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RESEARCH ARTICLE

CLASSIFICATION OF THERAPEUTIC PLANTS OF IVORY COAST BASED ON THE ARTIFICIAL IMMUNE SYSTEM AND WAVELET TRANSFORMATION

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Abstract

Leaf recognition plays an important role in plant classification. Its main problem is whether the selected features are stable and have a good ability to distinguish between different leaf types. In this paper, we propose a new method for plant classification from a set of leaf images based on artificial immune system (AIS) and wavelet transforms. AIS are a type of intelligent algorithm; they imitate the human defense mechanism and they use its principles, to give them the power to be applied as a classifier. Moreover, the wavelet transform offers fascinating features for texture classification. The experimental results show that it is possible to use the artificial immune system and the wavelet transform to recognize the image of the leafy plant, and the recognition accuracy is encouraging.

Introduction:-

Artificial immune systems (AIS) are a relatively new class of metaheuristics that mimic aspects of the human immune system to solve computational problems [1]. They are massively distributed and parallel, highly adaptive and responsive, and scalable where the learning is native. AIS can be defined [5] as the composition of intelligent methodologies, inspired by the natural immune system for solving real-world problems.

Growing interest surrounds these systems due to the fact that natural mechanisms such as recognition, identification and elimination of intruders, which allow the human body to achieve its immunity. AIS suggest new ideas for computational problems. Artificial immune systems consist of a few typical intelligent computational algorithms [2] called immune network theory, clone selection, negative selection and recently danger theory [3].

However, AIS have successful applications which are cited in the literature [1]; the non-self self paradigm, which performs a discriminatory process by tolerating entities of the self and reacting to foreign entities, has been much criticized for many reasons, which will be described in section 2. Therefore, a controversial alternative to this paradigm has been proposed: the theory of danger [4].

The hazard theory offers new perspectives and insights to AIS [6]. It states that the immune system reacts to danger and not to foreign entities. In this context, it is a question of distinguishing the non-self but harmless from the self but the harmful invaders, called: antigen. If the self and non-self labels were to be replaced with interesting and uninteresting data, a distinction would prove beneficial. In this case, AIS is applied as a classifier [6].

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In addition, plant recognition is an important and difficult task [7] due to the lack of suitable models or representation schemes. Compared to other methods, such as cell and molecular biology methods, leaf image-based classification is the first choice for plant classification. Leaf sampling and photoetching is inexpensive and convenient.

Moreover, the leaves can be very easily found and harvested everywhere. By calculating some effective characteristics of leaves and using an appropriate pattern classifier, it is possible to recognize different plants successfully.

Much work has focused on extracting leaf features for plant recognition. We can notably cite [10]. In [7], the authors proposed a plant classification method based on wavelet transforms and support vector machines.

The approach is not the first in this way, as the authors of [8] have previously used support vector machines as a plant recognition approach but using color and texture feature space. In [9], a leaf image recognition method based on shape features using and comparing three classifier approaches was introduced.

In [10], the author proposes a plant classification method based on leaf recognition. Two methods called gray level co-occurrence matrix and principal component analysis algorithms were applied to extract the texture features of the leaves. This article proposes a new approach to classify plant leaves. The classification uses the dendritic cell algorithm of the danger theory and uses the wavelet transform as spatial characteristics.

The wavelet transform [11] provides a powerful tool to capture localized features and gives developments for more flexible and useful representations. Furthermore, it presents a constant analysis of a given signal by projection onto a set of basis functions which are scaled by means of frequency variation. Each wavelet is a scale-shifted version of an original or parent wavelet. These families are generally orthogonal to each other, which is important because it allows for computational efficiency and ease of numerical implementation [7].

The rest of the article is organized as follows. Section 2 contains relevant background information and motivations regarding the immune theory. Section 3 describes the dendritic cell algorithm. In section 4, we define the wavelet transform. Section 5 presents a description of the approach. Section 6 is devoted to experiments. The article ends with a conclusion and future work.

The immune theory

The main purpose of the immune system is to protect our body against invading entities, called antigens, which cause damage and disease. Initially, traditional immune theory considers that protection occurred by distinguishing self and non-self within the body and eliminating the non-self. Incompetent to explain certain phenomena, the discriminating paradigm of the immune system has many shortcomings, such as [3]:

1. There is no immune reaction to foreign bacteria in the intestines or to the food we eat although both are foreign entities.
2. The system does not govern bodily changes, even self changes.
3. On the other hand, there are some helpful autoimmune processes like certain diseases and types of tumors that are fought by the immune system (both attacks on the self) and successful transplants.

Thus, a new area of AIS emerges, dubbed the theory of danger, which offers an alternative to the self-non-discrimination approach. The danger theory states that the immune response is a reaction to a danger and not to a foreign entity. In this sense, the immune system is activated upon receipt of molecular signals, which indicate damage or stress to the body, rather than pattern matching in the no-self paradigm. Moreover, the immune response is in reaction to signals during the intrusion and not by the intrusion itself. These signals can be mainly of two types [3]: safety signal and danger signal. The first indicates that the data to be processed, which represents an antigen in nature, was collected under normal circumstances; while the second signifies potentially anomalous data. The danger theory can be apprehended by: the dendritic cell algorithm (DCA), which will be presented in the next section.

The Dendritic Cell Algorithm

The Dendritic Cell Algorithm (DCA) is a bio-inspired algorithm. It was introduced by Greensmith et al [12] and demonstrated its potential as a classifier for machine learning static data [13], as a simple port scan detector in

offline conditions and in experiments in real time [17]. DCA accomplished the task of classification by correlation, data fusion and filtering [16]. Early implementations of DCA have provided promising classification accuracy results on a number of benchmark datasets. However, the basic DCA uses several stochastic variables which make its systematic analysis and understanding of features very difficult. In order to overcome these problems, an improvement of the DCA has been proposed [17]: the dDCA (deterministic DCA). In this article, we focus on the new version. Its pseudo code can be found in [17]. dDCA is based on a population algorithm in which each agent in the system is represented by a virtual cell, which performs the signal processing and antigen sampling components. Its inputs take two forms, antigens and signals. The former are items that act as a description of the items in the problem domain. These elements will be classified later. While the latter are a set dedicated to monitoring certain informative data features. Signals can be of two types: "safe" and "danger" signal. At each iteration t, the dDCA inputs consist of the values of the safety signal St, the danger signal Dt and the antigens At. The dDCA proceeds in three steps as follows:

a)Initialization
DC population and algorithm parameters are initialized and initial data is collected.

b)Signal processing and update phase
All antigens are presented to the DC population so that each DC agent samples only one antigen and performs signal processing. At each step, each cell i calculates two separate running sums, called $\mathbf{CSM_i}$ and $\mathbf{K_i}$, and places them in its own storage data structure. The CSM and K values can be given by equations (1) and (2) respectively:

$$\mathbf{CSM = St + Dt} \qquad (\mathbf{1})$$
$$\mathbf{K = Dt - 2St} \qquad (\mathbf{2})$$

This process is repeated until all presented antigens have been assigned to the population. At each iteration, incoming antigens undergo the same process. All DCs will process the signals and update their $\mathbf{CSM_i}$and $\mathbf{K_i}$values. If the number of antigens is greater than the number of DCs, only a fraction of the DCs will sample additional antigens. The DCi updates and accumulates the $\mathbf{CSM_i}$and $\mathbf{K_i}$values until a migration threshold Mi is reached. Once the $\mathbf{CSM_i}$is greater than the migration threshold Mi, the cell presents its temporary output $\mathbf{K_i}$as an output entity Kout. For all antigens sampled by DCI during its lifetime, they are labeled as normal if $\mathbf{K_{out}}$<0 and abnormal if $\mathbf{K_{out}}$>0. After saving the results, the $\mathbf{CSM_i}$and $\mathbf{K_i}$values are reset to zero. All sampled antigens are also discarded. DCi then continues to sample signals and collect antigens as before until the stop criterion is met.

Aggregation phase
Finally, in the aggregation step, the nature of the response is determined by measuring the number of cells that are fully mature. In the original DCA, antigen analysis and data context assessment is performed by averaging the mature context antigen (MCAV) value. A representation of fully mature cells can be made. An abnormal MCAV is closer to the value 1. This MCAV value is then thresholded to reach the final binary classification of normal or abnormal. The Kα metric, an alternative metric to MCAV, has been proposed with dDCA in [21]. The Kα uses the average of all Kout output values as the metric for each type of antigen, instead of limiting them to zero in binary tags.

The wavelet transform
In mathematics, a wavelet $\mathbf{\Psi}$ is a summable square function of the Hilbert space $\mathbf{L^2}(\mathbb{R})$, most often oscillating and with zero mean, chosen as a tool for multi-scale analysis and reconstruction. Wavelets are generally found in families, made up of a mother wavelet and the set of its images by the elements of a subgroup $\mathbf{\Lambda}$ of the group of affine transformations of $\mathbb{R}^{\mathbf{n}}$.
We thus define a family $\boldsymbol{\psi_{s,\tau}}$ (where $\mathbf{(s,\tau)} \in \mathbb{R}^{+*} \times \mathbb{R}$) of wavelets from the mother wavelet $\mathbf{\Psi}$:

$$\forall \mathbf{t} \in \mathbb{R}, \qquad \boldsymbol{\psi_{s,\tau}(t)} = \frac{\mathbf{1}}{\sqrt{\mathbf{s}}}\mathbf{\Psi}\left(\frac{\mathbf{t-\tau}}{\mathbf{s}}\right) \qquad (\mathbf{3})$$

By extension, families of functions on submanifolds of $\mathbb{R}^{\boldsymbol{n}}$ invariant by a transformation group locally isomorphic to the affine group can also be qualified as families of wavelets. We distinguish two types of wavelet transforms depending on whether the subgroup Λ is discrete or continuous.

a)Continuous wavelet transform

Analyzing a summable square function in wavelets consists in calculating the set of its scalar products with the wavelets of the family. The numbers obtained are called wavelet coefficients, and the operation associating a function with its wavelet coefficients is called a wavelet transform. We thus define the continuous wavelet transform of a function $\boldsymbol{f} \in \boldsymbol{L^2}(\mathbb{R})$ by:

$$\boldsymbol{g(s,\tau)} = \int_{-\infty}^{+\infty} \boldsymbol{f(t)\psi^*_{s,\tau}(t)dt} \qquad (\mathbf{4})$$

Where $\boldsymbol{\psi^*_{s,\tau}}$ is a is a wavelet of the family of wavelets, ***** designates the conjugate complex, $\boldsymbol{\tau}$ is the translation factor and s the dilation factor.

To recover the original signal $\boldsymbol{f}$, we use the continuous wavelet transform given by:

$$\boldsymbol{f(t)} = \frac{\mathbf{1}}{\boldsymbol{C}} \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \frac{\mathbf{1}}{\boldsymbol{|s|^2}} \boldsymbol{g(s,\tau)\psi_{s,\tau}(t)dsd\tau} \qquad (\mathbf{5})$$

Where

$$\boldsymbol{C} = \int_{-\infty}^{+\infty} \frac{\left|\widehat{\boldsymbol{\Psi}}(\boldsymbol{\omega})\right|^2}{|\boldsymbol{\omega}|} \boldsymbol{d\omega}$$

$\widehat{\boldsymbol{\Psi}}$étantlatransforméedeFourierde$\boldsymbol{\Psi}$,l'ondelettemère.

$\widehat{\boldsymbol{\Psi}}$being the Fourier transform of $\boldsymbol{\Psi}$, the mother wavelet.

b)Discrete wavelet transform

We can adapt the wavelet transform in the case where we are in a discrete set. This technique is used in particular in the compression of digital data with or without loss. The compression is carried out by successive approximations of the initial information from the coarsest to the finest. The size of the information is then reduced by choosing a level of detail.

It is then a question of sampling $\boldsymbol{s}$ on a dyadic scale and $\boldsymbol{\tau}$. We then write:

$$\boldsymbol{\psi_{m,n}[t]} = \boldsymbol{S_0^{-\frac{m}{2}} \psi(S_0^{-m} t - \tau_0)} \qquad (\mathbf{6})$$

Where $\boldsymbol{S_0}$ and $\boldsymbol{\tau_0}$ are constants.

In the case where the $\boldsymbol{\psi_{m,n}}$ form a Hilbert basis of $\boldsymbol{L^2}(\mathbb{R})$ (this is the case for example of the Haar wavelet), the wavelet decomposition of a signal $\boldsymbol{g}$ consists in calculate the scalar products $\langle \boldsymbol{g},\ \boldsymbol{\psi_{m,n}} \rangle$. The recomposition of the signal is then obtained by:

$$\boldsymbol{g} = \sum_{\boldsymbol{m}\in\mathbb{Z}} \sum_{\boldsymbol{n}\in\mathbb{Z}} \langle \boldsymbol{g}, \boldsymbol{\psi_{m,n}} \rangle \boldsymbol{\psi_{m,n}} \qquad (\mathbf{7})$$

During the last decades, the wavelet transform has become a powerful tool for the analysis and decomposition of signals and images at several resolutions. It is used for noise reduction, feature extraction or signal compression.

The wavelet transform proceeds by decomposing a given signal into its scale and space components. Information can be obtained both about the amplitude of any periodic signal as well as when or where it occurred in time or space. Wavelet analysis is thus localized both in time/space and in frequency [11]. The wavelet transform can be defined as the decomposition of a signal $\boldsymbol{g[t]}$ using a series of elementary functions called wavelets and scaling factors equation (7).

In wavelet decomposition, the image is generally segmented into a so-called approximation image and into so-called detail images. The image is divided into a first level of approximation and detail. The first level of approximation is then divided into a second level of approximation and detail.

The transformed coefficients in the approximation and detail sub-images are the essential features, which are equally useful for image classification. A tree wavelet packet transformation can be constructed [11]. Where S denotes the signal, D denotes the detail, and A the approximation, as shown in Figure 1.

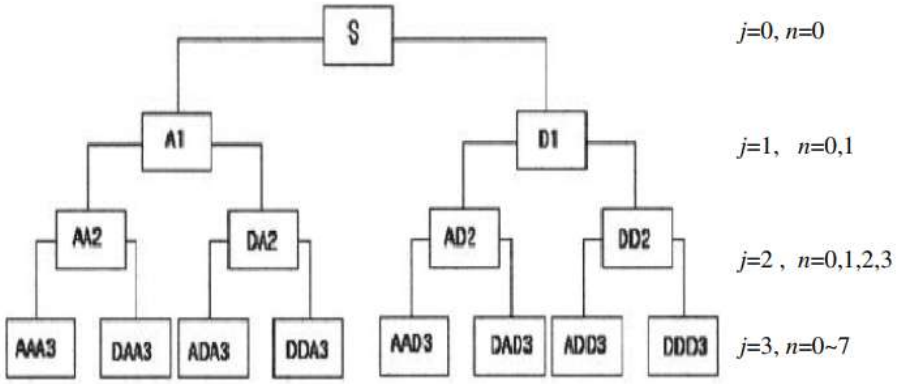

Fig. 1:- The tree wavelet transform.

For a discrete signal, the wavelet packet decomposition coefficients can be computed iteratively by Equation (8):

$$x_{2n,j+1}^{k} = \sum_{l} h_{l-2k} x_{n,j}^{l} \quad ; \quad x_{2n+1,j+1}^{k} = \sum_{l} g_{l-2k} x_{n,j}^{l} \qquad (8)$$

Where $x_{n,j} = \{x_{n,j}^{k}\}$ is the sequence of decomposition coefficients of the n^{th} node at level j of the wavepacket tree.

A method of classifying leaves

An approach based on the artificial immune system must describe two aspects:

1. The projection and models advocating the immune elements in the real world problem.
2. Using the appropriate immune algorithm or approach to solve the problem.

These two aspects are presented in the following sections.

Immune representation using dDCA

For the sake of clarity, before describing the immune representation, we need to represent the feature space. In this article, we consider the decomposition using the wavelet transform in order to obtain the mean energy [11]. It is as follows: Texture images are decomposed using wavelet package transformation. Then, the average approximation energy and the detail sub-image of the two-level decomposed images are calculated as features using the formulas given in (9) as follows:

$$E = \frac{1}{N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} |f(x,y)| \qquad (9)$$

Where: N denotes the size of the sub-image, $f(x,y)$ denotes the value of an image pixel. Now we describe the different elements used by the dDCA for image classification:

Antigens: In AIS, antigens symbolize the problem to be solved. In our approach, the antigens are images of leaves intended to be classified. We consider the average energy of the wavelet transform coefficients as features.

For texture classification, the unknown texture image is decomposed using a wavelet transform and a similar set of average energy features are extracted and compared to the corresponding feature values that are assumed to be known a priori using a distance vector formula, given in equation 10:

$$D(j) = \sum_{i=1}^{N} abs\left[f_i(x) - f_j(j)\right] \qquad (10)$$

Or;$\boldsymbol{f_i(x)}$ represents the characteristics of an unknown texture, while $\boldsymbol{f_j(j)}$ represents the characteristics of a jth known texture. So:
Signals: the input signals correspond to a set of information on a class considered. In this context, we suggest that:
1. Danger Signal: Refers to the distance between an unknown leaf texture and known $\boldsymbol{j}$ texture features.
2. Safety Signal: Refers to the distance between unknown sheet texture features and known texture features.

Lesdeuxsignauxpeuventêtredonnéspar$\boldsymbol{D_{danger}}$et$\boldsymbol{D_{safe}}$commedécritdansl'équation 11 et 12 àlamanièredel'équation (10).
Both signals can be given by $\boldsymbol{D_{danger}}$ and $\boldsymbol{D_{safe}}$ as described in equation 11 and 12 like equation (10)

$$D_{danger} = \sum_{i=1}^{N} abs\left[\boldsymbol{f_i(x)} - \boldsymbol{f_j(j)}\right] \quad (11)$$

$$D_{safe} = \sum_{i=1}^{N} abs\left[\boldsymbol{f_i(x)} - \boldsymbol{f_j(j')}\right] \quad (12)$$

Overview of the proposed approach
In this section, we describe the proposed approach in the context of leaf image classification. The approach works as follows:

Initialization
First, the system is initialized by setting various parameters, such as: Antigen collection and signal input construction. Simultaneously with the collection of the image of the leaves, the signals are gradually built. Known leaf images, selected from a labeled set, are decomposed using wavelet packet transformation. Then, the average approximation energy and the detail sub-image of the two-level decomposed images are calculated as features using the given formulas Eq. (5). Each leaf image (antigen), collected from the leaf image collection, is decomposed using wavelet packet transformation and a similar set of average energy features are extracted (two images labeled randomly selected) and compared to corresponding feature values that are assumed to be known a priori using a distance vector formula, given in equation 6, to construct the hazard $\boldsymbol{D_{danger}}$ and the safety signals $\boldsymbol{D_{safe}}$ as in equation 11 and 12. The two streams are presented to the **dDCA**.

Signal processing and update phase
Data update: we collect the leaf image and we randomly choose two images from a set of labeled images. Next, we evaluate the $\boldsymbol{D_{danger}}$ danger and the safe $\boldsymbol{D_{safe}}$ signals as shown in Eq.11 and 12. Both streams are presented to the **dDCA**. (This process is repeated until the number of frames present at each instant i, is assigned to the entire DC population).

Cell cycle
The DC population is presented by a matrix, in which the rows correspond to the cells. Each cell of line i has a maturation mark $\boldsymbol{CSMi}$ and a temporary release $\boldsymbol{Ki}$. For each cell i, a maturation mark $\boldsymbol{CSMi}$ is evaluated and a cumulative output signal $\boldsymbol{Ki}$ is calculated as follows:

$$\boldsymbol{CSMi = D_{danger}t + D_{safe}t \quad et \quad Ki = D_{danger}t + 2D_{safe}t}$$

When data is present, the cell cycle is continually repeated. Until the maturation mark becomes greater than a migration threshold $\boldsymbol{Mi}$ ($\boldsymbol{CSMi > Mi}$). Then the cell prints a context: Kout, it is removed from the sampling population and its contents are reset after being logged for the aggregation step. Finally, the cell is returned to the sample population. This process is repeated (cycling cells and updating data) until a stopping criterion is satisfied. In our case, until the iteration number is reached.

Aggregation phase
At the end, during the aggregation phase, we analyze the data and we evaluate their contexts. In this work, we only consider the MCAV metric (the mature context antigen value), as it generates a more intuitive output score. We

calculate the mean mature context value (MCAV): the total fraction of mature DCs presenting said leaf image is divided by the total number of times the leaf image has been presented.

Thus, the semi-mature context indicates that the collected sheet is part of the class. While mature context means the collected leaf image is part of another class. More precisely, the MCAV can be evaluated as follows: for all leaf images in the total list, the number of leaf types is incremented. If the leaf image context is equal to one, the number of mature leaves is incremented then, for all leaf types, the MCAV of the leaf type is equal to the number of mature leaves / number of leaves.

Results and Discussion:-

In our approach, the classifier needs more information about the classes in order to give a meaningful indication about the context of the image. For this we used a set of leaf images. Samples usually include different green plants, with simple backgrounds, which involve leaves of different color and texture, with varying lighting conditions. Thus, in order to form signal inputs.

The collection is presented at runtime along with the image to classify. During the experiment, we select 10 types of medicinal plants with 100 leaf images for each plant. The leaf image database is a set of web collections, the list of medicinal plants is shown in Figure 2.

The size of the plant leaf images is 240*240. The following experiments are designed to test the accuracy and efficiency of the proposed method. The experiments are programmed using Matlab. The parameters of the algorithm play an important role in the accuracy of the classification.
Therefore, we considered 100 agent cells in the DC population and 100 iterations as stopping criteria that coincide with the number of leaf images.

The maturation mark is evaluated by $\boldsymbol{CSMi}$. For an unknown texture of a sheet image, if $\boldsymbol{CSMi = D_{danger} + D_{safe} = D_{danger}}$. the unknown textures have a high chance of being classified in the jth texture, if the distance D(j) is minimal among all the textures. Insofar as, if $\boldsymbol{CSMi = D_{danger} + D_{safe} = D_{safe}}$, the unknown texture has a strong chance of being classified in the jth texture, if the distance $\boldsymbol{D(j')}$ is the minimum.

To achieve one-step classification, a migration threshold **Mi** is introduced which can accommodate the data by overlapping the different leaf textures. The migration threshold **Mi** is fixed to one of the input signals. In the sense that if **CSMi** tends towards one of the two signals, it implies that one of the two signals tends towards zero. Thus, we can conclude that the pixel is more likely to belong to one of the signals approaching zero.

N°	Plant denominations		Chromatographicimprints	Ethno-medical uses
1	Botanicalname	AlstoniabooneiDeWild		body aches, intercostal pain, jaundice, cough, sore throat and certain dermatoses.
	Family	Apocynaceae		
2	Botanicalname	BaphianitidaLodd		amenorrhea, diarrhea, jaundice, venereal diseases, sterility, hemorrhoids, chickenpox, hernias, leprosy, eye pain, rheumatism, headache.
	Family	Fabaceae		
3	Botanicalname	Costus afer Ker Gawl		In association with other plants for complex treatments of yellow fever, jaundice, elephantiasis, gonorrhea and eye diseases.
	Family	Costaceae		
4	Botanicalname	Ecliptaprostrata		bleeding from the digestive tract, wounds, jaundice and convulsions in young children.
	Family	Asteraceae		

5	Botanicalname	Elaeis guineensis Jacq		rheumatism, would enter into the composition of the drugs used before and after childbirth.
	Family	Arecaceae		
6	Botanicalname	Heterotisrotundifolia		diabetes in pregnant women, typhoid fever, blood hemorrhages.
	Family	Melastomataceae		

N°	Plant denominations		Chromatographicimprints	Ethno-medical uses
7	Botanicalname	Kalanchoecrenata		Vomiting, intercostal and intestinal pain, blood hemorrhages.
	Family	Crassulaceae		
8	Botanicalname	Mallotusoppositifolius		headaches, feverish body aches, venereal diseases, dysentery, female sterility, leprosy, chickenpox; it would be aphrodisiac and haemostatic.
	Family	Euphorbiaceae		
9	Botanicalname	Monodoramyristica		snakebites, sores, diarrhea, pain affecting the whole body, pain in the kidneys or ribs, or general fatigue, antidotes to poisons
	Family	Annonaceae		
10	Botanicalname	Psidiumguajava L		diarrhea, sore throat, dental pain, vomiting, blood pressure, cardiovascular disease, diabetes, cough, cold, scurvy and high blood pressure
	Family	Myrtaceae		

Fig. 2:- Sample images used in testing [18-20].

In order to evaluate the membership of pixels to a class, we evaluate the metric MCAV. Each leaf image receives an MCAV coefficient value which can be compared to a threshold. In our case, the threshold is set at 0.90. Once a threshold is applied, it is then possible to classify the sheet. Therefore, relevant true and false positive rates can be reported. We can conclude from the results that the system gave encouraging results for both classes of plant and soil inputs. The use of the wavelet transform to evaluate the texture features improves the performance of our system and gives a recognition accuracy of 85%.

Conclusion and future work:-

In this paper, we proposed a classification approach for leaf recognition of medicinal plants based on the danger theory of artificial immune systems. The features of the leafy plant are extracted and processed by wavelet transforms to form the input of the dDCA. We presented our preliminary results thus obtained. The experimental results indicate that our algorithm is feasible with a recognition rate greater than 85% on 10 types of medicinal plant leaf images. However, we recognize that the proposed method should be compared to another approach in order to assess its quality.

To improve it, we will further investigate the potential influence of other parameters and we will use alternative information signals to measure the correlation and representation space. Wewillalsoconsiderleafshapesalongsideleaf textures.

Références:-

[1]	DeCastro,L.,Timmis,J.(eds.):ArtificialImmuneSystems:ANewComputationalApproach.Springer,London(2002)
[2]	Hart,E.,Timmis,J.I.:ApplicationAreasofAIS:ThePast,ThePresentandTheFuture.In:Jacob,C.,Pilat,M.L.,Bentley,P.J.,Timmis,J.I.(eds.)ICARIS2005.LNCS,vol.3627,pp.483–497.Springer,Heidelberg(2005)
[3]	Aickelin,U.,Bentley,P.J.,Cayzer,S.,Kim,J.,McLeod,J.:Dangertheory:ThelinkbetweenAISandIDS?In:Timmis,J.,Bentley,P.J.,Hart,E.(eds.)ICARIS2003.LNCS,vol.2787,pp.147–155.Springer,Heidelberg(2003)
[4]	Aickelin,U.,Cayzer,S.:Thedangertheoryanditsapplicationtoartificialimmunesystems.In:The1thInternationalConferenceonArtificialImmuneSystems(ICARIS2002),Canterbury,UK,pp.141–148(2002)
[5]	Dasgupta,D.:ArtificialImmuneSystemsandtheirapplications.Springer,Heidelberg(1999)
[6]	Greensmith,J.:TheDendriticCellAlgorithm.UniversityofNottingham(2007)
[7]	Liu,J.,Zhang,S.,Deng,S.:AMethodofPlantClassificationBasedonWaveletTransformsandSupportVectorMachines.In:Huang,D.-S.,Jo,K.-H.,Lee,H.-H.,Kang,H.-J.,Bevilacqua,V.(eds.)ICIC2009.LNCS,vol.5754,pp.253–260.Springer,Heidelberg(2009)
[8]	Man,Q.-K.,Zheng,C.-H.,Wang,X.-F.,Lin,F.-Y.:RecognitionofPlantLeavesUsingSupportVectorMachine.In:Huang,D.-S.,etal.(eds.)ICIC2008.CCIS,vol.15,pp.192–199.Springer,Heidelberg(2008)
[9]	Singh,K.,Gupta,I.,Gupta,S.:SVM-BDTPNNandFourierMomentTechniqueforClassificationofLeafShape.InternationalJournalofSignalProcessing,ImageProcessingandPatternRecognition3(4)(December2010)
[10]	Ehsanirad,A.:PlantClassificationBasedonLeafRecognition.InternationalJournalofComputerScienceandInformationSecurity8(4)(July2010)
[11]	Zhang,Y.,He,X.-J.,Huang,J.-H.H.D.S.,Zhang,X.-P.,Huang,G.-B.:TextureFeatureBasedImageClassificationUsingWaveletPackageTransform.In:Huang,D.-S.,Zhang,X.-P.,Huang,G.-B.(eds.)ICIC2005.LNCS,vol.3644,pp.165–173.Springer,Heidelberg(2005)
[12]	Greensmith,J.,Aickelin,U.,Cayzer,S.:IntroducingDendriticCellsasaNovelImmuneInspiredAlgorithmforAnomaly Detection.In:Jacob,C.,Pilat,M.L.,Bentley,P.J.,Timmis,J.I.(eds.)ICARIS2005.LNCS,vol.3627,pp.153–167.Springer,Heidelberg(2005)
[13]	Oates,R.,Greensmith,J.,Aickelin,U.,Garibaldi,J.,Kendall,G.:TheApplicationofaDendriticCellAlgorithmtoaRoboticClassifier.In:The6thInternationalConferenceonArtificialImmune(ICARIS2006),pp.204–215(2007)
[14]	Greensmith,J.,Twycross,J.,Aickelin,U.:DendriticCellsforAnomalyDetection.In:IEEEWorldCongressonComputationalIntelligence,Vancouver,Canada,pp.664–671(2006b)
[15]	Greensmith,J.,Twycross,J.,Aickelin,U.:Dendriticcellsforanomalydetection.In:IEEECongressonEvolutionaryComputation(2006)
[16]	Greensmith,J.,Aickelin,U.,Tedesco,G.:InformationFusionforAnomalyDetectionwiththeDendriticCellAlgorithm. JournalInformationFusion11(1)(January2010)
[17]	Greensmith,J.,Aickelin,U.:Thedeterministicdendriticcellalgorithm.In:Bentley,P.J.,Lee,D.,Jung,S.(eds.)ICARIS2008.LNCS,vol.5132,pp.291–302.Springer,Heidelberg(2008)
[18]	A.Bouquet,lm.Debray:PlantesmédicinalesdelaCôted'Ivoire,O.R.S.T.O.M.PARIS(1974)
[19]	J.Kerhao,A.Bouquet:PlantesmédicinalesettoxiquesdelaCôted'Ivoire–HauteVolta,Missiond'étudedelaPhannacopéeindigèneenA.O.F.(1950)
[20]	K.N'Guessan,E.KouassiKonan,M.S.Tiébré:Plantesutiliséesdansletraitementdestroublesgynéco-obstétriquesparlespeuplesAbbeyetKroboud'Agboville(Côted'Ivoire),Laboratoiredebotanique,UFRbiosciences,universite´deCocody,22,BP582Abidjan22,Côted'Ivoire(2009)