STUDENT SESSION

PLANT CLASSIFICATION USING FIREFLY ALGORITHM AND SUPPORT VECTOR MACHINE

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Abstract:

The importance of plants for survival of all living beings as well as the humans' agricultural needs is great as the identification and classification have a key role for their use. Plants are recognized by leaf, flower, or fruit and linked to their suitable cluster. Classification methods are used to isolate and select traits that help identify plants. An automated approach aims to help farmers grow crops easier and better. Computer vision technologies have attracted significant interest in precision agriculture in recent years. This research proposed an approach based on swarm intelligence algorithms and support vector machines to extract features and classify plant images. The nature-inspired firefly algorithm models mating patterns of fireflies, and adapts them to optimization problems for which it excels at resolving. Combined with support vector machines methods, that are often used for solving classification problems with great accuracy, this work proposes a novel approach used to handle plant identification.

Keywords:

SVM, firefly algorithm, plant classification, swarm intelligence, optimization.

INTRODUCTION

Plants play an important and significant role in human life, ecosystem and agriculture. As plants are of great importance for the survival of live, it is a serious task to nurture and cultivate plant. With the advancement of technology and the use of advanced algorithms and proper identification we can help agriculture making decisions such as spraying appropriate fertilizers, irrigation system, and weeding. To address these challenges, the complex, multivariate and unpredictable agricultural ecosystems need to be better understood by monitoring, measuring, and analyzing continuously various physical aspects and phenomena. Images constitute, in many cases, a complete picture of the agricultural environments and could address a variety of challenges. Imaging analysis is an important research area in the agricultural domain and intelligent data analysis techniques are being used for image in various agricultural applications.

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Identification of plants based on leaf image involves feature extraction, classification as well as optimization. In this paper the authors use the firefly algorithm FA for comparison with other algorithms and present the best solution for the use of plants in agriculture.

The process of plant identification includes feature extraction, optimization, and classification. Generally, feature extraction is performed by speed-up robust features (SURF) [1], scale-invariant feature transform (SIFT) [2] among many other approaches. The feature optimization phase is an important step where an individual can deploy an algorithm to select the best feasible set of features. Researches have applied whale optimization algorithm (WOA) [3], bat algorithm (BAT) [4], differential evolution (DE) [5], salp swarm algorithm (SSA) [6], sine cosine algorithm (SCA) [7], and many other swarms and evolutionary algorithms for solving this combinatorial optimization problem. Most of the recent research in the domain of plant identification used artificial neural network (ANN) and support vector machine (SVM) [8], and deep residual networks [9] have been proposed for optimization. This work proposes a novel approach based around SVM [10] as well as a swarm intelligence (SI) algorithm, FA, in an attempt to address classification in an efficient manner.

2. RELATED WORKS AND BACKGROUND

2.1. SUPPORT VECTOR MACHINE

A support vector machine [11] is a computer algorithm that learns by example to assign labels to object. SVMs are becoming popular in a wide variety of biological applications. Because of their relative simplicity and flexibility for addressing a range of classification problems, SVMs distinctively afford balanced predictive performance, even in studies here sample sizes may be limited.

SVM, because of its property of convex optimization, is best suited for finding the global minimum. With the radial basis function being its kernel, it is beneficial for both linearly and nonlinearly separable data and is thus predominantly used in plants recognition. SVM is used to address a binary pattern classification problem.

When we notice a binary classification problem, with a total of l training samples (x_i, y_i), $I = 1,2\ldots, l$; When x_i is part of the first category $yi = 1$, accordingly $y_i = -1$ should x_i be part of the second category. With this in mind a hyperplane dividing these samples across the two categories is defined according to Eq. (1)

$$\omega^T x + b = 0 \tag{1}$$

with ω being the coefficient vector normal to the dividing plane and b representing the origins bias. The linear SVM finds the optimal separating margin by solving the following optimization task according to Eq. (2)

$$\begin{aligned} &Min\left\{\frac{1}{2}|\omega|^2 + C\sum_{i=1}^{l}\varepsilon_i\right. \\ &s.t., y_i\left(\omega^T x_i + b\right) \geq 1 - \varepsilon_i \quad I = 1,2,\ldots,1 \end{aligned} \tag{2}$$

The minimum problem can be reduced by using the Lagrangian multiplier α_i, giving us Eq. (3)

$$\begin{aligned} &Max\left(\sum_{i=1}^{l} a_i - \frac{1}{2}\sum_{i,j=1}^{l} a_i a_j y_i y_j x_i x_j\right) \\ &s.t., \sum_{i=1}^{l} a_i y_i = 0; \quad a_i \geq 0 \end{aligned} \tag{3}$$

The equation can now be solved using the quadratic programming techniques with best values of a begin $a* = \left[a_1^*, a_2^*, \ldots, a_l^8\right]$, and optimal values of w and b being ω* and b* respectfully in Eq. (4)

$$\begin{aligned} &\omega^* = \sum_{i=1}^{l} a_i^* x_i y_i \\ &b^* = -\frac{1}{2}\omega^*\left(x_r + x_s\right) \end{aligned} \tag{4}$$

where x_r and x_s represent a support vector pair of two classes. Finally, a linear discriminant function is attained according to Eq. (5)

$$f(x) = sgn\left(\sum_{i=1}^{l} a_i^* y_i (x_i x) + b\right) \tag{5}$$

The widely used kernel function is the radial basis function (RBF), because of its accurate and reliable performance. This research makes use of the RBF shown in Eq. (6)

$$K(x, x_i) = exp\left(-\gamma \|x - x_i\|^2\right) \tag{6}$$

The γ is the predetermined smoothness parameter that controls the width of the RBF kernel.

2.2. SWARM INTELLIGENCE

Swarm intelligence is the discipline that deals with natural and artificial systems composed of many individuals that coordinate using decentralized control and self-organization. Focus is on the collective behaviors that result from the local interactions of the individuals with each other and with their environment. Examples of systems studied by swarm intelligence are colonies of ants and termites, schools of fish, flocks of birds, herds of land animals.

Some human artifacts also fall into the domain of swarm intelligence, notably some multi-robot systems, and also certain computer programs that are written to tackle optimization and data analysis problems. This is one of the computational intelligence techniques which are used to solve a complex problem. SI involves the collective study of the individual's behavior of population interacts with one another locally. Especially for biological systems nature often act as an inspiration. Simple rules are followed by agents and no centralized control structure exists in order to predict the behavior of individual agents.

Biologists and natural scientists have been studying the behavior of social insects due to their efficiency in solving complex problems such as finding the shortest path between their nests and food source or organizing their nests. In spite of the fact that these insects are unsophisticated individually, they make wonders as a swarm by interacting with each other and their environment. In the last two decades, the behaviors of various swarms that are used in finding prey or mating are simulated into a numerical optimization technique. Some of the popular SI algorithms included Particle Swarm Optimization (PSO), Artificial Bee Colony (ABC), and Ant Colony Optimization (ACO). Swarm intelligence can be described by considering five fundamental principles:

1. Proximate principle: The population should be able to carry out simple space and time computation.
2. Quality principle: The population should be able to respond to quality factors in the environment.
3. Diverse response principle: The population should not commit its activity excessively narrow channels.
4. Stability principle: The population should not change its mode of behavior every time with the environment change.
5. Adaptability change: The population should be able to change its behavior made when it is worth the computational price.

3. PROPOSED METHOD

3.1. ORIGINAL FIREFLY ALGORITHM

The firefly algorithm [12] [13] [14] is a swarm intelligence-based algorithm and has been shown to be effective in solving nonlinear optimization problems, especially multimodal problems where the objective landscape can have many maxima or minima. There are two important issues regarding the firefly algorithm, namely, the variation of light intensity and the formulation of attractiveness. Yang simplifies the attractiveness of a firefly by determining its brightness which in turn is associated with the encoded objective function. The attractiveness is proportional to the brightness. Three basic rules are established for this algorithm:

1. The fireflies are unisex, and each firefly can be attracted to the other firefly.
2. The attractiveness and brightness are proportional, and their values decrease as their distance increases. For a couple of fireflies, the firefly with less brightness moves toward the other firefly; if they both have the same brightness, then their movement will be random.
3. The brightness of a firefly is obtained by the objective function.

The movement of a firefly *i* is attracted to another, more brighter firefly *j* is determined by Eq. (7)

$$x_i^{t+1} = x_i^t + \beta_0 e^{-\gamma r_{ij}^2}\left(x_i - x_j\right) + \alpha\varepsilon_i \tag{7}$$

Where $\beta_0 e^{-\gamma r^2}(x_i - x_j)$ is due to the attraction of the firefly x_j and $\alpha\varepsilon_i$ a randomization parameter; so if $\beta_0=0$ then it turns out to be a simple random movement.

The attractiveness, which is its brightness, *I* of firefly *i* on the firefly *j* is based on the degree of the brightness of the firefly *i* and the distance r_{ij} between the firefly *i* and the firefly *j* as in Eq. (8)

$$I(r) = \frac{I_s}{r^2} \tag{8}$$

Suppose there are *n* fireflies and x_i corresponds to the solution for firefly *i*. The brightness oh the firefly *i*, is associated with the objective function $f(x_i)$. The brightness I of a firefly is chosen to reveal its recent position of its fitness value or objective function $f(x)$ as in Eq. (9)

$$I_i = f\left(x_i\right) \tag{9}$$

The less bright firefly is attracted and moved to the brighter one; and each firefly has a certain attractiveness value β. However, the attractiveness value β is relative based on the distance between fireflies. The attractiveness function of the firefly is shown in Eq. (10)

$$\beta(r) = \beta_0 e^{-\gamma r^2} \tag{10}$$

Where is β_0 is the attractiveness at the distance r=0, and the second term is due to the attraction.

The algorithm compares the attractiveness of the new firefly position with old one. If the new position produces higher attractiveness value, the firefly is moved to the new position. Otherwise, the firefly will remain in the current position. The termination criterion of the FA is based on an arbitrary predefined number of iterations or predefined fitness value. The brightness firefly moves randomly based in Eq. (11)

$$x_i(t+1) = x_i(t) + a\varepsilon_i \tag{11}$$

4. RESEARCH FINDINGS AND ANALYSIS

4.1. DATASET DESCRIPTION

The dataset is used to research and compare the design of the model and testing is procured by Plant Village and Kaggle, the party in order to best compare previous results. This dataset contains over 10000 images, in four subcategories which are called apple, cherry, pepper, and tomato. From each category are used 200 images for training and testing this model. This dataset is used to measure the performance of the proposed method in terms of the accuracy of classification of each class using a leaf image dataset. In order to train the model 70% of available data is used, while the 30% has been utilized for testing.

4.2. PLANT LEAF IMAGE CLASSIFICATION METRICS AND RESULTS

The proposed method has been compared with the methods used for testing and obtaining results with other methods applied for the same problem. In this experiment we used methods SCA, SSA, DE, WOA, and BAT algorithms, original FA was also implemented and validated [15]. Each class has the same number of sets of images to compare with these algorithms. The comparisons can be in seen Table 1. The results are measured by calculating the F1 score, precision, recall, and accuracy.

The best results for the classification of plants will be obtained by using the SVM method with a radial base core (RBF) function, and this core was used in experiments. To validate proposed method, dataset that consists of healthy plants leaves images are used. All images are retrieved from the repository that consists of 61,486 images of healthy and plant leaves with 39 different classes of diseases.

By further analysis, it can be stated that among original metaheuristics, FA, WOA and SCA perform similarly establishing average results, while SSA, BA and DE show worst results.

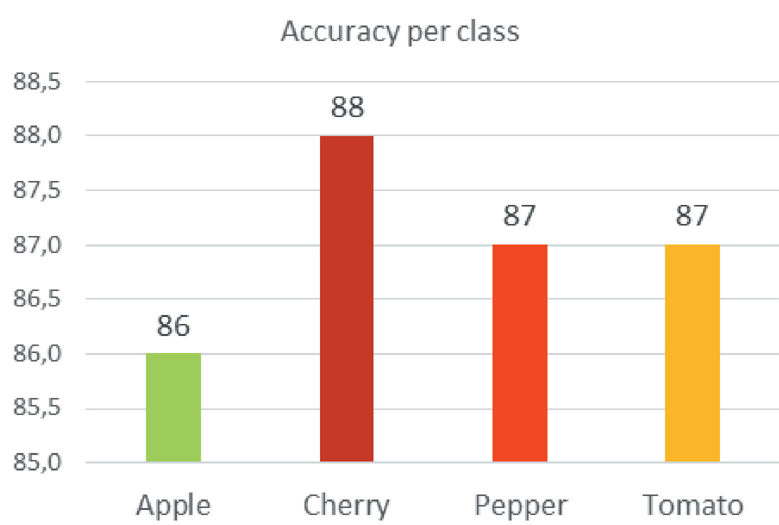

Figure 1 - Accuracy of FA per tested classes.

Algorithm	Accuracy	Plant Leaf Class	n Truth	Precision	Recall	F-measure	Acc. per. class
BAT	69.58%	Apple	125	0.70	0.63	0.66	0.84
		Cherry	134	0.73	0.67	0.70	0.86
		Pepper	156	0.62	0.78	0.69	0.83
		Tomato	142	0.76	0.71	0.73	0.87
DE	65.13%	Apple	98	0.61	0.49	0.54	0.80
		Cherry	136	0.74	0.68	0.70	0.86
		Pepper	132	0.52	0.66	0.58	0.76
		Tomato	155	0.78	0.78	0.78	0.89
SCA	76.41%	Apple	144	0.76	0.72	0.74	0.88
		Cherry	137	0.83	0.69	0.75	0.89
		Pepper	169	0.73	0.85	0.78	0.88
		Tomato	161	0.77	0.81	0.79	0.89
SSA	71.64%	Apple	134	0.72	0.67	0.69	0.85
		Cherry	122	0.75	0.61	0.67	0.85
		Pepper	163	0.67	0.82	0.73	0.85
		Tomato	154	0.74	0.77	0.76	0.87
WOA	75.01%	Apple	148	0.73	0.74	0.73	0.87
		Cherry	151	0.78	0.76	0.79	0.88
		Pepper	158	0.74	0.79	0.76	0.87
		Tomato	143	0.76	0.72	0.74	0.87
MWOA	79.03%	Apple	162	0.73	0.81	0.77	0.88
		Cherry	151	0.87	0.76	0.80	0.91
		Pepper	170	0.73	0.85	0.79	0.89
		Tomato	145	0.84	0.73	0.78	0.90
FA	74.32%	Apple	151	0.72	0.76	0.74	0.86
		Cherry	144	0.78	0.72	0.75	0.88
		Pepper	154	0.73	0.77	0.75	0.87
		Tomato	145	0.75	0.73	0.73	0.87

Table 1 - Performance comparisons of the proposed method and other algorithm

5. CONCLUSION

Using a plant leaf image dataset, this study presents a new plant classification method. This research showcases the best plant classification technique and methods based on FA algorithm. Converging towards the plants with high economic importance ten different plants have been selected for this study. The support vector machine is used for the classification of the leaves. FA is very efficient and can outperform other conventional algorithms based on statistical performances measured using standard stochastic test functions. FA algorithm works based on global communications among the fireflies. The results are evaluated by the obtained accuracy on the utilized plant datasets. The suggested FA-SVM method obtained the best recall, precision, F1 score, and ultimately the overall accuracy of 81.68%, surpassing other algorithms used for comparison, namely BAT, DE, SCA, SSA, WOA and MWOA metaheuristics.

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