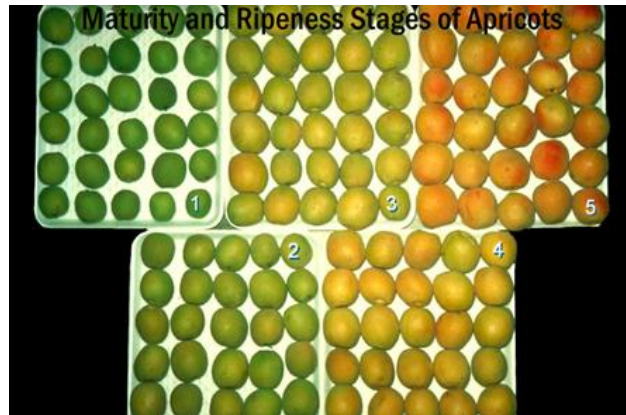


Figure 1. Maturity and ripeness stages of apricot fruit. Photo credit: Don Edwards, University of California, Davis.

Maturity stage 1	Maturity stage 2	Maturity stage 3	Maturity stage 4	Maturity stage 5
NO: 190	NO: 197	NO: 205	NO: 241	NO: 199
				

Figure 2. Representative images and the number of apricot fruits at different stages of physiological maturity.

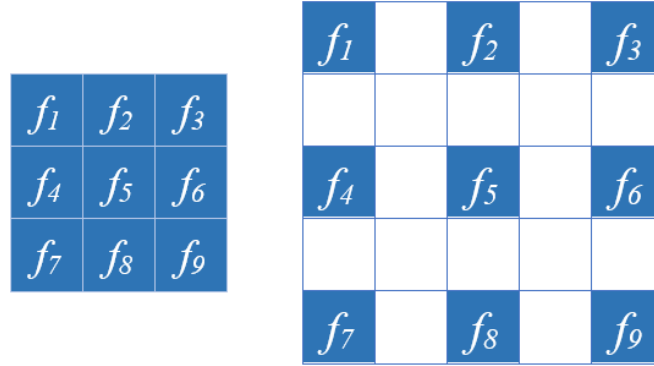


Figure 3. Regular convolution filter of size 3×3 (left) with 3×3 receptive field vs. dilated convolution filter of size 3×3 with dilation factor of 2 and 5×5 receptive field (right).

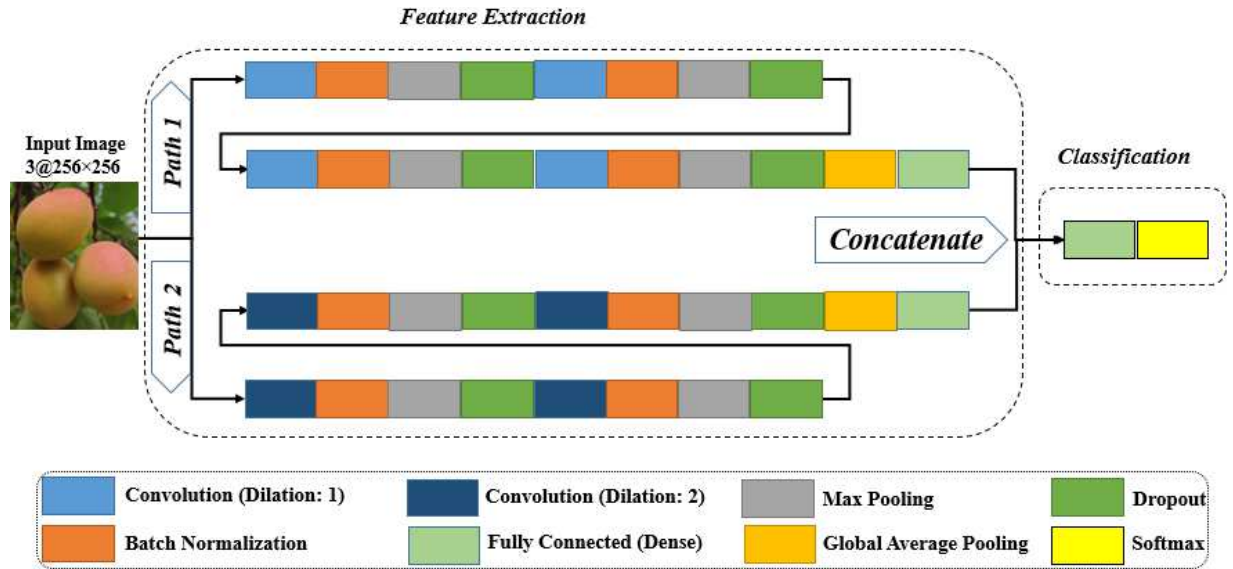


Figure 4. Topology of the proposed dual-path lightweight network architecture.

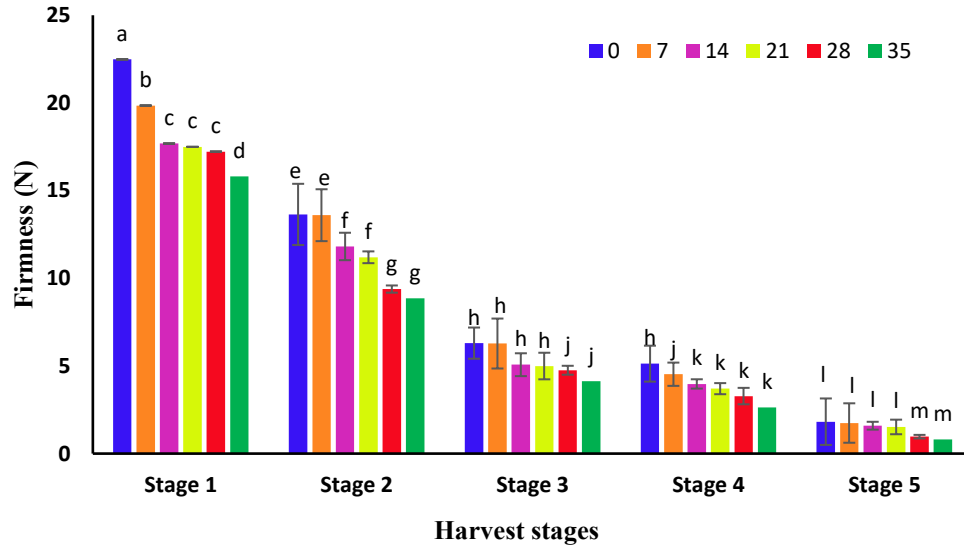


Figure 5. Effects of harvest maturity stage and storage duration on firmness of apricot fruit during cold storage at 6 °C for 35 days. Different lowercase letters indicate significant differences among treatment combinations according to Duncan's multiple range test ($p \leq 0.05$). Error bars represent the standard error of the mean ($n = 3$).

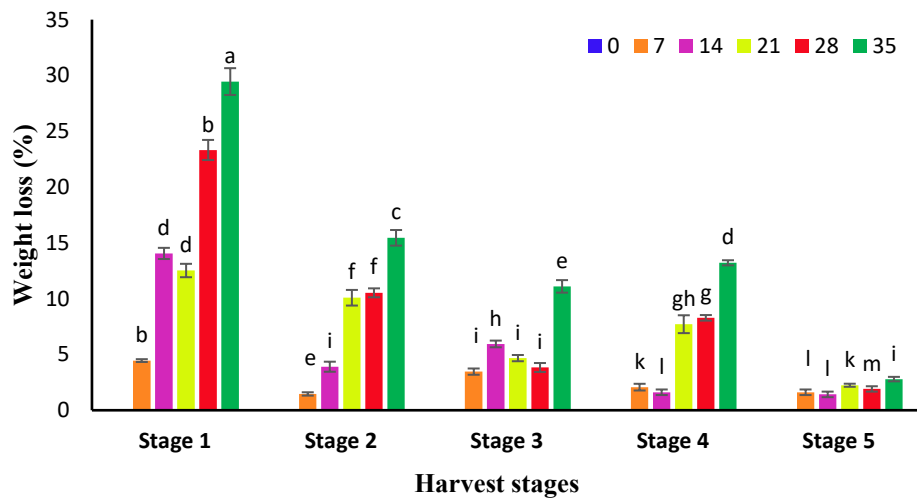


Figure 6. Effects of harvest maturity stage and storage duration on weight loss of apricot fruit during cold storage at 6 °C for 35 days. Different lowercase letters indicate significant differences among treatment combinations according to Duncan's multiple range test ($p \leq 0.05$). Error bars represent the standard error of the mean ($n = 3$).

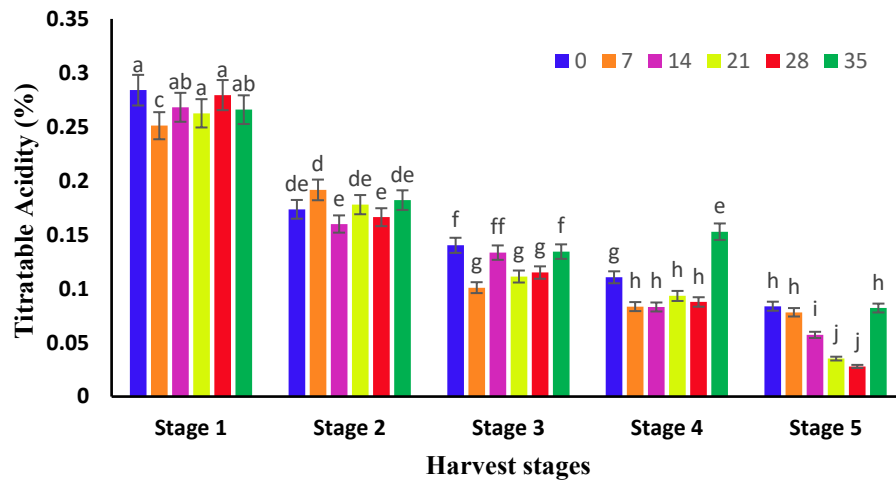


Figure 7. Effects of harvest maturity stage and storage duration on titratable acidity of apricot fruit during cold storage at 6 °C for 35 days. Different lowercase letters indicate significant differences among treatment combinations according to Duncan's multiple range test ($p \leq 0.05$). Error bars represent the standard error of the mean ($n = 3$).

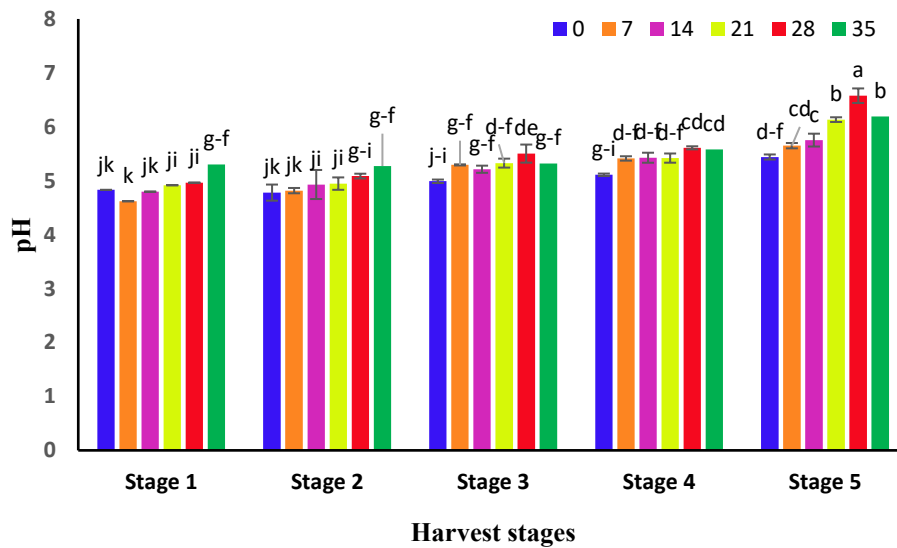


Figure 8. Effects of harvest maturity stage and storage duration on pH of apricot fruit during cold storage at 6 °C for 35 days. Different lowercase letters indicate significant differences among treatment combinations according to Duncan's multiple range test ($p \leq 0.05$). Error bars represent the standard error of the mean ($n = 3$).

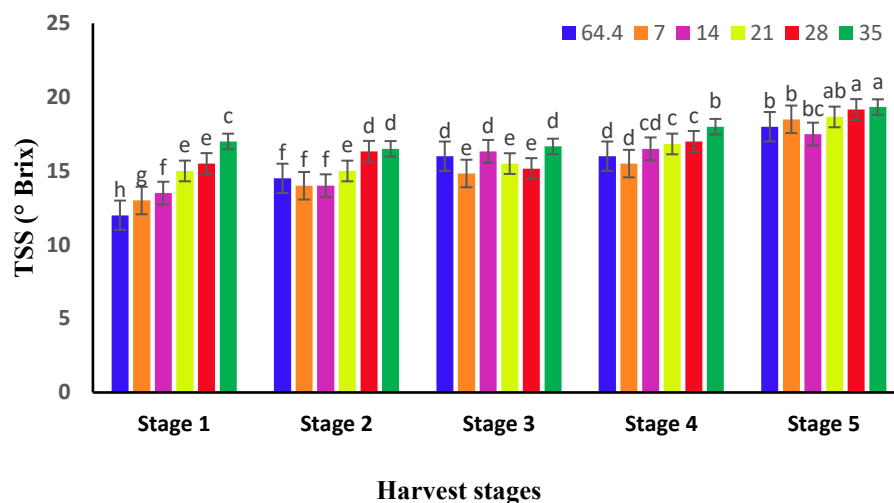


Figure 9. Effects of harvest maturity stage and storage duration on total soluble solids (TSS) of apricot fruit during cold storage at 6 °C for 35 days. Different lowercase letters indicate significant differences among treatment combinations according to Duncan's multiple range test ($p \leq 0.05$). Error bars represent the standard error of the mean ($n = 3$).

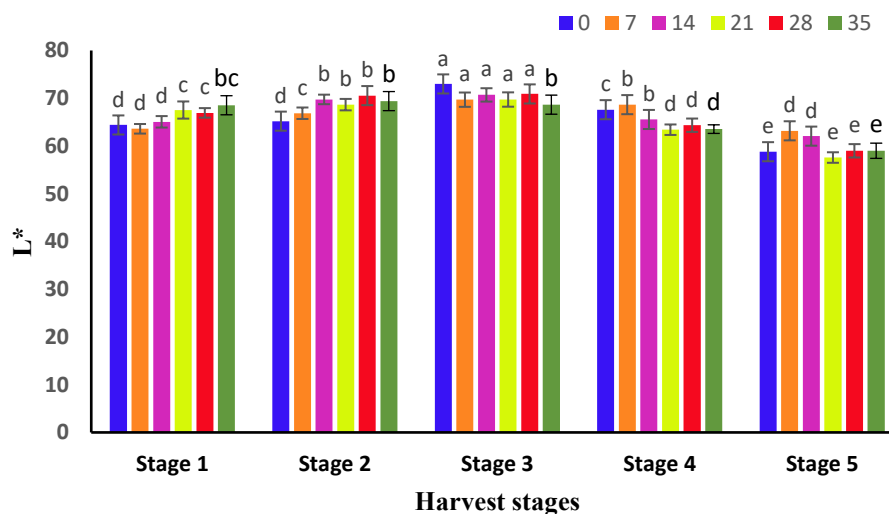


Figure 10. Effects of harvest maturity stage and storage duration on lightness (L^*) of apricot fruit during cold storage at 6 °C for 35 days. Different lowercase letters indicate significant differences among treatment combinations according to Duncan's multiple range test ($p \leq 0.05$). Error bars represent the standard error of the mean ($n = 3$).

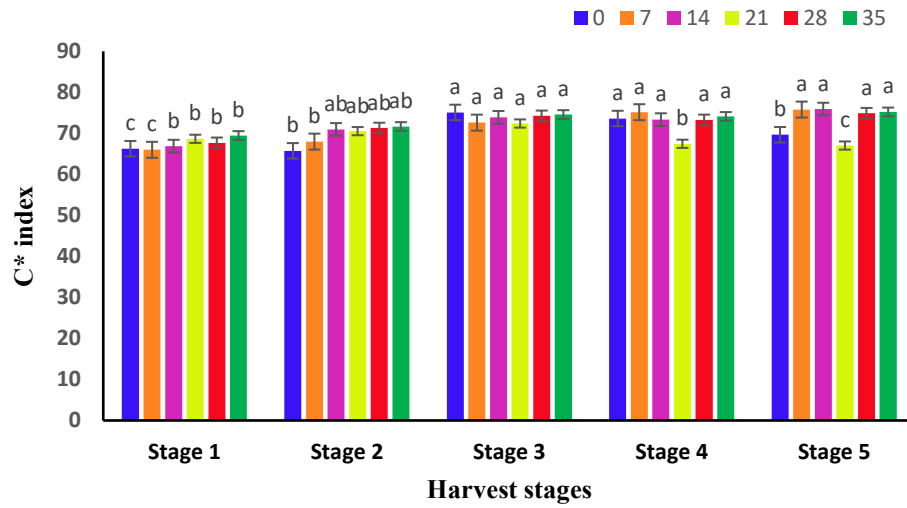


Figure 11. Effects of harvest maturity stage and storage duration on chroma (C*) of apricot fruit during cold storage at 6 °C for 35 days. Different lowercase letters indicate significant differences among treatment combinations according to Duncan's multiple range test ($p \leq 0.05$). Error bars represent the standard error of the mean ($n = 3$).

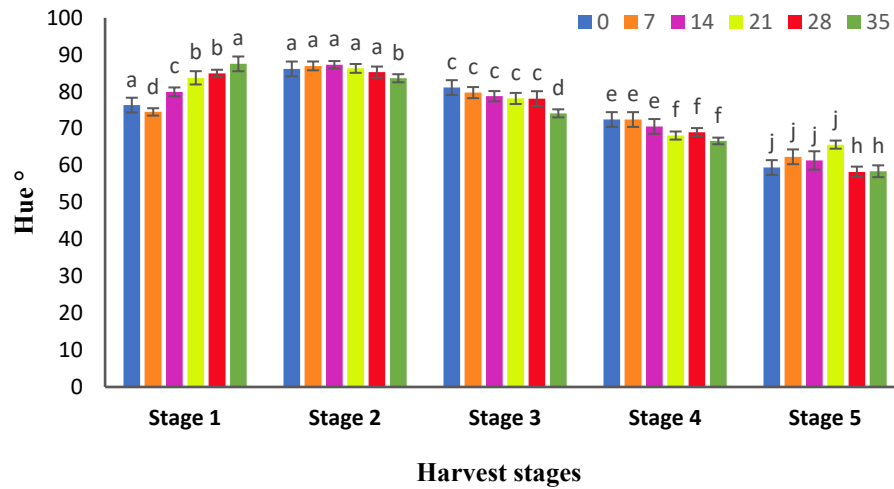


Figure 12. Effects of harvest maturity stage and storage duration on hue angle (h°) of apricot fruit during cold storage at 6 °C for 35 days. Different lowercase letters indicate significant differences among treatment combinations according to Duncan's multiple range test ($p \leq 0.05$). Error bars represent the standard error of the mean ($n = 3$).

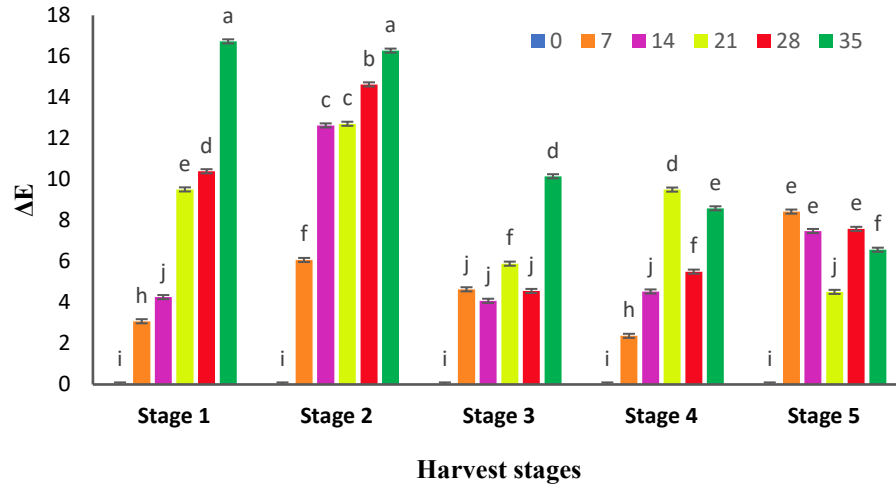
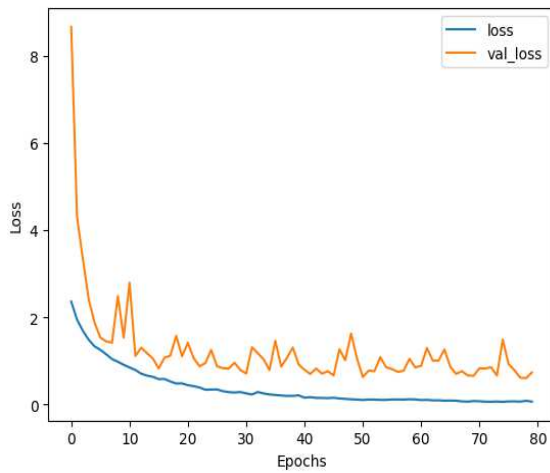
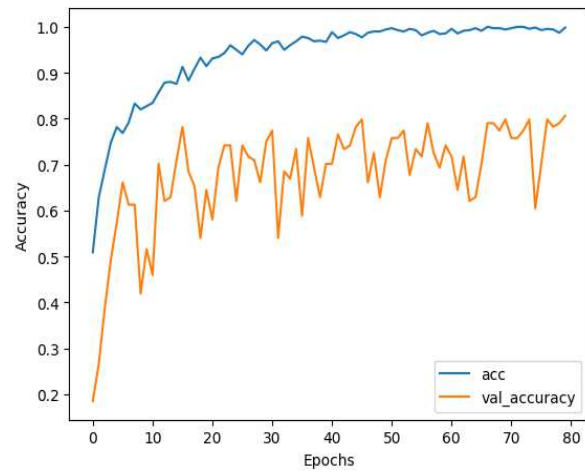


Figure 13. Effects of harvest maturity stage and storage duration on total color difference (ΔE) of apricot fruit during cold storage at 6 °C for 35 days. Different lowercase letters indicate significant differences among treatment combinations according to Duncan's multiple range test ($p \leq 0.05$). Error bars represent the standard error of the mean ($n = 3$).



(a)



(b)

Figure 14. Accuracy and loss trends for the proposed dual path CNN during training process for train and validation data.

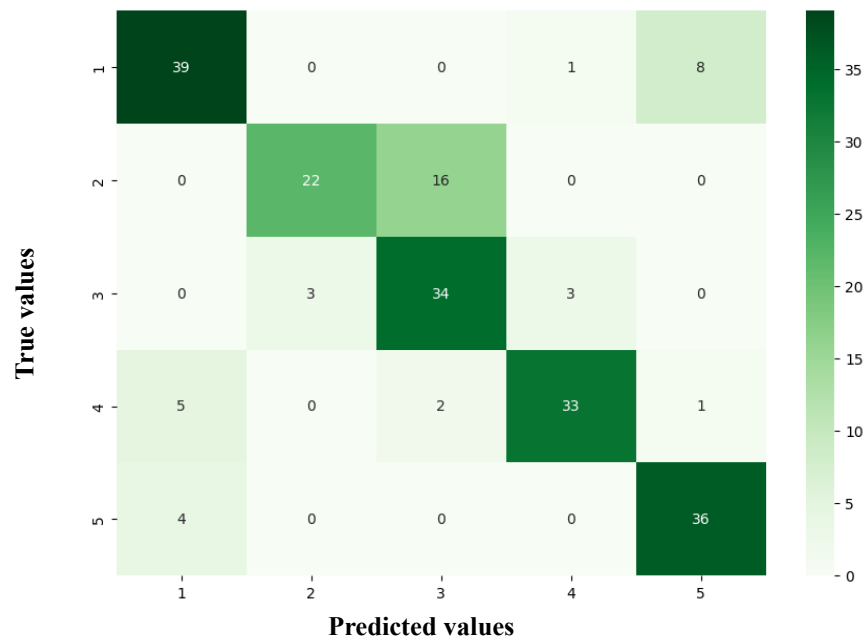


Figure 15. Confusion matrix for the classification of apricot fruit based on maturity stages.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [Tables.docx](#)