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Insect Identification and Insecticide Recommendation System

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ABSTRACT

Around 70 percent of the Indian population depends on the agriculture sector. There has been a tremendous increase of around 11.32 percent in the export of agricultural produce in the past 3 years. However, this percentage can be increased by increasing the crop production by protecting the crops from bugs and other plant-infecting insects. Agriculture production decreases as the insects feed on the crops and further destroy the crop quality. If farmers could get the proper guidance for using insecticides for the specific insects, there would be an enormous increase in production level. Through this paper, we present a system to help farmers identify the insects that pose a hazard to their crop and recommend specific insecticides. The solution is to collect real-time data from farmers and analyze and recommend appropriate insecticides using advanced machine learning techniques.

KEYWORDS: Crop protection, Crop insect detection, image processing, Machine learning, recommendation system.

1. INTRODUCTION

Agriculture, which is considered the backbone of the economy, contributes to the country's economic growth, and determines the standard of life. The agriculture and food processing industry are among the major sectors in any country and plays an essential role in expanding the export quality of agricultural and food products. In developing countries, the increase in food processing transformations is mainly due to the impact of export earnings and domestic market demands. In specific conditions, it requires storage, constant maintenance of equipment, and workspaces very frequently. Pest attack[7] is one of the significant problems in the agriculture sector that results in degradation of crop quality. Pests, germs, and weeds cause massive loss to crops and results in a low market for the final products. Finding new ways to gain even small increases in efficiency can make the difference between turning them into a profit or a loss. It must take care of the pest attack on crops that affects the growth of the field crops. The highly essential cash crops mostly contribute to the vast quantities of production. The insects are the main reason behind crop quality degradation and reduce the productivity of crops, therefore. Hence, monitoring and evaluating the losses due to insects is necessary to ensure crop quality and safety in agriculture. Machine vision applied in monitoring of crop and soil, fruit grading, plant disease detection, insect pest recognition, and detection[11]. Recently, many developments have been made in the agriculture sector, using machine learning to detect and classify the insects under stored grain conditions. Fruits and vegetables quality evaluation performed using computer vision-based quality inspection comprising the main steps, such as acquisition, segmentation, feature extraction, and classification. Moment invariant techniques applied for extracting shape features and neural networks were developed to classify 20 types of insect images. Yue et al[8] proposed a super-resolution model based on a deep recursive residual network for agricultural pest surveillance and detection. Pest identification in the complex background using deep residual learning was developed to improve the recognition performance for ten classes of crop insects[19]. Various unsupervised feature learning methods and multi-level classification frameworks were developed for the automatic classification of field crop pests. More recent studies[9] reported that image processing applied effectively for insect detection due to less computation cost, fast detection, and easy to distinguish insects with similar clothes and shape. In clustering segmentation with descriptors is implemented to detect the pests in grape vine with different orientations and lighting environments[21]. The contthe- based and region-based segmentation are combined and applied for detecting individual moths and touching insects

2. Literature survey

In this part, related research work for insect identification using Convolutional Neural Networks is discussed. Min Dai, Md Mehedi Hassan Dorjoy and Shanwen Zhang, Bernard D. Roitberg[1] have proposed a New Pest Detection Method Based on Improved YOLOv5m. Insect pests can damage crops and food production, causing problems for farmers. The detection of plant pests is essential for ensuring the excellent productivity of plants and food. Traditional methods for pest detection are generally time- consuming and inefficient. There has been a lot of use of deep learning for detecting plant pests in recent years. YOLOv5 is one of the most effective deep learning algorithms used for object detection. A new pest detection method with higher accuracy based on a deep convolutional neural network (CNN) is proposed in this paper. Experimental results on the pest dataset indicate that the proposed method performs well and can achieve high precision and robustness for recognizing plant pests. The proposed method is more effective and can detect pests precisely with higher accuracy.

Ana Claudia Teixeira ,Jos ´ e Ribeiro ,Raul Morais ,Joaquim J. Sousa ´ and Antonio Cunha proposed a Systematic Review on Automatic Insect Detection Using Deep Learning.[2] Globally, insect pests are the

primary reason for reduced crop yield and quality. Although pesticides are commonly used to control and eliminate these pests, they can have adverse effects on the environment, human health, and natural restheces. As an alternative, integrated pest management has been devised to enhance insect pest control, decrease the excessive use of pesticides, and enhance the output and quality of crops. The purpose of this article is to outline the leading techniques for the automated detection of insects, highlighting the most successful approaches and methodologies while also drawing attention to the remaining challenges and gaps in this area. The aim is to furnish the reader with an overview of the major developments in this field. This study analyzed 92 studies published between 2016 and 2022 on the automatic detection of insects in traps using deep learning techniques.

M. Chithambarathanu M. K**.** Jeyakumar performed a survey on crop pest detection using deep learning and machine learning approaches[3]. It is critical to seek and develop new tools to diagnose the pest disease before it caused major crop loss. Crop abnormalities, pests, or dietetic deficiencies have usually been diagnosed by human experts. Anyhow, this was both costly and time-consuming. To resolve these issues, some approaches for crop pest detection must be focused on. A clear overview of recent research in the area of crop pests and pathogens identification using techniques in Machine Learning Techniques like Random Forest (RF), Support Vector Machine (SVM), and Decision Tree (DT), Naive Bayes (NB), and some Deep Learning methods like Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Deep convolutional neural network (DCNN), Deep Belief Network (DBN) was presented. This survey provides knowledge of some modern approaches for keeping an eye on agricultural fields for pest detection and contains a definition of plant pest detection to identify and categorize citrus plant pests, rice, and cotton as well as numerous ways of detecting them. These methods enable automatic monitoring of vast domains, therefore lowering human error and effort.

Denan Xia ,Peng Chen, Bing Wang ,Jun Zhang ,Chengjun Xie have proposed insect Detection and Classification Based on an Improved Convolutional Neural Network**.** Regarding the growth of crops, one of the important factors affecting crop yield is insect disasters. Since most insect species are extremely similar, insect detection on field crops, such as rice, soybean, and other crops, is more challenging than generic object detection. Presently, distinguishing insects in crop fields mainly relies on manual classification, but this is an extremely time-consuming and expensive process.[4]

3. About Dataset

Pests are a huge threat! Farmers are hard at work however their productivity is reduced due to pests, so this dataset can be used to identify pests or maybe other use cases involving pest identification.

Dataset Description

a. Type of dataset: Image Dataset
b. No. of training images: 300 images per pest
c. No. of testing images: 50 images per pest
d. Data Sthece: Automatic script to scrape images of pest from Google through Selenium and Chrome Driver
e. Pests: aphids, armyworm, beetle, bollworm, grasshopper, mites, mosquito, sawfly, stem borer

Type of dataset: Image Dataset

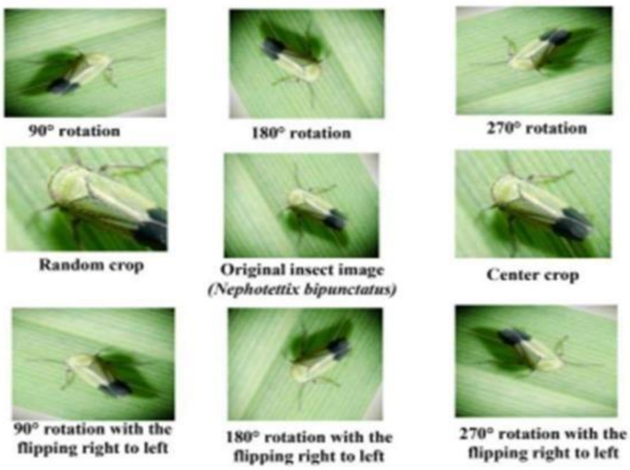

Fig. 1: Rotation images of an insect in the dataset

It has two folders: one is "train" and the other is "test" which is the usual bifurcation done when model must be trained.

4. Methods

Insect classification using CNN model

A convolutional neural network, or CNN, is a deep learning neural network sketched for processing structured arrays of data such as portrayals. CNN are very satisfactory at picking up on design in the input image, such as lines, gradients, circles, or even eyes and faces. The CNN model comes under the class of deep, feedforward neural networks applied to analyze visual imagery of insect images and computationally efficient due to automatic feature learning and weight sharing [5-8]. The size of the insect image is rescaled to 64 x 64. The CNN model can run over each insect image fast and reduce the computational operations per layer and memory. The CNN model contains five convolutional layers and three max-pooling layers, a flatten layer, a fully connected layer, and a soft max output layer to classify insect.

The size of the insect image is rescaled to 64 64. The CNN model can run over each insect image fast and reduce the computational operations per layer and memory requirements. Each convolution layer and max-pooling layer use 3 3 and 2 2 filter sizes, respectively. A fully connected layer is designed in such a way to learn high level features for final insect.

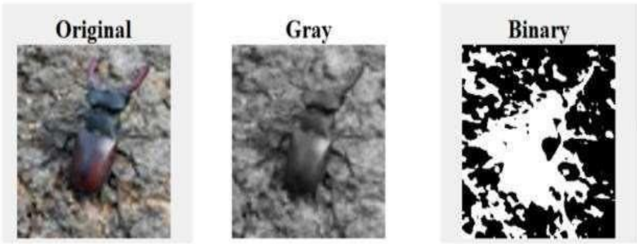

Fig.2 Image Preprocessing into gray and binary images.

In scenarios where data is difficult to obtain, models trained with a lower amount of data can benefit from the use of TF, rather than having the models trained from scratch [10-14]. Most studies have their models pre-trained on large data-sets for image classification such as ImageNet or COCO.

Recommendation using Support Vector Machine

In the proposed solution we have used Support vector machine(SVM),Decision Tree classifier and Naïve Bayes' classifier to recommend the most appropriate insecticide for the crops.

The objective of the support vector machine algorithm is to find a hyperplane in an N- dimensional space(N — the number of features) that distinctly classifies the data points. Hyperplanes are decision boundaries that help classify the data points. Data points falling on either side of the hyperplane can be attributed to different classes. Support vectors are data points that are closer to the hyperplane and influence the position and orientation of the hyperplane. Using these support vectors, we maximize the margin of the classifier.

Decision tree classifiers work like flowcharts. Each *node* of a decision tree represents a decision point that splits into two leaf nodes. Each of these nodes represents the outcome of the decision and each of the decisions can also turn into decision nodes. Eventually, the different decisions will lead to a final classification[11]. Decision trees work by splitting data into a series of binary decisions. These decisions allow you to traverse down the tree based on these decisions. You continue moving through the decisions until you end at a leaf node, which will return the predicted classification.

Naïve Bayes' algorithm works by calculating the probability of a given instance belonging to each class and then selecting the class with the highest probability. It uses Bayes' theorem to calculate these probabilities. Bayes' theorem relates the conditional probability of an event to its prior probability. There are different variations of Naive Bayes, including Multinomial Naive Bayes, Gaussian Naive Bayes, and Bernoulli Naive Bayes. Each variation makes certain assumptions about the distribution of the features and is suitable for different types of data.

The following table provides a comparison of the accuracy.

CLASSIFIER NAME	ACCURACY (%)
DECISION TREE CLASSIFIER	80
NAÏVE BAYES' CLASSIFIER	70
SUPPORT VECTOR MACHINE(SVM)	65

Table 1: Accuracy comparison for classifiers.

5. Flowchart

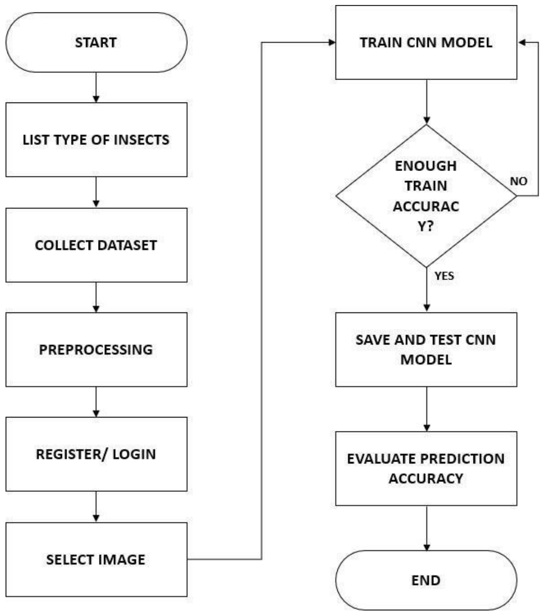

Fig. 3 : Process Flowchart

This diagram is a graphical representation of the ―flow‖ of data through an information system, modelling its process aspects. A Data flow diagram is often used asa preliminary step to create an overview of the system without going into detail, which can later be elaborated.

6. System Architecture

In this architectural diagram given below, the user/ farmer will register in the application. Then he/she will login in successfully to the home page where they will be able to upload the live data of any insect which is to be identifies. The model will hence train this data and test whether the given input is having enough accuracy. Then the model will test this data and identify the class of insect. It will also recommend respective pesticide for that class of insect.

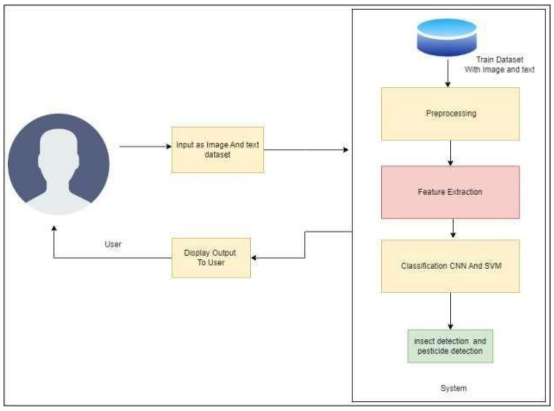

Fig. 4: System Architecture

7. Implementation

For the implementation phase of the project, we propose to implement various module required for successfully getting expected outcome at the different module levels. With inputs from system design, the system is first developed in small programs called units, which are integrated in the next phase. Each unit is developed and tested for its functionality which is referred to as Unit Testing. Given below are graphs which show the model accuracy and model loss as we vary the epochs for training the model.

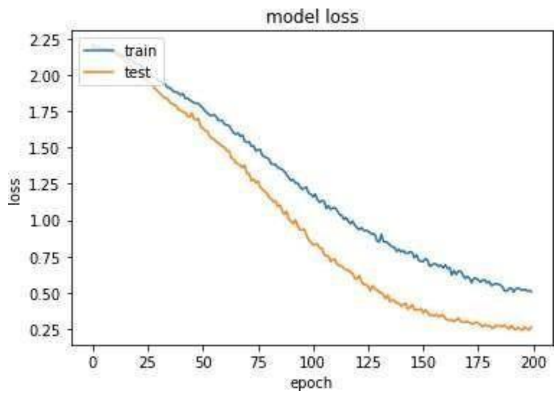

Fig. 5 : Model Loss

The above graph shows how the loss errors in the model vary as we vary the epochs or instances of model training and testing. We can see that as we increase the number of epochs, the model loss decreases. The following table better illustrates the model loss with varying epochs.

EPOCHS	ERROR RATE
50	1.75
100	0.80
150	0.30
200	0.20

Table 2: Model loss

The model accuracy can be shown in a similar way. Below graph shows varying accuracy with varying epochs for the model.

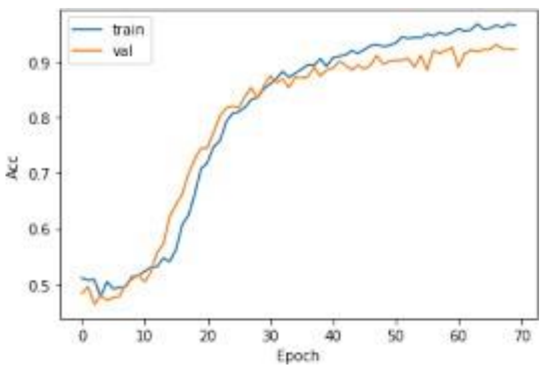

Fig. 6 : Model accuracy

The accuracy of the training model is 98.52% and testing model is 94.22%.

The following table better illustrates the model accuracy with varying epochs.

EPOCHS	ACCURACY RATE
50	0.31
100	0.56
150	0.69
200	0.94

Table 3: Model accuracy

8. CONCLUSION

In this paper, we have proposed a machine learning based Insect identification and insecticide recommendation system. In this project, the farmer/user will upload an image of the insect in application and detect the type of insect which will also provide the best suitable insecticide for that insect. Detection and classification of pests and diseases can be performed using computer vision and deep-learning algorithms based on CNN models, which show better performance when compared with older image classification approaches based on “manual” features extraction. This system is better than the previous system as it provides the information of the problem and solution.

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