Adaptive Elitist Differential Evolution Extreme Learning Machines on Big Data: Intelligent Recognition of Invasive Species

Konstantinos Demertzis(✉) and Lazaros Iliadis

Lab of Forest-Environmental Informatics and Computational Intelligence,
Democritus University of Thrace, 193 Pandazidoust., 68200 N Orestiada, Greece
{kdemertz, liliadis}@fmenr.duth.gr

Abstract. One of the direct consequences of climate change lies in the spread of invasive species, which constitute a serious and rapidly worsening threat to ecology, preservation of natural biodiversity and protection of flora and fauna. It can even be a potential threat to the health of humans. These species, do not appear to have serious morphological variations, despite their strong biological differences. Due to this fact their identification process is often quite difficult. The need to protect the environment and safeguard public health, requires the development of advanced methods for early and accurate identification of some particularly dangerous invasive species, in order to plan and apply specific and effective management measures. The aim of this study is to create an advanced computer vision system for the automatic recognition of invasive or other unknown species, based on their phenotypes. More specifically, this research proposes an innovative and very effective Extreme Learning Machine (ELM) model, which is optimized by the Adaptive Elitist Differential Evolution algorithm (AEDE). The AEDE is an improved version of the differential evolution (DE) algorithm and it is proper for big data resolution. Feature selection is done by using deep learning Convolutional Neural Networks. A Geo Location system is used to detect the invasive species by Comparing with the local species of the region under research.

Keywords: Big data · Invasive species · Adaptive Elitist Differential Evolution · Extreme Learning Machine · Machine vision · Convolutional Neural Networks

1 Introduction

1.1 Invasive Species

The potential impacts of climate change are evident at various levels of biological organization and especially in disorders found in Biodiversity, in changes done in the level of biocoenosis and in the extinction of organisms with the simultaneous appearance of invasive species [1]. Invasive species are the ones that enter into new unfamiliar habitats, they overwhelm native flora or fauna and they damage the environment. Their impacts are considered as extremely serious. The consequences are related to human health, agriculture, fisheries and food production. The usual reason for

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moving is searching for colder climate conditions. A typical reason is the fact that their physical environment does not meet the temperature range in which they can survive. Also they follow different plant species or organisms which migrate to cooler habitats. Although not all migrating species are harmful, the preparation of proper invasive species management plans (depending on their risk profile) is imposed preemptively and also institutionally. Their control and potential eradication should be a parallel process with the restoration of ecosystems affected by them.

The identification and classification of the invasive species, exclusively with the use of phenotypic markers, is an extremely difficult and dangerous process, as in this case there might be neither major morphological differences nor significant similarities capable of reflecting the affinity or not of the organisms (species problem) [2]. However, it is a necessary and an extremely important process in the overall strategy to address alien species. Specifically, the above method is a key preventive mechanism, as it can be used easily in low cost devices e.g. Smart phones without significant expenses, unlike the genetic methods of identification, like DNA barcoding, or methods using comparison with biochemical or molecular markers [3]. Moreover, it can be used by personnel without specialized knowledge, such as farmers or breeders.

1.2 Machine Vision and Big Data

Machine vision [4] is a scientific field of artificial intelligence which algorithmically attempts to reproduce the sense of sight. It is associated with the theoretical background and the design-manufacturing technologies of data analysis systems when data is derived from digital images, video, views from multiple cameras, multi-dimensional shapes and others. In machine vision there is a high probability of information loss, especially when converting from two to three dimensions, which is due to the transformation of the image perspective. Also, the brightness is given by the natural formation of the image, which is quite complicated. This fact makes its representation a quite complex and laborious process [5].

Some other important peculiarities to be taken into account when designing the algorithmic approach to machine vision systems are related to the change of angle, the variation of the optical scale of the objects, the deformation, the intracategorical variance of the displayed objects and the possibility of noise being [6]. Thus, the results obtained from the analysis of an image with different scenes and geometrical properties, but with different lighting conditions or with similar colors could result in misleading the system and towards incorrect categorizations.

Under this light, this is a case of big data processing, as data extracted from images require large storage space (especially if the images are in high resolution) and they should be solved by a deterministic polynomial time automaton [7]. They also require dynamic assigning of computing resources and coordination of complex data analysis procedures.

1.3 Literature Review

The authors in [8] presented a computer vision-based system that reliably classifies different fish species based on length measurement and weight determination. In [9], an ANN-based platform for fish species identification is presented that uses several statistical methods such as discriminate function analysis and principal component analysis. Rova et al. in [10] applied SVM algorithm to fish recognition and constructed a texture-based mechanism that distinguishes between the Striped Trumpeter and the Western Butterfish species. Lee et al. in [11] carried out shape analysis of fish and developed an algorithm for removing edge noise and redundant data point base on nine species with similar shape features. Also in [12] a SVM-based technique for the elimination of the limitations of some existing techniques and improved classification of fish species is proposed. In [13], an ANN and Decision Tree-based platform for fish classification based on feature selection, image segmentation and geometrical parameter techniques is presented. On the other hand, to find the near optimal network parameters of ELM, several methods have been proposed [14–18]. Also, many scholars have combined ELM with other intelligent optimization algorithms, such as particle swarm optimization (PSO) [19], differential evolution (DE) [20], cuckoo search (CS) [21], firefly algorithm (FA) [22], Grey Wolf optimizer (GSO) [23], harmony search (HS) [24], biogeography-based optimization (BBO) [25], animal migration optimization (AMO) [26], gravitational search algorithm [27], ant colony optimization [28] and interior search [29].

1.4 Innovation of the Project

An innovative element of this work is the development of a hybrid model that employs Extreme Learning Machines combined with the optimization Adaptive Elitist Differential Evolution algorithm (AEDE) [30] aiming in the optimal selection of the input layer weights and the bias. This is done in order to achieve a higher level of generalization. Another interesting point is the performance of feature extraction using Convolutional Neural Networks (CNN) [31] (ELM classifier) and the optimization with the AEDE approach. This hybrid method combines two highly effective, biologically inspired, machine learning algorithms, for solving a multidimensional and complex machine vision problem. Another important issue that supports the autonomous operation of the system is the addition of geolocation capability (using global position systems) of the identified species and the performance of comparisons with native ones. The system is pouring artificial intelligence to digital cameras that can easily (quickly and at low cost) identify invasive or rare species on the basis of their phenotypes. This would result in strengthening biosecurity programs.

2 Materials and Methods

2.1 Data

The fish image data set [32] (currently consisting of 3,961 images) is related to 469 species. This data consists of real-world images of fish captured in conditions defined as “controlled”, “out-of-the-water” and “in-situ”. The “controlled”, images consist of fish specimens, with their fins spread, taken against a constant background with controlled illumination. The “in-situ” ones are underwater images of fish in their natural habitat and so there is no control over background or illumination. The “out-of-the-water” are related to fish specimens, taken out of the water with a varying background and limited control over the illumination conditions. A tight red bounding box is annotated around the fish. Sketch images are not used in this paper. There are two main difficulties when performing classification on the fish imagery.

In many cases, different species are visually similar, as shown Fig. 1(a)–(d). Also many times, there is a high degree of variability in the image quality and environmental conditions (see Fig. 2). Approximately half of the images have been captured in the “controlled” condition, where the image of the fish has been captured out-of-the-water with a controlled back-ground. The “in-situ” condition consists of images taken underwater with no control over the background and with significant pose and illumination variations. Approximately one third of the data was captured in this manner. Finally, the remaining images are captured “out-of-the-water”, but without a controlled background and may contain some minor pose variation [32].

Fig. 1. Example images of four different fish species. All of them have similar visual appearance despite being distinct species. (Images taken by J.E. Randall) [30]

2.2 The Curse of Dimensionality and Feature Simplification

Convolution Neural Networks are a case of Feed Forward Neural Networks (FFNN). Their particularity lies in the neuronal levels preceding the FFNN which are viewed as filters in particular subsets of the available data. The neuronal levels commonly used in CNN networks are divided into the following main categories namely: Convolutional Layers (CL), Max-Pooling Layers (MaxPL), Feed Forward Layer (FFL) [31]. In the Machine Vision applications of Deep Learning architectures, the input parameters are the pixels. Each pixel is considered as a distinct feature. The classification by this method is too complex, since assuming a 200 × 200-pixel image it actually contains 40,000 pixels which correspond to the input data features. In this case 40,000 neurons are required to form a fully connected topology. The final result is the employment of 1,600,000,000 parameters. It is obvious that the computational cost with the described architecture is huge and that the application of an effective feature simplification method would offer invaluable services.

A CNN model is commonly applied in Machine Vision cases for this purpose. In this research effort, CNN has been employed as a method of feature simplification [31] and the extracted data have been fed in the input layer in standard machine learning systems.

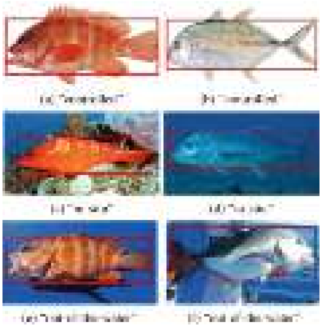

Fig. 2. The three different capture conditions: “controlled”, “in-situ” and “out-of-the-water”. Significant variation in appearance due to the changed imaging conditions (session variation) is evident. Ground truth bounding boxes are shown in red [32].

The dimensions of the pictures used in this research were 81 × 42 and 96 filters were applied (feature map). The picture was divided in frames of 9 × 7 pixels (in order to avoid the frame of 1 × 1 pixels that would lead to an intangible to handle feature vector. To perform feature extraction, the following procedure was used:

The dimensions of the convolution layer were 81 × 42 × 96 which means that it contained 81 × 42 = 3402 neurons for each one of the 96 used filters, which leads to a total number of neurons equal to 81 × 42 × 96 = 326,592. Each one of these neurons had 9 × 7 × 3 + 1 = 190 weights plus a bias, (the number 3 is used due to the RGB color model used that requires 1 channel for each color), which gives a total number of 326,592 × 190 = 62,052,480 weights and biases values which corresponds to an intangible number of input data to be analyzed.

In order to avoid this huge problem, we accepted that the neurons belonging to the same filter were assigned the same weights. This means that a filter with 3402 neurons can have only 190 weights instead of 3402 × 190 = 646,380. In this way the weights plus bias were reduced significantly to 96 × (9 × 7 × 3 + 1) = 18,240. This assumption is not arbitrary but it is based on the logical statement that the application of a filter can have useful results (obtained characteristics) regardless the position in which it may be applied [33, 34].

A determining factor for delivering high precision and low uncertainty in machine vision metrology is the resolution of the acquired image. As a gauge, the smallest unit of measurement in a machine vision system is the single pixel. As with any measurement system, in order to make a repeatable and reliable measurement one must use a gauge where the smallest measurement unit (as a general rule of thumb) is one tenth of the required measurement tolerance band [6].

3 The Proposed Algorithm

3.1 Extreme Learning Machines (ELM)

Extreme Learning Machines are a kind of the Single-Hidden-Layer feed forward Neural Networks (SLFNs). ELMs are characterized by the possibility to establish the parameters of hidden nodes at random, before they see the training data vectors. They are extremely fast and effective and they are capable of handling a wide range of activation functions (e.g. stopping criterion, learning rate and learning epochs [35]. The output of an ELM with a training set $\{(x_i, t_i)\}_{i=1}^{N}$ consisting of N discrete samples $(x_i \in R^n \, and \, t_i \in R^m)$ with an activation function $g(x)$ and l hidden nodes is given by the following function 1 [35]:

$$t_i = \sum\nolimits_{j=1}^{l} \beta_j g\left(\omega_j x_i + b_j\right), i = 1, 2, \ldots, N, \tag{1}$$

Where $\beta_j = \left[\beta_{j1}, \beta_{j2}, \ldots, \beta_{jm}\right]^T$ is the weight vector connecting the output neurons and the *j-th* hidden neuron, $\omega_j = \left[\omega_{j1}, \omega_{j2}, \ldots, \omega_{jm}\right]^T$ is the weight vector connecting the input neurons and the *j-th* hidden neuron, b_j is the bias of the *j-th* hidden neuron, and $\omega_j . x_i$ indicates the inner product of ω_j and x_i. Function 1 can also be written as follows:

$$H\beta = T, \tag{2}$$

where

$$H\left(\omega_j, b_j, x_i\right) = \begin{bmatrix} g(\omega_1 x_1 + b_1) & \cdots & g(\omega_l x_1 + b_l) \\ \vdots & \ddots & \vdots \\ g(\omega_1 x_N + b_1) & \cdots & g(\omega_l x_N + b_l) \end{bmatrix}_{N \times l}, \tag{3}$$

Also H is called the hidden layer output matrix of the network. Before training, the input weights matrix ω and the hidden biases vector b are created randomly in the interval [−1, 1], where $\omega_j = \left[\omega_{j1}, \omega_{j2}, \ldots, \omega_{jm}\right]^T$ and $\beta_j = \left[\beta_{j1}, \beta_{j2}, \ldots, \beta_{jm}\right]^T$.

Then the hidden layer output matrix H is calculated by the activation function and by using the training set based on the function $H = g(\omega x + b)$.

Finally, the output weights matrix β is estimated by the equation $\beta = H^+ T$, where H^+ is the Moore–Penrose generalized inverse of matrix H and $T = [t_1, t_2, \ldots, t_N]^T$ [35].

3.2 Adaptive Elitist Differential Evolution (AEDE)

In evolutionary computation, Differential Evolution (DE) [36] is a method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. In the DE, the parameters such as mutant factor F and crossover control parameter CR and trial vector generation strategies have significant influence on its performance. To overcome the common limitations of optimization algorithms such as the use of a huge volume of resources (e.g. high computational cost) the Adaptive Elitist Differential Evolution algorithm (AEDE) [30] introduces two alternatives. The first one is applied in the mutation phase and the second one in the selection phase, in order to enhance the search capability as well as the convergence speed of the DE algorithm. The new adaptive mutation scheme of the DE uses two mutation operators. The first one is the "rand/1" which aims to ensure diversity of the population and prohibits the population from getting stuck in a local optimum. The second is the "current-to-best/1" which aims to accelerate convergence speed of the population by guiding the population toward the best individual. On the other hand, the new selection mechanism is performed as follows: Firstly, the children population *C* consisting of trial vectors is combined with the parent population *P* of target vectors to create a combined population *Q*. Then, *NP* best individuals are chosen from the *Q* to construct the population for the next generation. In this way, the best individuals of the whole population are always stored for the next generation. This helps the algorithm to obtain a better convergence rate [30]. The elitist selection operator is presented in the following Algorithm 1.

[redacted]

The AEDE method is summarily shown as in Algorithm 2 below [30]:
where *tolerance* is the allowed error; *MaxIter* is the maximum number of iterations; and randint(1, D) is the function which returns a uniformly distributed random integer number between 1 and D.

3.3 Adaptive Elitist Differential Evolution ELM (AEDE-ELM)

Given that ELMs produce the initial weights (weights) and (bias) randomly, the process may not reach the optimal result, which may not imply as high classification accuracy as the desired one. The optimal choice of weights and bias, create the conditions for maximum potential accuracy and of course the best generalization performance of the ELMs. To solve the above problem, we recommend the use of the AEDE optimization method for the optimal selection of weights and bias of the ELMs. Initially, each individual in the first generation is obtained randomly, and it is composed of the input weights and hidden biases: $x = [\omega_1, \omega_2, \ldots, \omega_l, b_1, b_2, \ldots, b_l]$.

Secondly, the corresponding output weights matrix for each individual is calculated in the manner of the ELM algorithm. Then, we apply AEDE to find the fitness for each individual in the population. Finally, when the evolution is over, we can use the optimal parameters of the ELM to perform the classification.

The procedure of AEDE-ELM algorithm is shown by Algorithm 3.

Algorithm 2. The adaptive elitist Differential Evolution (aeDE) algorithm [30]

Generate the initial population
Evaluate the fitness for each individual in the population
//Definition of searching criteria
while delta > tolerance or *MaxIter* is not reached **do**
//Find the best individuals
for i =1 to *NP* **do**
//Generate the initial mutation factor
    F = rand[0.4, 1]
//Generate the initial crossover control parameter
    CR = rand[0.7, 1]
//Select a random integer number between 1 and D
    j_{rand} = randint(1, D)
//Find the optimal parameters
    for j =1 **to** D **do**
//Check the crossover operation
    if rand[0, 1] < CR or j == j_{rand} **then**
//Check the mutation
    if delta > threshold **then**
//Select the optimal parameters
        Select randomly r1 ≠r2 ≠r3 ≠i;
        $\forall i \in \{1, \ldots, NP\}$
        $u_{ij} = x_{r1j} + F \times (x_{r2j} - x_{r3j})$
    else
        Select randomly r1 ≠r2 ≠best ≠i;
        $\forall i \in \{1, \ldots, NP\}$
        $u_{ij} = x_{ij} + F \times (x_{bestj} - x_{ij}) + F \times (x_{r2j} - x_{r3j})$
    end if
    else
        $u_{ij} = x_{ij}$
    end if
    end for
Evaluate the trial vector $\mathbf{u_i}$
end for
Do selection phase based on **Algorithm 1**
Define f_{best}, f_{mean}
delta = $\left|\frac{f_{best}}{f_{mean}-1}\right|$
end while

3.4 GPS Country Location

The Global Positioning System (GPS) can locate stationary or moving users, based on a "grid" of 24 Earth satellites equipped with special tracking devices, called "GPS transceivers". These transceivers are providing accurate coordinates for the position of a point (Longitude - Latitude). For the accurate determination of the country to which the coordinates (reported by a GPS device) belong, the system follows a process which considers the global borders of the countries as they originally appear in the shapefiles which are free available online at the following link: http://thematicmapping.org/downloads/world_borders.php. In the following script example, the shapefile is imported through the Python platform and the coordinates 39.35230, 24.41232 belonging to Greece are checked [37]:

```
import countries
    cc = countries.CountryChecker('TM_WORLD_BORDERS-0.3.shp')
    print cc.getCountry(countries.Point(39.35230, 24.41232)).iso
print Greece
```

Algorithm 3. aeDE-ELM algorithm

Input:
Training set, testing set;
aeDE algorithm parameters, *NP*;

1: Create a random initial population;
2: Evaluate the fitness for each individual with training set;
3: **while** (stopping criteria not met) **do**
4: Randomly generate F_i and CR_i
5: **for** i=1 to NP **do**
6: Call the **Algorithm 2**;
7: Use the optimal parameters of ELM;
8: **end for**
9: **end while**
10: Evaluate the optimized model by testing set;
Output:
Classification result;

4 Algorithmic Steps of the Proposed Hybrid Approach

The algorithmic approach of the proposed hybrid scheme includes (in the first stage) the feature extraction process using CNN, in order to extract features from each photo of the fish dataset. In the second stage, these features are introduced in the proposed ELM, which is optimized by the AEDE approach, to yield the maximum classification accuracy in order to identify the type of fish detected by the machine vision system. Having identified the type, the coordinates are obtained by the GPS and they are mapped to the country where they belong. Then a crosscheck is made to find out whether the type identified is indigenous in this country, or otherwise it is labeled as invasive species. The lists of indigenous and invasive species were exported from the Invasive Species Compendium (http://www.cabi.org/isc/) [38], the most authoritative and comprehensive database on the subject that exists worldwide. The algorithm for identifying as invasive species a species is presented below (Fig. 3):

Algorithm 4. Geolocation Process

Input:
Recognized_Fish;
Country;
Country_Native_Fishes;
1: Read Recognized_Fish, Country, Country_Native_Fishes;
2: **for** i=1 to Country_Native_Fishes [max]**do**
3: **if** Country_Native_Fishes[i]= Recognized_Fish **then**
4: Recognized Fish=! Recognized Fish;
5: Recognized Fish=Native_Fish
6: **else**
7: Recognized Fish=Invasive_Fish
8: **end if**
9: **end**
Output:
Fish Identity;

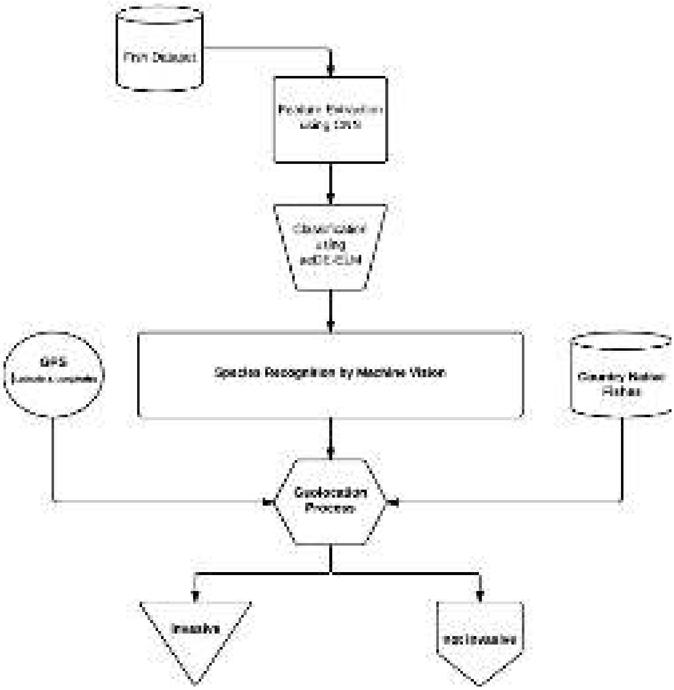

Fig. 3. The proposed architecture of the proposed machine vision system

5 Results and Comparative Analysis

It is extremely comforting and hopeful, the fact that the proposed hybrid system manages to solve a particularly complex computer vision problem with high accuracy, regardless the fact that the dataset used for training and evaluation of the proposed AEDE-ELM is highly complex, given the similarity between the species tested and the specificities resulting from the feature extraction process using CNN. It is also characteristic that in the process of categorization of the species tested, the accuracy rate in all cases ("controlled", "in-situ", "out-of-the-water") was very high. This fact suggests and confirms the generalization capabilities of the proposed system.

The following Table 1, presents the analytical values of the predictive power of the AEDE-ELM by using a 10 Fold Cross Validation approach (10-FoldCV) and the corresponding results when competitive algorithms were used, namely: Differential Evolution ELM (DE-ELM), Artificial Neural Network (ANN) and Support Vector Machine (SVM).

The Precision measure shows what percentage of positive predictions where correct, whereas Recall measures what percentage of positive events were correctly predicted. The F-Score can be interpreted as a weighted average of the precision and recall. Therefore, this score takes both false positives and false negatives into account. Intuitively it is not as easy to understand as accuracy, but F-Score is usually more useful than accuracy and it works best if false positives and false negatives have similar

Table 1. Performance metrics and comparisons

Classifier	Classification accuracy (ACC) & Performance metrics						
	ACC	RMSE	Precision	Recall	F-Score	ROC	Evaluation
AEDE-ELM	**94.81 %**	**0.1673**	**0.948 %**	**0.948**	**0.949 %**	**0.985**	**10-Fold CV**
DE-ELM	93.97 %	0.1711	0.940 %	0.940	0.940 %	0.985	10-Fold CV
ELM	93.13 %	0.1726	0.932 %	0.932	0.932 %	0.982	10-Fold CV
ANN	92.89 %	0.1804	0.930 %	0.929	0.929 %	0.978	10-Fold CV
SVM	91.35 %	0.2031	0.914 %	0.914	0.914 %	0.960	10-Fold CV

Table 2. Performance metrics and comparisons of "Lagocephalus Sceleratus"

Classifier	Classification accuracy (ACC) & Performance metrics						
	ACC	RMSE	Precision	Recall	F-Score	ROC	Evaluation
AEDE-ELM	**97.52 %**	**0.1247**	**0.972 %**	**0.972**	**0.972 %**	**0.993**	**10-Fold CV**
DE-ELM	97.01 %	0.1289	0.970 %	0.970	0.971 %	0.990	10-Fold CV
ELM	95.86 %	0.1461	0.960 %	0.958	0.959 %	0.965	10-Fold CV
ANN	95.70 %	0.1482	0.957 %	0.957	0.957 %	0.957	10-Fold CV
SVM	95.62 %	0.1502	0.956 %	0.956	0.957 %	0.957	10-Fold CV

cost, in this case. Finally, the ROC curve is related in a direct and natural way to cost/benefit analysis of diagnostic decision making. This comparison generates encouraging expectations for the identification of the AEDE-ELM as a robust classification model suitable for difficult problems. This method was tested with great success in the control and automatic recognition of the highly dangerous for the public health Mediterranean invasive species fish "Lagocephalus Sceleratus" (Table 2).

6 Discussion and Conclusions

An innovative biologically inspired hybrid computational intelligence approach suitable for big data was presented in this research paper. It is a machine vision system which can recognize various fish species in order to rank them as to whether they are invasive in the region identified or not. Specifically, the hybrid and innovative AEDE-ELM algorithm was suggested which uses the innovative and highly effective algorithm AEDE in order to optimize the operating parameters of an ELM. The CNN feature extraction method was also used for the training of the model. The system can operate in an autonomous mode, because it estimates the geolocation of the species and it decides if it can be considered local or invasive. The wide application of the proposed method which simplifies and reduces to a minimum the computation cost and the identification time and the wide collection of respective data vectors are prerequisites for the establishment of an effective management and risk prevention system.

A future extension would be the use and incorporation to the system, of other methods for similar characteristics determination like: Representational Similarity Analysis, Local Similarity Analysis, Isoperimetry and Gaussian Analysis. Finally, it would be very important to use and test the performance of the Deep Extreme Learning Machines technology for this specific case.

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