Detection of the affected area and classification of pests using convolutional neural networks from the leaf images

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Abstract— Pest infection is the most crucial problem in vegetable plants. One way to control pest infection is to use proper pesticides. Early detection of the pest or the initial presence of pests is a key element for crop protection. The identification of the pest was made manually at the beginning. This takes time and also requires ongoing monitoring of experts. An automatic pest detection system is needed to examine the infestation and classify the type of pest. Today, there are many techniques and methods for identifying pests and detecting plant diseases. In these techniques, image processing techniques are very efficient and reliable. First, the proposed model detects whether the leaf is affected or not and calculates the affected area in the image. Next, the region of the detected pest and classification were performed using convolutional neural networks. The severity of the infection can be observed by calculating the percentage of the affected area, which leads to taking the appropriate measures.

Keywords- segmentation, the region of interest, pest detection, convolution neural networks.

I. INTRODUCTION

Agriculture is one of the main economic activities of the Batticaloa District in the eastern province of Sri Lanka. More than 60% of the population depends mainly on agriculture. It is therefore important to increase crop productivity. Different vegetable crops are grown in the Batticaloa region. Such as ladies' fingers, tomato, long beans, brinjal, squash, chili and onion. But one of the most important problems at the moment is the “pest infection” on vegetable plants. The identification of the leaves of harmful or affected vegetable plants, the symptoms of the pests play a key role in the successful cultivation of crops. Pesticides are the only way to stop the effects of these pests. Pesticides will remove some species of pests. And more pesticide use is very destructive for crops, air, soil, water resources and animals that come in contact with pesticides. The use of pesticides decreases the overall biodiversity of the soil. In our research, we focus on the early detection of pests. The images are acquired using a camera and also obtained from imagenet.org and other Internet resources. Then, the images must be preprocessed in order to retrieve the image content by the image processing methods.

This study describes the automatic detection of leaf affectedness and determines the type of presence of the pest on various plant leaf images. Then comes a simple and effective method based on image processing using the convolutional neural network for the classification of pests.

In this respect, it is difficult to recognize the vegetable field pests due to the strong articulation of pests, the size and color of the pests, and the visual difficulty of some pests, despite the structure of the pests. The task becomes more difficult when pests are to be recognized from still images using an automated system. Images of an insect pest can be taken from different viewpoints, on a congested background, or can transform such as rotation, noise, etc. It is, therefore, likely that two images of the same pest are different and that intra-pest variations make it difficult to detect the type of pest [2]. To meet these challenges, we must propose an effective segmentation method. Image segmentation is the most critical work in many image processing systems such as pattern recognition, image retrieval and reduced surveillance. The result of segmentation is mainly used for the understanding of image content and the recognition of visual entities via the identification of the region of interest [13]. In this study, a color transformation technique used for image pre-processing and an adaptive thresholding method is applied to separate the leaf region in the presence of a pest. And the region properties considered identifying the affected area and the pest region. The method is implemented in MATLAB 2014a.

The main objectives of this research are:

- To acquire the images from vegetable gardens as a dataset.
- To identify the number of classes of insect pests from the dataset.
- To develop a model to detect the leaf is affected or not by the pests, considering the texture properties.
- To identify the suitable segmentation method for the region of interest in pest detection.
- To build a model for classification algorithm and configure that for the recognition.
- To evaluate and analyze the results from the result of the classification.

The rest of the paper is organized as follows: section (II) describes similar works done by others related to the problem domain. Section (II-A) elaborates on the proposed methodology and the outcome of the stepwise processes. Then, Section (II-B) describes the experimental setup for the classification, followed by the results and discussion in section (III). Lastly, section (IV) concludes on the classification results and includes future works based on our research work.

II. THE MATERIAL AND METHOD

This section presents some relevant works related to the problem domain. It also provides a brief overview of different types of segmentation methods to detect the objects given in the leaf images, the feature extraction methods for various classification methods to classify the pests and the experimental setup for the classification experiments.

In [2], the authors developed a framework for classifying insect pest images for paddy fields using gradient-based features using the bag-of-words method. Images of twenty classes of pests for paddy fields were obtained from Google Images and photographs taken by the Faculty of Agriculture, Jaffna University, Sri Lanka. The images were then classified via the system involving the identification of regions of interest and the representation of these regions in the form of scaled invariant feature transform descriptors (SIFTs) or speeded-up robust feature descriptors (SURFs), constructing codebooks that allow descriptors to be a fixed-length vector in the histogram space, and multi-class classification of feature histograms using support vector machines (SVMs). Also, the histograms of the oriented gradient descriptors (HOG) were applied in the classification. As a basic classifier, the nearest neighbor approach was used and compared to SVM-based classifiers. Their experimental results in three categories. In the first category, the performance of the bag-of-words approach using the SIFT and SURF descriptors were compared when classifying paddy field insect pests. For this approach, the SIFT or SURF features were extracted from the local patches on each image of the same class. These features were then quantified in a visual codebook in which the descriptors of the same class were represented as a bag-of-words.

In the second category, the performance of the HOG features was tested during the pest classification. For this approach, they maintained that all HOG parameters were consistent for different classes of pests. The detection window of 128 × 128 pixels was divided into 15 blocks horizontally and 15 blocks vertically, for a total of 225 blocks. Each block contains 4 cells with a histogram of 8-bin for each cell, for a total of 32 values per block. This brings the final size of the vector to 15 blocks on 15 blocks vertically × 4 cells per block × 8 cells per histogram = 7200 values. Finally, the concatenation performances of SIFT and SURF features with HOG were compared.

Their test results indicate that the HOG descriptors significantly outperform the existing local invariant features: SIFT and SURF in the pest classification for paddy field insect pests. HOG descriptors, when combined with SURF features, give a classification accuracy of about 90%. For simplicity and speed, the linear SVM was used as a classifier throughout the study.

In [10], the authors proposed to review various segmentation techniques used in image processing to detect plant diseases. There are thresholds such as the surface threshold, the Otsu threshold, the SVM (support vector machine), the nearest neighbor K classifiers, the fuzzy logic, the artificial neural network. The different techniques compared through accuracy and time.

In [1] the authors proposed a software solution for early pest detection on the affected crops in the greenhouse. Whiteflies are chosen for the study. The samples collected by using the pan-tilt camera with 20X zoom maintaining equal illumination to the object in the greenhouse. The images were converted into grayscale. Then images resized by using bi-cubic interpolation as it generates more accurate results than any other methods like Nearest-neighbor interpolation and bilinear interpolation. The average filter applied to reduce the noise and improve the visual quality of the image. The properties such as entropy, mean, standard deviation, eccentricity, Euler number, filled area, solidity, gray co-occurrence matrix, contrast, and energy are calculated from the filtered images in order to apply the classification. For classification, the SVM classifier is used. SVM classifier helps to detect the pests and in the classification of pests based on their features. The support vector machine generates the output based on the comparison with the parameters of the database. A special type of mask is used for the identification of pests followed by the average filtering. Then the filtered image is convolved with the mask. Then extracting the region properties and gray co-occurrence matrix properties the classification is done in two types, whiteflies and aphids. They have considered region properties like standard deviation and contrast for the identification part. They again used the SVM classifier to determine the category.

The results indicate more precision in identifying the presence of the pest at an early stage. They divided the images into two categories affected and unaffected. The affected category is also divided into two classes: aphids and whiteflies. Their result shows that the SVM training was performed with 100% accuracy.

In [4], the authors developed an algorithm for detecting and classifying the pests. Their advanced system provides a simple, effective and fast solution for detecting pests. They explain a simple and effective method based on image processing using a neural network for the classification of pests. The acquired images are resized and converted to grayscale. There are different properties such as region properties, gray covariance matrix properties. Among them; properties such as entropy, mean, standard deviation, contrast are extracted from the image. These properties are used as inputs for the Neural Networks classifier. That the characteristics of the input image are extracted and given as input to the network. The classification of diseases is carried out on the feed-forward network. Affected images and unaffected images used to form the network. Their results indicate that there is a difference in standard deviation, contrast, variance, entropy, and so on. If a leaf is affected by the pest, the next step is to look for the type of pest that is whitefly or aphid. They represent derived features as inputs into a feedback neural network, resulting in zero or one. Zero considered unaffected and one represents an affected image.

The authors claim that their method is as profitable and straightforward. Furthermore, we can also conclude that when parasites are detected at an early stage, the use of pesticides is reduced by up to 80%.

In [15], a method proposed by the authors is to examine crops for pest infestation and to classify the type of pest on crops. The proposed algorithm counts the pests on the leaves and then estimates the number of whiteflies per leaf. This document presents a method for automatically identifying whiteflies from leaves. Color images require large-scale storage and processing time during pre-processing. For this reason, images are converted to grayscale so that they can be easily manipulated and require less storage space during processing. The grayscale images obtained by considering the following equation on the images.

$$I(x, y) = 0.2989*B + 0.5870*G + 0.1140*B$$

Bi-cubic interpolation was used to resize images, which gives better results than other resizing techniques, such as bilinear interpolation and nearest neighbor. The average filter used for filtering. The background of the image is calculated using morphological operators, which is essential once this image is subtracted from the original image, in order to detect the pests of the images. Thus, the resulting image will only have the 0 background pixel values and the objects with the pixel 1 values. They mentioned that their methodology gives better results than the watershed and Gaussian mixture segmentation models. These algorithms use a large number of complex arithmetic operations such as division, multiplication and mean, which exponentially increase the execution time. The proposed method, therefore, improves performance and gives better results.

The erosion algorithm was used to eliminate the noise. After the noise was removed, the next objective was to improve the pest detected after the segmentation performed using the dilation algorithm. The gray level co-occurrence matrix (GLCM) and the regional properties of the images are calculated for the feature extraction process. These properties were used to train the support vector machine for image classification. Moore's neighborhood tracing algorithm and Jacob's stopping criterion were used to counting pests on the 1% of plants per square of the field.

In [12] a model developed for the detection of plant diseases. First, the input RGB image has been converted to HSI, because RGB is used for color generation and this is for the color descriptor. Then, the green pixels are masked and deleted using a specific threshold value, then the image is segmented and the useful segments are extracted. Finally, the texture statistics are calculated from the SGDM matrices. Finally, the presence of diseases on the leaf of the plant is evaluated.

In [8], the authors proposed an automatic diagnostic system for the classification of tea pests using correlation-based feature selection (CFS) and the incremental backpropagated learning network (IBPLN). The authors created a database focusing on eight major pests from separate tea garden records in the districts of northern Bengal in India. The database consists of 609 instances belonging to eight classes described by eleven attributes (signs and symptoms); which are all nominal. The classification was performed using artificial neural networks. The results of the classification were compared with the original feature set and with a reduced set of features. Their research indicates that CFS can be used to reduce the feature vector and that the CFS + IBPLN combination can be used for other classification problems.

In [6], the proposed methodology involves reduced computational complexity and aims to detect pests not only in a greenhouse environment but also in a farm environment. The acquired images are converted from RGB to luminance and Chroma components (YCbCr). Mixture models and watershed segmentation algorithms are used to extract whiteflies from the background of the converted image. These algorithms involve a large number of arithmetic calculations in the form of divisions, multiplications and calculation averages, which leads to an exponential increase in execution time. To obtain only whiteflies, the erosion algorithm used. The image enhancement in the form of dilation is also performed to improve the clarity of the segmented whiteflies. The counting algorithm is implemented using Moore Neighbor tracing and Jacob stopping criteria from counting the number of whiteflies on each affected leaf. Their illustrated experience, the RDI algorithm, uses only two subtractions and a pixel comparison operation to separate the whiteflies. They state that many factors, such as the variation in light intensity illuminating the leaf, the presence of insects or pests other than those of interest to us, and the whiteflies in the vicinity have been taken into account in order to verify the precision algorithm.

It is noted that most of the researchers considered the gray images than RGB images due to the computational complexity while processing the images. And, the region properties mostly considered for the classification process especially when they applying the various neural network architectures for the classification task

A. The step-by-step procedure of the proposed methodology:

- RGB image acquisition
- Converting input images from RGB to HSV.
- Apply a threshold to hide green pixels.
- Remove hidden green pixels.
- Segment the leaf portion and form edges for the region of interest.
- The model detects which leaf component is affected or not based on the characteristics of the texture.
- Detect and remove holes other than the pest region using morphological operations.
- Calculate the properties of the region.
- Detect the affected region using the selection frame among the holes using the area value calculated from the region properties.
- Count the number of pests.
- Create a classification model to identify the type of pest detected from the affected leaf using the convolutional neuron network.
- Identification of the type of pest.

First, the images (RGB) of the leaves are taken by the camera from the garden and some images are downloaded from imagenet.org. The input images are then converted from the RGB color space to a representation of the HSV color space (saturation hue value). The RGB format is ideal for color generation. Nevertheless, the HSV model is an ideal tool for color perception. Hue is a color attribute that describes the pure color perceived by an observer. Saturation refers to the relative purity or amount of white light added to the hue and the value means the amplitude of the light. The Hue component is used for further analysis, followed by the color transformation structure. Then, the Saturation and Value components are removed because they do not provide additional information.

Set the pixel value in an image to zero or some other background value called the masking process. Here, we focus on identifying pixels of predominantly green color. This is accomplished according to the specified threshold value calculated for these pixels. The green components of the pixel intensities are set to zero if they are less than the pre-calculated threshold value.

Fig 01 shows the region of interest and the HSV components after removing the background. To remove the background, the threshold value obtained from the value level in the image of the value component. Images taken in different environmental conditions, as well as lighting, affect the threshold value. For these reasons, the threshold value is changed for each image.

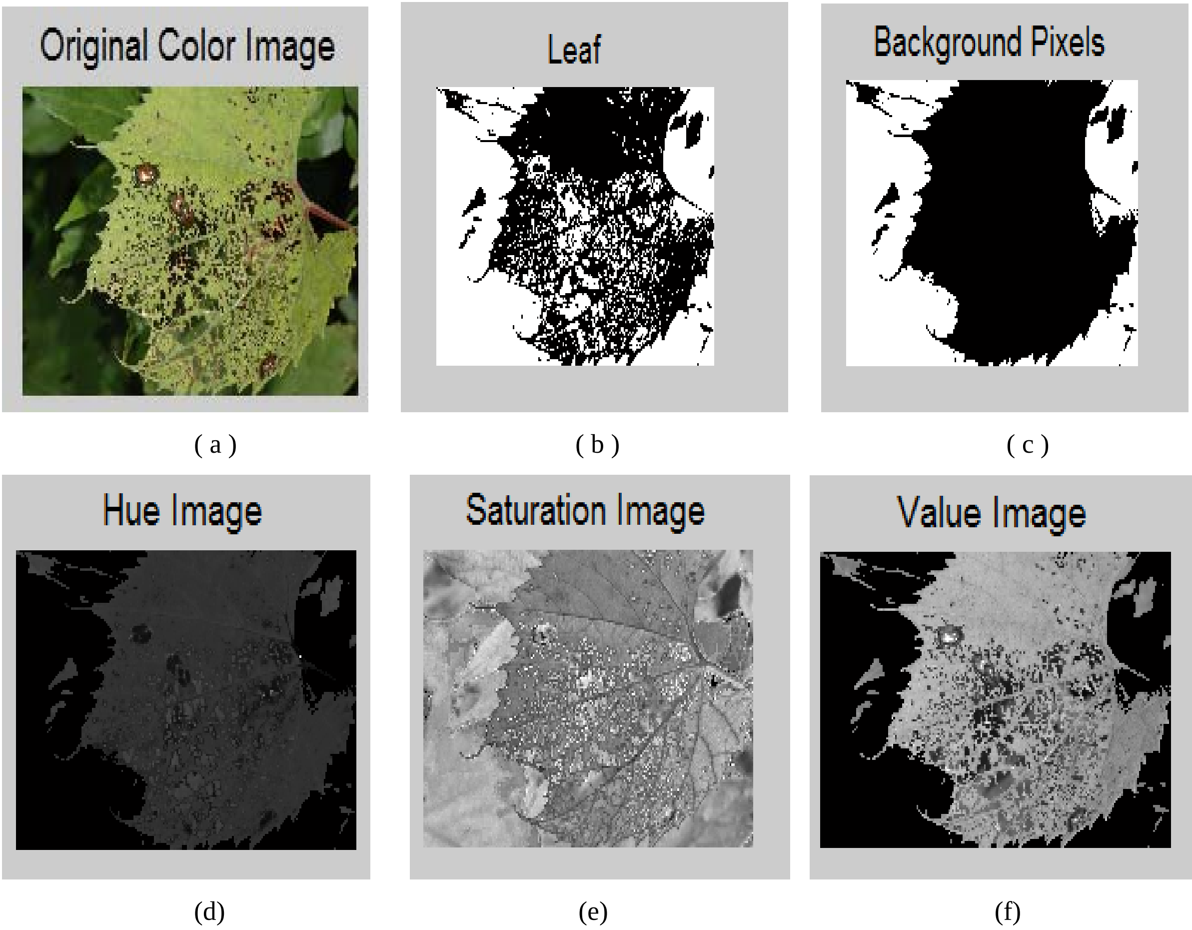


Figure 01: (a) Input image (b) Green regions (c) Background removed (d) Hue components (e) Saturation components (f) Value components

(i) Obtaining leaf Segments:

In this step, the leaf segments are separated. A histogram obtained from the image of the Hue component. Based on the histogram, the regions of the leaves are separated from the binary image. And the non-interested areas outside the leaf considered noise and which have been suppressed by the properties of the regions and the related components. Then, the leaf region obtained with the holes using & logical operation in the image. Fig 02 shows the hue histogram and leaf area with holes and pests.

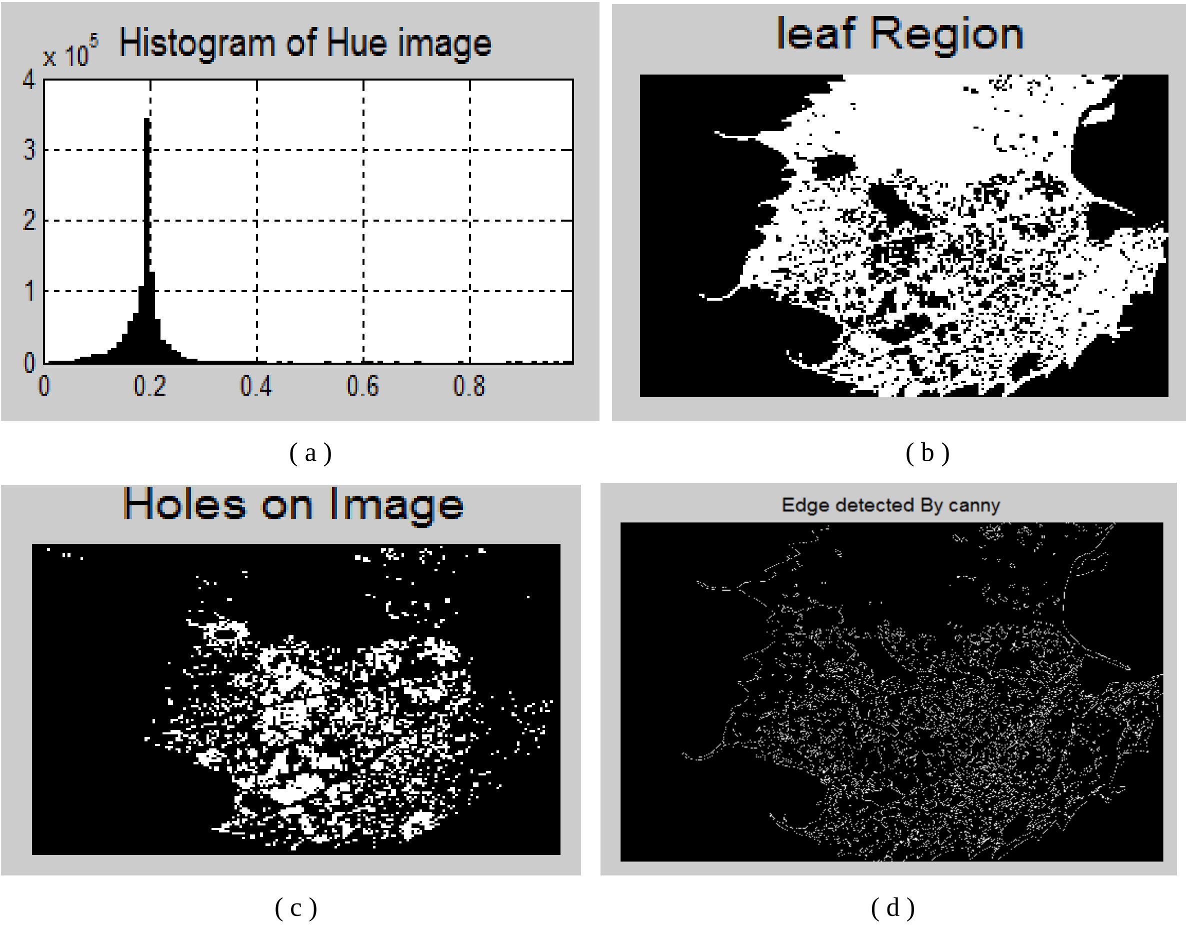


Figure 02: (a) histogram of hue image (b) Leaf region (c) Holes in Leaf region (d) Edge detection for leaf region with holes.

(ii) Compute the affected area from leaf potion with the pest region

In this step, the percentage of the affected region is calculated taking into account the holes in Fig 02 (c) and the total number of pixels available in the leaf region of the image. It should be noted that the affected area included harmful areas in the image. So that the area of the pest in the image is detected.

(iii)Morphological operations to detect the pest region in the leaf image:

Morphological image processing is suitable for removing small holes in the image. The bwareaopen operation removes all connected components (objects) having less than 08 pixels from a binary image. Then, the morphological closing operation is applied, followed by a filling operation to detect the region of the pests from the image of the leaf. The distances between the centers of mass with all the pixels along the limit for each object were calculated. Then, some holes are removed from the image based on the appropriate range selection. The result of the process given in Fig 04 below.

(iv) Pest regions detected by considering the region properties:

In this step, the region properties such as area, eccentricity, Euler number and etc. were calculated. Then the pest regions selected by tracing the boundaries using bwboundaries and the proper selection of the area (calculated under the region properties). The output obtained from this step given below.

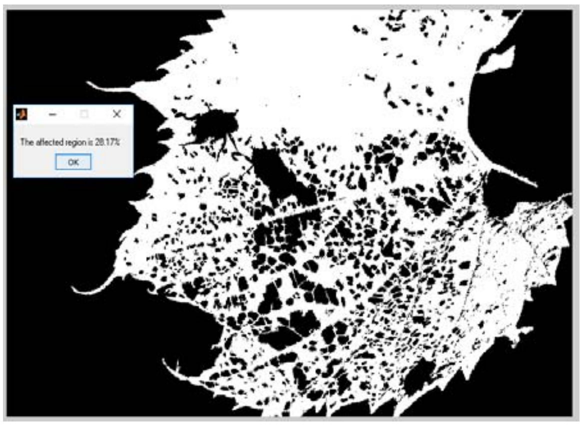


Figure 03: Affected region calculated from leaf image (with pest region).

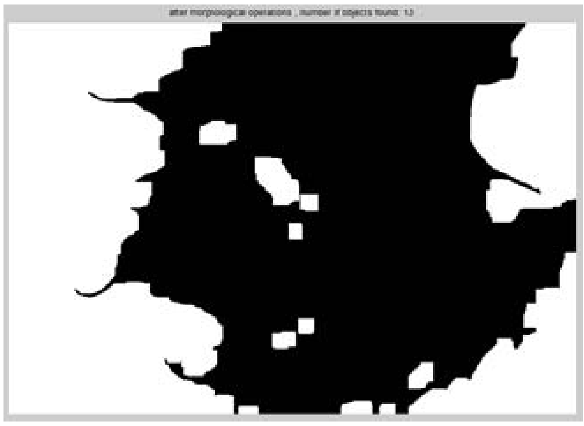


Figure 04: Output image after the morphological the operations

Figure 05: Pest regions detected from the binary image

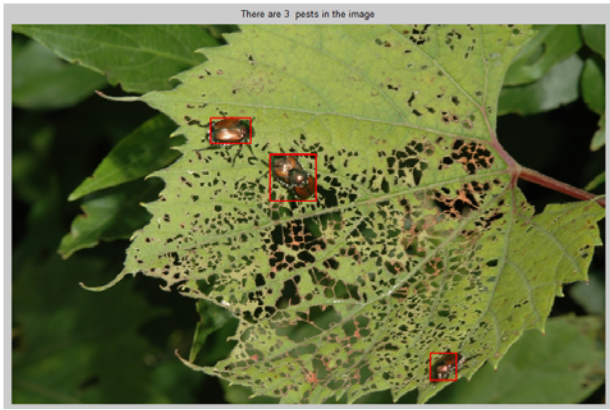


Figure 06: Pest regions detected from the binary image

Depending on the region properties and the bounding box option, the regions of the pest detected in the affected leaf images. Counting pests on the leaves is one of the objectives of the research so that it can give an idea of the amount of harmful attack on a leaf. In Fig 06, the number of harmful organisms counted and that displayed at the top of the image.

B. Classification model using a convolution neural network

To detect the type of pest from the leaf image, a classification model must be constructed. In order to build the classification model, a Matlab "MatConvNet" toolbox was used in the experiment. MatConvNet is an implementation of the convolutional neural networks (CNN) for MATLAB. The toolbox is designed with an emphasis on simplicity and flexibility. It introduces CNN building blocks as easy-to-use MATLAB functions, providing routines for calculating linear convolutions with filter banks, pooling capabilities, and more. In this way, MatConvNet allows rapid prototyping of new CNN architectures; at the same time, it supports efficient computing of processors and GPUs to form complex models on large data sets such as ImageNet ILSVRC. In our experience, microprocessor (CPU) based computing architecture has been used to train and test the dataset model. The version of Matconvnet-1.0-beta-17 and Matlab R2014a was also used for implementations.

There were five classes of pest images considered in the research work listed given below.

For the classification model, data set divided into training, testing and validation sets. In each class 70% of the images selected for training purposes and the remaining 30% of images selected for testing purposes. Then 70% of images selected to build the training model from the training images and the remaining 30% of the training images used to build the validation model. And the classification performances calculated based on the training model applied to the testing images.

Fig 07 depicts the dataset preparation for the classification model in a pest class.

Table 1: Types of pests and the number of images

Type of pest (Class label)	Number of pests
Flea beetle	679
June beetle	922
Lady bug	948
Squash bug	541
Tarnish plant bug	328

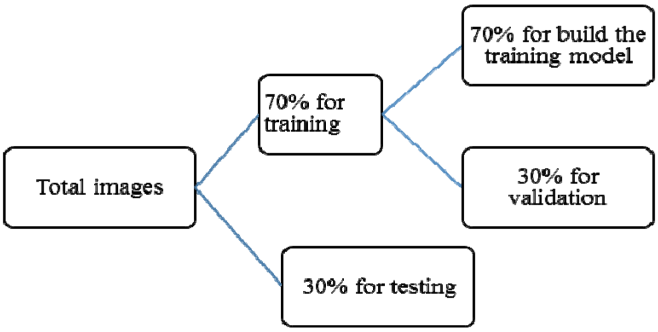
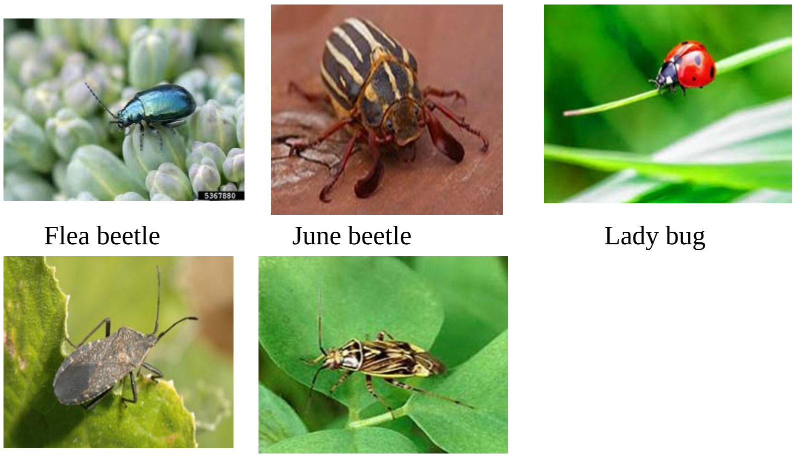


Figure 07: Data set model for experiments



Flea beetle June beetle Lady bug

Squash bug Tarnish plant bug

Figure 08: Types of pest considered for the recognition process

Fig 08 shows some examples of selected five pest species that mainly found in the Batticaloa area.

(i) MatConvNet configuration to build the training model on the dataset

The two commonly used approaches to deep learning are the formation of a model from scratch and transfer learning. Both approaches have advantages and can be used for different in-depth learning tasks. Developing and training a model from scratch works best for very specific tasks for which pre-existing templates cannot be used. The disadvantage is that this approach usually requires a large amount of data to produce accurate results. In our research, the dataset provides fewer images it was not enough to build the training model from scratch. So that the training model has built from the dataset by using the pre-trained networks. There are a lot of pre-trained networks available to build the training network models such as alexnet, vgg16, resnet18 and etc. [17].

In this research "imagenet-vgg-m" pre-trained networks model have used to build the training model. The classification procedure using the MatConvNet explained in the following diagram.

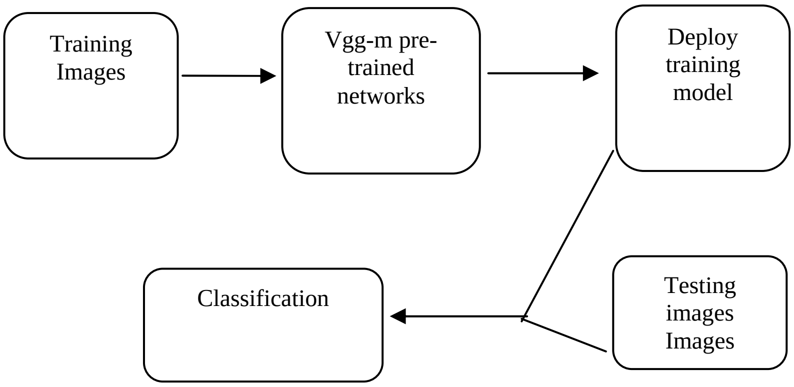


Figure 09: MatConvNet procedure

III. RESULTS AND DISCUSSION

The classification rate calculated on the testing images by using the following equation.

$$\text{Rate}=\frac{\text{Number of images which are correctly classified}}{\text{Total number of testing images}} \times 100$$

The deployed training model was used to calculate the classification rate. The rate calculated for each class listed below.

Table 2: classification rate for the testing image set

Type of pest	Total number of testing images	Correctly classified images	Classification rate
Flea beetle	197	151	76.65 %
June beetle	266	221	83.08 %
Lady bug	283	203	71.73 %
Squash bugs	156	104	66.67 %
Tarnish plant bugs	89	58	65.17 %

From the above table, we can observe the tarnish plant bugs has a low classification rate. Because the squash bugs and the tarnish plant bugs have a small variation which is only the surface color. So most of the testing images under the tarnish plant bugs misclassified into the squash bugs. Also the number of images taken from the type of pest also less amount. Due to this reason, the classification rate may differ from others.

IV. CONCLUSIONS

In our research, a method suggested to find the affected area, detect the number of pests and determine the type of insect pest, a classification model built using the convolutional neuron network. Implementation of the system of identification of pests to using image processing techniques has caused many problems. Major difficulties are due to minor changes. Due to the change of light, the characteristics of the image such as color, intensity, contrast, etc. may vary. Also, the methodology not fully supported for the detection of the pest region due to these reasons, hence the work semi-automated for the pest detection then the classification process continued.

Another difficulty is that we need a number of pests in each class to get a higher classification rate by using a convolution neural network. Due to this reason the pre-trained networks model used to build a training model. Also, the different class pest has more similarity that made effects to decide the pest type.

Here we have considered the Convolution neural network implementation by using the MatConvNet (matconvnet-1.0-beta17) for the classification process, but there are the latest versions with the extended versions of the convolution neural networks such as R-CNN, Fast R-CNN and Faster R-RCNN for the object detections. In order to accomplish the latest feature advantages, we need more computational power like GPU based computer architecture than CPU based architecture. Also, CUDA - a parallel computing platform and other image processing toolboxes need to be considered to gain a higher classification rate. In the future, we will focus on this type of work with a large amount of data.

Finally, this research makes it possible to identify pests at an early stage. So we can reduce pesticides. Accuracy can be improved by using different methods using image processing techniques compared to manual systems. And, to suggest the appropriate pesticides based on the affected pattern and the recognition of the pest type we need more research on this domain.

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