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Tracing pistachio nuts' origin and irrigation practices through hyperspectral imaging

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Abstract

The commercialisation of pistachio nuts often faces issues of adulteration or misrepresentation concerning their cultivation practices and geographical origins. In this investigative study, we harnessed the capabilities of Hyperspectral Imaging (HSI) employing a SPECIM IQ camera to discern the irrigation treatments and geographical variations in pistachio nuts harvested from two distinct orchards in Spain, namely "La Seca" and "La Moraleja". Two experimental plots were designated as control and high irrigation within each orchard. Hyperspectral data, covering the spectral range of 400-1000 nm, were meticulously captured and analyzed to unravel the contrasts in water management practices and their implications on pistachios' commercial quality and yield.

The ensuing image analysis encompassed a broad spectrum of parameters, including water supplied and yield, and assessing percentage distribution among split, non-split, and blank nuts. Additionally, the origin and commercial calibre were evaluated to gauge the commercial viability of the yield. Three different Machine Learning (ML) models were used: Partial Least Squares-Discriminant Analysis (PLS-DA), Support Vector Machine (SVM) and XGBoost, which robust models were conceived. The results show that pistachio origin and water treatment predictions showed high accuracy with F1 scores of 0.99 and 0.92, respectively, and a combined prediction achieving 0.97, indicating the significant impact of location and irrigation. In contrast, other predictions like yield were strong (R2 score of 0.88), but shell split and calibre predictions were less accurate, highlighting the potential of advanced modelling to enhance pistachio quality predictability.

Our analysis accentuates the profound potential of HSI, especially when deployed with a SPECIM IQ camera, in delineating the irrigation treatment and tracing the geographical origin of pistachio nuts. This endeavour paves the way for ensuring authenticity and commercial quality in the pistachio trade. It augments our understanding of the interplay between irrigation practices and nut commercial quality, fostering a sustainable and informed agricultural paradigm.

Keywords: Commercial Quality, Machine learning, *Pistacia vera*, Post-harvest, Traceability.

1. Introduction

Pistachio trees, originating from southern Central Asia, have spread globally, reaching regions such as modern-day Syria around 2000 years ago (Mir-Makhamad *et al.*, 2022). Pistachio nuts are renowned for their unique flavour and are celebrated for their high protein, dietary fibre, and essential vitamins and minerals (Mandalari *et al.*, 2021). As significant crops in global agriculture, pistachios are in high demand. In 2022, Iran led in harvested area with 497,484 hectares, followed by Turkey (408,709 hectares) and the United States (173,207 hectares) (FAO, 2024). However, production quantities were highest in the United States (400,070 tons), with Turkey and Iran producing 241,669 tons and 239,289 tons, respectively. Despite market instability and import competition, Spain has seen increased interest in pistachio cultivation and rising consumption (CBI, 2020). The pistachio industry faces challenges such as adulteration, mislabelling, and the diverse

impacts of irrigation practices on yield and quality. These issues necessitate robust, non-invasive techniques to trace the geographical origin and determine irrigation treatments. Spectroscopy, which analyses material interactions with electromagnetic radiation, offers a solution by examining light spectra. This technique, used to evaluate fruit quality (Lin & Ying, 2009), leaf water content (Rodríguez-Pérez, 2017), and disease assessment (Vélez *et al.*, 2024; Xie *et al.*, 2017), has been applied in the agri-food sector. Hyperspectral Imaging (HSI), combining imaging systems and spectroscopic instruments to provide spatially resolved spectral data, has gained popularity in this field (Wu *et al.*, 2022).

Unlike traditional spectrometers, HSI captures spectral profiles across areas, offering comprehensive characterization of absorption and reflection bands linked to objects and their conditions (Khan *et al.*, 2022). HSI has proven feasible for disease detection, classification, grading, and chemical attribute detection in various agricultural products (B. Wang *et al.*, 2023). By capturing and analysing images across a broad spectrum of wavelengths, HSI systematically detects nuances in grains, fruits, vegetables, and meats (Zhu *et al.*, 2020). Over the past two decades, HSI has shown promise in measuring quality and protecting horticultural and agricultural products, evolving from remote sensing, computer vision, and point spectroscopy to provide superior defect and contamination detection (Sethy *et al.*, 2022). These spectral signatures are crucial for acquiring agricultural information and detecting quality attributes of products like pistachio nuts (C. Wang *et al.*, 2021). The post-harvest phase, critical for biosecurity, diagnostics, and quality assessment, significantly impacts commercial value and consumer acceptance (Palumbo *et al.*, 2022). HSI contains hundreds of spectral bands, unlike RGB images with three colour channels. Despite the complexity of analysing this data, its potential is undeniable, with new techniques continually evolving (L. Wang & Zhao, 2016). Machine Learning (ML) has enhanced HSI applications for non-destructive, real-time food quality and safety assessments, from sorting to sales (Kang *et al.*, 2022). Integrating HSI with ML has revolutionized non-destructive testing in agriculture and food quality assessment. ML has enabled precise pistachio mass estimation (Saglam & Cetin, 2022), damage detection in mango using NIR hyperspectral images (Vélez Rivera *et al.*, 2014), accurate prediction of apple quality parameters (Çetin *et al.*, 2022), and mango ripeness estimation via field hyperspectral imaging and ML (Gutiérrez *et al.*, 2019). These advances highlight the significant impact of HSI and ML in improving food quality, agri-food production, and safety inspection.

This study explores HSI technology and ML's potential to differentiate between irrigation treatments and the geographical origins of pistachios from two Spanish orchards. Using Python, Scikit libraries, and ML models like PLS-DA, SVM, and XGBoost, the study hypothesizes that irrigation methods and locations significantly affect pistachio yield and commercial quality. HSI images were used to build models for classifying pistachios based on origin and irrigation treatments, enhancing their traceability and authenticity.

2. Materials and Methods

In 2022, a study was conducted in two pistachio orchards in Valladolid, Castilla y León, Spain. These orchards, named "Moraleja de las Panaderas" (M) and "La Seca" (S), hosted pistachio plants from the *Pistacia vera* cv. Kerman variety. These 7-year-old (Moraleja) and 15-year-old (La Seca) plants were grafted onto UCB rootstock, a *P. atlantica* × *P. integerrima* hybrid, and planted in a 7 × 6 m triangular pattern to maximise sunlight and resource use. The male cultivar used was cv. Peter. Standard agricultural practices, including agrochemical applications, were followed to ensure optimal yield. Two irrigation treatments were applied: a high irrigation treatment (H) delivering 50% more water than the control (C). In "La Seca", irrigation from January to October used a computer-controlled drip system, providing 2,750 m³ ha⁻¹ for the control (SC) and 4,660 m³ ha⁻¹ for the high irrigation treatment (SH). In "Moraleja", irrigation from May to October provided 844 m³ ha⁻¹ for the control (MC) and 1,161 m³ ha⁻¹ for the high treatment (MH). This systematic variation aimed to study the effects of different irrigation levels on pistachio growth and productivity.

By October 2022, twenty trees (five per treatment and location) were harvested. Agronomic and commercial quality metrics were assessed, including yield (kg per tree) and nut size (number per ounce). In addition, percentages of open husk (Split), closed husk (Non-Split) and empty nuts (Blank) were determined from representative subsamples of twenty-five nuts per tree.

Hyperspectral imagery was captured using the SPECIM IQ camera, equipped with a VNIR CMOS sensor, offering a 400-1000 nm spectral range. The camera, controlled via Specim's software, stored data on SD cards and operated on a 5200 mAh Li-Ion battery. This setup facilitated capturing high-quality images under optimal conditions (temperatures between +5°C and +40°C, and up to 95% non-condensing humidity). The collected pistachios were obtained from three bunches per tree across different orientations and heights. Due to tree age differences, some height samples were unobtainable from the Moraleja site. After processing, peeling and drying, a total of 158 images (2,818 pistachio nuts) were captured.

Python 3.9 was used for image processing and model creation alongside libraries like *Pandas*, *Numpy*, *Scikit-learn*, and *Scikit-image*. The reflectance of the images was corrected using white and dark references, and Scikit-image's Otsu's binarisation removed the background. The spectra were scatter-corrected using standard normal variate (SNV) before analysis. Hyperspectral data analysis involved extracting the mean spectra of each pistachio and using Machine Learning (ML) models to predict various parameters. The models employed were Partial Least Squares Discriminant Analysis (PLS-DA), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost), trained on an Intel i9 processor with 16 GB of RAM and an NVIDIA GeForce RTX 3070Ti GPU. Model evaluation used metrics like F1 scores, confusion matrices, R^2 , Mean Absolute Error (MAE), and Mean Squared Error (MSE). The dataset was split into training (70%) and validation (30%) sets. Scikit-learn's RandomizedsearchCV optimized model parameters using 10-fold cross-validation to achieve high accuracy and low Root Mean Squared Error (RMSE).

3. Results

Origin

The study found notable spectral differences between the two locations, particularly in the Near-Infrared (NIR) region around 970 nm, associated with water content (Büning-Pfaue, 2003). More pronounced differences were observed at wavelengths 675 nm (chlorophyll) and 450 nm (carotenoids) (Wellburn, 1994), especially in the "La Seca" location. The predictive models reflected these spectral variations, with all achieving F1 scores above 94%. The PLS and SVM models performed similarly overall (both with an F1 score of 0.99). However, SVM excelled in predicting "La Seca" pistachios, while PLS was better for "Moraleja" pistachios (Table 1).

Irrigation Treatment

The study also identified spectral differences based on irrigation treatments, especially in the NIR region at 970 nm, linked to water content, and at 480 nm, related to carotenoids. These differences were more noticeable in the "La Seca" location. The predictions reflected these spectral variations with high F1 scores. XGBoost had the lowest performance (F1 score of 0.72), while PLS achieved the highest F1 score of 0.92 (Table 1).

Origin and Irrigation Treatment

Combining origin and irrigation treatment for predictions provided better results than mixing different locations, which could lead to poorer outcomes. Table 1 shows significant differences across the entire wavelength range for the four origin and irrigation treatment combinations. This approach improved classification accuracy, obtaining higher F1 scores. SVM produced the highest F1 score of 0.97, while XGBoost had the lowest at 0.87 (Table 1).

Table 1. Prediction results of the pistachio origin and irrigation treatment models and their interaction classification.

Origin																	
PLS					XGBoost					SVM							
F1 = 0.99					F1 = 0.94					F1 = 0.99							
Real	Class	Predicted				Real	Class	Predicted				Real	Class	Predicted			
		La Seca		Moraleja				La Seca		Moraleja				La Seca	Moraleja		
Real	La Seca	412		3		Real	La Seca	391		24		Real	La Seca	415		0	
	Moraleja	5		428			Moraleja	22		409			Moraleja	7		424	
Irrigation treatment																	
PLS					XGBoost					SVM							
F1 = 0.92					F1 = 0.72					F1 = 0.77							
Real	Class	Predicted				Real	Class	Predicted				Real	Class	Predicted			
		High	Control	High	Control			High	Control	High	Control						
Real	High	259		59		Real	High	170		148		Real	High	254		64	
	Control	9		519			Control	93		435			Control	128		400	
Origin and irrigation treatment																	
PLS					XGBoost					SVM							
F1 = 0.95					F1 = 0.87					F1 = 0.97							
Real	Class	Predicted				Real	Class	Predicted				Real	Class	Predicted			
		MH	SH	MC	SC			MH	SH	MC	SC			MH	SH	MC	SC
Real	MH	121	0	0	0	Real	MH	90	17	7	7	Real	MH	120	0	1	0
	SH	0	310	0	0		SH	1	296	9	4		SH	0	308	2	0
	MC	0	2	166	29		MC	1	9	161	26		MC	0	0	189	8
	SC	0	0	10	208		SC	2	5	23	188		SC	0	0	15	203

MH, Moraleja High; **SH**, La Seca High; **MC**, Moraleja High; **SC**, La Seca control

Yield and commercial quality traits predictions.

In pistachio production, yield, split, non-split, blank, and calibre are critical quality factors. PLSR, XGBoost, and SVM regression models were tested to predict these parameters. Accurate yield prediction, crucial for economic planning, showed high R^2 scores of 0.89 for PLS, 0.88 for SVM, and 0.38 for XGBoost. For split pistachios, SVM performed best with an R^2 of 0.58, while PLS and XGBoost had R^2 values of 0.56 and 0.37, respectively. Non-split predictions were lower, with PLS achieving the highest R^2 of 0.37. PLS excelled with an R^2 of 0.71 for blanks, compared to XGBoost's 0.48. Lastly, SVM predicted calibre most accurately with an R^2 of 0.57 (Table 2).

Table 2. Prediction results of the regression models for pistachio yield, split, non-split, blank and calibre.

<i>Model</i>	Yield	R²	MAE	MSE	Calibre	R²	MAE	MSE				
PLS		0.89	0.72	0.81		0.54	0.71	0.75				
XGBOOST		0.38	1.84	4.57		0.45	0.90	1.21				
SVM		0.88	0.72	0.89		0.57	0.63	0.70				
<i>Model</i>	Split	R²	MAE	MSE	Non-Split	R²	MAE	MSE	Blank	R²	MAE	MSE
PLS		0.56	6.74	74.15		0.37	5.30	55.53		0.71	5.11	49.56
XGBOOST		0.37	8.96	104.33		0.23	6.13	68.10		0.48	6.92	90.69
SVM		0.58	6.28	70.98		0.27	4.97	64.26		0.67	4.94	57.23

MAE, Mean Absolute Error; MSE, Mean Squared Error.

4. Discussion

This study investigates the use of non-invasive techniques, specifically HSI in the 400-1000 nm range, to predict the geographic origin of pistachios and evaluate the impact of different irrigation practices. The research also aims to predict key quality and yield metrics of pistachios. Models using Partial Least Squares (PLS), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost), performed excellently distinguishing pistachios from the La Seca and Moraleja locations, achieving F1 scores above 94%. PLS and SVM models achieved an F1 score of 0.99 for water content and colour pigments, demonstrating precise differentiation based on these spectral characteristics. In predicting geographic origin, the models were inspired by previous research using deep learning techniques, which have also achieved high accuracy in classifying pistachio types (Singh *et al.*, 2022). For instance, the EfficientNet-B3 model successfully identified Iranian pistachio cultivars with an average precision, recall, and F1 score of around 96.7% (Soleimnipour *et al.*, 2022). This demonstrates the strong capability of machine learning models to ensure the traceability and authenticity of agricultural products.

The study also explored the effects of irrigation treatment on pistachio spectral signatures, revealing significant differences, particularly at the 970 nm peak in the Near-Infrared (NIR) region, which is linked to water content (Büning-Pfaue, 2003). The best F1 score for distinguishing between different irrigation treatments was 0.92 with the PLS model. Differences at the 675 nm and 450 nm bands associated with chlorophyll and carotenoids were also noted (Walsh *et al.*, 2020; Wellburn, 1994). Combining geographic origin and irrigation treatment variables improved classification performance, achieving higher F1 scores. The SVM model reached an F1 score of 0.97, demonstrating its effectiveness in this combined approach. Similar results were found in predicting the origin of *Zanthoxylum bungeanum* Maxim with a 97% accuracy (Ke *et al.*, 2020) or in *Jatropha curcas* L. seeds (Gao *et al.*, 2013) with a 94% correct classification. This highlights the subtle impact of both geographical origin and irrigation practices on the spectral signatures of pistachios.

Regression models developed in the study showed high R^2 scores for predicting yield and commercial quality factors. The yield prediction achieved an R^2 of 0.88 with the SVM model, while the prediction of blank quality reached an R^2 of 0.71 with the PLS model. As previous research (Caporaso *et al.*, 2018; Elmasry *et al.*, 2012; Torres-Rodríguez *et al.*, 2022; B. Wang *et al.*, 2023), these models effectively forecast essential agricultural metrics, offering valuable tools for optimizing pistachio production. However, modelling the split and non-split conditions of pistachios proved challenging, with lower R^2 scores highlighting the difficulties in using spectral data for these specific quality attributes.

The study underscores the potential of combining HSI with machine learning in agricultural science, particularly for identifying the unique characteristics of pistachios based on their geographic origin, irrigation methods, and quality markers. Despite challenges in classifying certain features accurately, the findings lay a foundation for future research into the spectral analysis of various pistachio varieties. Integrating these insights with precision agriculture technologies could significantly improve agricultural productivity and management. Advancements in HSI technology, such as its application through drone technology, offer promising avenues for optimizing water usage, enhancing crop quality, and promoting sustainable management practices in pistachio orchards. These developments could lead to more efficient and sustainable

pistachio production, benefiting increased efficiency, improved productivity, and reduced environmental impact.

5. Conclusions

This study demonstrates the effectiveness of Hyperspectral Imaging (HSI) and Machine Learning (ML) in accurately identifying the geographic origin of pistachios and assessing the impact of irrigation practices on their spectral properties. By using advanced models like Partial Least Squares (PLS), Support Vector Machine (SVM), and Extreme Gradient Boosting (XGBoost), high F1 scores above 94% were achieved, particularly in distinguishing pistachios from La Seca and Moraleja. PLS and SVM models excelled with F1 scores of 0.99 in evaluating water content and colour pigments, underscoring HSI's potential in precision agriculture. The study also highlighted distinct spectral signatures from different irrigation treatments, especially the NIR region's notable peak at 970 nm. The PLS model stood out with an F1 score of 0.92, illustrating HSI's role in improving sustainable agricultural resource management. Regression models showed promising results, with an R^2 score of 0.88 for yield predictions using SVM and 0.71 for blank predictions with PLS. Despite challenges in predicting shell split and calibre, the study confirms HSI as a precise tool for identifying pistachio characteristics and forecasting commercial quality and yield, marking a significant advancement in optimizing pistachio production.

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