

Prediction Method for Pomegranate Chlorophyll Content Based on Multi-feature Fusion of Unmanned Aerial Vehicle

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Abstract. The aim of this study was to obtain RGB and multispectral images of fruit tree canopy during the flowering period of pomegranate by multispectral unmanned aerial vehicle (UAV) to quickly and accurately predict the chlorophyll content in order to improve the monitoring efficiency of the orchard. A handheld chlorophyll meter was used to obtain the actual chlorophyll values, and image processing techniques were combined to extract parameters such as color features and texture features of the RGB images as well as vegetation index of the multispectral images. A chlorophyll content prediction method based on the support vector regression model and the convolutional neural network model (CNN-Attention) combined with the attention mechanism was established. The results showed that (1) the accuracy of the prediction model was improved by the fusion of RGB image features and multispectral image vegetation index. (2) After model comparison, the CNN-Attention model built under the fused features was the best in chlorophyll content prediction with R^2 , RE, and RMSE of 0.9699, 0.0052, and 0.6013, respectively. This study provides a more accurate method for fruit tree chlorophyll content prediction using UAVs, which provides a practical reference for orchard management.

Keywords: Chlorophyll content; UAV; Multi-spectral imagery; Feature fusion; Prediction model

1. Introduction

Pomegranate cultivation, as a pillar industry of agricultural development in Lintong, Xi'an City, Shaanxi Province, has a planting area of 120,000 mu and an annual output of about 100,000 tons of pomegranates. However, realizing high yield and quality of pomegranate fruits requires an in-depth understanding of the growth and health status of fruit trees, of which chlorophyll content is a key parameter. Chlorophyll content is related to the photosynthetic capacity, nutrient utilization, energy accumulation and stress tolerance of fruit trees. Therefore, rapid and accurate prediction of chlorophyll content is of great significance for efficient management of large-scale orchards^[1].

Traditional chlorophyll detection in fruit trees uses chemical analysis, which is cumbersome and has poor real-time performance. Although the SPAD chlorophyll meter is portable, its measurement range is limited and it is not suitable for rapid assessment of large orchards. In contrast, drone technology has been widely used in modern agriculture due to its flexibility and wide coverage. Multi-spectral remote sensing technology can quickly obtain comprehensive image information and more accurately monitor plant growth conditions by analyzing multi-band data^[2]. In 1977, Krockover et al.^[3] found that there is a strong correlation between plant chlorophyll content and its corresponding spectral curve. Horle et al.^[4] studied and proposed the role of the spectral "red edge" position in predicting vegetation chlorophyll concentration. Yue et al.^[5] constructed a ramie chlorophyll content inversion model based on remote sensing images using machine learning methods. The optimal model determination coefficient R^2 was 0.892. Narmilan et al.^[6] used drone multi-spectral images and ground-measured chlorophyll values as indicators to predict sugarcane chlorophyll content using machine learning algorithms.

UAV RGB images provide a new method for chlorophyll content prediction by analyzing the red, green, and blue band features as well as texture feature information in the images. He et al.^[7] acquired maize RGB images by UAV and established various regression models, and the results showed that the random forest regression model excluding soil background had the highest accuracy ($R^2 = 0.8247$, RMSE = 4.3); Qiao et al.^[8] constructed a BP neural network model based on color and texture features for estimating maize chlorophyll content. These studies show that the

combination of UAV data, computer vision and deep learning techniques can effectively monitor large-area orchards, which is of significant significance in promoting orchard modernization [9].

At present, low-cost and easy-to-operate UAVs equipped with multi-spectral cameras effectively meet the needs of modern agriculture. And yet, existing studies mostly rely on single features and traditional machine learning models. Therefore, in this study, a multi-spectral UAV was used to collect RGB and multi-spectral images in a natural environment, extract color and texture features and vegetation indices, respectively, and combine with ground chlorophyll data to predict the chlorophyll content of pomegranate trees using a deep learning method under multi-feature fusion. The best model was evaluated in terms of the coefficient of determination (R^2), root mean square error (RMSE), and relative error (RE), aiming to provide a fast and accurate new method for predicting the chlorophyll content of fruit trees.

2. Materials and Methods

2.1 Data acquisition

The experiment was conducted in May 2024 at the Pomegranate Red Ecological Science and Technology Park (34°27' N, 109°20' E) in Lintong District, Xi'an. The climate of Lintong District is suitable for pomegranate growth, possessing a continental warm-temperate monsoon climate characterized by moderate annual temperature differences and abundant rainfall.

During the flowering period of pomegranate (May 9), we used a DJI MAVIC 3M UAV (Shenzhen DJI Technology Innovation Co, Ltd.) flying at an altitude of 50 m during the midday hours (12:00~15:00) to acquire the RGB images of the orchard canopy and the multi-spectral images containing green, red, red-edge, and near-infrared bands. Subsequently, the pomegranate canopy image datasets was obtained by stitching the remote sensing images into TIF format by Pix4D software (Pix4D, Lausanne, Switzerland) and correcting and cutting the multi-spectral images with the help of ENVI software (Exelis Visual Information Solutions, USA).

To ensure the timeliness of the data, we synchronized the acquisition of canopy images with ground chlorophyll data. Using a handheld chlorophyll detector, 20 leaves were evenly collected from different parts of each pomegranate tree. Each leaf was measured three times and the average value was taken. The average chlorophyll value of the 20 leaves was used as the SPAD value of the tree, and the chlorophyll content data of the pomegranate canopy of the entire orchard was obtained. This synchronization method ensures the unity of airborne and ground data and improves the reliability of chlorophyll content prediction.

2.2 Data processing

The pomegranate canopy layer is difficult to completely obscure the soil background, and the color value parameters and reflectance of the soil image elements are different relative to the pomegranate canopy layer, so the soil background needs to be culled to retain the canopy part.

In RGB images, the Mean-Shift method is used for image segmentation to remove the background. The method first finds the peaks of color distribution in the color space and then clusters the pixels of similar colors by shifting the mean. Based on the clustering results, specific color clusters can be selectively removed or retained to achieve the effect of background removal [10]. The basic formula for mean shift is as follows:

$$M_h = \frac{1}{k} \sum_{x_i \in S_K} (x_i - x) \quad (1)$$

Where S_K denotes the data points of the datasets where the distance from the point to x is less than the radius h of the sphere. x_i is the position update of the center of the ball x . The update formula is:

$$x_i = x + M_k \quad (2)$$

As for the multi-spectral image, the normalized shading index (NSVI) needs to be calculated in the ENVI software, and the thresholding method is used to separate the pomegranate tree image

elements from the soil image elements and to remove the soil background^[11]. The normalized shading vegetation index is calculated as follows:

$$NDVI = \frac{NIR - R}{NIR + R} \quad (3)$$

$$SVI = NDVI \times NIR \quad (4)$$

$$NSVI = \frac{SVI - SVI_{MIN}}{SVI_{MAX} + SVI_{MIN}} \quad (5)$$

Where, R is the reflectivity of red band, NIR is the near infrared band reflectivity, $NDVI$ is the normalized difference vegetation index, SVI is the shaded vegetation index, SVI_{MAX} is the maximum value of SVI , and SVI_{MIN} is the minimum value of SVI .

2.3 Build the dataset

After background removal, the orthophoto of the orchard was cut into 528 canopy images of a single pomegranate tree, and the color characteristics and texture features of the RGB image were extracted, and the feature parameters and calculation formula were shown in Table 1 and Table 2. In addition, the spectral reflectance data for each sample image were extracted using ENVI software, and the vegetation index for the multi-spectral image was subsequently calculated, and each vegetation index and the calculation formula were shown in Table 3. Pearson correlation analysis was performed between these parameters and the ground chlorophyll data, and the parameters with higher correlation were selected to establish the RGB feature set, the vegetation index set, and the feature fusion set integrating the two features.

Table 1. Color feature parameters of the RGB images

Parameter	Formulas	Parameter	Formulas
Red-mean	r	Normalized red index	$r / (r + g + b)$
Green-mean	g	Normalized green index	$g / (r + g + b)$
Blue-mean	b	Normalized blue index	$b / (r + g + b)$
Red and green difference index	$r - g$	Red-blue difference normalized index	$(r - b) / (r + g + b)$
Red and blue difference index	$r - b$	Red-green difference normalized index	$(r - g) / (r + g + b)$
Green and blue difference index	$g - b$	Green-blue difference-normalized index	$(g - b) / (r + g + b)$
Red and green ratio index	r / g	Normalized red-blue difference index	$(r - b) / (r + b)$
Red and blue ratio index	r / b	Normalized red-green difference index	$(r - g) / (r + g)$
Green-blue ratio index	g / b	Normalized green-blue difference index	$(g - b) / (g + b)$
Green-red ratio index	g / r	Hue-mean	h
Blue-red ratio index	b / r	Saturation-mean	s
Blue-green ratio index	b / g	Value-mean	v

Table 2. Texture feature parameters of the RGB images

Texture standard deviation	$\sqrt{\sum_i \sum_j P(i, j) * (i - Mean)^2}$	Texture entropy	$\sum_{i=0}^{L-1} P(Z_i) \log_2 P(Z_i)$
Texture smoothness	$\sum_{i=0}^{L-1} Z_i P(Z_i) \frac{\sigma^2}{(1 + \sigma^2)}$	Texture uniformity	$\sum_{i=0}^{L-1} P^2(Z_i)$
Texture third_moment	$\sum_{i=0}^{L-1} (Z_i - m)^2 P(Z_i)$	Texture mean	$\frac{1}{L-1} \sum_{i=0}^{L-1} i P(Z_i)$

Table 3. Vegetation index associated with the SPAD values in the multi-spectral images

Parameter	Formulas
Differential vegetation index (DVI)	$DVI = NIR - R$
Normalized difference vegetation index (NDVI)	$NDVI = \frac{NIR - R}{NIR + R}$
Normalized difference red edge index (NDRE)	$NDRE = \frac{NIR - RE}{NIR + RE}$
Normalized green degree vegetation index (GNDVI)	$NDVI = \frac{NIR - G}{NIR + G}$
Ratio vegetation index (RVI)	$RVI = \frac{NIR}{R}$
Green degree ratio vegetation index (GRVI)	$GRVI = \frac{NIR}{G}$
Red-edge ratio vegetation index (RERVI)	$RERVI = \frac{NIR}{RE}$
Enhanced vegetation index (EVI)	$EVI = \frac{2.5 \times (NIR - R)}{NIR + 6R - 7.5B + 1}$
Triangle vegetation index (TVI)	$TVI = 0.5 \times [(120RE - G) - 200(R - G)]$
Nitrogen response index (NRI)	$NRI = \frac{G - R}{G + R}$
Red-edge-wide dynamic range vegetation index (REWDRVI)	$REWDRVI = \frac{0.12NIR - RE}{0.12NIR + RE}$
Soil-regulated vegetation index (SAVI)	$SAVI = \frac{1.5(NIR - R)}{NIR + R + 0.5}$
Optimize the soil regulation vegetation index (OSAVI)	$OSAVI = \frac{1.6(NIR - R)}{NIR + R + 0.6}$
Meris Terrestrial Chlorophyll Index (MTCI)	$MTCI = \frac{NIR - RE}{RE + R}$

Note: R , G , NIR and RE are the reflectances of the red band, green band, near infrared band and red edge band respectively.

2.4 Methods and Evaluation

Based on the RGB and multi-spectral image features of the pomegranate canopy, the study established two feature sets and a fusion set. For the three feature sets as independent variables, a support vector regression model (SVR) and a neural network model (CNN-Attention) combined with an attention mechanism were established. The ratio of the modeling set to the validation set in the entire data set was 7:3. The model's performance was evaluated using the coefficient of determination (R^2), relative error (RE), and root mean square error (RMSE). The larger the R^2 of the calibration and validation model, the smaller the corresponding RMSE and RE, and the better the prediction ability of the model. The calculation formula is as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - p(x_i))^2}{\sum_{i=1}^n (y_i - \bar{y}_i)^2} \quad (6)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (p(x_i) - y_i)^2} \quad (7)$$

$$RE = \frac{1}{n} \sum_{i=1}^n \left| \frac{p(x_i) - y_i}{y_i} \right| \quad (8)$$

Where n is the number of samples in the predicted set, $p(x_i)$ is the predicted value, y_i is the actual value, and \bar{y}_i is the actual mean.

3. Results and analysis

3.1 Correlation analysis between SPAD value and image characteristic parameters of pomegranate leaves

The obtained RGB feature parameters and multi-spectral vegetation indices were analyzed by Pearson correlation with the measured SPAD values, and the feature parameters and vegetation indices with higher correlation are listed in the table below.

Table 4. Results of correlation analysis between characteristic parameters and SPAD

Parameter	Correlation coefficient	Parameter	Correlation coefficient
r	-0.837101*	$r / (r + g + b)$	-0.801065
g	-0.811397*	$g / (r + g + b)$	-0.286131
b	-0.567273	$b / (r + g + b)$	0.809886
$r - g$	-0.110806	$(r - b) / (r + g + b)$	-0.818638*
$r - b$	-0.912302*	$(r - g) / (r + g + b)$	-0.673528
$g - b$	-0.921239*	$(g - b) / (r + g + b)$	-0.752425
r / g	-0.688491	$(r - b) / (r + b)$	-0.819890*
r / b	-0.823228*	$(r - g) / (r + g)$	-0.696225
g / b	-0.766042	$(g - b) / (g + b)$	-0.768556
g / r	0.702086	h	0.095099
b / r	0.811868*	s	-0.858364*
b / g	0.769260	v	-0.810192*
Texture Std	-0.550324	Texture entropy	-0.859536*
Texture smoothness	0.328527	Texture uniformity	0.798602*
Texture third moment	-0.017672	Texture mean	-0.808483*
DVI	0.752361	EVI	0.836452*
NDVI	0.796014*	TVI	0.795105*
NDRE	0.801254*	NRI	0.815036*
GNDVI	0.832647*	REWDRVI	0.694520
RVI	0.805202*	SAVI	0.703516
GRVI	0.923241*	OSAVI	0.720529
RERVI	0.856523*	MTCI	0.902354*

Note: * represents a significant correlation

It can be seen from the table that 13 RGB image features such as R , G , $R - B$ and 10 multi-spectral vegetation indices such as NDVI, NDRE, and GNDVI are significantly correlated with the measured SPAD values.

3.2 Prediction model for chlorophyll content of pomegranate trees with single image features

The SVR and CNN-Attention models for pomegranate tree chlorophyll content prediction were constructed using 13 RGB image feature parameters(RGB-Feature) and 10 multi-spectral image vegetation indices, respectively(MSI-Feature), and the R^2 , RE, and RMSE of the two models were calculated, and the results are shown in Table 5. After the effect comparison, the CNN-Attention model built under the multi-spectral vegetation index feature set (MSI-Feature) had the best prediction effect. The model R^2 , RE, and RMSE were 0.9339, 0.0135, and 0.7523, respectively.

Table 5. Model prediction results under a single feature

Model	Feature	Model set	Validation set
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		R ²	RMSE	R ²	RE	RMSE
SVR	RGB-Feature	0.8896	1.6562	0.8660	0.0341	2.3701
	MSI-Feature	0.9129	1.2521	0.9047	0.0276	1.5047
CNN-Attention	RGB-Feature	0.9285	1.4513	0.9247	0.0108	1.3911
	MSI-Feature	0.9539	0.6953	0.9334	0.0135	0.7523

3.3 Prediction model for chlorophyll content of pomegranate trees by integrating two image features

Fusing 13 RGB image feature parameters and 10 multi-spectral image vegetation indices to get the feature fusion set (Combine-Feature), using the feature fusion set to construct the SVR and CNN-Attention model for the prediction of chlorophyll content of pomegranate tree, and calculating the R², RE, and RMSE of the model, the results are shown in Table 6. After the effect comparison, the CNN-Attention model built under the Combine-Feature has the best prediction effect. The model R², RE, and RMSE are 0.9699, 0.0052, and 0.6013, respectively.

Table 6. Model prediction results under the Combine-Feature

Model	Feature	Model set		Validation set		
		R ²	RMSE	R ²	RE	RMSE
SVR	Combine-Feature	0.9250	1.3896	0.9145	0.0289	1.3294
CNN-Attention	Combine-Feature	0.9802	0.3910	0.9699	0.0052	0.6013

3.4 Predictive model for optimal pomegranate tree chlorophyll content

Three different feature sets are used to validate the predictive ability of SVR and CNN-Attention models. R², RE and RMSE are used as the evaluation indexes to filter the optimal estimation model, as shown in Table 5 and Table 6, the CNN-Attention model works better under different types of datasets, and the R² is improved by an average of 0.034 compared to the SVR model, and the effect of using the Combine-Feature is better than that of using a single feature.

The effects of prediction models constructed under the Combine-Feature are shown in Figure 1.

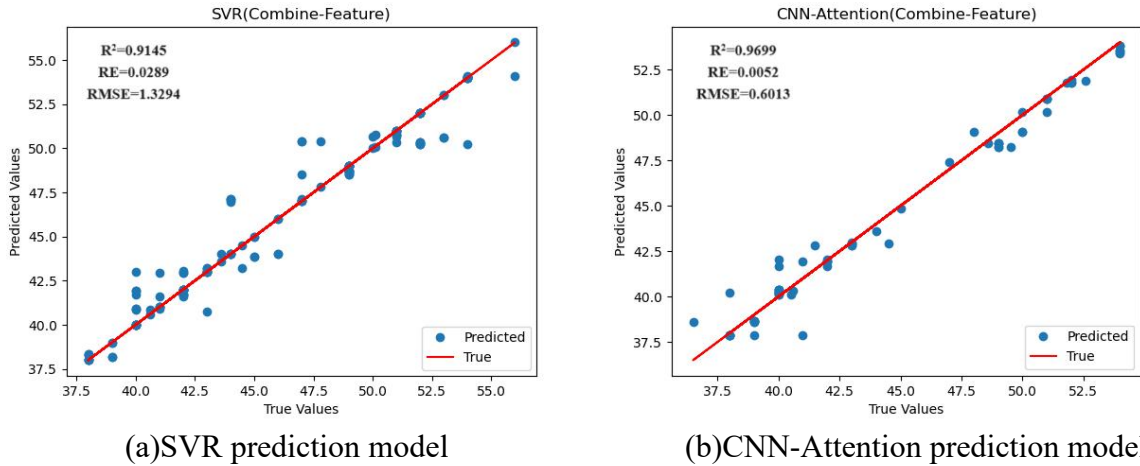


Fig. 1 The prediction model constructed under the Combine-Feature

As can be seen from the figure, the R², RE and RMSE of the CNN-Attention model validated under Combine-Feature were 0.9699, 0.0052 and 0.6013, respectively, and compared with the SVR model, the R² was improved by 0.0554, and the RE and RMSE were reduced by 0.0237 and 0.7281, respectively. After comprehensive comparison, this study used Combine-Feature to construct a CNN-Attention model to predict the chlorophyll content of pomegranate trees.

The use of Combine-Feature to construct the model makes full use of multiple feature information and improves the prediction accuracy, and the use of multiple feature fusion to predict the chlorophyll content of pomegranate trees has potential prospects.

4. Conclusion

In this study, a low-cost, high-resolution multi-spectral UAV was utilized to acquire canopy images of pomegranate during the flowering period. RGB image features as well as multi-spectral vegetation indices were extracted based on orthophotos. These features were correlated with SPAD and three different feature sets were constructed, and SVR model and CNN-Attention model were built based on the different feature sets. The R^2 , RE and RMSE for model validation were comprehensively evaluated. Finally, the chlorophyll content of pomegranate trees was predicted using the CNN-Attention model constructed by Combine-Feature. The conclusions of the study are as follows:

1. Selected 13 RGB image features and 10 multi-spectral vegetation indices were significantly correlated with SPAD. Among them, GRVI had the strongest correlation with SPAD (0.923241), and NDVI had the weakest correlation with SPAD (0.793014).

2. The prediction model for chlorophyll content of pomegranate trees were established by selecting 70% of the sample data random (a total of 370 samples). The remaining 30% of the sample data (158 samples in total) were used to validate the estimated model. Among them, the CNN-Attention model built based on the feature fusion set was the most effective. The calibration and validation accuracy of this model $R^2=0.9802$, RMSE=0.3910 and $R^2=0.9699$, RE=0.0052, RMSE=0.6013.

3. A low-cost, high-resolution multi-spectral drone that can quickly and accurately predict the chlorophyll content of pomegranates from orthophotos provides a fast, low-cost technique for pomegranate tree monitoring and chlorophyll management.

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