Neural Network-Based Approach For Insect Classification In Cotton Ecosystems

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Abstract: Cotton is the single agricultural commodity that uses the highest percentage of pesticides used globally. Concerns for environmental pollution has lead to a new trend in combating insects in agricultural ecosystems, namely, Biological Control. This paper describes a computer-vision-based system to recognize and classify insects as being harmful and non-harmful to the growth of cotton. Recognition is based upon a neural network approach to classifying insects. We speculate that in the future, field-deployable systems would allow farmers to identify the type of insects that inhabit specific ecosystems, and choose among the most efficient mix of biological and/or pesticide control.
Key words: Image processing, Artificial Neural Networks, Feature extraction, Pattern recognition, Insect classification, Soft Computing.

1. Introduction

Farmers around the globe use pesticides as a main source to combat and eliminate insects from agricultural fields. The applications of pesticides lead to serious health and environmental problems. The Food and Agricultural Organization (FAO) of the United Nations indicates that number of worldwide fatalities caused by accidental pesticides poisoning each year reached 20,000, and the number of non-fatal pesticide poisoning worldwide reached 3,000,000. In 1996, an international labor office report drew attention to dangers in the agricultural sector, where pesticides cause 14 % of all known occupational injuries and 10 % of all fatal injuries. In addition to health problems, pesticides are known to be a major threat to water pollution and wildlife habitat.

In addition to the problems mentioned above, insects are known to develop resistance to pesticides and this is another major problem for Entomologists throughout the world. At least 520 insects and mites, 150 plant diseases, and 113 weeds have become resistant to pesticides that are meant to control them. Besides the above problems, pesticide application is expensive. The loss of food and crops to insects has risen from 7 to 13 % and according to the FAO and 1995 the cost of insecticides used worldwide exceeded US $ 12 billion. All the above problems and the tightening of regulations in many nations, has forced entomologists to look for alternative solutions to combat insects in a more natural way.

The idea to use natural control was investigated during the early 1950's by a group of researchers from the University of California at Berkeley. The original intent of these entomologists was to integrate the use of pesticides and natural enemies (predators and parasites) to manage insect pests. This led to the thinking that a science must be developed to address the issue of pest control. Such a science is referred to as Integrated Pest Management (IPM).

The goal of IPM is not to eliminate all pests; some pests are tolerable and essential so that their natural enemies remain in the crop. Rather, the aim is to reduce pest populations to less than damaging numbers, to ensure production of agricultural products and goods in sustainable and environmentally friendly conditions, and to minimize hazards and risks to humans as well as to wildlife. Farmers should be able to collect samples of insects in cotton field, and should be able to identify the ratio of good to bad insects and be able to make decisions on whether or not to apply pesticide.

Among agricultural crops, cotton is the major non-food crop worldwide and the one on which pesticides are used most. It accounts for about 25 % of global insecticides sales (1994) and about 10% of pesticides sales.

2. Framework for classifying insects

The need for correct identification of insects is an important component of any biological control system, be it human-based or machine-based. In this paper we will show the possibility and the benefits for a computer-vision based system capable of identifying insects in the cotton fields of Southwestern United States.

Earlier attempts to classify insects in the cotton were all based upon classical statistical approaches. The number of classes of insects to be identified was met with various degrees of success. Insect appearances in agricultural field depend on many parameters such as weather conditions, humidity, wetness, season, host plants, crop type, and many other parameters. It is therefore difficult, if not impossible, to obtain satisfactory statistical models to predict or classify insect categories.

In this paper we discuss a Soft Computing approach which is distinctly different from classical statistical techniques to identify and classify insects. This method is model-free, and uses Artificial Neural Networks (ANN) for the recognition process. As stated previously, the appearance of insects during a particular season is a complex process, and the need for a model free approach in classifier design is extremely important. The classification will be based solely on features extracted from all possible known insects that may appear in the cotton field in various seasons, and under various conditions. The selected features will be the crucial component of any correct classification. These extractable features will be used to train the ANNs. Figure 1 illustrates the framework for developing a visual decision based system to insects' classification.

The basic idea expressed in Figure 1 is that, once a sample of insects has been collected, a computer-vision-based system would identify, or classify, the sampled insects two fundamental groups. These could be classed as "Desirable" and "Undesirable" insects. By "Desirable" is meant those insects, which comprise the Biological Control species. The "Undesirable" naturally belongs to the pest species.

Classification of this nature provides for the formulation of appropriate pest control strategies based upon the ratio of Desirable to Undesirable insect species. Specifically, this would provide a framework for the appropriate mix of biological and pesticide controls.
In the following sections, we discuss several aspects of the recognition process, namely, image analysis, and feature selection and extraction.

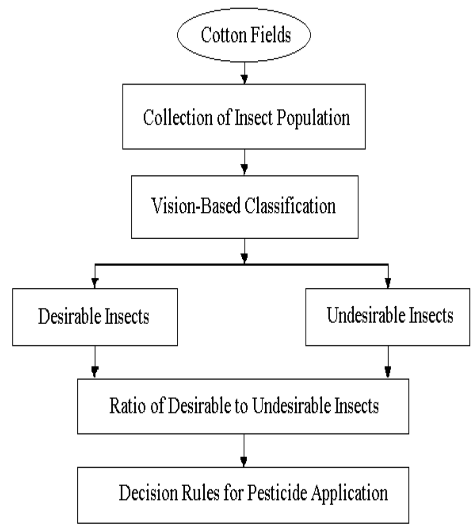
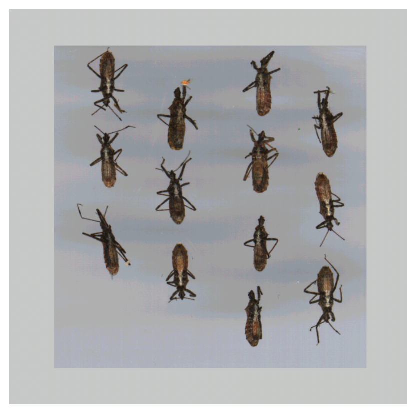


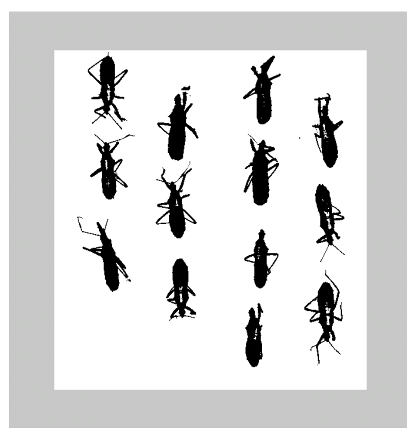
Figure 1: Framework for Insect Classification

3. Image analysis

Figure 2 shows a couple of raw images and their binary version. The binary images shown here are obtained after applying image enhancement.



a. Original Image



b. Binary Image

Figure 2.1: Assassin Bug

a. Original Image

b. Binary Image

Figure 2.2: Three-Corned Alfalfa Hopper

Clearly, these sample images and their binary version show various form of distortion. The first step in analyzing these images is to reduce it to its basic components or objects without loosing its important and useful features. This process is known as *image segmentation operation*.

Image segmentation operation is the process of partitioning a digital image into disjoint sets by investigating connected sets of pixels. All imaging systems create various forms of distortion. Distortion can involve lighting system, lenses, and digitization function. All these components can contribute to the degradation of the final image. Images are occasionally exposed to certain situations or malfunctions that can introduce unwanted form of noise. Due to these degradations, we need to apply image enhancement to a given image. Image enhancement involves the application of image morphology. Image morphology is a set of binary image processing operations developed from a set-theoretic approach and is that part of digital image processing that is concerned with image filtering and geometric analysis by structuring elements.

For binary images, the major basic morphological operators are *dilation* and *erosion*. Dilation and erosion are the two fundamental operations that define the algebra of mathematical morphology. These two operations can be applied in different combinations to obtain more sophisticated operations Dilation operation is a morphological transformation that combines two sets by using vector addition of set elements. For a binary image, a dilation of the set of black pixels in *A* by another set say *B*, is the set of all points obtained by adding the points of *B* to the points in the underlying point set of the black pixels in *A*. The dilation operation uniformly expands the size of objects with respect to their background. When we perform dilation operation, white objects grow in size. Small features will enlarge, and if we continue to perform dilation, white objects will continue to expand. The dilation operation is useful when we want to join white objects in a particular image.

The erosion operation (which is the inverse of dilation) uniformly reduces the size of objects in relation to their background. In terms of image processing, when we perform erosion on a binary image, the white objects shrink in size. Very small white objects will disappear entirely. If we continue to apply erosion, white objects will continue to shrink, and they may ultimately disappear entirely from the image. Other morphological operations are easy to obtain just by combining these two morphological operations.

After applying image enhancement techniques to a given image using morphological operations, the next step is extract useful features to train the ANN. Feature selection and extraction is discussed in the following section.

4. Features selection and extractions

The ability to perform pattern recognition at some level is fundamental to image analysis. A pattern is a quantitative description of an object or some other entity of interest in an image and is generally formed by one or more descriptors such as length of the contour, diameter of a boundary, area, curvature, perimeter, and compactness. The goal of mapping the space into a reduced feature space is to:

- Retain as much of the original information as possible

- Remove as much redundancy (highly correlated features) among features as possible, and remove irrelevant information as much as possible

Feature selection and extraction in pattern classification is concerned with mathematical tools for reducing the dimensionality of pattern representation. A major problem associated with pattern recognition is what is known as the curse of dimensionality. One of the reasons to reduce the number of features to a minimum is to reduce the computational complexity of the system. A second reason is to reduce the degradation and minimize error classification performance. It is a good practice to make features meaningful to humans as much as possible. Features can be classified into three groups:

1. Physical sensory features such as using sensors to detect motion and temperature
2. Structural features are relationship of physical sensory features such as relative location, relative area, edges, curve
3. Mathematical features are obtained by mapping pattern measurements or observations via a function of measurements

The selection of features requires some experience with the population of object classes on hand. This allows humans familiar with these objects to perceive the difference of the subset of objects. Each selected feature should have at least one of the following properties:

1. The feature must clearly discriminate between two or more classes
2. The feature should not be correlated with another feature to a higher degree of correlation. The correlation among features is determined by determining which features strongly depend on each other. This can be done by examining features pair wise [1]
3. The feature has something meaningful to human understanding and perception
4. Features should have large variance. Feature with low variance are not of help in separating object classes

The first step in image segmentation consists of separating objects from the image so that feature measurements can be made. Figures 3.1 and 3.2 show some sample images in which the object has been isolated from the image. The isolation is performed over a rectangular box as illustrated. These segmented and enhanced objects provide a basis for appropriate feature extraction.

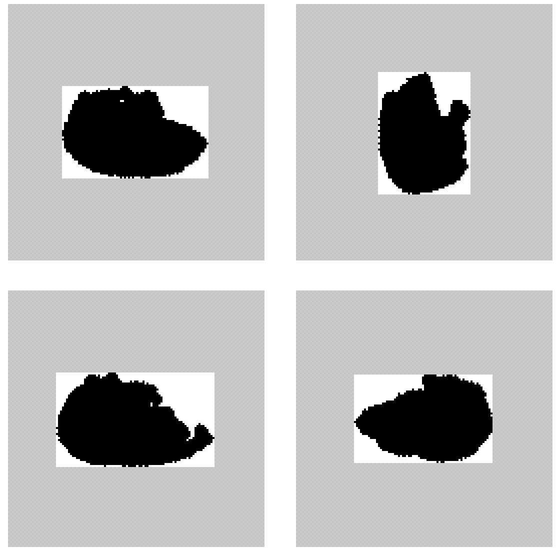


Figure 3.1: Individual Selected Objects from The Three-Corned Alfalfa Hopper

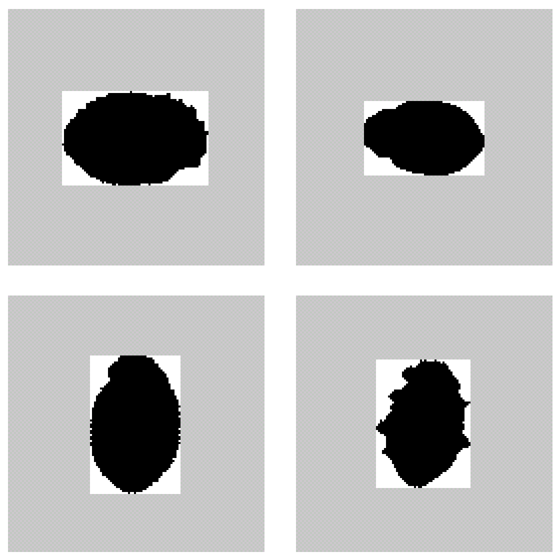


Figure 3.2: Individual Selected Objects from The Hopper and Hippodamia Lady Beetle Adult

In order to extract features, it is necessary to select a set of descriptors that establish distinguishing characteristics between various insect classes. Typically, there are several empirical features that are used in image recognition. In our work, we have used the following empirical features as characteristics of the insect commonly found in cotton ecosystems.

$$Form\ Factor = \frac{4\pi.Area}{Perimeter^2}$$

$$Roundness = \frac{4.Area}{\pi.Max\ Diameter^2}$$

$$Aspect\ Ratio = \frac{Max\ Diameter}{Min\ Diameter}$$

$$Compactness = \frac{\sqrt{\left(\frac{4}{\pi}\right)Area}}{Max\ Diameter}$$

$$Extent = \frac{Net\ Area}{Bounding\ \ Rectangle}$$

Although these features form the basic set of features required to classify insects, some additional features can also be used as distinguishing characteristics. For example, the symmetry of the object along the major/minor axes of an ellipse circumscribes around an object can provide sufficient information about the object class. This additional feature is found to be useful in establishing class separability.

5. Artificial neural networks (ANN)

ANNs are universal approximators that are ideally suited for solving model independent systems and/or processes. ANNs are massively parallel-distributed processor that has a natural propensity for storing experiential knowledge and making it available for use. The primary motivation to employ ANN is:

- The network through a learning process acquires knowledge
- Inter-neuron connection strengths are used to store the knowledge

In our work, we have used supervised learning where each feature vector is fed to the ANN along with its known class identifier as the desired output vector. The weight and biases are adjusted until the mean-squared error converges to a desired threshold.

6. Classification results

In this work, we are interested in 12 insect classes. The set of features consists of eight different features. Additionally, two other sets of features were obtained.

- Set of features with legs removed from insects. The removal of legs is done by applying 2-D filtering
- Set of features with legs not removed

These features are the basis for classifying insects. The classification was done based upon a decision tree approach. Similarity among insects made this problem a complicated one. Variance among features was not large enough to design one ANN structure capable of separating all insects at once. Therefore, we had to look for an alternative way to use these features. This leads us to use decision tree as depicted in figure 5.

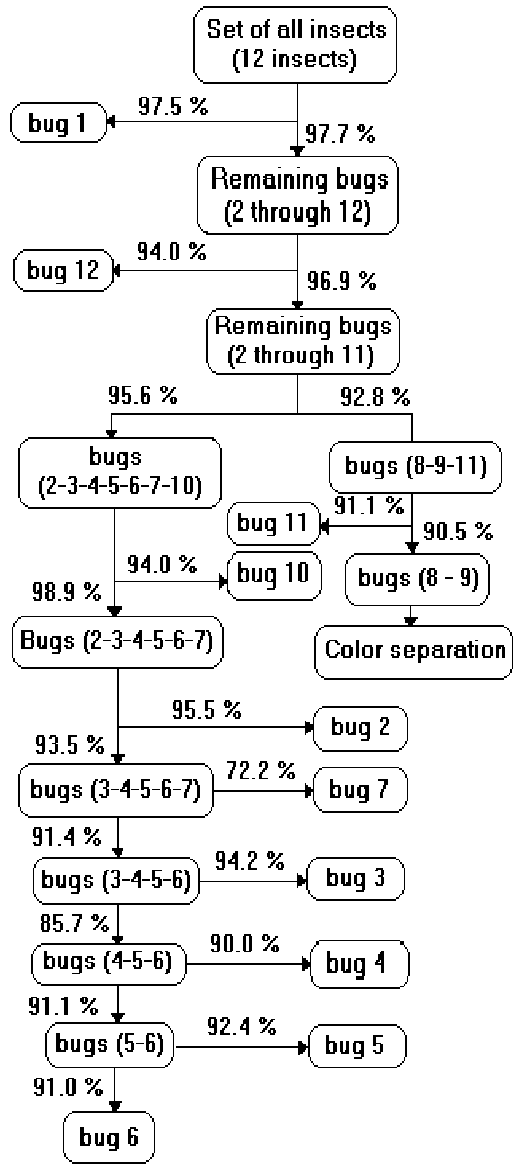


Figure 5: Tree Structures Showing ANNs Performance

The tree shows the type of insects that have been separated at each twig. The numbers in the diagram indicate the percentage of correct insect classification achieved by the ANN structure.

As seen in the table of results, most correct classification is achieved with high percentage except in the case of separation of bug 7. This is due to quality of images used in this study.

Figure 6 shows the original image and its binary image to illustrate the effect of the quality of the image on the recognition rates.

a. Original Image

b. Binary Image

Figure 6: Hippodamia Ladybug Larva (bug7) and its binary image

Consider for example the classification of a group of insects as shown in figure 5, namely the group “Bugs(3–4–5–6)”. Here bug 3 is classified correctly 94.2 % of the sample input. However, we see that the collective classification of the remainder of bugs namely (4–5–6) is 85.7 %. Further investigation of such a low rate of classification shows that the individual classification of bugs 4, 5, and 6 yield 91.5 %, 77.0 %, and 95.6 % respectively. The reason for poor classification of Bug 5 is that the images had high reflective surfaces that lead to loosing a lot of information. Hence the combined classification is low as indicated in figure 5.

In this work, we have shown that features extraction is a crucial component of image understanding. Therefore, by appropriate selection of features that provide strong discrimination characteristics, a neural network is capable of producing satisfactory classification results. This work can be generalized to other pattern recognition areas as well. For instance, this research work can be extended to many other agricultural ecosystems that require pest management control.

Figure 7 shows convergence characteristics for the trained neural network.

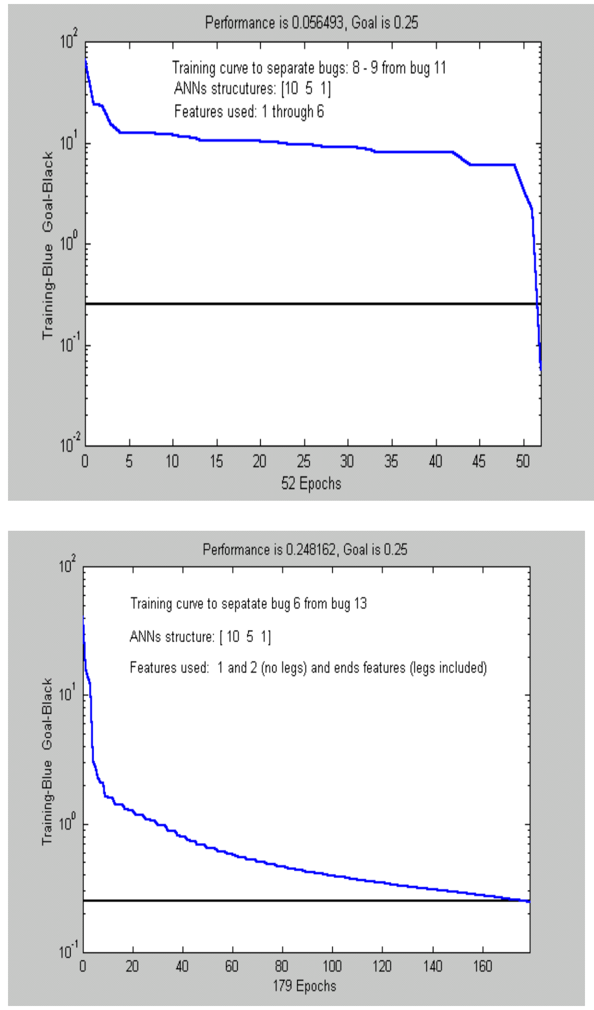


Figure 7: Example of ANNs Converging Curves

7. Conclusion

In this paper we have outlined a soft computing approach using neural networks for classifying insects in agricultural ecosystems. We have specifically focused on insects that commonly inhabit cotton ecosystems. We have shown that neural networks can be effectively used in classifying insects from many classes.

Further work is needed to demonstrate the viability of using trained neural networks directly in a field setting. For this, rapid real time image processing techniques need to be developed to segment and isolate insects of interest from trash and other debris collected during the sampling process. Such effort can potentially lead to field deployable systems that can greatly benefit future agricultural practices.

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