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Machine learning optimization of 1-MCP and chitosan/*Aloe vera* coatings for climate-resilient, sustainable fig postharvest preservation

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Abstract. Figs (*Ficus carica*) are among the most popular fruit crops, loaded with an ample supply of essential elements, dietary fiber, and bioactive molecules with high antioxidant activity. Despite this, they are quite perishable in nature, hence, extremely susceptible to postharvest microbial spoilage. To prevent this loss, researchers have been trying different methods, including cold storage, modified atmosphere packaging, chemical treatments, and coatings. However, measuring shelf life based on laboratory analysis is quite challenging, laborious, and involves the use of chemical reagents for quality assessment, indirectly impacting the environment. Therefore, the current study is designed to promote a dry lab approach to predict the shelf life of Fig fruits treated with 1-Methyl cyclopropane (1-MCP), and edible coating based on *Aloe vera* (AV) and chitosan (CH). After treatment, fruits were kept for storage at 2ºC with 80-85% RH. Quality studies were done every week, and the data produced was used to predict the shelf life using Artificial Neural Networks (ANNs) and Extreme Gradient Boosting (XGBoost) machine learning platforms. The results indicated that the ANN performed worse than a simple mean predictor, whereas XGBoost performed well. Therefore, this approach can help create the best model for shelf-life prediction, as it supports climate-resilient and sustainable postharvest practices.

Introduction

Figs (*Ficus carica*) are frequently accepted as a significant fruit crop for human dietary needs throughout the period (1). Figs contain an extraordinary collection of phenolic compounds (2, 3) and various biologically active compounds with high antioxidant activity that provide numerous health benefits (4, 5). According to clinical studies, 40g of fresh figs can provide 444 mg of polyphenol, which is enough for the daily intake (6). Despite these notable qualities, its highly perishable nature creates a significant challenge in preserving the postharvest nutritional quality, contributing to the postharvest losses (7).

Figs are considered climacteric fruits due to the production of ethylene at the onset of ripening (8). The purple color fig cultivars are mainly harvested at their half-purple stage, an indication of an ethylene surge. After harvest, the fruits tend to lose their quality and start entering the senescence stage. Hence, the postharvest shelf life of fig fruit is about 3-4 days (9). Various strategies, including cold storage, chemical treatments, and edible coatings (bio-based), have been previously applied to enhance the shelf life of figs (10, 11); however, controlling ethylene-mediated postharvest changes and improving the quality and shelf life is still challenging

During the past decade, various approaches have been developed to suppress ethylene production in fruits, aiming to achieve nominal ethylene concentrations in fruits after harvest. For example, 1-MCP (1-methyl cyclopropane), an inhibitor of ethylene receptors, was found to give promising results in modulating the ethylene production in many fruits, including nectarines, kiwi,

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pear, pomegranate, and banana (12-15). Therefore, 1-MCP was chosen as a postharvest treatment to delay the postharvest quality changes in fig fruits during cold storage. Recently, the effect of *Aloe vera* (AV) and chitosan (CH) was optimized as a stand-alone coating on fig fruits during cold storage (16).

Studying the effect of such treatments and measuring the shelf life of fruit requires a combination of physiological, chemical, and physical analysis by various quantitative and destructive methods (17). Furthermore, these methods require extensive labor, cost, and time, and most of these procedures involve environmentally unfriendly materials and chemicals (18). On the other hand, shelf-life prediction is challenging when it is highly dependent on experimental analysis, due to variability in several parameters such as storage conditions, quality indicators, and harvest season (19). Therefore, researchers are mainly focusing on developing a working model for shelf-life assessment studies. Machine learning-based computational tools have recently emerged to support the agriculture and food industries. Machine learning works on the input data values that are further translated into a programming language to provide meaningful results. Several ML tools, such as vector machines (SVMs), decision trees (DTs), random forests (RFs), k-nearest neighbors (k-NNs), extreme learning machines (ELMs), Extreme Gradient Boosting (XGBoost), and artificial neural networks (ANNs), have been applied in shelf-life prediction of various horticulture products, such as berries, grapes, radishes, avocados, and oranges (20-22). Integrating these tools with experimental data will provide a novel approach for developing a shelf-life prediction model and quality management of figs under the mentioned conditions.

The current study has optimized ANNs and the XGBoost method of machine learning. This research aims to optimize a machine learning model for producing a strong and reliable platform for fig preservation and quality maintenance. Furthermore, this research will contribute to reducing postharvest loss, enabling analytics-focused, efficient strategies in preservation and fruit supply optimization

Materials and methods

Fresh Figs (*Ficus carica* L. cv. Brown Turkey) were sourced from commercial farms in Al Ain City. The fruits were picked at the stage of commercial maturity, characterized by 50% purple skin color. Fresh, disease-free AV leaves of consistent size were collected from AV plants grown in a greenhouse at the UAE University in Al Ain City, United Arab Emirates.

Edible coatings preparation. The AV gel was extracted and prepared for the coating treatment (23). A CH stock solution (1%, w/v) was made in 1% lactic acid. This solution was then utilized to develop various coating formulations in combination with the AV gel (Table 1). All formulations were stored in sterile tubes to maintain stability. The homogeneity of the formulations was assessed by measuring the absorbance of the solutions at 600 nm immediately after preparation. Subsequently, absorbance readings were taken from both the lower and upper portions of the solution after 24 hours to evaluate homogeneity. 1-MCP (0.4 ppm) solution was prepared in lukewarm water just before application.

Sample preparation and treatment. Fruit samples after harvest were immediately brought to the laboratory and sorted to discard any damaged fruit. Fruits of similar size and appearance were distributed to 5 groups (~50 fruits per group). The control group was immersed in water for 1 minute, and the rest of the fruits were given a specific coating treatment. Then the fruits were kept on a steel mesh to drain off the excess coating solution and kept for drying at room temperature for 3 hours. Subsequently, the fruits were arranged in plastic trays with perforated resealable plastic covers and stored in a cold environment at 2°C with 80–85% relative humidity for 28 days. Samples of 8 figs from each treatment were removed from storage weekly for various analyses, conducted in triplicate. The data was collected in a CSV file in a specific format for a machine learning experiment.

Statistical analysis. The experimental design employed was a completely randomized design (CRD) with three replicates. The collected data were statistically analyzed by two-way analysis of variance (ANOVA) using Minitab statistical analysis software version 21. Mean comparisons were performed using the Fisher LSD test at a significant level of $p \leq 0.05$.

Shelf-life validation by ANNs and XGBoost method of machine learning. R Studio version 4.2 was used to perform machine learning algorithms. The "Neuralnet" and "Xgboost" packages were used for ANNs and XGBoost, respectively. The dataset was partitioned into training and testing subsets following a 50%-50% two-way split. Subsequently, data was scaled for training an ANN, and an XGBoost was trained on the training subset using default hyperparameter settings.

Results

The regression metrics obtained by the XGBoost and ANN algorithms are presented in Table 1. The XGBoost showed excellent agreement between predicted and observed values ($R^2 = 0.9398$, RMSE ≈ 0.76, MAE ≈ 0.49). Overall, the model shows good predictive performance. Whereas, the ANN showed poor predictive performance, with $R^2 = -2.73$, RMSE = 2.12, MAE = 1.82, and MAPE = 365.95%. A negative R^2 indicates that the ANN predictions are worse than simply using the mean of the observed values as a predictor. Overall, these metrics confirm that the XGBoost provides reliable shelf-life predictions, making it a valuable tool for practical implementation.

Table 1. *Performance evaluation metrics of the trained machine learning model, including error measures and goodness-of-fit indicators.*

Regression Metric	Extreme Gradient Boosting (XGBoost)	Artificial Neural Networks (ANNs)
Mean Squared Error (MSE)	0.5771	4.487495
Root Mean Squared Error (RMSE)	0.7597	2.118371
Mean Absolute Error (MAE)	0.4939	1.815491
R-squared	0.9398	-2.733817

Higher R-squared values (closer to 1) indicate better model fit, while lower MSE, RMSE, and MAE values indicate smaller prediction errors and therefore better predictive performance.

Discussion

Shelf-life studies are important, especially for fresh and perishable items. The shelf life of fruits depends on several factors, including their physiological condition and the external environment (24). Moreover, performing shelf-life studies using laboratory protocols are often impractical and unsustainable due to the time-consuming, labor-intensive, and resource-intensive nature of these experiments (19). Contrastingly, machine learning algorithms offer a more efficient and accurate approach to shelf-life prediction by harnessing previous data and treatment conditions to model complicated decay processes. The current study deals with the comparative analysis of ANNs and XGBoost algorithms for predicting the shelf life of figs treated with 1-MCP and AV/CH coating, indicating that XGBoost possesses distinct advantages in handling the datasets with an R-squared value of 0.9398. These results are in accordance with the previous studies (21, 22, 25). The results suggest that XGBoost may be more suitable for rapid and reliable shelf-life predictions in practical settings, especially when dealing with diverse treatments and limited data. On the other hand, the

ANN is not suitable for this dataset and may be mis-specified or overfitted suggest, that more complex models like ANN do not necessarily outperform simpler or alternative machine-learning methods. Nevertheless, XGBoost provides substantially better accuracy, providing a valuable tool for optimizing postharvest management and extending the shelf life of figs coated with specific treatments.

References

[1] A. Sarkhosh, A. Yavari, L. Ferguson. The fig: Botany, production and uses, reprint, CABI. (2022).

[2] A.K. Sandhu, M. Islam, I. Edirisinghe, B. Burton-Freeman. Phytochemical composition and health benefits of figs (fresh and dried): a review of literature from 2000 to 2022, Nutrients. 15(11) (2023) 2623. https://doi.org/10.3390/nu15112623.

[3] J.P. Singh, B. Singh, A. Kaur. Polyphenols in fig: A review on their characterisation, biochemistry during ripening, antioxidant activity and health benefits, IJFST. 57(6) (2022) 3333-42. https://doi.org/10.1111/ijfs.15740.

[4] M.Y. Alzahrani, A.I. Alshaikhi, J.S. Hazzazi, J.R. Kurdi, M.F. Ramadan. Recent insight on nutritional value, active phytochemicals, and health-enhancing characteristics of fig (*Ficus craica*), Food Saf. Health. 2(2) (2024) 179-95. https://doi.org/10.1002/fsh3.12034.

[5] N. Kaur, C. Somasundram, Z. Razali, Z.F.R. Ahmed. *Aloe vera* and chitosan coating, an eco-friendly and sustainable approach to reduce postharvest loss of figs (*Ficus carica*), Acta Hortic. 1404, (2023) 725-732. https://doi.org/10.17660/ActaHortic.2024.1404.99.

[6] J.A. Vinson, Y. Hao, X. Su, L. Zubik. Phenol antioxidant quantity and quality in foods: vegetables, J. Agric. Food Chem. 46(9) (1998) 3630-4. https://doi.org/10.1021/jf980295o.

[7] Z.F.R. Ahmed, E.M.A Taha, N.A.A. Abdelkareem, W.M. Mohamed. Postharvest Properties of Unripe Bananas and the Potential of Producing Economic Nutritious Products, Int J Fruit Sci. 20(sup2) (2020) S995-S1014. https://doi.org/10.1080/15538362.2020.1774469.

[8] N. Marei, J.C. Crane. Growth and respiratory response of fig (*Ficus carica* L. cv. Mission) fruits to ethylene, Plant Physiol. 48(3) (1971) 249-54. https://doi.org/10.1104/pp.48.3.249.

[9] Z.E. Freiman, Y. Rosianskey, R. Dasmohapatra, I. Kamara, M.A. Flaishman. The ambiguous ripening nature of the fig (*Ficus carica* L.) fruit: a gene-expression study of potential ripening regulators and ethylene-related genes, J. Exp. Bot. 66(11) (2015) 3309-24. https://doi.org/10.1093/jxb/erv140.

[10] E. Kucuker, E. Aglar, M. Sakaldaş, F. Şen, M. Gundogdu. Impact of Postharvest Putrescine Treatments on Phenolic Compounds, Antioxidant Capacity, Organic Acid Contents and Some Quality Characteristics of Fresh Fig Fruits during Cold Storage, Plants. 12(6) (2023) 1291. https://doi.org/10.3390/plants12061291

[11] Z.F.R. Ahmed, J.P. Palta. A natural lipid, Lysophosphatidylethanolamine, may promote ripening while reducing senescence in banana fruit, HortScience. 50 (7) (2015) 1035–1040. https://doi.org/10.21273/HORTSCI.50.7.1035.

[12] L-Y. Chang, J.K. Brecht. Responses of 1-methylcyclopropene (1-MCP)−treated banana fruit to pre− and post−treatment ethylene exposure, Sci. Hortic. 309 (2023) 111636. https://doi.org/10.1016/j.scienta.2022.111636.

[13] G.Ld. Jesus, R.Sd.A. Silva, M.B.D. Tofanelli, F.L. Cuquel. Soft figs shelf life increasing with and 1-methylcyclopropene and cold storage, Rev. Ceres. 69 (2022) 538-43. https://doi.org/10.1590/0034-737X202269050006.

[14] H. Ma, N. Liu, G. Xie, S. Tan, Y. Xu, Z. Luo. Postharvest ripening combined with 1-MCP keeps the shelf quality of kiwifruit after cold storage by regulating the antioxidant system and defense enzymes, Postharvest Biol. Technol. 222 (2025) 113370. https://doi.org/10.1016/j.postharvbio.2024.113370.

[15] R. Wan, J. Song, Z. Lv, X. Qi, Z. Feng, Z. Yang, et al. Effects of 1–MCP Treatment on Postharvest Fruit of Five Pomegranate Varieties during Low-Temperature Storage, Horticulturae. 9(9) (2023) 1031. https://doi.org/10.3390/horticulturae9091031.

[16] N. Kaur, C. Somasundram, Z. Razali, Z.F.R. Ahmed. Sustainable *Aloe vera*/chitosan-based edible coatings reduce postharvest loss of stored fresh figs (*Ficus carica* L.), Front. Sustain. Food Sys. 8 (2024). https://doi.org/10.3389/fsufs.2024.1459600.

[17] R. Aslam, N. Sivapragasam, K.G. Lawal, Z.F.R. Ahmed, S. Maqsood. Bionanocomposite films from camel skin gelatin reinforced with tannic acid and date seed nanocellulose, Food Biophysics. 20(3) (2025) 119. https://doi.org/10.1007/s11483-025-10000-z.

[18] F.Y.Y. Al Shaibani, N. Kaur, Z.F.R. Ahmed. Reducing postharvest loss by improving fruit quality, shelf life, bioactive compounds of Rutab date (*Phoenix dactylifera* L. Barhi) using natural elicitors, Acta Hortic. 1340 (2021) 119-124. https://doi.org/10.17660/ActaHortic.2022.1340.18.

[19] B. Kumaravel, A.L. Amutha, T.P. Mary, A. Agrawal, A. Singh, S. Sa, et al. Automated seafood freshness detection and preservation analysis using machine learning and paper-based pH sensors, Sci. Rep. 5(1) (2025) 1-14. https://doi.org/10.1038/s41598-025-08177-x.

[20] W. Huang, X. Wang, J. Zhang, J. Xia, X. Zhang. Improvement of blueberry freshness prediction based on machine learning and multi-source sensing in the cold chain logistics, Food Control. 145 (2023)109496. https://doi.org/10.1016/j.foodcont.2022.109496.

[21] A. Owoyemi, M. Balaklav, B. Kochanek, R. Porat, N. Koenigstein, Y. Salzer et al. Deviations from optimal storage temperature and its impact on postharvest quality of table grape cv. Scarlotta Seedless, Postharvest Biol. Technol. 215 (2024) 113013. https://doi.org/10.1016/j.postharvbio.2024.113013.

[22] A. Owoyemi, T. Holdr, R. Porat, A. Lichter, N. Koenigsten, Y. Salzer. Temperature interruptions harm the quality of stored 'Rustenburg' navel oranges and development of dynamic shelf-life prediction models, Postharvest Biol. Technol. 204 (2023) 112458. https://doi.org/10.1016/j.postharvbio.2023.112458.

[23] N. Kaur, C. Somasundram, Z. Razali, A.H.I. Mourad, F. Hamed, Z.F.R. Ahmed. *Aloe vera*/Chitosan-Based Edible Film with Enhanced Antioxidant, Antimicrobial, Thermal, and Barrier Properties for Sustainable Food Preservation, Polymers. 16(2) (2024) 242. https://doi.org/10.3390/polym16020242.

[24] D. Li, L. Bai, R. Wang, S. Ying. Research Progress of Machine Learning in Extending and Regulating the Shelf Life of Fruits and Vegetable, Foods. 13(19) (2024) 3025. https://doi.org/10.3390/foods13193025.

[25] A. Owoyemi, R. Porat, A. Lichter, A. Doron-Faigenboim, O. Jovani, N. Koenigstein, et al. Evaluation of the storage performance of ‘valencia’oranges and generation of shelf-life prediction models, Horticulturae. 8(7) (2022) 570. https://doi.org/10.3390/horticulturae8070570.