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Pest Identification Using Deep Learning

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Abstract - Pest infestation is indeed a major problem faced by farmers, and it can lead to significant damage to crops. In order to combat this issue, farmers often use pesticides asa means of pest control. Due to less awareness about pesticide and its quantity; lot of experiments are carried out on crops. The excessive and improper use of pesticides can have serious consequences on the environment, wildlife, plants, and human health. It causes various health disorders such as breathing problem, skin cancer and many more. In order to overcome this problem framers should know which pest is harming the crop so that they can use pesticides made for that pest. Our system focuses on pest attacking and harming grapes. Seven classes of insects like Climbing cutworm, Yellow jacket, Grape flea beetle, Multi colored Asian lady beetle, Leaf hopper, Grape phylloxera , Grape berry moth. The system uses deep learning algorithm for Identification of pests. CNN along with YOLOV3 is used for pest identification. An accuracy of 98% is achieved in pest identification. We have developed web application using Django framework where we get by default IP address. The system is developed in the form of web application where the farmer can upload an image, and the pest isidentified immediately with accuracy.

Keywords— Agriculture, CNN, YOLOV3

1. INTRODUCTION

Agriculture is often considered the backbone of the economy, contributes to the country's economics growth and determines the standard of life. In the agricultural industry, detecting and managing crop and fruit pests pose significant challenges for farmers. However, advancements in modern agricultural techniques have been introduced to assist farmers in achieving improved fruit crop quality and higher yields. Pest attacks are a major concern in agriculture as they can lead to a decline in the overall quality of fruits and result in substantial losses for farmers. We also discuss about the presence of pesticides and insecticides in fruit. Pests causes massives loss to fruits and results in a low market for the final product.[2]

To address these challenges, farmers resort to spraying pesticides. However, successful pesticide application requires a deeper understanding of both the pests and the pesticides being used. Farmers face numerous challenges when they lack suitable information about pests and pesticides. Spraying pesticides without adequate knowledge can lead to various issues. Manual pesticide application can result in significant health disorders, including skin diseases, respiratory problems, and even an increased risk of skin cancer and other illnesses. It is crucial for farmers to have proper training and understanding of pest management practices and pesticide handling to ensure both effective pest control and safeguard their health. To avoid losses the pest identification is required. Proposed system detects pests damaging grape fruit The color, texture and shape features extracted from the insect images and deep learning algorithm are applied to identify the insect classes.

This study aims to identify and detect insects on grapes using deep learning. The color, texture and shape feature were used for insect Identification by applying CNN(YOLOV3) module. The integration of deep learning algorithms for pest identification has the potential to bring about a revolutionary transformation in fruit cultivation and plant health management. These techniques can provide more accurate pest and improved crop yield. Moreover, the advancement of these algorithms can open up novel job prospects at the intersection of computer science and agriculture, fostering greater collaboration and gap between these two fields. We will be able to find the output in the web-app.

2. LITURATURE REVIEW

Pest prevention offers a compelling solution to reduce soil erosion and limit pesticide application, ensuring the production of pollution-free vegetables. Conventional use of agrochemicals and pesticides often results in poor control efficacy, environmental contamination, and excessive residues on vegetables. Additionally, pests develop resistance, leading to lower efficiency, higher costs, andsubjective and imprecise management. A manual approach to quantify insect numbers exists, but it is time-consuming and prone to errors. Fortunately, information technology offers innovative methods for pest identification. This paper presents an automatic pest detection system for fruit crops, utilizing image processing and Deep Neural Networks (DNN). The image data collected from IoT traps deployed by Nectars under real environmental conditions form the basis for the model. Through pre-processing techniques, we can effectively identify objects in the images obtained from the traps. These images form the training database for the DNN, and data augmentation is used to expand the dataset, reducingthe risk of over-fitting and enhancing the performance of theDNN.[1]

In agriculture, detecting crop pests has always been a challenging task for farmers. However, the introduction of an automatic insect detection system utilizing machine vision and image analysis has significantly improved the identification process, enabling early-stage detection with higher accuracy and reduced time. This technological advancement has proven beneficial for farmers as it helps increase crop yield. The current study focuses on the application of digital image processing techniques to analyze images of crop insects, specifically in sugarcane crops. The process involves several key steps, including preprocessing, segmentation, and feature extraction, all of which contribute to identifying the shape of insects in the sugarcane fields. The segmentation process employs Sobel edge detection to effectively separate the insect images from the background. Subsequently, feature extraction comes into play, using nine geometric shape features to recognize the shape of the insects in the sugarcane crop. Results from this insect shape identification method have been promising, showing high accuracy for identifying round (circle), oval, triangle, and rectangle shapes of sugarcane crop insects. The implementation of this work was successfully executed MATLAB 2015b, utilizing the Image Processing Toolbox. [2].

In 2009, Tessaratomas papillosa (Drury) invaded Taiwan, causing severe damage to the longan crops each year. To effectively manage this pest problem, this study applies novel applications of edge intelligence to establish an intelligent pest recognition system. The research utilizes a detecting drone equipped with a camera to capture images of the pest. These images are then processed using a Tiny-YOLOv3 neural network model, integrated into an embedded NVIDIA Jetson TX2 system. This AI-powered system enables real-time recognition of T. papillosa in the orchard, providing accurate positioning information of the pests. Using this pest position data, the system optimizes the pesticides spraying route for an agriculture drone. By selectively spraying pesticides only where needed, the drone minimizes pesticide use, reduces environmental damage, and increases crop yield. Moreover, the TX2 embedded platform transmits the pest positions and generation information to the cloud, allowing farmers to record and analyze the longan crop's growth usinga computer or mobile device. This real-time data enables farmers to better understand the pest distribution and take appropriate precautions promptly. Overall, this study empowers farmers with an advanced pest management solution, enhancing their ability to mitigate the impact of T. papillosa on longan crops while promoting sustainable agricultural practices [3].

The identification of plant diseases plays a crucial role in cropmonitoring systems. To address this challenge, computer vision and deep learning (DL) techniques have emerged as state-of-the-art solutions in agriculture. This research focused on localizing and identifying diseases in plant leaves, employing three DL meta-architecture: Single Shot MultiBox Detector (SSD), Faster Region-based Convolution Neural Network (RCNN), and Region-based Fully Convolution Networks (RFCN). The TensorFlow object detection framework was utilized for training and testing these models on a controlling environment dataset, enabling disease recognition in various plant species. To enhance the performance of the DL architecture, different state-of-the-artdeep learning optimizers were explored, aiming to improve the mean average precision (mAP). Among them, the SSD model trained with an Adam optimizer demonstrated the highest mAP of 73.07%. The remarkable success of this work lies in its ability to identify 26 different types of defected leaves and 12 types of healthy leaves within a single framework, showcasing its novelty. Moreover, the proposed detection methodology holds promise for future adoption in other agriculture application. The generated weights from this research can be repurposed for real-time plant disease detection in both controlled and uncontrolled environments, providing valuable insights for sustainable farming practices[4].

Effective pest management and control are paramount in ensuring commercial food standards. Crop pests can significantly impact crop quality and productivity, necessitating the development of tools for early diagnosis and prevention of major crop losses. Traditionally, crop abnormalities, pests, or deficiencies were diagnosed by human experts, but this approach proved to be both costly and time-consuming. To address these challenges, crop pest detection approaches leveraging Machine Learning Techniques such as Random Forest (RF), Support Vector Machine (SVM),Decision Tree (DT) and Naive Bayes(NB), along with Deep Learning methods like Convolution Neural Network (CNN), Long Short-Term Memory (LSTM), Deep convolution neural network (DCNN), and Deep Belief Network (DBN), have been explored. These techniques offer promising solutions for efficient and accurate pest identification. By integrating these approaches, crop productivity can be improved, while providing enhanced crop protection. This survey outlines modern methods for monitoring agricultural fields to detect and categorize citrus plant pests, rice pests, and cotton pests, among others. These automated pest detection methods enable continuous monitoring of large areas, reducing human error and effort. Overall, these advanced techniques contribute to better crop efficiency and protection, leading to higher yields and ensuring the quality of commercial food standards [6].

In India, the GDP heavily relies on agriculture, and the production of high-quality crops plays a vital role. However, frequent pest attacks pose a significant threat by causing extensive damage to crops, reducing yields,and compromising the nutritional value of food products, thereby endangering food safety. These issues have a profound impact on the economy and can lead to massive losses for farmers, even resulting in the loss of livelihoods and lives. Regular crop monitoring is crucial to promptly address pest- related issues by taking appropriate measures, such as employing suitable pesticides, to protect the crops from damage. Pest detection technologies are essential tools that can assist farmers in avoiding early crop contamination and ensuring timely pesticide application. Artificial intelligence (AI) has emerged as a promising solution for addressing agricultural challenges. By leveraging AI-based technologies, farmers can benefit from improved agriculturalproduction. In this research paper, the MobileNet V2 algorithm is employed to classify pests into different classes. The algorithm reshapes the images and extracts relevant features to classify pests accurately based on their respective classes. The results demonstrate that MobileNet V2 outperforms other pre-trained models, achieving a higher accuracy of 0.85.By incorporating AI technologies like MobileNet V2 for pest classification, farmers can enhance their pest management practices, leading to more effective crop protection and increased agricultural production [7]

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3.BLOCK DIAGRAM AND DESCRIPTION

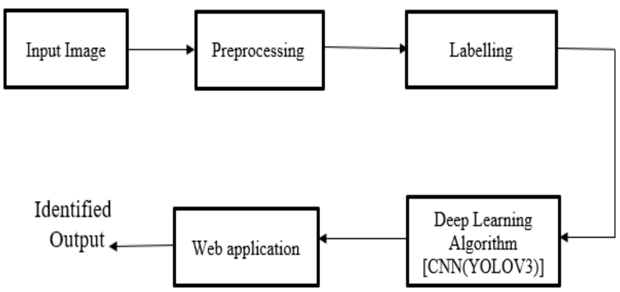

Fig 1.Block Diagram

BLOCK DIAGRAM DESCRIPTION:

The main purpose of the Pest Identification Using Deep Learning is to identify the pest to protect fruit crop from massive losses using proper pesticides.

1. Input image : When working on deep learning project, choosing right dataset is crucial for evaluation. Choice of dataset depends on specific problem you are trying to solve. We have collected dataset of 7 classes of pest. Consider the source of the dataset. It could be publicly available datasets from repositories like search engine databases. The dataset are around(407) images. The dataset consists of images of different classes of pest and each pest in different from other depending on their features they are segregated into different classes.


Fig2.Insects Images

2. Image preprocessing : Data preprocessing is an essential stage in machine learning, involving the preparation and cleansing of data before feeding it into a deep learning algorithm. The goal is to enhance data quality and make it suitable for effective model training and analysis. In image preprocessing, image enhancement techniques are applied to reduce noise and sharpen the images, aiming for better accuracy and improved image quality for insect identification. In pest identification, we have applied image augmentation techniques such as random rotations which can help the deep learning model generalize better and handle different variations in the input images. This enables the model to identify pests accurately even in real-world scenarios with varying environmental conditions. Images are rotated in all the directions.

3. Augmentation: In pest identification, we have applied image augmentation techniques such as random rotations which can help the deep learning model generalize better and handle different variations in the input images. This enables the model to identify pests accurately even in real-world scenarios with varying environmental conditions. Images are rotated in all the directions.


Fig 3.Augmented Images

4. Labelling: All Augmented images are labelled using Labellmg application. Start by installing the Labellmg application on your computer. It is available for Windows, macOS, and Linux. You can download it from the official GitHub repository. Once the installation is complete launch the Labellmg application. Open the image(s) you want to annotate by clicking on the "Open" button or selecting "Open Dir" to load a directory containing multiple images. Choose the object class you want to annotate. If it's your firsttime using Labellmg, you will need to define the classes by creating an XML file specifying the class names. To annotatean object, click and drag a bounding box around the object of interest. Adjust the box to enclose the entire object accurately. Repeat this process for all instances of the object in the image. Once you have annotated all the objects in the image, click the "Save" button to save the annotations. The annotations are typically saved in an XML file format, following the PASCAL VOC format. After saving the annotations for the current image, you can move to the next image in the sequence by clicking on the "Next Image" button or using the keyboard shortcuts provided. If needed, you canreview and edit the annotations by selecting an annotated object and modifying the bounding box or class label. Once you have annotated all the images, you can export the annotations into a format suitable for your deep learning framework or further processing. Labellmg supports various formats like Pascal VOC, YOLO, COCO, and others. Repeatthe annotation process for all the remaining images in your dataset.

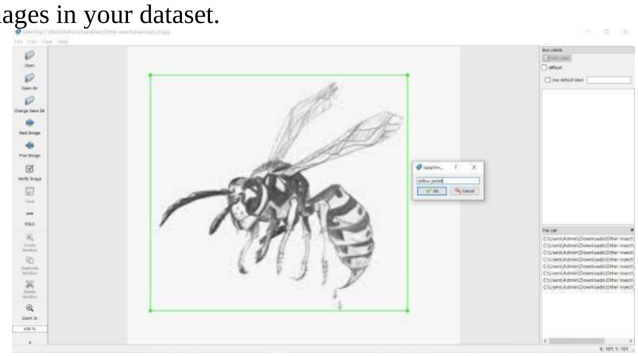
Fig 4.Labelled Image

5. Deep learning Algorithm[CNN(YOLOV3)]: YOLO (You Only Look Once) is an object detection algorithm that has been widely used in computer vision tasks. While it is primarily designed for detecting objects in general images, itcan also be applied to pest identification with some modifications and training data specific to pests. To use YOLO V3 for pest identification using deep learning, a labeled dataset of images containing various pests along with their corresponding bounding boxes. This dataset would need to be annotated with the pest class labels and the location of the pests with in the image.

4. SOFTWARE DESIGN

A. Algorithm

- Start.
- We collected a dataset of pests, encompassing multiple classes of pest species.
- The collected images underwent preprocessing to enhance their quality and improve accuracy.
- We applied augmentation methods to the images, generating additional variations such as rotations.
- The augmented images were labeled using the labellmg application to mark the location of pests within each image.
- We applied the CNN YOLOV3 algorithm to the labeled images, enabling the identification of pest characteristics such as color, shape, and texture.
- The identified pest results are displayed on a web application.
- Stop.

B. Flowchart

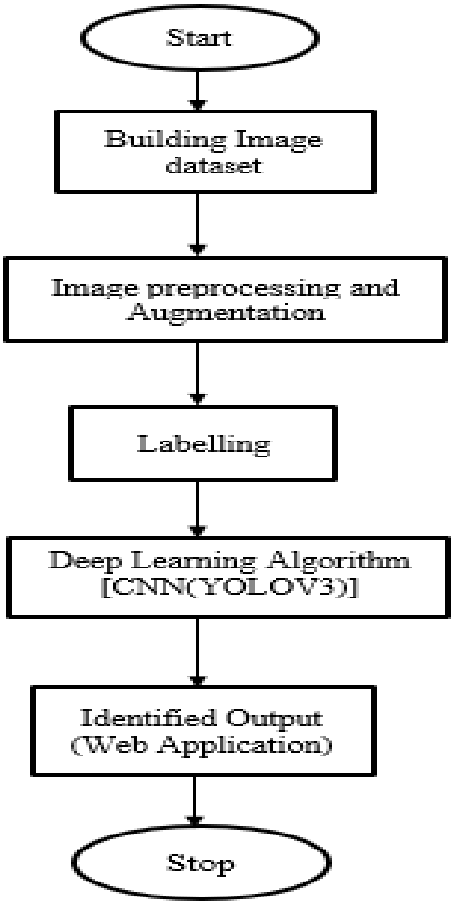

Fig 5.Flowchart

5. RESULT AND DISCUSSIONS

Fig 6.Identified Pest

The images show the result of pest identification system. The label above the pest provides the name of the pest. The pest identification deep learning algorithm for fruit has demonstrated great accuracy in detecting different pest. The algorithm was able to identify the pest with 56% accuracy rate.

6. FUTURE SCOPE

1.Edge computing and mobile applications: Deploying deep learning models on edge devices, such as smartphones or specialized pest monitoring devices, could bring pest identification directly to the field. This would eliminate the need for transmitting data to remote servers, reducing latency and enabling real-time decision-making. Mobile applications could provide on-the-spot pest identification and offer recommendations for pest control measures.

2.Automated Pest Counting: Deep learning models can be developed to count the number of pests in a given area automatically. By analyzing images or sensor data, these models can estimate the population density of pests in a field. Such information can assist in determining the severity of an infestation and help farmers make informed decisions regarding pest control measures.

3.Mobile Applications for Farmers: Deep learning-based pest identification can be incorporated into user-friendly mobile applications, empowering farmers with an accessible tool for pest detection and diagnosis. Farmers can capture images of pests or affected crops using their smartphones,deep learning model within the app can quickly provide identification.

7. CONCLUSION

We conclude that, different insects datasets were identified by applying the deep learning and result were displayed. All the insect images were pre-processed, and augmented to increase the dataset to improve the accuracy. The result proved that the CNN model provides the highest identification accuracy of 91.5% and 90% for 7 classes of insect from dataset. The pest identification algorithm will be implemented in Convolution Neural Network model to identify the insect with class labels for large insect dataset.

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