

Augmented Reality in Identification of Pests on Crops

Ms. Chandana KR¹, Ms. Chaithra Shree M², Ms. Deepthi B³, Ms. S P Preethi⁴, Ms. Sankalana CM⁵

Faculty, Department of Computer Science and Engineering¹

Students, Department of Computer Science and Engineering^{2,3,4,5}

S J C Institute of Technology, Chikkaballapura, India

Abstract: The agriculture division can benefit from improved methods for identifying and managing pests to ensure a steady supply of safe and nutritious food. Traditional pest identification methods, which rely on the expertise of taxonomists to identify pests based on morphological features, can be time-consuming and require significant resources. To address this challenge, a new pest classification system has been developed that uses close-up image extraction and object recognition to identify pests in the IP102 dataset. This system achieved high classification rates of 91.5% and 90% for nine and 24 class pests, respectively, using a convolutional neural network (CNN) model. In addition to this classification system, an innovative application of Augmented Reality (AR) is being developed to assist farmers in pest identification and management. This system aims to help farmers distinguish between harmful and beneficial insects and provide recommendations for appropriate pesticides and treatments. By providing farmers with this information in real-time, the AR system can help improve crop yields and reduce the negative impacts of pests on the environment.

Keywords: Deep learning, pest identification, deep learning, augmented reality, crop insect detection, machine learning

I. INTRODUCTION

Agriculture plays a pivotal role in India's economy, serving as a primary source of employment and livelihood for a significant portion of its population. However, Indian farmers often fight with a critical challenge: protect the crops from the insects [1]. To address this need, we are developing automated pest detection and pesticide recommendation system. Information Technology can play a role here where automated image recognition and augmented reality can automate to a large extent the role played by experts in aiding farmers. Farmers no longer have to remember the bugs and their information, a cognitively challenging task for them. The insight is that a cell phone today, is really a miniature computer in the hands of the farmer. Leveraging on this information, we can turn the cell phone into a device that provides instantaneous information about various entities like bugs.

We have attempted to address the problem of bug identification by developing an Augmented Reality based system application that we have integrated with an existing system-based information.

II. LITREATURE SURVEY

A literature survey, in a amplify report shows up the diverse examinations and examine made inside the field of charmed and the comes about as of now disseminated, taking into thought the distinctive parameters of the wander and the degree of the wander. So, the taking after subjects not since it was laying out the foundation of the meander but besides uncover the issues and blemishes which prompted to propose courses of activity and work on this increase. Most routinely related with academic-oriented writing, such as a suggestion, a peer-reviewed journal article, a piece audit more frequently than not goes some time recently the method and comes almost sectional in show disdain toward of the reality that typically frequently not ceaselessly the case. Composing studies are in addition common in are see suggestion or diagram (the record that's embraced a few times as of late an understudy formally begins a proposal or proposition). Its primary objectives are to organize the current consider interior the body of writing and to donate setting for the particular per user. Composing reviews are a introduce for asking almost each academic field. A literature survey includes the following:

- Existing speculations around the subject which are acknowledged all around.
- Books composed on the subject, both generic and particular.
- Inquire about the field ordinarily within the arrange of most seasoned to most recent

Detecting and Classifying Pests in Crops Using Proximal Images and Machine Learning

Author: Jayme Garcia Arnal Barbedo, Embrapa Agricultural Informatics, Campinas, MDPI

Both administration is among the foremost critical exercises in a cultivate. Observing all diverse species outwardly may not be viable, particularly in huge properties. In like manner, impressive inquire about exertion has been went through towards the advancement of viable ways to remotely screen potential pervasions. In this setting, the targets of this article are [1] to briefly describe a few of the foremost pertinent examinations on the subject of programmed bug discovery using proximal advanced pictures and machine learning; [2] to supply a bound together diagram of the inquire about carried out so distant, with extraordinary accentuation to inquire about crevices that still wait; (3) to propose some conceivable targets for future inquire about.

Drawbacks:

- The most calculate anticipating more far-reaching selection of programmed bother checking frameworks is their need of vigor to the tremendous assortment of circumstances.
- It couldn't center on making instruments to encourage and empower the association of agriculturists and entomologists within the handle of picture collection and labeling.

Plant diseases and pest detection based on deep learning

Author: Jun Liu, Xuewei Wang, BMC

Plant infections and bothers are imperative variables deciding the surrender and quality of plants. Plant maladies and bothers recognizable proof can be carried out by implies of advanced picture preparing. In later a long time, profound learning has made breakthroughs within the field of advanced picture preparing, distant prevalent to conventional strategies.[3] How to utilize profound learning innovation to think about plant illnesses and bugs recognizable proof has ended up a inquire about issue of awesome concern to analysts. This audit gives a definition of plant illnesses and bugs location issue, puts forward a comparison with conventional plant maladies and bugs discovery strategies. Agreeing to the contrast of organize structure, this ponder diagrams the investigate on plant maladies and bothers location based on profound learning in later a long time from three angles of classification arrange, location arrange and division arrange, and the focal points and drawbacks of each strategy are summarized.[4] Common datasets are presented, and the execution of existing ponders is compared.

Trim Infections and Bugs Discovery Utilizing Convolutional Neural Network

Author: Pruthvi P. Patel, Dineshkumar B. Vaghela,

The Indian economy is amazingly dependent on the agrarian efficiency. In arrange to fulfill the citizen's request and to allow more benefits to ranchers, expanding edit generation is exceptionally significant errand these days. Edit illnesses and bothers play a key part in diminishing trim generation and quality. Manual discovery of infections takes extra time and endeavors on the bigger range of the cultivate. Profound learning approach can be utilized to identify the maladies and bother more precisely on takes off and other parts of the edit. The proposed strategy is supportive in identifying edit maladies as well as bugs. In this paper, the profound learning strategies related to illnesses and bug location has been checked on and the profound learning show for programmed conclusion of edit infections and bugs is proposed.

Drawbacks:

- The methods used in this paper it cannot work on one crop and verify the performance of the proposed work.

III. EXISTING SYSTEM

Mohanty et al. utilized Alex Net and Google Net CNN structures within the recognizable proof of 26 diverse plant illnesses. Ferentinos et al. utilized diverse CNN structures to recognize 58 diverse plant infections [4], accomplishing tall levels of classification exactness. In their approach, they moreover tried the CNN engineering with real-time pictures. Sladojevic et al. outlined a DL design to recognize 13 distinctive plant maladies. They utilized the Caffe DL system to perform CNN preparing. Kamilaris et al. comprehensively investigated diverse DL approaches and their downsides within the field of farming. The creators proposed a nine-layer CNN show to recognize plant maladies [5]. For experimentation purposes, they used the Plant Town dataset and data-augmentation strategies to extend the information measure.

DRAWBACKS OF EXISTING SYSTEM:

- Many existing system analyses is based on color change, which leads to less accuracy in prediction.
- In the existing method, the pest detection algorithm has not focused on detecting insects with complex backgrounds.
- The KNN and SVM were not sufficient to classify the pests of similar features.
- The existing system provided the highest classification accuracy for only a few classes of insects.

Drawbacks:

- It isn't conceivable for picture investigation at the surface level to recognizable proof of the event component of illnesses and bothers, and move from straightforward exploratory environment to commonsense application research that comprehensively considers edit development law, natural variables.

IV. PROPOSED SYSTEM

Picture information enlargement strategies such as turn, flipping, and reshaping administrators are utilized to extend the preparing set for accomplishing made strides exactness and dispensing with the issues of overtraining.[8] The 9-fold cross approval was connected to make strides the execution of the classification models. The most noteworthy classification rate of 91.5% and 90% was accomplished for nine and 24 lesson creepy crawlies utilizing the YOLO v8 show. The discovery execution was finished with less computation time utilizing YOLOv8 calculations. Once bug identified our framework will propose the pesticides to ensure the protection from the pest attacks.[9]

ADVANTAGES:

- Low cost of Implementation
- Accuracy is improved.
- Suggest the treatment for detected pest.

V. WORKING

The main objective of this to implement a deep learning model based on CNN to classify the pests, early detection of pests to avoid damage and degradation of the quality of crops.

VI. DESIGN AND METHODOLOGY

In the block diagram we are passing visual features as input system will preprocess the frame and apply YOLOv8 and detect insect name.

In this project we are using YOLOv8 deep learning model to detect the insect.

We construct our Consecutive CNN demonstrate with different layers such as Conv2D, MaxPooling2D, Smooth, Dropout and dense.

In the last Dense layer, we utilize the 'soft max' work to yield a vector that gives the likelihood of each of the four classes. [10] Here, we utilize the 'adam' optimizer and 'Binary cross entropy' as our misfortune work as there are asit were two classes. Moreover, you'll be able to indeed utilize the YOLOv8 for superior exactness.

BLOCK DIAGRAM

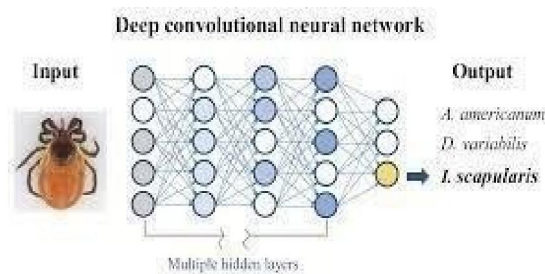


Figure 6.1 Block Diagram

In the block diagram we are passing visual features as inputs system will pre-process the frame and apply YOLOv8 and detect insect name.

ACTIVITY DIAGRAM:

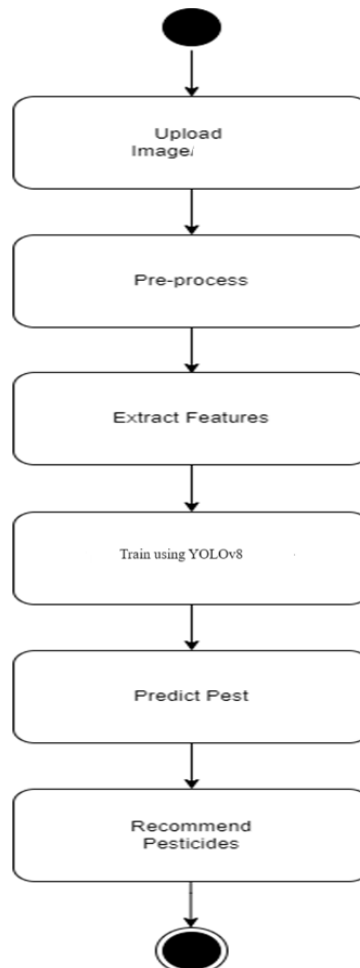


Fig:6.2: Activity diagram

The activity diagram describes the workflow and interactions involved in the system. Here are the steps involved in the process:

- The user or system uploads an image or video.

- The image or video is pre-processed, which may involve resizing, normalization, and other techniques to prepare the data for analysis.
- Features are extracted from the pre-processed image or video. This step may involve using a pre-trained model like to identify important features.
- The extracted features are used to train a machine learning model, which can predict the type of pest present in the image or video.
- Based on the predicted pest, the system recommends pesticides or other treatments to address the pest

STATE CHART DIAGRAM

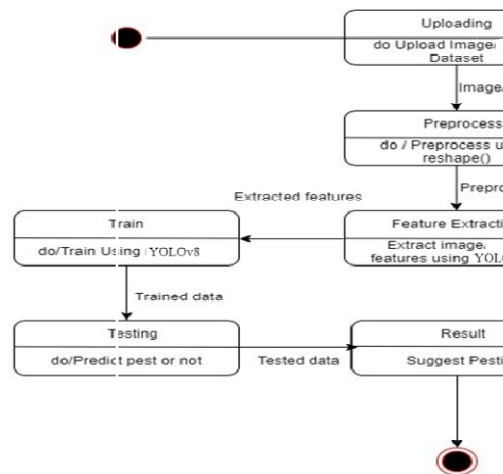


Figure. 6.3: State chart diagram

The state chart diagram includes several steps or actions, such as uploading an image or video, reshaping the data, converting it to RGB or grey scale, pre-processing the data, extracting features, training the model, testing the model, and displaying the detected pest and recommended pesticide.

Steps involved are:

- Start: The initial state.
- Uploading: The user uploads an image or video.
- Dataset: The uploaded image or video is added to the dataset.
- Image or Video: The image or video is pre-processed.
- Preprocessed Image: The pre-processed image or video is extracted.
- Extracted Features: The extracted features are used to train a model.
- Trained Data: The trained model is tested on new data.
- Result: The detected pest and recommended pesticide are displayed.

The diagram includes the following components:

- User: The person or system using the software.
- Pre-processor: A component that processes the input data before feature extraction.
- Feature Extraction: A component that extracts relevant features from the pre-processed data.
- YOLO v8: A pre-trained model used for image classification.
- Performance Analysis: A component that evaluates the performance of the trained model.
- Prediction: A component that predicts the detected pest and recommended pesticide based on the extracted features.

The purpose of this state chart diagram is to illustrate the process of detecting insects in images or videos and recommending appropriate pesticides.

The diagram includes the following states:

- Start: The initial state.
- Uploading: The user uploads an image or video.
- Dataset: The uploaded image or video is represented

SYSTEM ARCHITECTURE

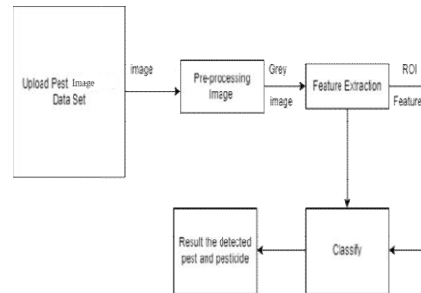


Figure. 6.4 System Architecture

The above diagram shows the system architecture, that includes the following:

- >Image/Video: This is the input to the system, which can be either a still image or a video.
- >Grey: This step likely refers to the process of converting the input image or video frames to grayscale. This is often done as a pre-processing step to reduce the computational complexity and to focus on the shape and brightness of the objects, rather than their color.
- >ROI (Region of Interest): This step involves identifying and isolating the region of the image or video frame that is of interest. In this case, the ROI would likely be the area containing the pest.
- >Pre-processing: This is a general term that refers to any additional processing that might be needed to prepare the data for the next step. This could include noise reduction, normalization, resizing, etc.
- >Upload Pest image/video: This is where the processed image or video frame would be uploaded for further analysis.
- >Dataset: This likely refers to the collection of images or video frames that have been processed and uploaded, which can be used for training and testing the model.
- >Feature Extraction: This is the process of extracting meaningful features from the data that can be used for classification. In this case, the features might include things like the shape, size, and texture of the pest.
- >YOLO v8: This is a type of convolutional neural network (CNN) that is often used for image classification tasks. It's designed to be lightweight and efficient, making it well-suited.
- >Image: This is the input to the YOLO v8 model, which would be the processed and prepped image or video frame.
- >Features: These are the output of the YOLO v8 model, which would be a set of features that the model has learned to associate with different classes.
- >Result the detected Classify: This step involves taking the features output by the YOLO v8 model and using them to classify the pest. This could involve comparing the features to a database of known pests, or using a separate machine learning model to make the classification.
- >Trained Model: This is the final output of the system, which would be a model that has been trained to classify pests based on the features extracted by the YOLO v8 model. This trained model could then be used to classify new, unseen pests.

VII. REQUIREMENTS

FUNCTIONAL REQUIREMENTS

- Create a desktop application using python tkinter framework.
- User should load the image dataset.
- System will extract the image features from the dataset.
- System will apply YOLO v8 algorithm to detect insect.
- Application should accurately detect insect from the user's input automatically.

NON-FUNCTIONAL REQUIREMENTS

These are prerequisites that are not useful in nature, that's, these are limitations inside which the framework must work.

- The program must be self-contained so that it can effortlessly be moved from one Computer to another. It is expected that organization will be accessible on the computer on which the program dwells.
- Capacity, versatility and accessibility.
- The framework should accomplish 100 per cent accessibility at all times. The framework might be adaptable to bolster extra clients and volunteers.

VIII. IMPLEMENTATION

Modules

- Data pre-processing
- Building and training YOLO v8 mode
- Testing the trained model
- Detection of insect image

Module Description:

Data Pre-Processing:

In preprocessing we preprocess data to enhance desired features and also rotate in different angles of the insect image in preprocessing module the process of reshaping the insect from image by ignoring the background by 224*224 pixels. The RGB image will be converted to grey scale and then the feature extraction process takes place to extract the features like area of the pest, number of wings, legs, etc.,

Building and Training of YOLO v8:

In this, models are trained by utilizing expansive sets of labeled information and convolutional neural network models that learn highlights specifically from the information without the requirement of manual highlight extraction like range, border, major hub length, minor pivot length, flightiness, circularity, robustness, frame calculate, and compactness

Testing the trained model:

In this module, we evaluate the performance of our trained, deep learning model using the test dataset.

Detection of insect image:

- Procedure Prediction()
- Input: image
- Output: Detected insect
- Begin:
- Step1: Read frame.
- Step2: Load YOLOv8 model
- Step3: Preprocess the input frame
- Step4: Predict the state using model
- Return insect name and suggest the Pesticides.
- End

Methodology:

YOLO v8 Architecture

In the realm of detecting bugs, our beacon is YOLOv8, a marvel of detection prowess. With a suite of features that dazzle, it's the premier choice for spotting insects. YOLOv8 melds various detection techniques—classification, object detection, and image segmentation—into its arsenal.

In our current project, we're leveraging the robust YOLOv8 object detection model to detect insects. YOLOv8 is an exceptional choice for object detection tasks, offering a rich set of features tailored to various requirements.

This model integrates multiple object detection methods, each serving distinct purposes:

1. **Classification:** This method assigns a class label to an entire image, providing a general overview of the image's content without specific object localization.
2. **Object Detection:** Object detection, a more advanced technique, identifies and locates multiple objects within an image, offering both class labels and precise bounding box coordinates for each object. YOLOv8 excels in this domain, making it invaluable for applications like autonomous driving and video surveillance.
3. **Image Segmentation:** Going beyond object detection, image segmentation identifies object shapes and boundaries at a pixel level, enabling detailed analysis and understanding of image content. Despite its computational demands, YOLOv8 seamlessly integrates this method, ensuring efficient and accurate object segmentation.

When focusing on object detection, YOLOv8 stands out for its powerful capabilities and flexibility. With simple steps, you can train and deploy the YOLOv8 model for specific tasks:

- **Fine-tuning:** YOLOv8 supports fine-tuning, allowing customization and specialization in object detection. This involves training the model on a specific dataset to enhance its accuracy and performance in detecting particular classes of objects.
- **Dataset Preparation:** Training YOLOv8 necessitates a dataset comprising images and corresponding annotations or labels, covering various instances of the target objects. Specifying the dataset descriptor file's path, which defines the dataset's location and format, is essential for training the model effectively.
- **Image Prediction:** Once trained, the YOLOv8 model enables image prediction by analyzing input images using the "predict" method. This yields predictions such as bounding boxes and class labels, providing crucial information about detected objects' presence and location.
- **Bounding Boxes:** Crucial for object detection, YOLOv8 generates accurate bounding box predictions, facilitating precise identification of detected objects' positions and extents.
- **Object Classes:** Whether working with predefined classes in a pre-trained model or customizing it for specific classes from your dataset, YOLOv8 supports the identification and classification of diverse object classes.

Training YOLOv8 Steps:

1. Prepare the dataset ensuring it contains images and annotations.
2. Specify the dataset descriptor file's path.
3. Use the "train" method with the dataset descriptor file to train the YOLOv8 model.
4. Fine-tune the model on specific object classes of interest.

Image Prediction Steps:

1. Load the trained YOLOv8 model.
2. Utilize the "predict" method with an input image for analysis.
3. Retrieve predictions, including bounding boxes and class labels.

Layer	OutputShape	Number of Parameters
Conv2d	(3, 608, 608)	1,792
BatchNorm2d	(64,608, 608)	128
LeakyReLU	(64,608, 608)	0
MaxPool2d	(64,304, 304)	0
Conv2d	(128,304,304)	73,856
BatchNorm2d	(128,304,304)	256
LeakyReLU	(128,304,304)	0
MaxPool2d	(128,152,152)	0
...
Conv2d	(1024, 76, 76)	2,359,296
BatchNorm2d	(1024, 76, 76)	2,048
LeakyReLU	(1024, 76, 76)	0
Conv2d	(255, 76, 76)	261,375

IX. CONCLUSION

The project is utilized to classify and distinguish diverse insect datasets utilizing the YOLO v8 algorithm, and to compare the comes about with other strategies. This can be an imperative assignment in horticulture, where recognizing and identifying creepy crawlies in real-time can offer assistance ranchers make informed decisions around bother administration.

To achieve this, to begin with we collected a dataset of creepy crawly pictures, which were at that point rescaled, pre-processed, and expanded to extend the dataset estimate and progress the exactness of the show. Pre-processing the pictures included resizing them to a standard estimate and normalizing the pixel values. Information increase strategies, such as revolution, flipping, and trimming, were moreover utilized to extend the diversity of the dataset and reduce overfitting.

At that point, connected the YOLO v8 algorithm to classify and identify the creepy crawlies within the dataset. YOLO v8 could be a lightweight convolutional neural arrange design that's well-suited for portable and implanted gadgets. It is outlined to be effective and quick, making it a great choice for real-time applications.

To encourage make strides the exactness of the show, you compared the comes about with other strategies and assessed the execution of the YOLO v8 calculation within the nearness of real-world challenges, such as shadow, takes off, soil, branches, and blossom buds. These challenges can altogether influence the execution of the show, making it troublesome to precisely classify and detectinsects in real- world situations.

To address these challenges, we may have utilized methods such as picture division to isolate the creepy crawly from the background, or utilized extra information increase strategies to reenact these real-world conditions.

REFERENCES

- [1] "Detecting and Classifying Bugs in Crops Utilizing Proximal Pictures and Machine Learning",Jayme Garcia Arnal Barbedo, Embrapa Rural Informatics, Campinas, MDPI, 2020.
- [2] "Application of Significant Learning in Arranges Bother Organization":A Real-Time Framework for Location and Determination of Oilseed Assault Pests", Yong He, Hong Zeng, Yangyang Fan, Shuaisheng Ji, Jianjian Wu, Hindawi, 2019
- [3] "Plant infections and bug location based on profound learning", Jun Liu, Xuewei Wang, BMC, 2021.
- [4] "Insect classification and discovery in field crops utilizing advanced machine learning techniques", Thenmozhi Kasinathan, Dakshayani Singaraju, Srinivasulu Reddy Uyyala, KeAi, 2020.
- [5] "Shallow and Profound Learning Design for Bugs Recognizable proof on Pomelo Leaf", Quoc Bao Truong, Tan Kiet Nguyen Thanh, Minh Triet Nguyen, Worldwide CONFERENCE ON Information AND Frameworks Designing (KSE), 2018.

- [6] "Detection Of Vegetation Zones Assaulted By Bugs And Illnesses Based On Adaptively Weighted Improved Worldwide And Neighborhood Profound Features", Yanshuai Dai, Li Shen, Yungang Cao, Tianjie Lei Wenfan Qiao , IEEE, 2019
- [7] "Crop bug classification based on significant convolutional neural organize and trade learning", K. Thenmozhi, U. Srinivasulu Reddy, Elsevier, 2019.
- [8] "Crop Illnesses and Bugs Location Utilizing Convolutional Neural Network", Pruthvi P. Patel, Dineshkumar B. Vaghela, IEEE, 2019.
- [9] "A Picture Acknowledgment Calculation of Soybean Illnesses and Creepy crawly Bugs Based on Movement Learning and Profound Convolution Network", Mingyuan Xin, Yong Wang, IEEE, 2020.
- [10] Liu, Y., Racah, E., Correa, J., Khosrowshahi, A., Lavers, D., Kunkel, K., Wehner, M., and Collins, W., 2016. Application of profound convolutional neural systems for identifying extraordinary climate in climate datasets. arXiv preprint arXiv: 1605.01156.