IARJSET ISSN (O) 2393-8021, ISSN (P) 2394-1588

International Advanced Research Journal in Science, Engineering and Technology
ISO 3297:2007 Certified ჯ Impact Factor 7.12 ჯ Vol. 10, Issue 2, February 2023
DOI: 10.17148/IARJSET.2023.10226

Computer Vision Application in Agriculture for Pest Control

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Abstract: According to one of the survey report,70% of India's population depends on the agricultural sector. A wide variety of diseases and various types of pests affect crop production, resulting in loss of quality and quantity of the yield. In current scenario farmers are opting for the option of pesticides to get rid of the pest, but the pesticides are ruining the soil quality level and effecting our environment. For this problem faced by many farmers across states the key solution is to detect the pests as early as possible and cut down the use of pesticides over vast areas and concentrate on particular areas where pest is been detected and destroy them as early as possible. Hence this paper gives a solution of such problem that is "Computer vision application in agriculture for pest control".

Keywords: pest detection, image procession, agriculture, pesticides.

I. INTRODUCTION

Agriculture in India includes various types of fruits and vegetables. Indian farmers also grow a variety of non-food products such as coffee, rubber, bamboo, cotton and tea. The development of such crops depends on the strength of roots and leaves. Various types of pests and diseases can affect plant growth or even cause serious damage due to lack of knowledge,farmers may have difficulty identifying such diseases and pest types, especially in the early stages. Hence pest detection covers the biomedical field. Biomedicine includes different types of processes, of which image processing techniques are most suitable for the current framework. This process begins with data collection, where an image of a plant leaf is captured using a camera, then feature extraction is performed. This is the easiest and most reliable method in the field of pest detection.

Research in this area can also help reduce the use of pesticides. To protect crops, extensive loss and damage to crops by bio aggressors such as insects and pests must be managed. India suffers about 18% of crop yield loss each year due to pest infestation worth about Rs 90,000 crore. Through visual inspection, identified and detected pests that required constant monitoring. However, this strategy becomes impractical when covering large areas of farmland. Moreover, this method is very time consuming, expensive and imprecise. In large-scale agriculture, the proposed scheme can be combined with IoT devices to accurately identify diseases through continuous image capture. All collected images can be processed using deep learning approaches. Convolutional neural networks are very efficient in processing large amounts of data in a very short time. Process images of parts of plants affected by disease or pests, such as leaves, stems, roots, and fruits, using fine-tuning of per trained CNN models.

The rest of this paper is organized as follows:

Section II contains a review of the literature.
Section III describes about CNN.
Section IV contains a detailed description of the proposed approach.
Section V contains references.

II. LITERATURE SURVEY

1. Pest Detection on Leaf using Image Processing

This paper describes an automated pest detection approach using Wavelet Transform and Oriented FAST and Rotated BRIEF (ORB). The main purpose of this work is to improve the feature extraction phase to improve recognition efficiency. The proposed approach has been implemented on caterpillar pest images of mustard crops and broad beans collected from farms in Rajasthan. Experimental results confirm the efficiency of the proposed approach.

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2. Crop Diseases and Pests Detection Using Convolutional Neural Network

This article reviewed deep learning techniques related to disease and pest detection and proposed a deep learning model for automatic diagnosis of plant diseases and pests.

3. An Efficient Approach for Crops Pests Recognition and Classification Based on Novel DeepPestNet Deep Learning Model

Crop pests cause significant economic, social and environmental losses worldwide. Different pests have different control strategies, and accurate identification of pests is essential for pest control and poses great difficulties in agriculture. There has been an interest in deep learning (DL) models. Pest identification approaches in the literature have relatively low accuracy in pest detection and classification due to algorithmic complexity and limited data availability. Misclassification of pests can lead to the use of the wrong pesticide, damaging agricultural yields and the environment. There is a need to develop automated systems that can more accurately identify and classify pests. In this whitepaper, we present a new end-to-end DeepPestNet framework for pest detection and classification. The proposed model has 11 wearable layers, including 8 convolutional layers and 3 fully connected (FC) layers. We used an image rotation technique to enlarge the size of the dataset and an image enlargement technique to test the generalizability of the proposed DeepPestNet approach. We evaluated the proposed DeepPestNet framework using the popular Deng's Crops dataset. Using the proposed method, plant pests were detected and classified into 10 classes of pests. H. Locusta migratoria, Euproctis pseudoconspersa strands, Chrysochus chinensis, Empoasca flavescens, Spodoptera exigua, Laspeyresia pomonella larvae, Parasa lepida, Acrida cinerea, S. exigua larvae, and his L.pomonella species of pests

4. Detection of Pest from Paddy Crop Leaf Using Image Processing Techniques

The leaves of paddy fields are photographed with a digital camera and processed with image processing technology. The final process in these techniques is image segmentation. In this case, the image is segmented using a clustering method. The clustering algorithm detects the affected parts of the leaves and also calculates the percentage of the affected area.

5. Pest detection for crop leaf disease detection and prevention

Users / farmers can upload images. Features are extracted from the uploaded image. Based on these features, k-means and EM clustering are performed to select clusters that provide the most information about the affected regions. Various parameters such as percentage of area affected, mean, entropy, energy, RMS, and pest classification are then performed using multi-SVM.

6. Review of Pest Attack Prediction and Detection Methodologies

Field pests and diseases are a major cause of crop loss. In a populous country like India, agriculture should be maximized. This is possible if we can control the infestation of pests in the field. In this digital world, many advanced technologies are available to combat pest infestations. These technologies can be used to predict pest infestations, identify which pests have attacked, and take necessary actions proactively to reduce losses. These technologies include machine learning, artificial intelligence, computer vision, deep learning, and more. In this paper, we look at some promising methods implemented by researchers to combat pest infestations in fields.

III. CONVULUTION NEURAL NETWORK(CNN)

A convolutional neural network is a special type of feed forward artificial neural network whose connections between layers are inspired by the visual cortex. Convolutional neural networks (CNNs) are a class of deep neural networks used for analysing visual images. They are applied to image and video recognition, image classification, natural language processing, and more. Convolution is the first level of extracting features from the input image. Convolution preserves relationships between pixels by learning image features using small squares of input data. This is a mathematical operation that takes two inputs, like an image matrix and a filter or kernel. Each input image is passed through a series of convolutional layers containing filters (kernels) to produce an output feature map. This is a clear description of how CNN works.

CNN Architecture:

Inspired by the organization and function of the visual cortex, the CNN architecture is designed to mimic the connectivity patterns of neurons in the human brain. Neurons within a CNN are organized into a three-dimensional structure, with each group of neurons analysing a small region or feature of an image. So each group of neurons specializes in identifying

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a part of the image. A CNN uses predictions from a layer to produce a final output that is a vector of probability values representing the probability that a given feature belongs to a given class.

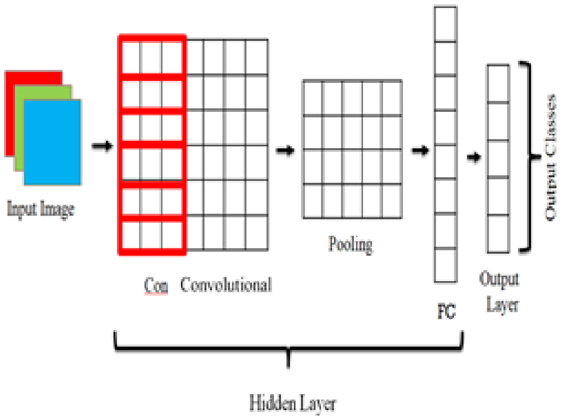

Fig.1 Typical CNN Architecture

CNN architecture has several layers they are:

1. Convolution layer: In a convolutional layer, the computer reads the image in pixel format and then uses a convolutional layer to retrieve a small portion of the image. These images or patches are called features or filters. By sending these rough feature matches at roughly the same locations in the two images, the convolution plane is much better at detecting similarities than whole-image matching scenes. These filters are compared with the new input image and if they match, the image is classified correctly. Here, we align the features and images, then multiply each image pixel by the corresponding feature pixel, add the pixels, and divide the total number of pixels in the feature. Create a map and enter the filter values in the appropriate places. Similarly, move the feature to other locations in the image to see how it matches that area. Finally, get the matrix as output.

2. ReLU Layer: A ReLU layer is just a rectified linear unit. This layer removes all negative values from the filtered image and replaces them with zeros. This is done to avoid zero values. This is a transform function that activates the node only if the input value is above a certain number and the input is less than zero. The output is zero, removing all negative values from the matrix.

3. Pooling layer: In this layer we reduce or reduce the size of the image. Here we first choose the window size, name the desired increment, and then run the window on the filtered image. Then get the maximum value from each window. This will combine the layers and reduce the size of the image and matrix. A reduced size matrix is given as input to a fully connected layer.

4. Fully connected layer: After going through the convolutional, ReLU and pooling layers, we need to stack all the layers. The fully connected level is used to classify the input image. These layers should be repeated as needed unless you end up with a 2x2 matrix. Finally, a fully connected layer is used where the actual classification is done.

IV. PROPOSED APPROACH

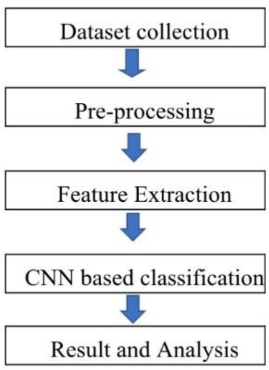

Fig.2 Proposed Approach

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1.Dataset collection

i. Online data set

We have used our major data set from **kaggle**, a platform where we can find various variety of data sets and can explore it.

https://www.kaggle.com/datasets/ranjeetsuthar/crop-pest-details?resource=download
https://www.kaggle.com/datasets/simranvolunesia/pest-dataset
https://www.kaggle.com/datasets/rtlmhjbn/ip02-dataset .
This is the link for the data set which we will be using for this project.

The Data Contains different pest categories with each having the following details:

Pest Category: Common name of the pest.
Host Crop: List of crops that are majorly affected by a particular pest.
Host Country: List of countries where a particular pest is established or commonly found.
Host Continent: List of continents where a particular pest is established.
The below table represents the detailed description of the pest category host crop host country and host continent.

ii. Field survey data set

1. Ragi Field

Fig. 3. Survey in Ragi field

This field is located in T.G halli (near Ramnagara) in this crop we could find a soppy foam like thing on almost one out of two plants. This foam was created by the spittle bug and tis foam is known as cuckoo. When we asked about this to the farmer of that land, they said that this is just the left over after they had used pesticides, they have been highly found in the months between July and August. So, they have used the pesticides all over the field to get this pest out.

The foam itself isn't inherently dangerous, but spittlebugs can act as carriers of the Xylella bacteria, which causes a deadly plant disease that could wipe out more than 650 native UK plant species.

2. Mulberry field

Fig.4. Survey in Mulberry field

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This field is located in kanakpura in this field we found a cater pillar type of worm but was not the silk worm. This worm is called as leaf webber. The infestation is observed on the onset of monsoon, that is, from June and lasts up to February. Peak period of infestation is November to February.It is a major defoliator pest known to cause extensive damage to mulberry in Karnataka, Andhra Pradesh and Tamil Nadu. The infestation is observed in mulberry plantations from 12 days through 70 days after pruning.

The target area of the leaf webber is the apical portion of the mulberry shoot. The larva binds mulberry leaf blades in tender shoot portion by silken thread hide inside and devours the soft green tissues of the leaf surface. Grown up caterpillars feed voraciously on tender leaves and its faeces can be seen over the leaves below the infested shoot. As this pest damage the apical shoot portion, growth of plants is affected which leads to adverse impact on leaf production.In this plant we have to be very careful when it comes to removing this pest as we can't use more pesticides because that can affect the silk worms. Hence through our application we can detect the pest count and location of pest and conclude whether it is better to hand pick or to use mild amount of soap solution to eradicate the pest.

3. Maize field

Fig.5. Survey in Maize field

This plant is located in T.G.Halli (near Ramnagara) ,in this field few of the plants was badly affected by the a worm which was in egg state and larval state . This worm is called as Fall Army Worm (FAW).FAW attacks all stages of maize crop from seedling to ear development. The young larvae of FAW feed in and around the whorl leaves by scraping and skeletonizing the upper epidermis leaving a silvery transparent membrane resulting into papery spots. The damage also results in pinhole symptoms on the leaves. Older larvae remain and feed inside the whorl. The damages by late instars result in extensive defoliation of leaves and presence of large amounts of faecal pellets in whorls. Damage during vegetative stage leads to leaf damage but if damage happens during reproductive stage it may damage tassels or may bore inside the corn ear and eat away the kernels. The whorl damage by FAW results in significant yield losses while ear feeding results in both quality and yield reduction.In this plant when the egg state develops into larvey it enters the nodes of leaf and does not die even when pesticide is used. From our application we can detect the pest at early stage and remove it at the early state and prevent it from developing and spreading.

4. Ladyfinger field

Fig.6. Survey in Ladyfinger field

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This was a small field of ladyfinger which is located in T.G.Halli (near ramnagara) in this small field almost all the plant had holes in its leaf which had happened due to a bug called Leaf-Footer bug. These bugs were present in only few number but had very bad effect on the plant.

Leaf-footed bugs are members of the Coreidae family of insects, which are primarily sap-suckers. Leaf-footed bugs are not beneficial insects. Although their relative bread, the squash bug, poses more of a threat to vegetable gardens, leaf-footed bugs should not be considered harmless. They use their proboscis, which is kept against their abdomen, to pierce leaves, stems, and fruit so they can suck the sap or juice from them. Both adults and nymphs will feed on the leaves of ornamental and vegetable plants, which may cause only slight visual damage.
The best method to remove this pest is to detect them in the early stage when they are eggs and remove those, and handpick the adult bugs and to use organic oils to get rid of them, which is the main motive of our application.

2. PRE-PROCESSING

Flowchart of pre-processing of the image obtained from the output of the previous step. This includes converting the image from RGB format to grayscale for ease of processing, using an averaging filter to remove noise, and using a global base threshold to remove the background. It involves displaying only the image and using a high-pass filter to sharpen and enhance the image. Finer details.

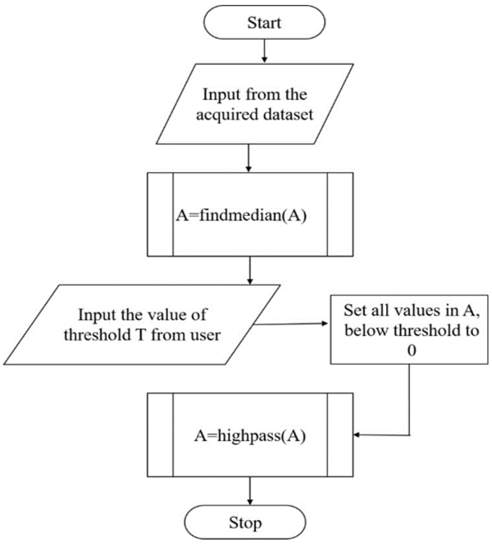

Fig.7. Flowchart for the pre-processing module

i.Conversion from RGB to Greyscale
The first step in preprocessing is to convert the image from RGB to grayscale. It is obtained by applying the following formula to the RGB image: Figure shows the conversion from RGB to grayscale.

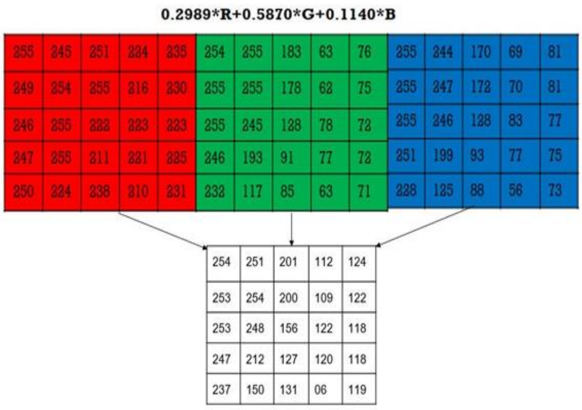

Fig.8. Conversion from RGB to Grayscale

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ii.Noise removal using media filtering

A de-noising algorithm is the process of removing or reducing noise from an image. De-noising algorithms reduce or eliminate the visibility of noise by smoothing the entire image and leaving regions near the contrast limit. De-noising is the second step in image pre-processing. Here, the grayscale image obtained in the previous step is given as input. Here we use the median filter, a de-noising technique.

Median filtering: A median filter is a nonlinear digital filtering technique commonly used to remove noise from an image or signal. Here the edge and corner zeros are added to the matrix that is the representation of the grayscale image. Then, for each 3 * 3 matrix, sort the elements in ascending order, find the median / average element of those 9 elements, and write that median value at that particular pixel location.

iii.Basic Global Thresholding

Thresholding is a type of image segmentation that modifies the pixels of an image to make it easier to analyze. A(i, j) is greater than or equal to the threshold T. Otherwise, replace the value with 0. Now the value of T can be manipulated on the front end to meet different needs for different images. Use trial and error here to determine the best threshold.

iv.Image Sharpening

Image sharpening is a technique that enhances the edges and details of an image. Larger values result in sharper images.
• High Pass Filter: The High Pass Filter can be used to make images appear sharper. These filters enhance image details. Here the output of thresholding is given as an input. Use filters here. First, add the closest pixel value to the border pixel.

3. FEATURE EXTRACTION

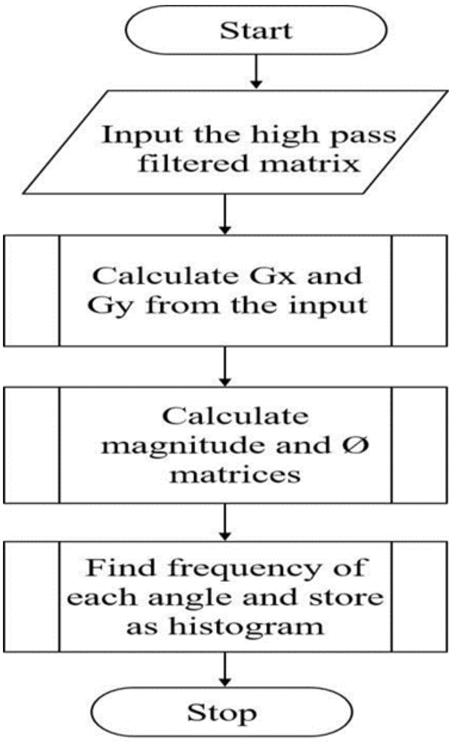

Fig.9. Feature Extraction

Here, we use a method called Histogram Orientation Gradient (HOG) to extract features from the pre-processed image received as input. This involves several steps, such as finding the gradients Gx and Gy around each pixel on the x and y axes. Then plug these gradients into the relevant formulas to get the size and gradient of the pixel placement. The angles and their respective frequencies are then plotted to form a histogram, which is the output of this module. A flowchart of the feature extraction model is shown in the figure

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• Histogram Oriented Gradients:

Histogram Oriented Gradients (HOG) are feature descriptors used in image processing for computer vision and object recognition purposes. This technique counts occurrences of gradient directions in localized parts of the image.

4.CNN BASED CLASSIFICATION

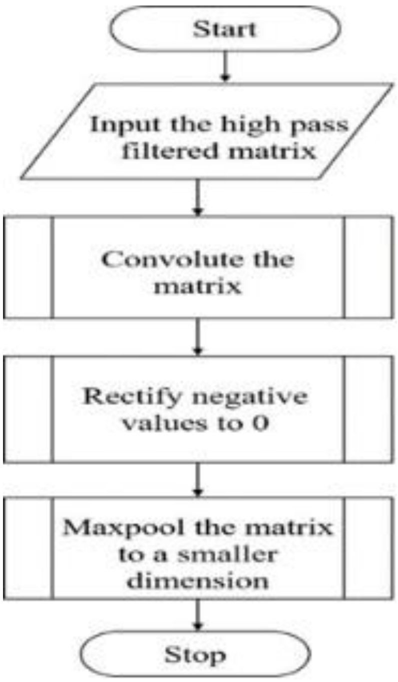

Fig.10. CNN based classification

In deep learning, convolutional neural networks (CNNs or ConvNets) are the most commonly used class of deep neural networks for analyzing visual images. They are also called shift-invariant or space-invariant artificial neural networks (SENS), based on their shared weight architecture and transform-invariant properties. When using CNN for classification, there is no need to perform feature extraction. Feature extraction is also done by CNN. Pass the pre-processed image directly to the CNN classifier and retrieve the weapon type, if any. A flowchart of classification by CNN is shown in Figure, by considering all features in the output layer that give some predictive value to the result. These values are calculated using the SoftMax activation function. SoftMax activations provide predictive values. Based on the predicted value, the final result is identified as Weapon.

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