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RESEARCH ARTICLE

Plant Classification Method Using Histogram and Machine Learning for Smart Agriculture Applications

Akıllı Tarım Uygulamaları için Histogram ve Makine Öğrenimi Kullanan Bitki Sınıflandırma Yöntemi

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ABSTRACT

Due to its high potential and value, the Internet of things (IoT) has been used in various areas such as information security, industry 4.0, and smart agriculture. IoT is used in agriculture through the use of sensors, unmanned aerial vehicles (UAV), satellite technologies, robots, image processing, and artificial intelligence technologies. These smart agricultural practices increase production and quality and lead to savings in irrigation, thereby reducing environmental pollution during production. This study proposes an ultra-lightweight automated plant species classification method for smart agriculture applications. A UAV is used to acquire a new image dataset. An ultra-lightweight classification method is then used to classify the acquired plant species images. Our proposed ultra-lightweight computer vision model presents a histogram-based simple feature extraction function. The presented feature extractor uses histogram extraction and median filter in conjunction. The generated features are fed to two shallow classifiers, which are the support vector machine (SVM), and k nearest neighbor (KNN). The utilized SVM and KNN classifiers have attained 96.45% and 94.11% accuracies consecutively. The results demonstrate that this model is very capable of plant image classification and is ready for use in a physical agriculture environment.

Keywords: Plant classification, smart agriculture, histogram, feature extraction, machine learning

ÖZ

Nesnelerin interneti (IoT) insanlık için çok değerli bir teknolojidir, dolayısıyla IoT bilgi güvenliği, endüstri 4.0, akıllı tarım gibi çeşitli alanlarda kullanılmaya başlanmıştır. Akıllı tarım uygulamaları sensörler, insansız hava araçları (İHA), uydu teknolojileri, robotlar, görüntü işleme ve yapay zekâ teknolojileri kullanılarak geliştirilmektedir. Akıllı tarım uygulamaları ile sulama alanında tasarruf sağlanmakta ve üretim sırasında çevre kirliliği azaltılmaktadır. Aynı zamanda üretimi ve kaliteyi arttırır. Bu çalışmada, akıllı tarım uygulamaları için ultra hafif otomatik bitki türleri sınıflandırma yöntemi geliştirilmiştir. Bir İHA kullanılarak yeni bir görüntü veri seti elde edilmiştir. Elde edilen bitki türleri görüntüsünü sınıflandırmak için ultra hafif bir sınıflandırma yöntemi önerilmiştir. Önerilen ultra hafif bilgisayarlı görü modelimizde, histogram tabanlı basit bir özellik çıkarma işlevi sunulmuştur. Sunulan öznitelik çıkarıcı, histogram çıkarımı ve medyan filtresi birlikte kullanılmıştır. Oluşturulan öznitelikler, destek vektör makinesi (SVM) ve k en yakın komşu (KNN) olan iki sığ sınıflandırıcıya beslenir. Kullanılan SVM ve KNN sınıflandırıcıları arka arkaya %96,45 ve %94,11 doğruluk elde etmiştir. Sonuçlar, bu modelin bitki görüntü sınıflandırması için oldukça başarılı olduğunu ve fiziksel tarım ortamında kullanıma hazır olduğunu göstermektedir.

Anahtar Kelimeler: Bitki sınıflandırması, akıllı tarım, histogram, özellik çıkarma, makine öğrenmesi

1. INTRODUCTION

Many factors influence agricultural productivity, including soil structure, irrigation type, spraying technique, and meteorological conditions. To enhance production output, it is important to continually monitor the plants and make the required modifications. Agricultural production has grown in recent years with the advancement of technology and smart agricultural systems. Smart agriculture can enable the development of applications such as water monitoring, soil monitoring, and disease monitoring. Temperature/humidity sensors, soil sensors, and cameras can all be used for these applications (Babayigit & Büyükpatpat, 2019), thereby automatically computing irrigation, fertilization, agricultural spraying, and yield analysis.

Plant species and disease detection are significant for smart agricultural applications. It is important to know the type of plant to assess its production, development, and disease. Furthermore, determining the plant species is required to detect diseases that may afflict them. In the literature, techniques for classifying plant species based on fruits and leaves have been developed (Atila, Uçar, Akyol, & Uçar, 2021; Hameed, Chai, & Rassau, 2018; Yalcin & Razavi, 2016; Zhu, Zhu, & Ren, 2018). Plants' fruits (Hameed et al., 2018), flowers (Pawara, Okafor, Schomaker, & Wiering, 2017), and leaves (Keivani, Mazloum, Sedaghatfar, & Tavakoli, 2020) are generally used to classify them (Yalcin & Razavi, 2016). Moreover, this also results in disease detection in the images as well (El, Es-saady, El, Mammass, & Benazoun, 2017; Wang, Yang, Yu, Dong, & Wang, 2021; Xie, Yang, & He, 2017). Table 1 summarizes the research and methodologies utilized in plant classification and disease detection in the literature.

Table 1
Studies and methods used in plant classification and disease detection in the literature

Studies	Year	Dataset	Number of species/groups	Explanation	Method
Atila et al. (Atila et al., 2021)	2021	PlantVillage dataset	38	Leaf disease classification	EfficientNet
Goyal et al. (Goyal, Kumar, & Gupta, 2021)	2021	Swedish leaf dataset	15	Plant recognition	1DPCA+ MTSVM
		Flavia dataset	-		1DPCA+ MTSVM
		Folio dataset	-		LDA+ MTSVM
Selvam et al. (Selvam & Kavitha, 2020)	2020	Self-collected dataset	3	Leaf disease classification	CNN
Murtaza et al. (Murtaza, Saba, Haroon Yousaf, & Viriri, 2020)	2020	Flavia dataset	3	Plant Species Identification	SURF + Bag of Words
		ImageClef dataset	3		SURF + Bag of Words
Adak (Adak, 2020)	2020	Self-collected dataset	43	Identification of Plant Species	CNN
Saleem et al. (Saleem, Akhtar, Ahmed, & Qureshi, 2019)	2019	Flavia dataset	25	Plant classification	CNN KNN Decision Tree Naïve Bayes Multi SVM
Yacin et al. (Yalcin & Razavi, 2016)	2016	TARBIL dataset	16	Plant Classification	CNN SVM
Dyrmann et al. (Dyrmann, Karstoft, & Midtiby, 2016)	2016	BBCH 12e16 dataset	22	Plant species classification	CNN

* CNN: Convolutional neural network, SVM: Support vector machine, KNN: k nearest neighbor

As can be seen in Table 1, many image processing, machine learning, and deep learning-based methods have been developed in the literature. There are many datasets of fruits, vegetables, and other plants in the literature. PlantVillage is a dataset containing leaf diseases in plants. The Swedish, Flavia, Folio, TARBIL, and BBCH 12e16 datasets are used for plant classification. Deep learning-based methods have high computational complexity necessitating methodical work and computers with high processors.

2. MATERIAL METHOD

2.1. The collected dataset

In the first step of this research, a new plant image dataset has been collected using a UAV. This dataset contains 17 plant species and consists of 6170 color images. The size of these images are fixed to 1280 × 720 × 3 since they are RGB images. They recorded as JPEG. This dataset contains common garden plants. The used species are watermelon, corn, pepper, eggplant, tomato, wild grass, bean, cucumber, zucchini, melon, white cabbage, black cabbage, basil, parsley, carrot, mint, and strawberry plants. The sample plant images and counts used in the collected dataset are shown in Figure 1.

Figure 1. Plant images and numbers in the collected dataset

As illustrated in Figure 1, plant images have been collected with a UAV camera.

2.2. Preprocessing

The dataset collected in this study was carried out on agricultural land of approximately 3000 square meters. There are thousands of roots belonging to each plant species here. Video recordings were collected by drone for each plant species. One image was extracted from the videos at 300 millisecond intervals. Thus, approximately 3 images were obtained in 1 second. The images were resized and used. The number of images obtained for each plant category is given in Figure 1 and Figure 5.

2.3. The proposed ultra-lightweight plant species classification model using images

This research presents an ultra-lightweight image classification model for plan image classification. This model consists of two basic phases: feature extraction using histogram extraction and median filter and classification. The block diagram of the proposed method in this study is summarized in Figure 2.

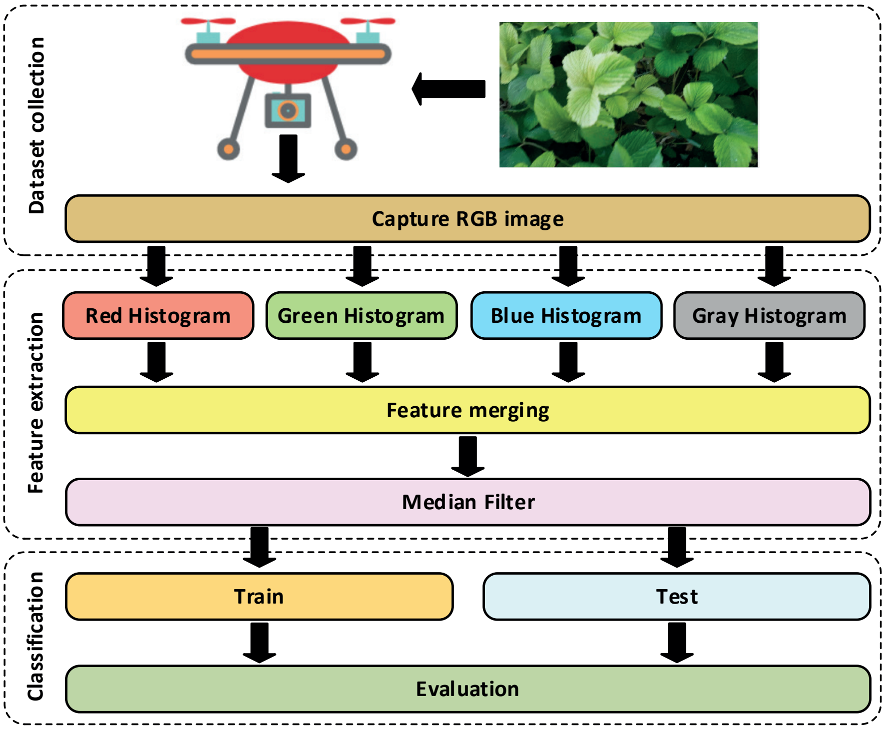

Figure 2. Block diagram of the proposed method

As shown in Figures 2, the collected images are RGB. RGB images consist of Red, Green, and Blue channels. In the proposed method, the histogram is used to extract features from the image. Separate histograms have been extracted from the Red, Green, and Blue channels. In addition, the RGB image has been converted to a gray image. Thus, four images have been obtained from an RGB image. The Red, Green, Blue, and Gray channels obtained from a sample RGB image are illustrated in Figure 3.

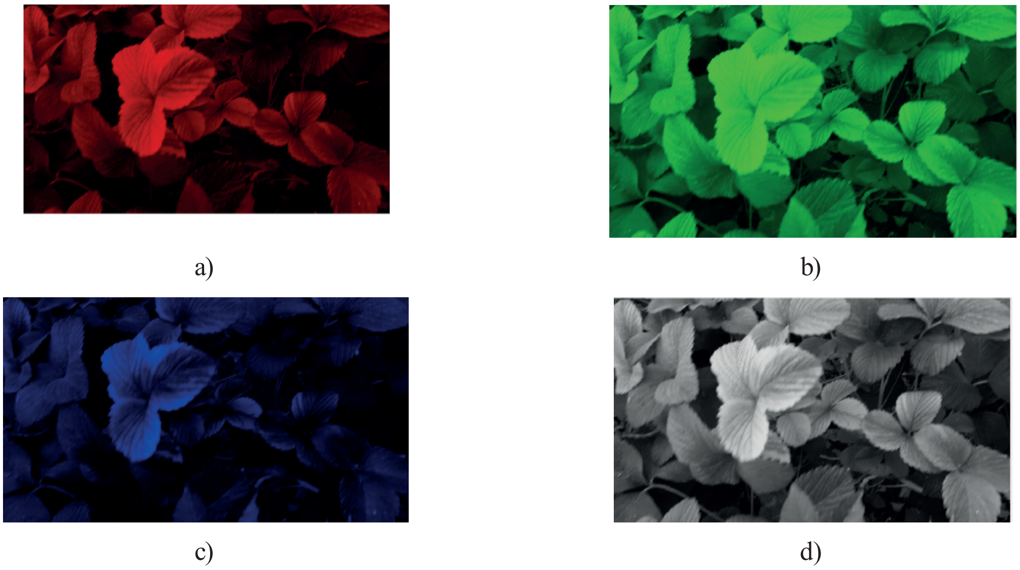

Figure 3. Red, Green, Blue and Gray channels from a sample RGB image
a) Red image b) Green image c) Blue image d) Gray image

In the proposed method, a histogram is used to extract features from the image. Separate histograms have been taken for the Red, Green, and Blue channels. A histogram is a graph that shows the number of color values in an image. In the histogram graph, the horizontal axis represents the color values between 0-255. The vertical axis represents the pixel numbers of these color values. The color distribution in the image is obtained by histogram extraction. Thus, feature extraction can be done from an image. Histogram graphics of the sample Red, Green, Blue, and Gray channels given in Figure 3 are illustrated in Figure 4.

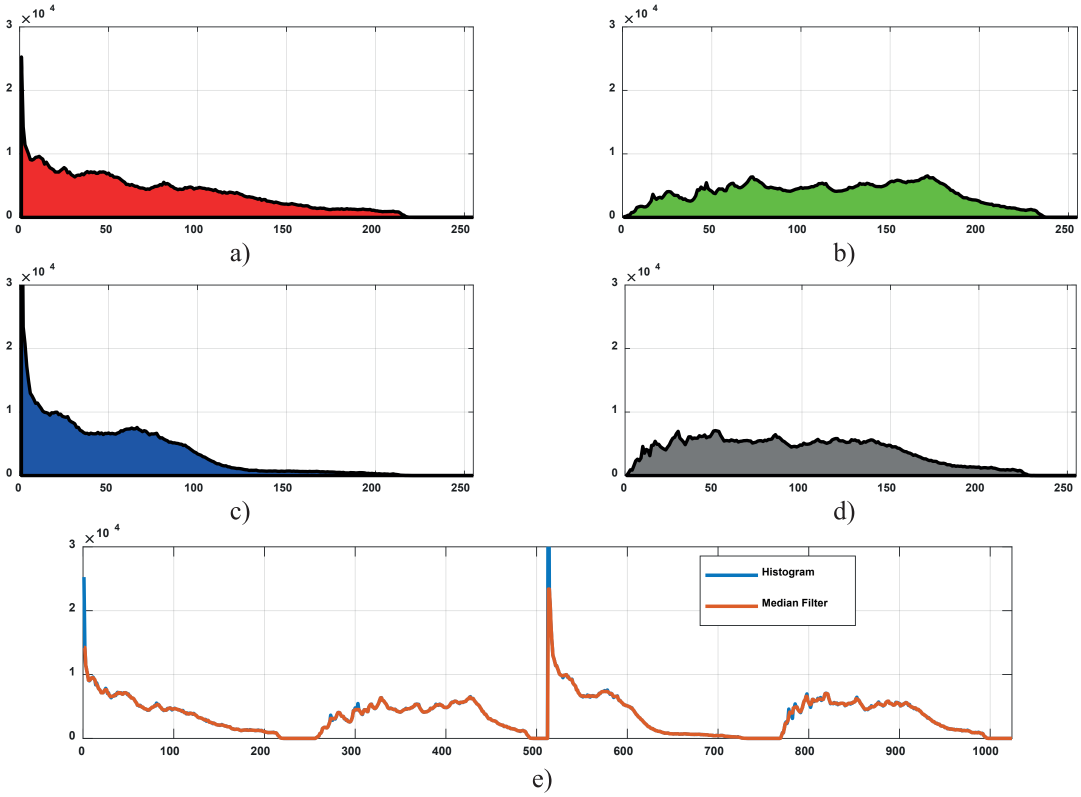

Figure 4. Example Red, Green, Blue and Gray channels histogram graphics
a) Red channel histogram b) Green channel histogram c) Blue channel histogram d) Gray channel histogram e) Merging histograms of Red, Green, Blue and Gray channels

As illustrated in Figure 4, the histogram graphs of Red, Green, Blue, and Gray channels have been obtained and concatenated. Thus, the length of the created feature is 256 × 4=1024. A median filter has been applied to the obtained histogram graphics. By applying the median filter, the noise in the extracted features is removed. The proposed feature extraction results for images of 17 plant species are demonstrated in Figure 5.

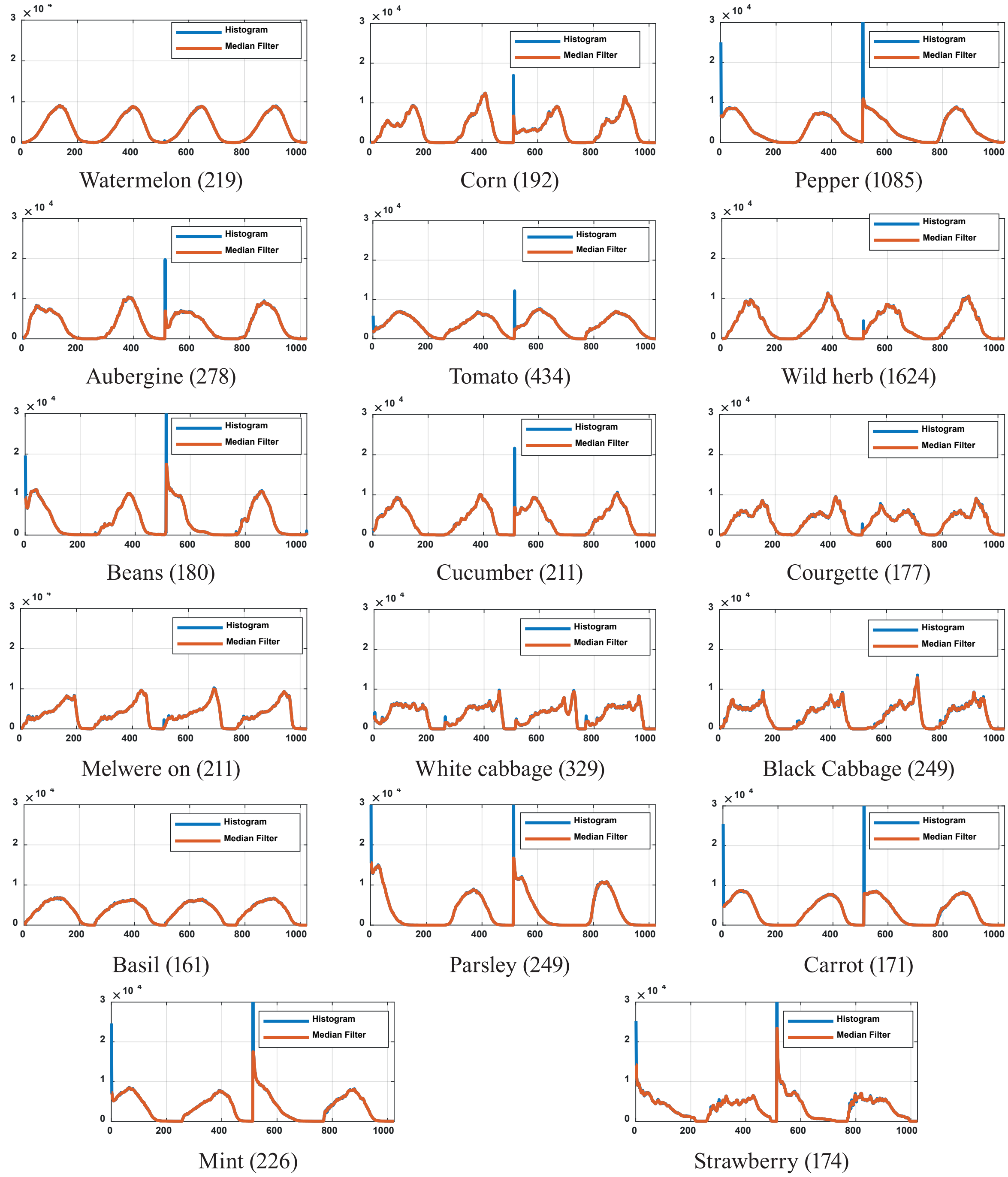

Figure 5. Proposed feature extraction results for images of 17 plant species

As shown in Figure 5, features have been extracted from RGB images through the histogram method. SVM and KNN algorithms have been used to classify the extracted features. SVM and KNN algorithms are commonly preferred machine learning algorithms in the literature (Pooja, Das, & Kanchana, 2018; Yaman, Ertam, Tuncer, & Firat Kilincer, 2020; Yaman & Tuncer, 2021). In order to choose these classifiers (KNN and SVM), five shallow classifiers have been used to test: Decision Tree (DT), Linear Discriminant (LD), Cubic SVM, Fine KNN, and Ensemble Boosted Trees (EBT). The calculated accuracies for these classifiers are depicted in Figure 6.

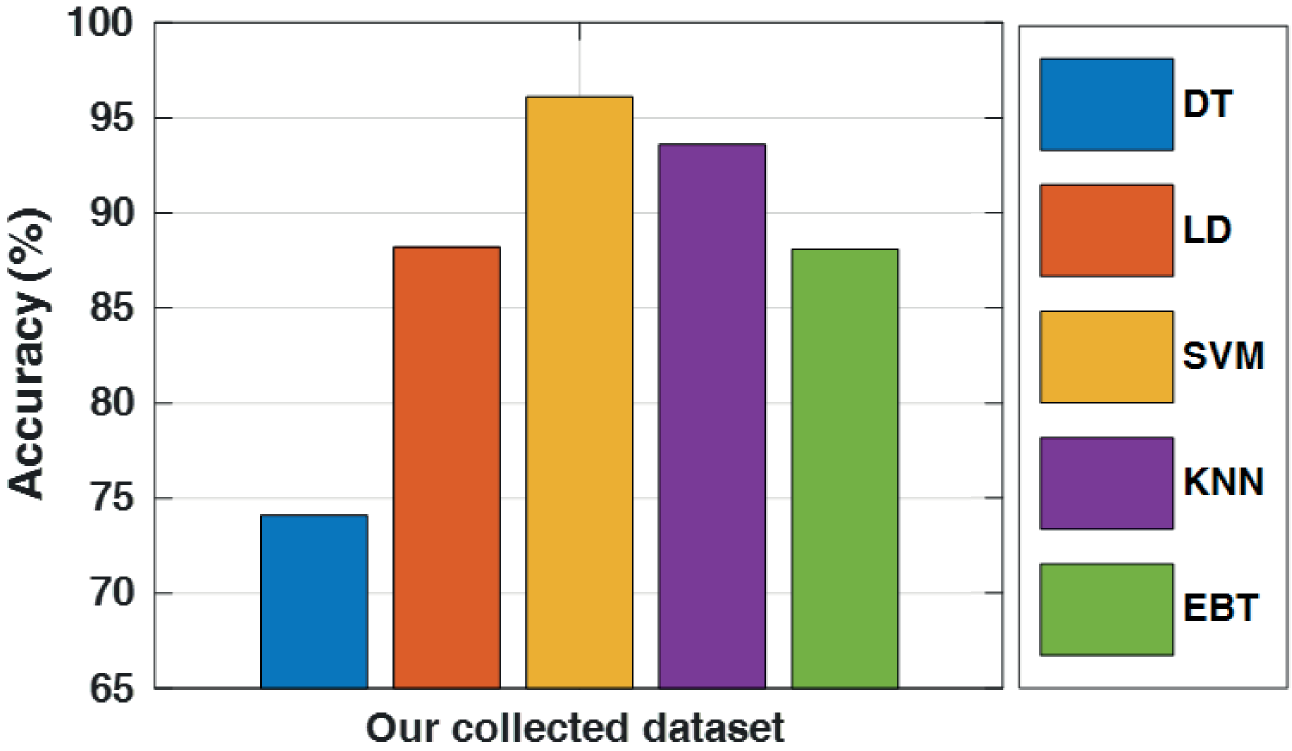

Figure 6. The accuracy results calculated for DT, LD, SVM, KNN, and EBT

As demonstrated in Figure 6, the highest accuracy has been computed with Cubic SVM and Fine KNN for our dataset. For this reason, the features extracted with the histogram have been classified using Cubic SVM and Fine KNN algorithms. 'Box constraint level=1', 'Kernel scale mode=Auto', 'Kernel scale=1' and 'Multiclass method= One-vs-All' are selected in Cubic SVM parameters. 'Number of neighbors=1', 'Distance metric=City block' and 'Distance weight=Equal' are selected in Fine KNN parameters.

3. EXPERIMENTAL RESULTS

In this study, the proposed method has been applied on a personal computer with i7-9700 CPU 3.00 GHz, 32GB RAM, and a 64-bit Windows 10 operating system. In the proposed method, preprocessing and feature extraction steps are developed in the MATLAB 2020a program as m-file. The classification process has been calculated using the MATLAB Classification Learner Toolbox. Confusion matrices have been computed using a 10-fold cross-validation. The confusion matrices are shown in Figure 7.

Predicted Class

True Class		2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	218	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0
2	0	186	0	5	0	0	0	0	0	0	0	0	0	0	1	0	0
3	0	0	1070	1	1	3	2	0	1	0	0	1	0	1	3	2	0
4	0	1	7	254	0	9	0	1	1	0	0	0	0	0	2	0	3
5	0	0	0	0	432	1	0	0	0	0	0	0	0	0	0	1	0
6	8	2	23	13	8	1551	2	3	2	0	1	4	3	2	1	0	1
7	1	1	3	0	0	1	171	0	0	0	0	0	0	1	2	0	0
8	0	0	0	3	0	1	0	204	1	0	0	0	0	1	1	0	0
9	1	0	0	0	0	3	0	4	169	0	0	0	0	0	0	0	0
10	0	0	0	0	0	3	0	1	0	207	0	0	0	0	0	0	0
11	0	1	0	0	2	5	1	0	2	0	307	8	1	0	0	2	0
12	0	0	1	0	0	9	0	0	0	0	6	231	1	0	0	1	0
13	0	0	0	0	0	3	0	0	0	0	0	0	158	0	0	0	0
14	0	0	1	1	0	0	0	1	0	0	0	0	0	243	2	1	0
15	0	0	1	0	0	0	2	0	0	0	0	0	0	3	163	2	0
16	1	0	0	0	0	0	0	0	0	0	0	0	0	0	2	223	0
17	1	0	1	1	0	2	0	0	0	0	2	0	0	1	0	2	164

a)

Predicted Class

True Class	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1	211	0	0	0	0	8	0	0	0	0	0	0	0	0	0	0	0
2	0	169	13	9	0	1	0	0	0	0	0	0	0	0	0	0	0
3	0	1	1068	0	1	6	1	0	0	0	0	0	0	5	3	0	0
4	0	6	23	233	1	8	2	1	1	0	0	0	0	0	1	0	2
5	0	0	3	0	428	2	0	0	0	0	0	0	0	1	0	0	0
6	39	3	49	13	19	1488	0	4	1	3	0	0	3	2	0	0	0
7	0	1	8	1	0	3	162	0	0	0	0	0	0	0	3	1	1
8	0	0	0	0	3	2	0	200	1	0	0	0	0	3	2	0	0
9	1	0	1	0	1	4	0	2	164	2	0	0	2	0	0	0	0
10	0	0	0	0	0	3	0	0	0	208	0	0	0	0	0	0	0
11	0	0	0	0	0	2	0	0	0	0	320	7	0	0	0	0	0
12	0	0	1	0	0	10	0	0	0	0	5	229	4	0	0	0	0
13	0	0	0	0	1	2	0	0	0	0	0	1	157	0	0	0	0
14	0	0	3	0	0	0	0	0	0	0	0	0	0	241	2	2	1
15	0	0	1	1	0	0	2	0	0	0	0	0	0	5	152	10	0
16	0	0	1	0	0	0	1	0	0	0	0	0	0	2	8	213	1
17	0	0	2	1	3	0	0	0	0	0	0	0	0	0	1	3	164

b)

Figure 7. Confusion matrices of the proposed method a) Cubic SVM b) Fine KNN

The class-wise computed with confusion matrices can be seen in Figure 8.

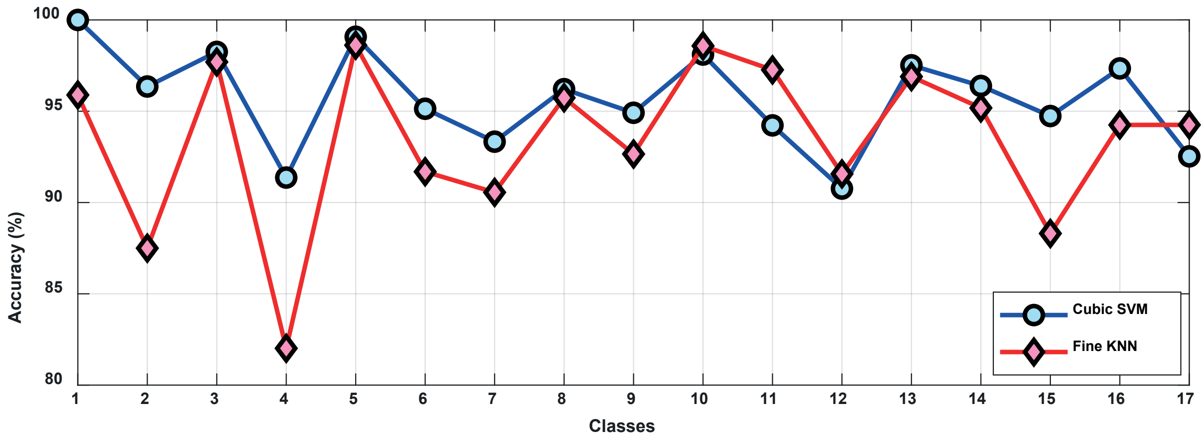

Figure 8. Class wise calculated with our collected dataset

The proposed method ran 100 iterations to calculate Accuracy, Precision, Recall, Geometric mean, and F1-Score parameters. At the end of 100 iterations, the maximum, minimum, mean, and standard deviation results of Accuracy, Precision, Recall, Geometric mean, and F1-Score parameters were computed. The Accuracy, Precision, Recall, Geometric mean, and F1-Score results computed with 100 iterations are tabulated in Table 2.

Table 2
Accuracy, Precision, Recall, Geometric mean, and F1-Score results calculated with 100 iterations

Dataset	Classifiers	Statistics	Accuracy	Precision	Recall	Geometric mean	F1-Score
Our collected dataset	Cubic SVM	Maximum	**96.45**	**96.04**	**96.28**	**96.25**	**96.16**
		Minimum	95.78	95.28	95.2	95.16	95.34
		Mean	96.09	95.7	95.82	95.79	95.76
		Standard deviation	0.12	0.16	0.17	0.18	0.15
	Fine KNN	Maximum	**94.11**	**94.09**	**93.83**	**93.75**	**93.92**
		Minimum	93.48	93.11	92.97	92.87	93.04
		Mean	93.82	93.67	93.44	93.33	93.56
		Standard deviation	0.12	0.16	0.17	0.18	0.15

As can be seen in Table 2, a maximum accuracy of 96.45% has been computed with Cubic SVM for our collected dataset. With Fine KNN, accuracy, precision, recall, geometric mean, and F1-Score results have been reckoned as 94.11%, 94.09%, 93.83%, 93.75%, and 93.92% for our collected dataset, respectively. Fold-wise results calculated in the proposed method can be seen in Figure 9.

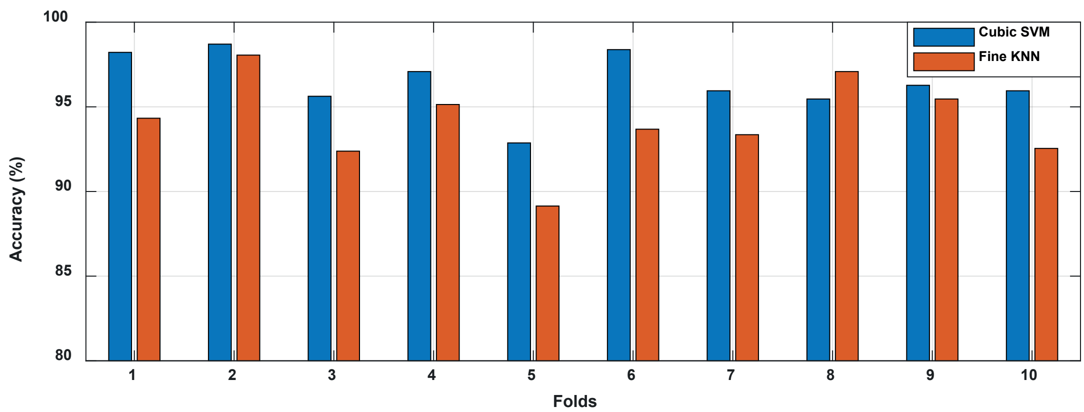

Figure 9. Fold-wise calculated with our collected dataset

The comparison of the proposed method and the literature are summarized in Table 3.

Table 3
Comparison of the proposed method and the literature

Studies	Dataset	Number of species/groups	Method	Accuracy	Precision	Recall	F1-Score
Atila et al. (Atila et al., 2021)	PlantVillage dataset	38	EfficientNet	99.97%	99.39%	-	-
Goyal et al. (Goyal, Kumar, & Gupta, 2021)	Swedish leaf dataset	15	1DPCA+ MTSVM	97.50%	-	-	-
	Flavia dataset	-	1DPCA+ MTSVM	98.15%	-	-	-
	Folio dataset	-	LDA+ MTSVM	89.5%	-	-	-
Selvam et al. (Selvam & Kavitha, 2020)	Self-collected dataset	3	CNN	94%	92%	95%	93%
Murtaza et al. (Murtaza, Saba, Haroon Yousaf, & Viriri, 2020)	Flavia dataset	3	SURF + Bag of Words	98%	-	-	-
	ImageClef dataset	3	SURF + Bag of Words	94%	-	-	-
Adak (Adak, 2020)	Self-collected dataset	43	CNN	87.57%	-	-	-
Saleem et al. (Saleem, Akhtar, Ahmed, & Qureshi, 2019)	Flavia dataset	25	CNN	99.48%	-	-	-
			KNN	98.93%	-	-	-
			Decision Tree	90.65%	-	-	-
			Naïve Bayes	94.5%	-	-	-
			Multi SVM	88.91%	-	-	-
Yacin et al. (Yalcin & Razavi, 2016)	TARBIL dataset	16	CNN	97.47%	-	-	-
			SVM	89.94%	-	-	-
Dyrmann et al. (Dyrmann, Karstoft, & Midtiby, 2016)	BBCH 12e16 dataset	22	CNN	86.2%	-	-	-
Our Methods	Our collected dataset	17	Cubic SVM	96.45%	96.04%	96.28%	96.16%
			Fine KNN	94.11%	94.09%	93.83%	93.92%

To evaluate the performance of the proposed method, feature extraction, training time, test time, and total test time have been computed. The calculated temporal complexity of the method is tabulated in Table 4.

Table 4
The average execution time of the proposed model per the used classifier

Classifiers	Feature extraction	Train time	Test time	Total test time
Cubic SVM	12.09 ms	6.41 ms	20.19 ms	32.28 ms
Fine KNN	12.09 ms	0.38 ms	15.91 ms	28 ms

The execution time of the proposed ultra-lightweight has been calculated for the proposed method in Table 2 and Table 4. It has been observed that a high accuracy has been obtained with SVM and KNN. The time taken for feature extraction and classification from an image (for 1280 × 720 × 3 sized images) has been computed as 32.28ms. 28ms has been reckoned using SVM and KNN respectively. Moreover, the time complexity (using asymptotic notation) of our presented ultra-lightweight model is calculated in Table 5.

Table 5
Time complexity analysis of our proposal

Step	Time complexity (Big O notation)
Layer separation	$O(n)$
Gray level conversion	$O(n)$
Histogram extraction	$O(4n)$
Median filtering	$O(4n)$
Classification using KNN	$O(nd)$
Classification using SVM	$O(nd^3)$
Total complexity using KNN	$O(10n + nd) \cong O(n + nd)$
Total complexity using SVM	$O(10n + nd^3) \cong O(n + nd^3)$

According to Table 5, this model has linear time complexity. Table 4 and 5 proves that our proposal meets the standards of an ultra-lightweight image classification model.

Moreover, these points can be highlighted for this research;

- A novel plant image dataset was acquired using a UAV.

- An ultra-lightweight feature creation method is proposed.

- Per Table 4 and Table 5, our proposal has low time complexity.

- Our ultra-lightweight model has a very simple structure, leading to a wide range of applications by researchers and developers.

- By using the presented ultra-lightweight model and an embedded system, a smart camera can be easily developed for plant species classification.

4. CONCLUSIONS

In this study, an image processing-based ultra-lightweight method is proposed. The proposed method has been developed in the MATLAB program and the results have been calculated. To test the method, 6170 images of 17 plant species have been collected. Features have been created by applying histogram extraction and median filtering functions to these images. For our collected dataset, 96.45% and 94.11% accuracies have been computed with SVM and KNN algorithms, respectively. The time complexity and execution times of our model have also been reckoned and these results show that our model is an ultra-lightweight model.

5. FUTURE WORKS

Classification of plant species and detection of disease in these plants are important for productivity in smart agriculture practices. Growth, disease symptoms, and yields are analyzed by monitoring plants continuously with cameras, thus leading to more efficient production. Real-time and inexpensive real-time implementation of smart agriculture applications is important for its usability. The proposed ultra-lightweight algorithms in future studies will be implemented in embedded systems. Consequently, operations such as automatic recognition of plants, identification of diseased leaves, and spraying will be carried out with cameras and embedded systems on the UAV.

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