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Automated Insect Classification Using Shape-Based and Color-Based Characteristics

Teena, Johnson . Department of Electronics, India

Research Article

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ABSTRACT

Since ancient times, entomology has been firmly ingrained in many societies for agricultural purposes. In order to preserve the variety of species within our environment, many scientists nowadays are interested in the topic of biodiversity. More than two thirds of the 1.3 million species that are known to exist on Earth are insects. Humans and insects have interacted in a variety of ways since 400 million years ago. There have been several efforts to develop a reliable technique for identifying insects. Accurate insect identification requires extensive entomology knowledge and expertise. The lack of qualified entomologists necessitates the automation of insect identification. We provide a framework for automatically identifying insects that can recognize butterflies and grasshoppers from colorful photos. For a proof-of-concept, two bug classes are selected. Since each class of sample cases has a different color and unique body form, classification is accomplished by changing the color and shape features of insects. The first step in the suggested insect identification procedure is to extract characteristics from samples and divide them into two training sets. While one training focuses on calculating RGB characteristics, the other is normalized to estimate the binary color area that represents the insect's form. The collected data is trained using an SVM classifier. The classifier's final conclusion determines which class an unknown instance belongs to by combining the results of these two attributes. The first findings show how effective and efficient our two-step automated insect identification method is, and they encourage us to expand this framework to recognize a wide range of additional insect species.

KEYWORDS

Vision-based Entomology, Color Features, Shape Features, Machine Learning

INTRODUCTION

Recently, vision-based object identification has become an important area of study. This is a result of the world's transition to an entirely electronic age. Previous methods for object identification relied too much on human experts; as a result, they did not accept expert absences and required more time and human effort. In addition to increasing accuracy, computerized image processing and object identification systems are the best way to address the drawbacks of this conventional approach. Numerous effective efforts have been made to automate labor-intensive processes using machine learning [8–10, 15–24]. Following successful identification, researchers are interested in classifying images from comparable family trees. The object's almost identical characteristics and small number of variation points make categorization difficult. Classifying an item may also be challenging since different species have different biological traits that make them hard to tell apart visually.Our effort to categorize insect families is presented in this study. The most prevalent species on Earth are insects. Insects have more species than any other group of terrestrial animals. Although insects may be predators, herbivores, hosts, or decomposers, their morphological characteristics are not very diverse. The head, thorax, and abdomen are the three parts of an insect's body. Insects belong to the arthropods category. The area that joins the head and

abdomen is called the thorax. Nevertheless, for certain bug species, the three sections may be combined. The fact that insects have legs and wings connected to their thorax is another unique characteristic. Many insects have antennae attached to their heads that serve as sensors for touch and scent.

TFor this insect categorization project, three types of insects—grasshoppers, butterflies, and other insects—are chosen. Butterflies and grasshoppers have different sizes, shapes, and colors. Easy identification and grouping are made possible by obvious and well-defined traits.



Figure 1: Insect Sample Data (butterfly and grasshopper)

The primary reason for doing this effort is since, apart from studies on animal species classification, there aren't many studies that exclusively address insect classification. As a result, this project offers a platform for the advancement of insect identification and categorization, which is one of its flaws and limitations. Second, the labor-intensive process of manually identifying insects might be replaced by automated vision-based categorization. The vast quantity of open-source bug photos on the internet would be the third factor. As a result, getting photos for training and testing data sets is an easy operation.
The use of insect detection and categorization is the fourth factor. There are several uses for image-based insect identification, particularly in environmental research, ecology, and agriculture [5]. In general, it may be used for plant quarantine, insect pest and disease control, and as a crucial component of eco-informatics research. This new clever technique is particularly helpful for laypeople who lack expertise in differentiating between various insect species [1].

Additionally, this work may be used as a reference to construct a classification system for any other variety of species, including fish, cockroaches, fruit, flowers, insects, and even microorganisms like bacteria.

1. Related Work

An overview of previous research on vision-based insect identification and classification is given in this section. Zhu Le Qing and Zhang Zhen presented their study on insect detection using color histograms and Gray Level Co-occurrence Matrix (GLCM). The insect picture's area of interest (ROI) is separated using an image preparation method. Next, color characteristics that may be used for coarse color matching are retrieved from ROI and represented by color histograms [1]. By comparing the correlation of the feature vectors with a predetermined threshold, the matching is completed [1]. The following step, fine level matching, will be applied to the picture samples that made it through this stage. Coefficients like energy, entropy, and correlation of the GLCM of preprocessed picture blocks are used to represent the fine-level features [1].
One hundred bug species are chosen as samples for the study. Every picture sample was taken from the insects' right wing. While some of them are forewing with backwing, the majority are forewing [1]. The mean shift technique is used to filter the picture after it has been scaled to increase processing speed [2]. After that, it is binarized using a certain threshold and turned to a grayscale picture.

Finding a universal coordinate requires connecting the foreground region's centroid and rotating the picture around it until the linked line is horizontal in order to minimize the impact of rotation and translation during image capture [1]. The insect wing's upedge and downedge are fitted with straight lines using the least-squares approach. Before feature extraction, the picture is aligned using Gaussian, and ROI is defined later.

Before creating the histogram, the color picture is converted from RGB (Red-Green-Blue) to HSV (Hue-Saturation-Value) space. Only hue and saturation are taken into account in order to reduce the impact of light change [1]. Calculating the hue and saturation component histogram reveals that the distribution of the histogram for the same species is comparable. GLCM approximates picture properties including energy, entropy, correlation, and homogeneity that are associated with second-order statistics. This method has been shown to be accurate and efficient in identifying insects from low-resolution wing photos [1].

Pattern recognition is another task that is connected to the categorization of insects. Kim, Lim, Cho, and Nam (2006) state that the goal of this study is to identify ladybugs and butterflies. The color information approach is used to analyze the picture of the insects and eliminate noise. Following pre-processing using top-hat filtering with a specific threshold, the edge detection approach is applied to RGB space. Chain code analysis is used to examine the identified edge line. The produced picture is subjected to max/min filtering to enhance the final product [11].
The data will be processed by the computer, and the software counts the ladybugs and butterflies in an image that contains a variety of insects [11]. The researchers reported that they achieved recognition of almost 90% overall by using this technique [3].

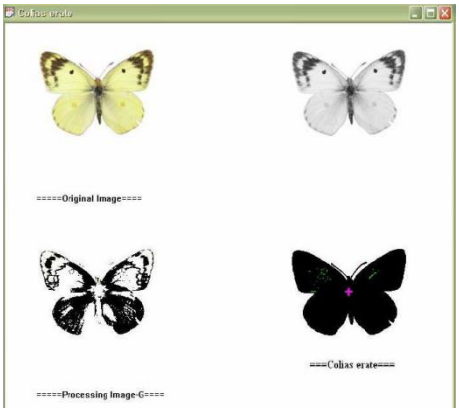


Figure 2: The program of insect discrimination [Adapted from Lim, Cho, Nam&Kim,2006]

Yang et al. [7] conducted a similar study in which they employed pattern recognition technology to identify insects. According to Yang et al. (2010), pattern recognition is precisely described as "the act of taking in raw data and taking an action based on the category of the pattern." They went on to clarify that the procedure consists of three steps: a feature extraction mechanism that computes numerical or symbolic data from the sample, a classification scheme that establishes the sample's group, and input data and information gathered from the sample using a sensor [7]. picture segmentation, on the other hand, is described as the process of dividing a picture into many sections, each of which groups together elements that have similar characteristics, such texture or intensity, to produce a non-overlapping image [7].

They gathered a number of insect characteristics, including rectangularity, elongation, roundness, eccentricity, sphericity, lobation, compactness, and seven Hu moment invariants, in order to successfully identify insects [7]. Color, texture, and edges are the three categories of visual attributes. However, as edge extraction allowed for less light and noise interference, it seems to be the optimum method [7]. This kind of approach used machine learning to train the algorithm to match the loaded picture, and the outcome was stored in a database. Numerous classifiers provide various methods for organizing a picture. In order to identify the best classifier that can effectively fit the data into the appropriate category, each classifier was evaluated on the samples. Because the Random Trees method outperformed other classifiers in the test of insect image data samples, the researchers concluded that it was the best option in this study [7].
The flowchart in Figure 3 shows the summary of training and recognition process involve in insect's classification. The solid line represent the flow of data signifies the process of training the classifiers whereas the dotted line signifies the path taken by a new loaded image to test the corresponding classifier.

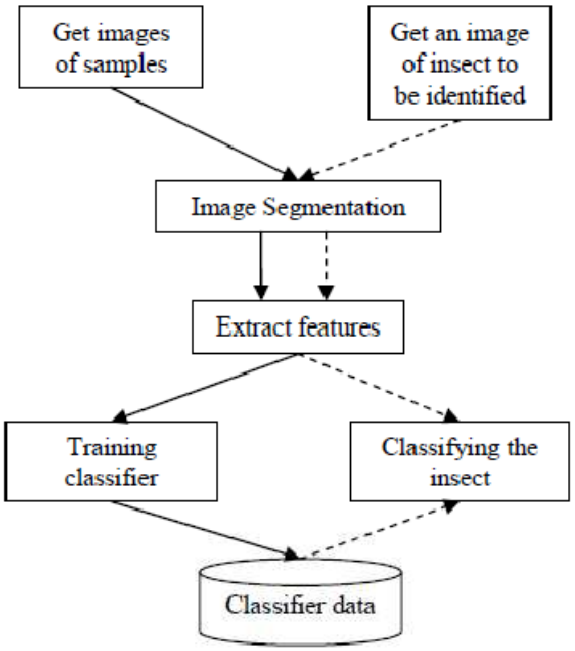


Figure 3: Main Flowchart of Training and Recognition [Adapted from Yang et al, 2010]

They have been practicing a seven-step insect classification process for picture segmentation. The seven steps are as follows: The picture is first loaded from a file. The picture is then changed to grayscale. Third, the Canny edge algorithm is used to extract the edges. The edges picture is subjected to the close operator. Finding an image contour using a contour algorithm would be the next step. The largest contour displays the shape of the previously loaded bug.

When processing images of varying sizes and perspectives, contour feature extraction is beneficial. However, the system's inability to distinguish between species with similar outlines would be a clear drawback. Therefore, taking use of the color and texture of the picture is the way to solve this issue.

Extension theory is another method for classifying insects. Using the mean and variance of the picture attributes, extension theory was used to generate the insect's matter element matrix [4]. The item itself, its feature, and its feature value—in this example, an insect—are all part of the matter-element matrix that has to be identified [4]. Feature extraction of insects is the initial stage in the extension approach for insect categorization. The picture will be taken in real time, transformed to grayscale, and then segmented using the adaptive approach to separate the binary insect image from the background and grain [4]. The binary picture is used to extract seventeen morphological characteristics, which are then normalized [13].

The matter component of the insects' characteristics is then built [4]. Every attribute of the item should be inside the threefold variance with 99.7% probability if it belonged to a class, according to the "3δ" property of the normal distribution [4]. If not, certain characteristics ought to fall outside of the threefold variance [4].

With 135 samples, the system is taught to recognize the nine bug species [4]. Each species' matrix of regulated and classical field matter elements is created [4]. The degree of correlation is computed. The item to be identified is considerably closer to a class if there is a greater correlation degree between it and that class. The degree of association was

quick, easy to use, straightforward to compute, and effective. When compared to k closest neighbor and fuzzy classifiers, the classifier's accuracy is higher [4].

An Lu, Xinwen Hou, Cheng-Lin Liu, and Xiaolin Chen attempt to categorize insects using a hybrid method known as discriminative local soft coding (DLsoft) in this study [5]. In soft coding techniques, a kernel function of distance encodes an insect image's feature vector. In order to address the shortcomings of soft coding alone, Multiple Kernel Learning (MKL) is employed for the classification in the discriminative section.

The fruit fly family Tephritidae, which includes many species, is used to test this technique. There are two parts to the dataset: the training set and the testing set. An picture of Tephritidae was used as a sample for both datasets. All of the pictures are first converted to grayscale. Each picture is heavily sampled in order to extract SIFT characteristics of patches. This is done in order for SIFT features to represent each picture. In order to perform SIFT, the pictures are divided into many square sections, each of which computes its own histogram. The discriminative and local soft codes are computed. Max pooling over all of the patch vectors in the same picture is then computed. Any machine learning technique may utilize the spatial pyramid pooling vector, which is the ultimate presentation of an image sample, for classification [6].Zhang et al. [12] suggested using form and color characteristics to identify cat heads. In this work, we examine whether insects may also be categorized using color and form characteristics.

2. METHODOLOGY

2.1. Data collection

The project's first stage was gathering data samples from several insect species. Butterflies and grasshoppers are the two insect species that we are categorizing in our study. For the data training, we gathered 15 data samples for each species, for a total of 30 photos. In the meanwhile, we are choosing four photos for each species to be evaluated on the system later for the data testing. The majority of the dataset was retrieved from Google Images, although part was also taken from the Caltech 101 dataset. These two bug species were selected for testing due to their large population and ease of obtaining certain traits via feature extraction, which will be covered in more detail in the next subtopic.

2.2. Feature extraction

The extraction of an image's features is the next step in the classification process. These days, a variety of feature extractors and descriptors are in use. We decided to employ color-based feature extraction in our work. The samples will undergo a number of preprocessing steps before to the feature extraction procedure. The samples will first be resized in matrix form to a fixed size, such as [100 100]. In order to increase processing speed, the picture is often resized to be smaller. Following that, the samples will be converted to double format

and grayscale images.

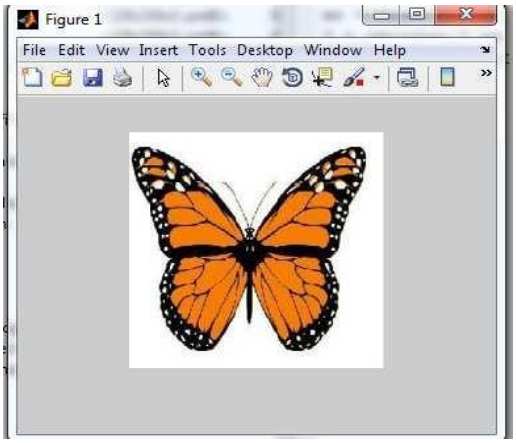


Figure 10: Resize image for Samples

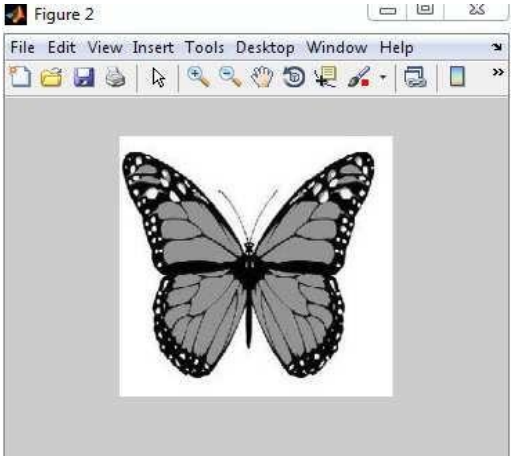


Figure 11: Grayscale Image of Sampled Data

Certain characteristics will be taken from the picture sample after the grayscale image has been acquired. In essence, the color characteristic is extracted using RGB. The picture is composed of matrices with pixels ranging from 0 to 256. Zhu Le Qing and Zhan Zhen claim that the distribution of the color histogram of the same species is comparable. As a result, it is simple to categorize the insects according to their color distribution and other characteristics like size and length.

Feature classification

picture classification groups data into categories by analyzing the numerical characteristics of different picture aspects. Training and testing are the two stages of processing that classification algorithms usually use. During the first training phase, each classification category, or training class, is given a unique description based on the distinctive attributes of typical picture features. These feature-space divisions are utilized to categorize image characteristics in the testing step that follows [14]. Similar to feature extraction, many classifiers may be used in picture classification. For instance, Support Vector Machine

(SVM), K-Nearest Neighbor, Naïve Bayes, and Kmeans. SVM is the classifier that we have chosen. This is because it is straightforward to use for training data sets. But SVM

can only categorize two kinds of samples. To categorize a greater variety of sample types, multi-class SVM should be used.SVM is chosen to be used in this work because of it regularization parameter and over-fitting may be avoided during classification. Besides, SVM uses kernel trick that receives the input data or images and transform it.

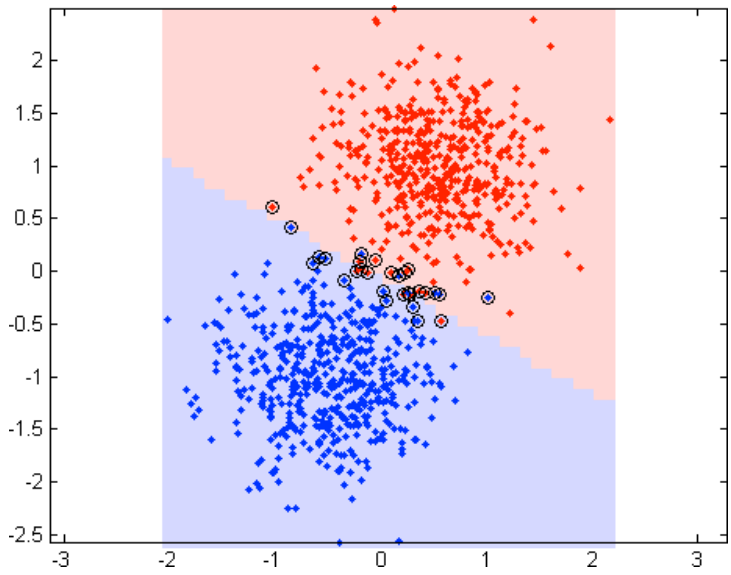


Figure 12: Example of SVM classifier (Linear) [14]

After the classifier is chosen, the samples collected is trained using 10 samples each for butterfly and grasshopper. The result of the system is in tabulate form and will be further discussed in experiments section.

3. EXPERIMENTS

Using the Google search engine, we gathered 300 photos of insects for instruction. Butterflies can be seen in 150 of the pictures, but not in the remaining 150. Additionally, we gathered 100 testing samples, 50 of which were pictures of grasshoppers and 50 of which were pictures of butterflies. Adult butterfly and grasshopper specimens may be seen in every example photograph. Matlab r2009a is used as a software development tool, and all tests are conducted on an Intel Core i3 with 2.16GHz and 2GB of RAM.

First, we are utilizing the feature extractor, vl_sift, under the open-source vl_feat program to categorize the insects. Important characteristics are extracted from picture samples using the Vl_sift function. Vl_sift calculates the picture's SIFT frames, or keypoints; the image must be in single precision and grayscale. Every sample goes through a number of preprocessing steps, including top-hat filtering, grayscale, and resizing.

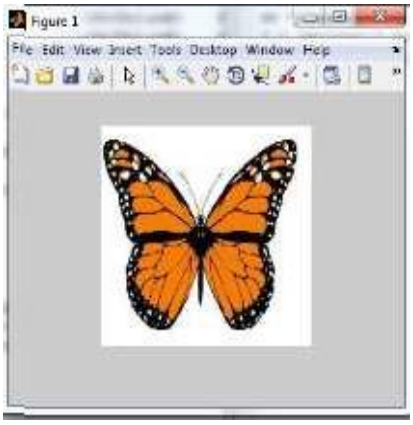


Figure 13: Sample Image of Adult Butterfly

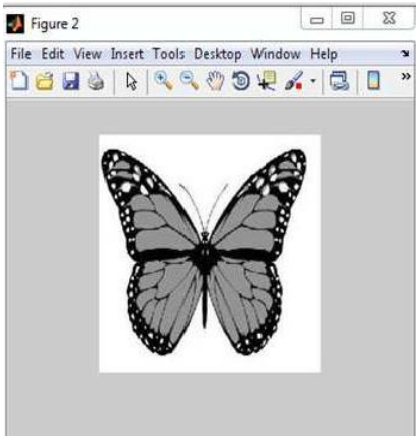


Figure 14: Grayscale Image

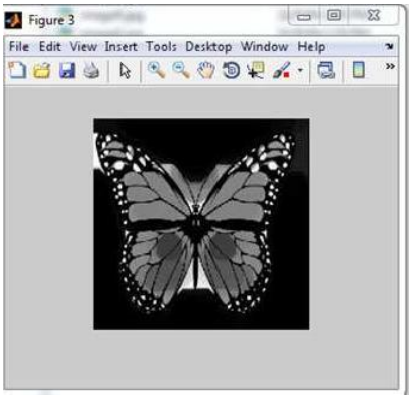


Figure 15: Filtered Image

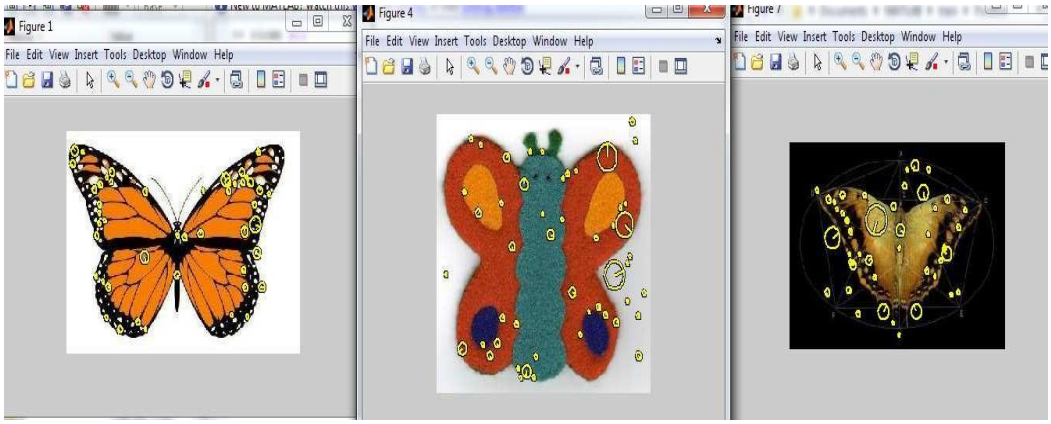


Figure 16: Detected features using vl_sift

However, we were unable to go on with the next phase, which is to classify the photos using a specific classifier, after the yellow circle in the above figure identified the attributes of the photographs. The retrieved characteristics could not be stored as tabular data. As a result, we came up with other ways to categorize the insects according to their types or groupings. We are using an SVM classifier with specific training data to complete our classification system. The thirty samples of data that we gathered are subjected to this technique in order to be categorized as belonging to either the grasshopper or butterfly group.

After being converted to grayscale, the example picture is resized to 100x100 matrices. As shown in Figure 13, the processed sample picture has been created and is kept in a database. The procedure of reading and saving was completed successfully. Since we are employing grasshopper and butterfly, these two elements make up two labels: "1" for the butterfly and "2" for the grasshopper.

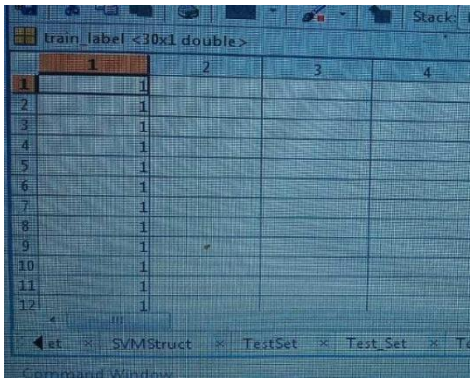


Figure 17: Data Input for Sample Image (Butterfly)

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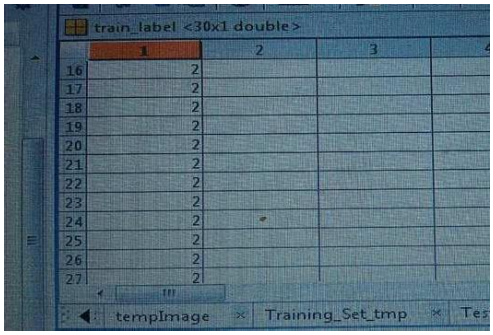


Figure 18: Data Input for Sample Image (Grasshopper)

The database for the reference classes has been created by identifying these two classes. At that point, the system is prepared to train SVM using a numerical matrix. The trained data is then put in the Trainingset matrix after the first SVM ru. The test picture is then loaded by the system to evaluate the classifier's dependability. The Group variable contains the test's outcome. We can see the test image's outcome by launching the variable workshop. Given that the picture is being

When one reads the folder holding the test picture from left to right, it is evident which image the number sequence belongs to.

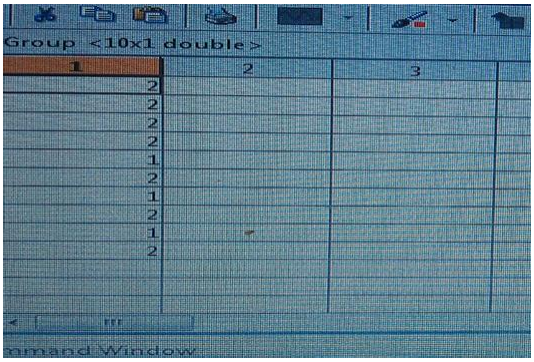


Figure 19: Result of Classifier is presented in Group variable.

The total number of accurate forecasts divided by the total number of predictions is the system's accuracy. A respectable accuracy score of 92% was obtained by the system. However, we discovered that although butterflies had an accuracy of 84%, grasshoppers have a better categorization accuracy of 98%. This might be because of the wide variances in butterfly color and form, which can lead to confusion in the classifier. The SVM classifier was completely unoptimized, even though the classifier did not achieve 100% accuracy. Only the standard SVM parameters were used. The accuracy may increase if the SVM parameters are optimized. SVM offers a number of important benefits. First, the regularization parameter in SVM is not affected by outliers. Another benefit is that SVM may be used to a variety of classification problems, including those in high-dimensional spaces with non-linear relationships. Despite the benefits, using SVM has a number of disadvantages. SVM performs poorly, particularly when handling data that needs more features than the provided examples.

4. Conclusion

An automatic insect identification framework that can recognize butterflies and grasshoppers f rom colored photos is proposed in this research. For a proof-of-concept, two bug classes are selected.

Since each class of sample cases has a different color and unique body form, classification is accomplished by changing the color and shape features of insects. The first step in the suggested insect identification procedure is to extract characteristics from samples and divide them into two training sets. While one training focuses on calculating RGB features, the other is normalized to estimate the binary color area that represents the insect's form. The collected data is trained using an SVM classifier. The classifier's final conclusion determines which class an unknown instance belongs to by combining the results of these two attributes. The suggested insect classification system was only designed as a proof-of-concept, despite the fact that it yielded satisfactory results. There are lots of areas that could be improved. We would like to get additional training samples for future work. Additionally, we want to use optimization methods like genetic algorithms to optimize the system parameters. Next, we want to use this framework to identify many different insect species.

References

[1] "Auto-classification of Insect Images Based on Color Histogram and GLCM," L. Q. Zhu and Z. Zhang, Seventh International Conference on Fuzzy Systems and Knowledge Discovery, 2010.
[2] "Mean shift: a robust approach toward feature space analysis" by Comaniciu, D., and Meer, P. IEEE Transactions on Pattern Analysis and Machine Intelligence, 24(5), 603-619, 2002.
[3] "Development of a Classification Algorithm for Butterflies and Ladybugs," J. H. Lim, J. M. Cho, T. W. Nam, and S. H. Kim, 2006.
[4] Yuxia Hu and H. T. Zhang, "Extension Theory for Classification of the Stored-Grain Insects," International Conference on Machine Vision and Human-machine Interface, 2010.

[5] An Lu, Xinwen Hou, C.L. Liu, and Xiaolin Chen, "Insect Species Recognition using Discriminative Local Soft Coding," 21st International Conference on Pattern Recognition, 2012.
[6] J. Yang, K. Yu, Y. Gong, and T. Huang, "Linear spatial pyramid matching using sparse coding for image classification," Computer Vision & Pattern Recognition (CVPR), 2009.
[7]H. Yang, L. Wei, K. Xing, J. Qiao, X. Wang, L. Gao, Z. Shen, "Insect Identification Based on Pattern Recognition Technology," Sixth International Conference on Natural Computation, 2010.
[8] Z.Z. Htike, S.L. Win, "Identification of Promoters in DNA Sequences Using Weightily Averaged One-dependence Estimators," Procedia Computer Science, Volume 23, 2013, Pages 60-67, ISSN 1877-0509.
[9] Z.Z. Htike, S.L. Win "Eukaryotic Splice-junction Genetic Sequence Classification Using Averaged One-dependence Estimators with Subsumption Resolution," Procedia Computer Science, Volume 23, 2013, Pages 36-43, ISSN 1877-0509.
[10] Z.Z. Htike, S. Egerton, and Y.C. Kuang, "A Monocular View-Invariant Fall Detection System for the Elderly in Assisted Home Environments," 7th International Conference on Intelligent Environments (IE), 2011, vol., no., pp.40,46, 25-28 July 2011.
[11] J. Lim, J. Cho, T. Nam, and S. Kim, "Development of a classification algorithm for butterflies and ladybugs," TENCON 2006. 2006 IEEE Region 10 Conference, vol., no., pp.1,3, 14–17 Nov. 2006.
[12] "Cat Head Detection: How to Effectively Exploit Shape and Texture Features" Lecture Notes in Computer Science Volume 5305, 2008, pp. 802-816, W. Zhang, J. Sun, and X. Tang.
[13] H. Zhang and H. Mao, "Feature Selection for the Stored-grain Insects Based on PSO and SVM," Second International Workshop on Knowledge Discovery and Data Mining, 2009. WKDD 2009, vol., no., pp.586,589, 23-25 Jan. 2009.
[14] Retrieved December 10, 2013,
[15] Z.Z. Htike, "Is it possible to predict the future?" Algorithms, Architectures, Arrangements, and Applications in Signal Processing (SPA), 2013, pp. 360-365, 26-28 September 2013.
[16] "Multi-horizon ternary time series forecasting," by Z.Z. Htike Algorithms, Architectures, Arrangements, and Applications of Signal Processing (SPA), 2013, pp. 337-342, 26-28 September 2013.
[17] S.L. Win et al., "Cancer Recurrence Prediction Using Machine Learning," International Journal of Computational Science and Information Technology (IJCSIT), Vol. 6, Issue 1, ISSN: 0975-3826, 2014.
[18] E.M. Azhari and colleagues, "Brain Tumor Detection and Localization in Magnetic Resonance Imaging," International Journal of Information Technology Convergence and Services (IJITCS), Vol. 4, Issue 1, ISSN 2231-1939, 2014.
[19] N.A. Mohamad et al., "Bacteria Identification from Microscopic Morphology Using Naïve Bayes," International Journal of Computer Science, Engineering and Information Technology (IJCSEIT), Vol. 4, Issue 1, ISSN 2231-3117, 2014.
[20] S.L. Win et al., "Cancer Classification from DNA Microarray Gene Expression Data Using Averaged One-Dependence Estimators," International Journal on

Cybernetics & Informatics (IJCI), Vol. 3, Issue 1, ISSN: 2320-8430, 2014.
[21] E.M. Azhari and colleagues, "Tumor Detection in Medical Imaging: A Survey," International Journal of Advanced Information Technology (IJAIT), Vol. 4, Issue 1, ISSN 2231-1548, 2014.
[22] E.M. Azhari and colleagues, "Brain Tumor Detection and Localization in Magnetic Resonance Imaging," International Journal of Information Technology Convergence and Services (IJITCS), Vol. 4, Issue 1, ISSN 2231-1939, 2014.
[23] N.A. Mohamad et al., "Bacteria Identification from Microscopic Morphology: A Survey," International Journal on Soft Computing, Artificial Intelligence and Applications (IJSCAI), Vol. 3, Issue 1, 2014, ISSN: 2319-1015.
[24] S.L. Win et al., "Gene Expression Mining for Predicting Survivability of Patients in Early Stages of Lung Cancer," Vol. 4, Issue 1, ISSN: 1839-9614, 2014.