Integration of weighted majority voting in machine learning algorithms to enhance pine tree crown mapping on UAV imagery

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Abstract

The shape and area of the crown of each tree are among the most influential parameters for identifying and controlling the processes of photosynthesis, respiration, transpiration and its management. In such a way that various physiographic functions, such as carbon dioxide absorption, light energy absorption, oxygen release and transpiration, which are vital for the growth and development of the tree, are done in the crown. In this research, the RGB image of the UAV with a spatial resolution of 2 cm was resampled to three pixel sizes of 10, 30 and 50 cm. Then, each image was classified separately by SVM, ANN and MLC algorithms, which are all part of Ensemble. In the next step, each of the obtained crowns was compared with the digitization of the same crown, and based on the area of the crown obtained from each classification and normalization method, the weight was obtained specifically for the same crown. Finally, by using the weighted majority voting method, classifications were fusioned at the decision level. The results showed that the ANN method gives better results in all pixel sizes compared to MLC and SVM. Also, the combination of different classification methods with the weighted majority voting method based on the weight assigned to the same crown based on each classification method has significantly increased the classification accuracy of the tree crown in all the sizes of the analyzed pixels.

1. Introduction

Due to the high demand of governments, large companies and farmers to organize the environment and reduce the effects of human activities, the number of reforestation projects has increased worldwide (Belmonte et al., 2020). As it is considered one of the important priorities in many developed countries (Sabatini et al., 2020; Weiss et al., 2004). In this regard, effective monitoring of man-made forests is necessary due to their role in reducing climate change (Khaine et al., 2015; Abad-Segura et al., 2020) and ensuring the preservation of ecosystem services and environmental diversity (Ghanbari Parmehr et al., 2021). The requirement of this issue is to continuously investigate and monitor the structural diversity of man-made forests (Morgenroth et al., 2020), measure and evaluate the process of changes in the physical characteristics of trees (Moe et al., 2020).

One of these physical characteristics is the crown area of a single tree. The crown of trees is the main place of primary production and indicates the general health and performance of trees (Ulmer et al., 2016). In the tree, various physiographic functions such as absorption of carbon dioxide, absorption of light energy, release of oxygen and transpiration are performed by the crown, which are vital for the growth and development of the tree (Mokashi et al., 2021). Crown measurement is effective for determining large quantities as well as tree performance in growth stage, stability and production efficiency. Therefore, it can be the main and important predictor of tree productivity and help in its growth and detailed study.
The shape and area of the tree crown is constantly changing due to various reasons, including growth processes, age, amount of sunlight, as well as the surface microclimate of each region (Miraki et al., 2021; Norris et al., 2024). In fact, according to the conditions of each region, season and type of each tree, the crown shape has different growth rates (Wu et al., 2021). Therefore, identifying and extracting information about a single tree is of special importance and position. One of the methods that can help this process is the use of drones.

The use of drones in obtaining very high resolution images as well as the possibility of flying at low altitude has led to a more accurate determination of Digital Terrain Model (DTM), which has a great impact on the measurement of tree crowns. Drones have been used in much man-made forest research in the past few years, which has resulted in significant savings in time, workforce and financial resources for various forestry projects. The estimated data from the UAV can be used in trees if they have sufficient statistical correlation with the measured field data (Abdollahnejad et al., 2018; Song et al., 2022).

Although there are many algorithms that have been developed and used for crown extraction, each algorithm has limitations in some areas. So that none of them can fully handle all kinds of crown extraction problems, such as uncertainty, finding the exact crown tip, heavy processing, high point cloud noise, manual adjustment of spectral parameters, and low geometric robustness. In addition, low spatial resolution images reduce inter-pixel variance due to the inclusion of different types of surface coverage in each pixel. In contrast, high spatial resolution images, such as drone images, divide the surface into smaller pixels and capture more variance. As a result, it increases the amount of processing and increasing the number of image segments (Chen et al., 2021; Surový et al., 2018).

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Due to the position of the crown of the pine trees at different angles, the pixels have different gray scales. On the other hand, each of the classification methods has its own advantages and disadvantages, so one method alone cannot correctly extract the crown of trees. To solve this challenge, based on the effectiveness of each method, an appropriate weight was assigned to each crown, so that by combining the methods based on the weighted majority voting, a more accurate area and more coverage of the crown can be obtained(Reis et al., 2019; Hasegawa et al., 2024). In other words, in this research, the effectiveness of common machine learning algorithms such as maximum likelihood (MLC), artificial neural network (ANN), support vector machine (SVM) with different pixel sizes (10, 30 and 50 cm) were investigated. Therefore, the use of different classification methods, each of which has been used separately and with a completely different approach in forest areas, and combining them with the weighted majority voting algorithm leads to more realistic decision-making, which, of course, needs further investigation.

The weights used in this research are specifically used for each crown based on the ratio of correct coverage of the crown compared to the digitization of each crown, according to the stated methods. The results can provide a clear view of reducing the processing volume and flight time, setting a more appropriate height to cover more area, and thus reducing the number of flight lines.
Figure 1 shows the research implementation process.

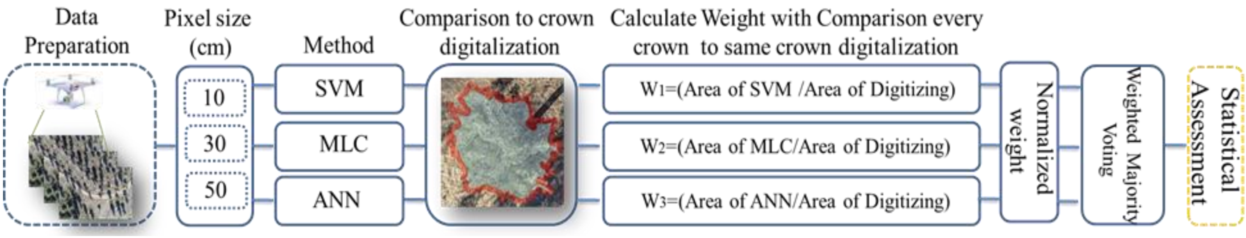


Figure 1. Research implementation process

2. MATERIALS AND METHODS

2.1 Study area

Pardisan Park is located in Bojnord city of North Khorasan province (N, Zone 40 N″57 ′28 °37-E″49 ′25 °57), at an average height of 1080 meters above sea level (Figure 2). This collection is purely covered with man-made pine species (Pinus eldarica), which is known as Tehran pine. The area is cold and semi-arid based on the coupon criteria(Roshani et al., 2021).

The average rainfall and temperature of that 10-year period (1390-1400) are 260 mm and 15 degrees Celsius, respectively. The main type of soil in this park is silty clay and silty loam. Due to the limitation in issuing presence and flight permits, a 14-hectare area was considered.

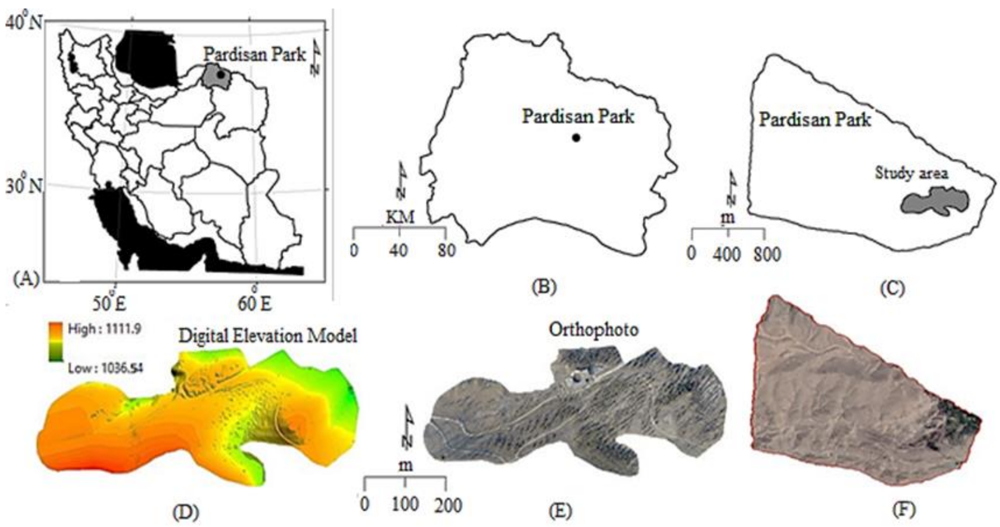


Figure 2. Iran and the study area (A), North khorasan province (B), the study area (C), Digital Elevation Model (D), Orthophoto (E), Pardisan park area (F).

2.2 Image acquisition

In this research, RGB images of a Phantom 4 Pro drone with a FC6310 camera with 20 mm focal length were used. According to the light conditions of the environment, the saturation, clarity, and contrast status of the camera was set to normal. In this research, according to the type of topography of the area, the UAV flew at a height of 40 meters and vertically with a longitudinal and transverse overlap of 80 and 40 percent. In order to prevent the stretching effect in the images, a speed of 4 meters per second and a shutter speed of 1/60 second were used. The output of the images was set in JPG format with dimensions of 5472 x 3448 pixels. Imaging was also done on March 4, 2021, at a speed of less than 1 Knot and clear sky conditions at 14:30 local time (GMT11:00) and 952 standard images were prepared along with 14 ground control points. After the necessary processes, the 3D model was created using the Structure from motion (SFM) algorithm.

2.3 Assessment

A series of equations were used to evaluate the classification results for each specific class so that the results could be properly evaluated. Equations 1 to 4 show Specificity, Sensitivity, Precision, Accuracy respectively. In this method of evaluation, TP and TN respectively represent the cells that are correctly assigned to the class and the cells that are not correctly assigned to the class. Cells that are incorrectly assigned to the desired class FP and FN also represent cells that are not incorrectly assigned to the desired class. Also, equation 3 was used to check the degree of spatial correspondence between the identified class on the aerial image and the ground reality, and equation 4 was used to evaluate the correctness of assigning a cell to the desired class. n also shows the total number of classified cells(Chenari et al., 2017).

$$Specificity = \frac{TN}{TN + FP} \tag{1}$$

$$Sensitivity = \frac{TP}{TP + FN} \tag{2}$$

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

$$Accuracy = \frac{TP + TN}{n} \tag{4}$$

3. RESULTS AND DISCUSSION

324 Tehran pine trees with different crown areas were captured image, and their statistical summary is shown in Table 1. As the numbers show, the trees of the study area have good physical diversity, which plays an important role in the more appropriate evaluation of the research data. In previous researches, it has been emphasized on the greater variety of data in the evaluations obtained from UAV data (Hosingholizade et al., 2023b).

Considering the relative distance of the trees in the study area and the low number of non-tree complications, pixel sizes of 10, 30 and 50 cm were considered for UAV image classification. Table 2 shows the number of training pixels, test data, overall accuracy, kappa coefficient and crown area for each pixel size, along with the classification method. Considering the direct effect of the number of pixels and their location on the overall accuracy and Kappa ceoficent (especially when the variation of digital number in a problem is high), it was determined separately and in the same range of equal training and testing points.(The conditions are the same for different classification methods) (Thanh and Kappas, 2017). In other words, in order to be equal in each method, the same occupation level and not the same number of pixels was used in each classification method. The results showed (Table 2) that the pixel size has a direct effect on the classification accuracy. By checking the overall accuracy and kappa coefficient in table 2, it can be seen that with the change of the pixel sizes, the overall accuracy and kappa coefficient have been changes. By increasing the pixel size, the values of kappa coefficient and overall accuracy have increased. In other words, the diversity in images with a pixel size of 10 cm is very high compared to images with pixel sizes of 30 and 50 cm (with an equal number of testing pixels of trees). Due to sunlight, the shadow effect, direction of branches, conical shape, and the loss of details, it is caused by reducing the spatial resolution of the tree. In other words, the more diversity of pixel values of a problem decreases; the classification is associated with better accuracy in completely equal conditions (Rafieyan et al., 2013, Baker et al., 2013). Therefore, the kappa coefficient and overall accuracy, especially when the pixel sizes change, are not suitable criteria for the correct understanding of the classifications. According to the purpose of the work and the type of problem, the appropriate pixel size and solar azimuth conditions (time) should be used to image acqusitio. In this research, appropriate statistical parameters were used, which are specific to more detailed assessment of classification and, unlike the Kappa coefficient and overall accuracy, they are not generalizing.

Characteristic	MAX	MIN	CV	STD	MEAN
Height (m)	13.1	0.5	38.9	2.6	6.6
Small crown diameter (m)	7.8	1.0	25.4	1.1	4.3
Large crown diameter (m)	11.6	2.3	23.4	1.4	5.8
Crown area(m^2)	49.9	0.8	49.7	7.9	15.9

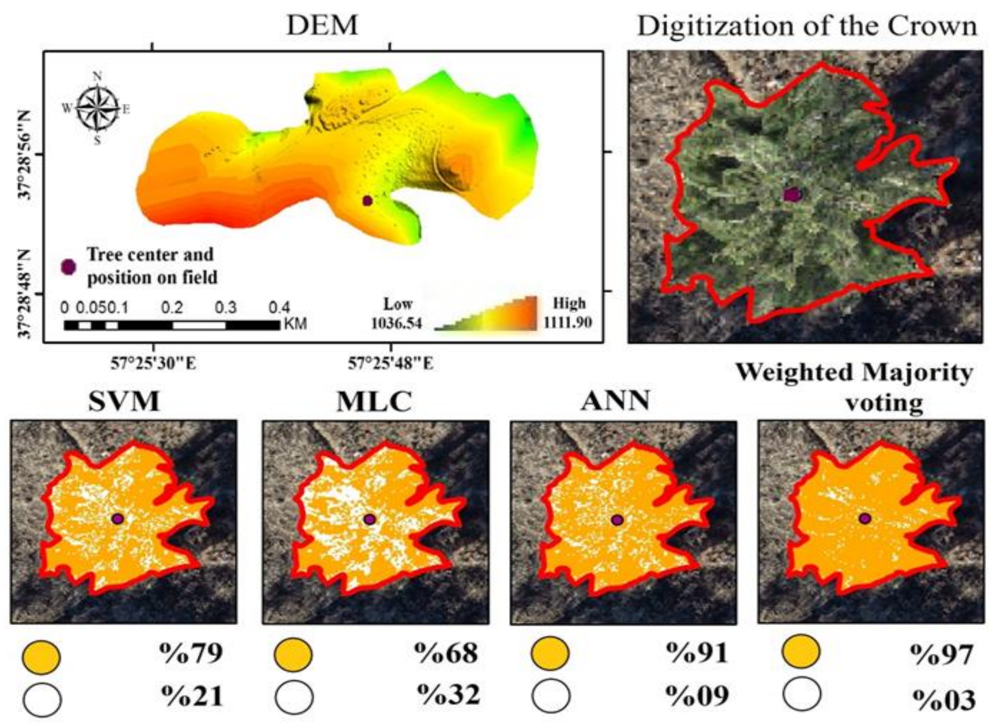
Table 1. summary of the statistical parameters of the crown area based on the RGB image data

As the numbers in Table 2 show, the weighted majority voting method has significantly reduced the environmental effects on the classification in all dimensions of the analyzed pixels. However, changing the pixel size to a certain ratio (from 10 cm to 50 cm) with the same ratio did not affect the results. Also, in the ANN classification algorithm, it has higher kappa and overall accuracy than MLC and SVM, which is improved by using a combination of three classification algorithms with the weighted majority voting method for all pixel sizes. Examining the crown surface in pixels of different sizes showed that the best case corresponds to a pixel size of 10 cm when using weighted majority voting. In other words, as the pixel size increases in all cases, the estimated area differs more from the actual crown area obtained from the 2 cm resolution ortho image. Furthermore, the variability of crown features was high in the ortho image with 10 cm spatial resolution compared to the ortho images with pixel sizes of 30 and 50 cm (with the same number of test pixels). It is probably caused by sunlight, the shadow effect, direction of branches and shape of cones and an increase in pixel size. In other words, the lower the diversity of pixels in a complex, the better the classification is done in completely equal conditions (Rafiian et al., 2013). Therefore, according to the objectives and research problem, UAV orthomosaic images with low resolution such as 50 cm pixel size should be classified with a combination of machine learning algorithms by weighted majority voting method to effectively identify crowns.

Method	Classification type	Pixel size (cm)	Sample data (N)	Test data (N)	Total Crown Area (m^2)	Sensitivity (%)	Specificity (%)	Accuracy (crown) (%)	Precision (crown) (%)	Overall Accuracy (%)	Kappa Coefficient (%)
		10	11250	5700	5001	88.3	85.1	90.2	85.6	72	65
	SVM	30	3750	1900	4791	84.2	84.5	82.5	83.2	74	69
	(RBF)	50	2250	1140	4259	80.5	75.2	73.2	74.2	78	72
		10	11250	5700	4876	82.2	83.0	83.7	82.9	67	61
Ensemble	MLC	30	3750	1900	4689	79.4	78.8	77.6	76.2	69	63
(Bagging)		50	2250	1140	4211	72.9	73.2	77.9	723	73	67
	ANN	10	11250	5700	5073	91.6	88.6	93.7	91.2	75	69
	(2 Hidden	30	3750	1900	4873	86.2	82.1	87.8	89.7	76	72
	layers)	50	2250	1140	4551	81.3	78.2	83.6	84.1	81	77
(Weighted Majority		10	11250	5700	5152	96.7	94.2	98.3	98.9	81	75
voting for		30	3750	1900	5075	94.3	93.4	96.1	96.5	83	79
SVM, MLC, ANN)		50	2250	1140	4687	92.2	91.1	95.8	95.1	87	81

Table 2. evaluation of classification parameters with different methods and pixel sizes

By comparing the results of this research with the research of Hosingholizade et al. (2023), which was conducted using the majority voting method, without considering the weight. it can be seen that the use of assigned weights based on classification methods has a significant effect on the results of the research. Although in the research of Hosingholizade et al. (2023), the basis of calculation was the crown obtained from the segmentation, but in this study digitization of the crown was used, which can be a valuable research path in its own way. Figure 2 briefly shows part of the outputs visually.



$$\text{weight for each crown} = \frac{\text{The identified area within the digitization}}{\text{Digitized crown (Red border)}} \times \frac{1}{\text{Sum of areas of all classification methods at each pixel size}}$$

Figure3. classification by ANN, SVM, MLC and decision fusion with weighted majority voting based on each crown

4. Conclusion

In order to extract the tree crown, there are different methods using point clouds. sometimes, due to the low overlap of the images, the presence of noise in the point cloud, the presence of unwanted (non-targeted) effects, heigh processing, existing technical limitations, the use of RGB images is unavoidable. Even in some cases, the point cloud is not easily accessible to everyone and this is a big challenge in many areas. Also, the rich archive of older images that have less overlap are not suitable for point cloud generation, however, a method should be used to make the best use of these valuable resources. By the observing the results, it can be used by scientists to classify UAV low resolution images. Therefore, it is suggested to use decision fusion by considering the weight based on the method and allocating it for each crown, which can significantly help to improve the classification results.

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