

Multispectral Analysis of Olive Fruits from UAV-based imagery

Ana Šarić Gudelj, Toma Sikora, Vladan Papić, Josip Musić

0009-0004-0516-0238, 0009-0002-9184-3777, 0000-0002-1873-6353, 0000-0002-9185-5762

University of Split

Faculty of Electrical Engineering, Mechanical Engineering and Naval Architecture

R. Boškovića 32, Split, Croatia

Email: anasarić@fesb.hr

Abstract—In this work, an automated approach for analysing olive fruit ripening using multispectral UAV imagery at the level of individual fruits is presented. RGB and multispectral images were collected from July to October using a DJI Mavic 3 Multispectral unmanned aerial vehicle. Fruits were first detected in RGB images using a YOLOv11 model finetuned for olive fruit detection, after which the corresponding bounding boxes were geometrically mapped to the G, R, RE, and NIR multispectral channels using calibration and homographic parameters extracted from the image metadata. After patch extraction, a filtering procedure was applied to retain representative and uniformly illuminated samples suitable for spectral analysis. NDVI (The Normalized Difference Vegetation Index) and NDRE (Normalized Difference Red Edge Index) vegetation indices, as well as reflectance values in the NIR (Near Infrared) and RE (Red Edge) channels, were analysed over time and separately for the cultivars *Istarska bjelica* (Croatian olive cultivar) and *Leccino*. The results showed statistically significant temporal differences for all analysed indicators, with NDRE exhibiting greater sensitivity to ripening-related changes than NDVI. Differences in the dynamics of change were also observed between the studied cultivars, indicating cultivar-specific ripening patterns. The relationship between NDRE values and the laboratory-determined oil content suggests that NDRE reflects physiological changes associated with the ripening process rather than oil accumulation directly. The obtained results confirm the potential of combining deep learning and multispectral UAV imaging for non-destructive monitoring of olive fruit ripening in precision agriculture applications.

I. INTRODUCTION

IN MODERN agricultural production, especially in perennial plantations such as orchards, the increasing need for precise and non-invasive crop monitoring methods has led to the rapid development of remote sensing techniques. Olive (*Olea europaea* L.) is one of the most important fruit crops in the Mediterranean region, and the quality of both the fruit and the oil largely depends on the degree of ripeness at the time of harvest. Multispectral imagery, which records plant reflectance in different parts of the electromagnetic spectrum, including the near-infrared region, enables the calculation of vegetation indices such as NDVI and NDRE, which are directly related to plant physiological status, chlorophyll content, moisture, and stress. Olive fruit ripening is a complex physiological and biochemical process involving changes in pigments, water content, texture, and oil accumulation, with the dynamics of these changes differing among cultivars [1], [2], [3], [4].

Conventional methods for monitoring fruit ripening and quality are based on visual assessment and laboratory analyses, but such approaches are often slow, invasive, and difficult to apply to a large number of samples [3]. Therefore, increasing attention has recently been given to non-invasive methods based on remote sensing and spectral analysis.

Unmanned aerial vehicles (UAVs), combined with multispectral sensors, enable rapid and accurate high-resolution data collection and have proven useful in precision agriculture, including the assessment of vigor, water status, and olive phenotyping [5], [6], [7], [8]. Vegetation indices such as NDVI and NDRE, calculated from the visible, red-edge, and near-infrared parts of the spectrum, are of particular interest because they reflect changes related to chlorophyll content and the physiological state of the plant [6], [7]. NDRE is often considered more sensitive than NDVI to subtle changes in chlorophyll content, especially in later stages of development and ripening [4], [6].

The application of this technology in olive groves brings additional specificities and challenges. Olive trees are perennial evergreen crops with pronounced canopy heterogeneity, and their fruits ripen gradually, often with green and black fruits present on the same tree at the same time. As a result, most research in olive production to date has focused on the canopy or tree level, while analyses at the individual fruit level remain much rarer [6], [7]. Such an approach makes it difficult to isolate spectral changes directly related to fruit ripening, because the recorded signal often includes leaves, branches, shadows, and background. On the other hand, studies based on optical and spectroscopic methods have shown that changes in fruit pigments and chemical composition can be monitored non-destructively, indicating the potential of spectral methods for assessing olive quality and ripening stage [2], [3], [9]. Therefore, the reliable application of multispectral imagery in olive groves requires adapted algorithms, high spatial resolution, and calibration with field data.

These challenges can be partially overcome by integrating multispectral sensors with UAV platforms. Drones enable the acquisition of imagery with high spatial and temporal resolution, allow flights to be planned over specific parts of the orchard, and provide flexibility in flight altitude and repeated measurements during key phenological stages. This

makes them an ideal platform for the operational application of multispectral techniques in olive groves.

However, several limitations remain, particularly the need for complex data processing and the influence of illumination geometry. One of the main challenges is the limitation of internal sensor calibration under dynamic lighting conditions. Most multispectral sensors mounted on drones rely on predefined calibration procedures that assume homogeneous scene illumination, typically using an integrating sphere or a reference reflectance panel recorded before the flight [10]. In orchards and olive groves, however, some fruits and canopy are simultaneously exposed to direct sunlight, while others are shaded by leaves or neighboring trees. This sharp contrast in illumination levels causes significant differences in measured spectral responses even for objects with identical physical properties.

Because the sensor's internal calibration cannot adjust the sensitivity of each individual pixel in real time according to local illumination conditions, systematic errors may occur in reflectance estimation. As a result, fruits in shaded areas may show artificially low vegetation index values and be misinterpreted as unripe or stressed, while overly bright sunlit areas may produce artificially high values. This may ultimately lead to incorrect estimates of ripeness and the optimal harvest time. An additional challenge is that the ratio between illuminated and shaded parts of the orchard changes throughout the day and depends on flight geometry and solar angle, making simple post hoc correction with a global factor insufficient. The use of additional ambient light sensors may partly address this issue by recording changes in total radiation during the flight, but such sensors still do not solve the problem of local shadows within the same image. Therefore, reliable application in olive groves requires the development and implementation of algorithms or procedures capable of reducing these effects.

Overall, the combination of UAVs and multispectral cameras opens the way toward automated, non-invasive, and economically feasible assessment of plant condition and fruit maturity, with the aim of optimizing harvest timing and improving olive oil quality.

This paper proposes a comprehensive procedure for collecting and processing multispectral olive images, which includes fruit detection in RGB images using deep neural networks and subsequent processing of the collected patches with the aim of selecting a set of fruit images that are uniformly illuminated and correspond to the internal calibration values on the drone.

To evaluate the procedure, measurements were conducted and the results compared on two olive varieties that were recorded at several times during one season.

II. MATERIALS AND METHODS

Multispectral photographs of olive trees were collected using a DJI Mavic 3M drone from July to October in an olive grove located in Tinj, Zadar County, Croatia. The olive grove comprises approximately 5,300 olive trees of different cultivars, with nine experimental trees from two cultivars selected for detailed monitoring. Imaging was carried out using

a DJI Mavic 3 Multispectral unmanned aerial vehicle equipped with one RGB sensor and four narrow-band multispectral sensors covering the green, red, red-edge, and near-infrared regions of the spectrum. Data were collected by acquiring individual photographs from a distance of approximately 2 m from the tree canopy. The camera was oriented approximately horizontally towards the tree canopy, providing a side-view perspective of the fruits similar to that of a human observer. Image acquisition was performed during daylight hours under stable weather conditions. The multispectral imagery was radiometrically calibrated using the integrated sunlight sensor of the DJI Mavic 3 Multispectral system, which continuously measures incident solar irradiance during image acquisition. No external reflectance calibration panel was used. To minimise the influence of changing illumination conditions, an additional filtering procedure was applied during image processing, retaining only uniformly illuminated fruits and excluding shaded or partially shaded samples. Since the analysis was performed at the individual fruit level using image-based patch extraction rather than georeferenced canopy mapping, RTK positioning was not required for this study.

A. Fruit detection in RGB images

Patches of olive fruits were extracted from the collected RGB images using a YOLOv11 model finetuned for olive fruit detection, achieving a precision and recall of approximately 0.85. The detection results consisted of bounding boxes defining the positions of individual fruits within the RGB photographs. These bounding boxes were then used as the basis for extracting the corresponding multispectral patches.

B. Geometric mapping to multispectral channels

A Python script was developed for the automatic mapping of annotated bounding boxes from RGB images to the G, R, RE, and NIR multispectral channels. The input consisted of a CSV file containing the RGB image filename and the bounding box coordinates.

Based on the RGB image filename, the names of the corresponding multispectral files were generated automatically. The geometric transformation was performed using calibration and homographic parameters extracted from the image metadata with the ExifTool utility. First, the RGB coordinates were corrected for lens distortion, and then homographic transformations were applied to map them into the coordinate systems of the corresponding multispectral images. After removing the RGB camera distortion, the points were transformed into a common coordinate system using the matrix H_{dewarp} , and then mapped into the coordinate system of the multispectral sensor using the matrix H_{calib} . The final transformation is given by the following expression:

$$X_{\text{MS}} = X_{\text{calib}} \cdot H_{\text{dewarp}} \cdot X_{\text{RGB}}^{\text{undist}}$$

where X_{MS} denotes the coordinates in the multispectral image, while $X_{\text{RGB}}^{\text{undist}}$ represents the coordinates after RGB image undistortion. Optionally, additional local alignment can

be applied using template-matching methods in order to determine the object position more precisely. The output of the procedure is a CSV file containing the bounding box coordinates for each multispectral channel separately.

C. Patches filtering and spectral feature extraction

After the geometric alignment of the RGB and multispectral images and the mapping of the bounding boxes to the corresponding multispectral channels, a patch filtering procedure was performed to extract representative, uniformly illuminated samples suitable for further vegetation index analysis.

A total of 3,573 olive fruit patches were initially extracted from the detected fruits. For each record in the input CSV file generated by the previous script, multispectral images corresponding to the G, R, RE, and NIR channels were retrieved, and a patch defined by the previously obtained bounding box coordinates was extracted from each image. To enable consistent pixel-by-pixel analysis, all patches were aligned to the smallest common dimension.

To reduce the influence of edge pixels and the potential mixing of fruit and background pixels, an elliptical mask inscribed within the rectangular crop was applied to each patch. All subsequent calculations were performed exclusively on pixels located within the defined mask.

The multispectral imagery was radiometrically calibrated using the DJI Mavic 3 Multispectral system, which incorporates a sunlight sensor that records incident solar irradiance during image acquisition. Since vegetation indices are sensitive to illumination conditions, additional filtering was performed to retain only fruits located under direct sunlight. Shaded or partially shaded fruits may exhibit reduced reflectance values that are unrelated to physiological changes in the fruit itself. Therefore, a minimum mean reflectance threshold was applied to the Green (G) channel, and patches with insufficient illumination were excluded from further analysis.

Based on reflectance values, the NDVI and NDRE vegetation indices were calculated:

$$NDVI = \frac{NIR - R}{NIR + R + \epsilon}$$

$$NDRE = \frac{NIR - RE}{NIR + RE + \epsilon}$$

where ϵ is a small constant is introduced for numerical stability. For each patch, a set of statistical descriptors was calculated to quantify signal quality and homogeneity. These included the mean NDVI value, standard deviation of NDVI values, mean Green channel reflectance, and additional distribution-based metrics. Patches were then classified into three categories according to predefined quality criteria:

- **accepted** - meets all quality criteria
- **review** - borderline cases requiring additional verification
- **rejected** - patches that do not meet the minimum quality requirements

Representative patches were defined as patches exhibiting sufficient illumination, low spectral heterogeneity, and stable vegetation index statistics, making them suitable for subsequent quantitative analysis.

Application of the illumination criterion resulted in the exclusion of 2,204 patches that were either fully or partially shaded. The remaining patches were subjected to further quality assessment, yielding 396 accepted patches and 973 review patches. Subsequently, all review patches were visually inspected, and 28 additional patches were transferred to the accepted category. Consequently, the final dataset used for statistical analysis consisted of 424 representative patches, while all remaining samples were classified as rejected. The whole processing pipeline is shown in Fig. 1.

This multi-criteria approach minimizes the influence of shadows, background contamination, and spectral inhomogeneities, thereby improving the reliability of the extracted vegetation indices and the subsequent ripening analysis..

D. Statistical Analysis

For each accepted patch, mean values of the *NDVI*, *NDRE*, *NIR*, and *RE* indicators were calculated. The analysis was performed by month and by individual sampling dates, separately for the cultivars *Istarska bjelica* and *Lecchino*. The normality of the distributions was tested using the Shapiro–Wilk test, while differences between months were analysed using the Kruskal–Wallis test. In addition, the relationship between the spectral indicators and the laboratory-determined free oil content was examined.

III. RESULTS

The mean monthly values of the analysed indicators are shown in Table I. The results indicate that the values of NDVI, NDRE, NIR, and RE changed during the period from July to October, suggesting the presence of temporal dynamics related to the fruit ripening process.

NDVI showed a decrease from 0.677 in July to 0.629 in October, while *NDRE* decreased from 0.220 to 0.156. *NIR* and *RE* values exhibited more pronounced fluctuations, with an increase in September followed by a decline in October. The standard deviation of *NDVI* values (St.dev.) remained relatively stable throughout all months, ranging from 0.068 to 0.075, which indicates satisfactory homogeneity of the analysed patches.

TABLE I
MEAN VALUES OF VEGETATION INDICES BY MONTH

Month	NDVI	NDRE	NIR	RE	St.dev.
July	0.677	0.220	0.0348	0.0236	0.073
August	0.638	0.167	0.0323	0.0244	0.068
September	0.639	0.179	0.0428	0.0314	0.075
October	0.629	0.156	0.0291	0.0222	0.075

The behaviour of the vegetation indices was then examined separately for the two cultivars, *Istarska bjelica* and *Lecchino*, at each sampling date. The results are presented in Table II.

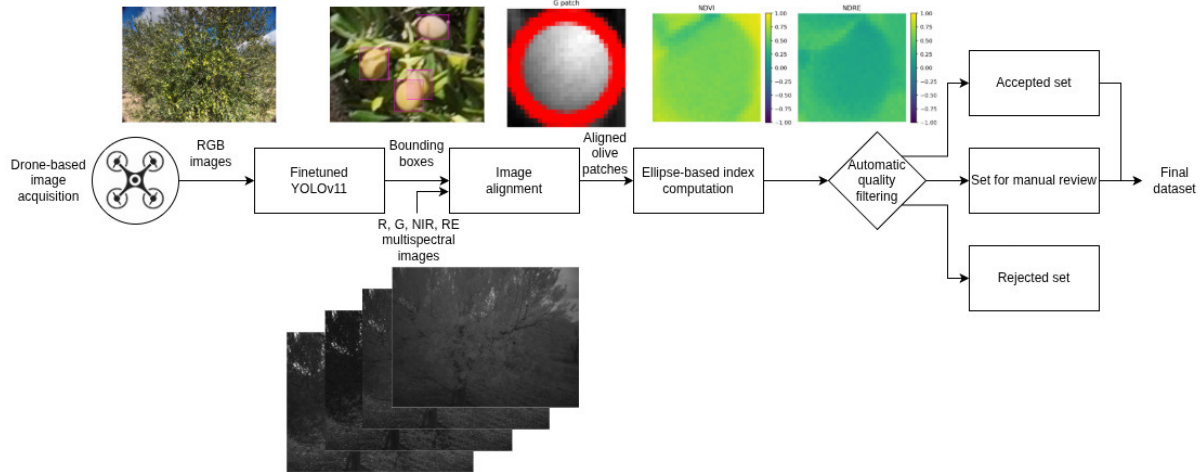


Fig. 1. Processing pipeline

TABLE II
MEAN VALUES OF VEGETATION INDICES BY HARVEST DATE FOR EACH CULTIVAR

Date	<i>Istarska bjelica</i>					<i>Leccino</i>				
	NDVI		NDRE		Oil	NDVI		NDRE		Oil
	Mean	St. dev.	Mean	St. dev.		Mean	St. dev.	Mean	St. dev.	
22 July 2025	0.6728	0.07	0.2193	0.0356	3.23%	0.6712	0.07	0.2146	0.0223	2.37%
19 August 2025	0.6387	0.06	0.1980	0.0249	8.93%	0.6599	0.07	0.1515	0.0183	5.90%
2 September 2025	0.6655	0.07	0.2212	0.0626	6.30%	0.6653	0.07	0.1800	0.0542	4.43%
15 September 2025	0.6771	0.07	0.2041	0.0326	10.17%	0.6111	0.08	0.2120	0.0360	6.93%
25 September 2025	0.6758	0.07	0.2391	0.0216	14.30%	0.6894	0.07	0.1551	0.0339	7.59%
7 October 2025	0.6484	0.07	0.1709	0.0272	13.22%	0.6987	0.06	0.2234	0.0313	6.58%
14 October 2025	0.5542	0.08	0.1172	0.0297	18.60%	0.6506	0.09	0.1223	0.0309	15.76%

Analysis of the mean values of vegetation indices by harvest date and cultivar provides a more detailed insight into the dynamics of fruit ripening. The results show that both cultivars, *Istarska bjelica* and *Leccino*, follow the general trend of changes in vegetation indices during the growing season, but with clearly pronounced differences in the intensity and timing of these changes.

In the *Istarska bjelica* cultivar, more pronounced oscillations in NDVI and NDRE values were observed between individual dates within the same month, indicating faster and more dynamic physiological changes during ripening. In particular, after the initial values recorded in July, a decline was observed in the later sampling dates in August, followed by a gradual increase in values toward September and October. This pattern may be associated with changes in chlorophyll content and other biochemical processes characteristic of olive ripening, since NDVI and especially NDRE are sensitive to variations in chlorophyll concentration [4]. Variability between dates may also reflect different cultivar sensitivities to environmental conditions such as temperature and water status, as water stress and environmental conditions have been shown to significantly affect physiological processes [11]. On the other hand, the *Leccino* cultivar showed a more stable and gradual trend throughout the observed dates. NDVI values remained

relatively higher in the later stages of ripening compared with *Istarska bjelica*, while the NIR and RE channel values were more pronounced at certain dates in September. This behaviour suggests a slower and more uniform ripening process than in *Istarska bjelica*, visible in Fig. 2, which is consistent with official data published on the Agrokub website, Croatia [12].

The standard deviation of NDVI values (St.dev.) remained relatively stable throughout all months for both cultivars (≈ 0.06 - 0.08), indicating satisfactory homogeneity of the analysed patches and the reliability of the obtained mean values. In general, NDRE showed more pronounced changes than NDVI, particularly during the transition from August to September, confirming its greater sensitivity to changes in chlorophyll content and the physiological state of the fruit. This is consistent with studies showing that chlorophyll-sensitive vegetation indices successfully track biochemical changes during olive ripening [13].

The normality of the distribution of the analysed variables was tested using the Shapiro-Wilk test. The results showed that NDVI ($p = 0.0599$) and NDRE ($p = 0.3265$) did not deviate significantly from a normal distribution, as shown in Fig 3.

The Kruskal-Wallis test was used to examine differences between months. The results showed statistically significant differences between months for all analysed indices (Table 3).



Fig. 2. Illustration of differences in fruit ripening dynamics between two cultivars on data collection dates

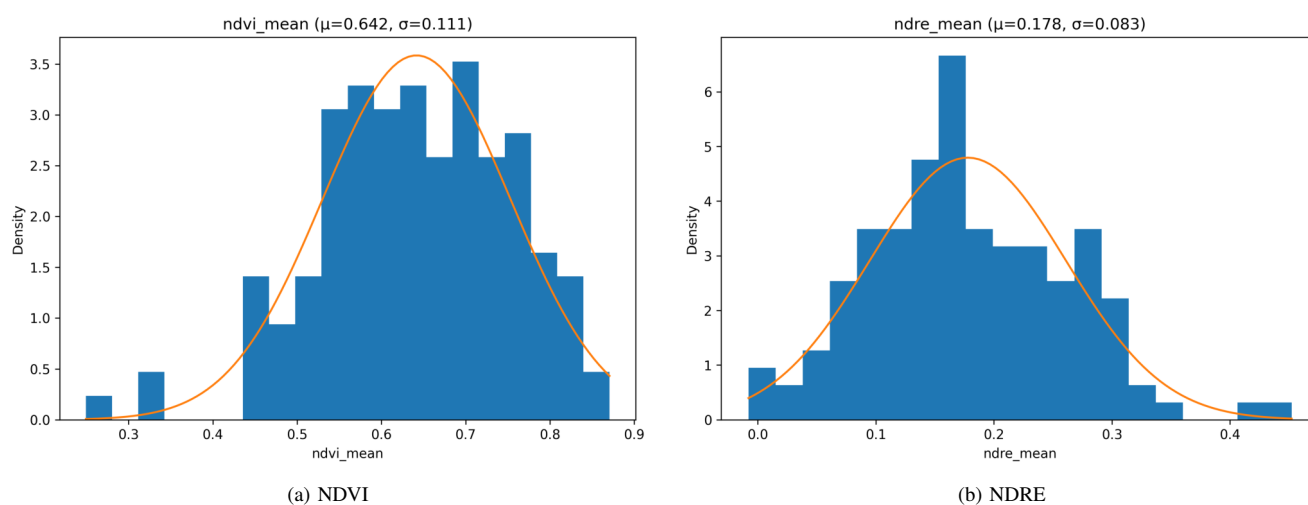


Fig. 3. Shapiro-Wilk Test

TABLE III
KRUSKAL-WALLIS TEST OF VEGETATION INDICES BY MONTH

Index	Month	<i>H</i>	<i>p</i> -value	Significance
NDVI	7–10	48.76	< 0.001	Yes
NDRE	7–10	62.62	< 0.001	Yes
NIR	7–10	249.38	< 0.001	Yes
RE	7–10	170.18	< 0.001	Yes

The obtained results confirm that all analysed indices changed over time, that is, throughout the fruit ripening process. Differences in the *H*-statistic values suggest that indices based on the infrared and red-edge regions of the spectrum (NIR and RE) differentiate monthly changes better than NDVI, which is consistent with their greater sensitivity to changes in the physiological state of the plant. To examine the relationship between the spectral indicators and the chemical composition of the fruit, the vegetation indices derived from the multispectral images were additionally compared with the laboratory-determined free oil content. The analysis was conducted separately for the cultivars *Leccino* and *Istarska*

bjelica at each sampling date. The results showed that, for both cultivars, there was a relationship between changes in the NDRE index and free oil content, with an inverse relationship observed in most cases. For the *Istarska bjelica* cultivar, this trend was particularly pronounced: higher NDRE values in July (0.2193) corresponded to a low oil content (3.23%), whereas in the later stages of ripening, especially in October, a marked decrease in NDRE (0.1172) was accompanied by a simultaneous increase in oil content (18.60%). This pattern indicates a link between decreasing chlorophyll content and increasing oil accumulation during fruit ripening. A similar trend was also observed for the *Leccino* cultivar, although it was less pronounced and showed greater variability between individual dates. For example, the lowest NDRE value (0.1223) was recorded in October, when the highest oil content (15.76%) was also observed. However, during September, fluctuations in NDRE did not follow linear changes in oil content, which may indicate a slower and more complex ripening process in this cultivar. Analysis by individual dates suggests that the NDRE index does not directly track oil content, but rather reflects changes in the physiological state of the fruit associated with

the ripening process, while oil accumulation is a consequence of those changes.

IV. DISCUSSION

The results of this study confirm that multispectral analysis at the level of individual fruits can provide useful information about the dynamics of olive ripening. The main contribution of this work lies in the development of an automated methodological approach that combines fruit detection based on deep learning with geometric mapping to multispectral channels, followed by the analysis of the spectral properties of the extracted patches. Unlike most previous studies, which have focused on canopy-level or whole-tree analysis, this study places the emphasis on the level of individual fruits. This reduces the influence of leaves, branches, shadows, and background, and enables more precise tracking of changes related to fruit ripening. The obtained results show that all analysed indicators changed over time, with NDRE standing out as a more sensitive indicator than NDVI. This finding is consistent with the literature, which suggests that red-edge indicators are particularly suitable for monitoring changes in chlorophyll content and the physiological condition of plant tissues [4], [12]. In this study, this was additionally confirmed at the level of olive fruit patches. In addition, differences were observed between the cultivars *Istarska bjelica* and *Leccino*. *Istarska bjelica* showed more pronounced changes between individual sampling dates, whereas *Leccino* exhibited a more uniform pattern of change. These results indicate cultivar-specific ripening dynamics, which should be taken into account when developing models for fruit maturity assessment.

A particularly important finding is that the date-based analysis revealed a relationship between NDRE values and the laboratory-determined oil content. This relationship was neither strictly linear nor direct, but it suggests that NDRE may serve as an indicator of physiological changes accompanying fruit ripening and preceding an increase in oil content.

The study also has certain limitations. The number of experimental trees was relatively small, and the analysis was conducted on a limited number of dates and cultivars. Additionally, although three additional sampling dates were available, they were not included in the present analysis. The relationship between spectral indicators and the chemical composition of the fruit is evidently complex and probably nonlinear, meaning that it cannot be fully described by a simple comparison of mean values alone. Future research should therefore include a larger number of samples, additional cultivars, and more advanced machine learning models.

V. CONCLUSION

In this work, an automated multispectral approach for the analysis of olive fruits at the level of individual patches is presented. The approach combines YOLOv11-based fruit detection, geometric mapping of RGB annotations to multispectral channels, and the filtering of representative samples for spectral analysis.

The results showed that the values of NDVI, NDRE, NIR, and RE changed significantly during the ripening period, with NDRE exhibiting greater sensitivity to ripening-related changes than NDVI. Differences were also observed between the cultivars *Istarska bjelica* and *Leccino*, confirming the importance of cultivar-specific analysis.

The relationship between NDRE values and free oil content suggests that spectral indicators can serve as indirect indicators of physiological changes associated with fruit ripening. The obtained results confirm the potential of combining UAV multispectral imaging and deep learning for the non-destructive monitoring of olive fruit ripening in precision agriculture applications.

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