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YOLO-Based Framework for Predicting Crop Diseases in Agricultural Systems

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Abstract: In agricultural applications, the essential job of detecting and quantifying plants in plot images is crucial for yield estimate, crop monitoring, and resource optimization. This research focuses on the YOLO (You Only Look Once) approach, which is painstakingly used to identify and count plants in plot photographs. The system was trained using a supervised learning approach on the Robo-flow platform, offering an advanced and automated solution for agricultural plant analysis using machine learning capabilities. The process involves obtaining a comprehensive collection of plot images including plants, each carefully labeled with accurate bounding boxes. The Robo-flow platform is used for efficient data management and annotation, while the YOLO approach, recognized for its real-time object identification skills, is employed for plant detection. YOLO attains exceptional detection speed while maintaining accuracy by using a grid-based methodology, forecasting bounding boxes and class probabilities for each grid cell inside the input picture. The suggested method demonstrates effective results in the precise identification and quantification of plants in plot photographs, providing farmers, agronomists, and researchers with essential information for crop management and decision-making. The system has potential for future improvement and promises wider applications, accommodating various plant species and climatic conditions in agricultural activities.

Keywords: *Plant Detection, Plant Counting, Precision Agriculture, YOLO Algorithm, Agricultural Plots, Image Analysis, Decision-Making, Resource Allocation, Crop Management, Fertilization, Sustainable Farming Practices, Agricultural Productivity.*

INTRODUCTION

To tackle the essential challenge of nourishing the rapidly expanding global population while promoting economic development, agriculture serves as a fundamental pillar. Faced with the problems of a growing global population and the need for a sustainable food supply, creative strategies are essential. Precision agriculture is set to transform the sector, with machine learning, particularly the YOLO algorithm, playing a crucial role in plant recognition and enumeration. This study explores the employment of the YOLO technique for automating plant recognition and enumeration, offering improved agricultural management and better resource use. Utilizing cutting-edge technology, we may enhance agricultural methods, therefore making substantial contributions to sustainable farming and global food security. This initiative aims to simplify the admissions process for health clubs and fitness centers, acknowledging the complications involved in hiring a trainer and managing gym admissions processes. Obtaining a designated time slot may provide difficulties. In this context, prioritizing health is important, since an individual's disposition often depends on their well-being. Robust health equips us with the vitality to confront challenges and attain objectives.

This research aims to accurately recognize and quantify plants in plot photographs to facilitate agricultural applications. The issue lies in developing a reliable algorithm capable of identifying and enumerating plants in diverse plot photographs, considering variations in species, growth stages, lighting conditions, and obstructions. The objective is to surmount these challenges and provide farmers, agronomists, and researchers with a robust instrument for plant analysis, enabling enhanced crop monitoring, yield assessment, and resource management.

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LITERATURE REVIEW

Recent breakthroughs in deep learning and mobile technology have profoundly impacted the creation of real-time image-based pest detection systems in agriculture [11]. Numerous research have investigated various CNN designs for mobile devices. Nonetheless, these systems often face restrictions such as limited pest class identification, hardware limits, and difficulties in attaining real-time performance [12] [13]. Numerous academics have examined object detection techniques for recognizing insect pests, each offering distinct strategies and emphasizing ongoing issues.

Fuentes et al. used SSD, R-CNN, and Faster R-CNN deep learning models with a VGG network and residual networks to identify nine distinct kinds of tomato plant pests and illnesses [14]. This method attained a mean Average Precision (mAP@0.5) of 83.06%, but was restricted to a narrow range of pest classes, hence limiting its use in more diverse agricultural contexts. Lin et al. used Fast R-CNN to create an anchor-free regional convolutional network using an end-to-end model methodology [15]. The model can classify 24 pest categories, attaining a mAP@0.5 score of 56.4% and a recall rate of 85.1%. These findings exceeded the efficacy of conventional Fast R-CNN in regulated settings. Nonetheless, the method's feasibility in real-time, dynamic agricultural settings remains ambiguous. Sabanci et al. performed a research that developed a convolutional recurrent hybrid network to detect pest-infested wheat grain [16]. They integrated AlexNet with bidirectional long short-term memory (BiLSTM). The model attained an exceptional cumulative accuracy of 99.50%. Although this shows considerable accuracy for certain tasks, the system's applicability was confined to wheat grain, since it can only differentiate between two categories: healthy wheat grains and those afflicted by sunn pests (SPD). Furthermore, it failed to fulfill the comprehensive pest detection requirements across diverse crops.

Koklu et al. developed a deep feature extraction technique with CNN-SVM [17]. The researchers identified five different kinds of grapevine leaves, with an accuracy of 97.60%. This strategy, although successful for leaf categorization, has not yet been evaluated in the more intricate field of insect pest identification. Li et al. developed a real-time method for the identification of pests and plant diseases with Faster R-CNN [18]. Their methodology successfully identified undetected rice illnesses in video recordings, although mostly concentrated on disease detection rather than insect pest identification. Zhong et al. presented a visual flying insect identification system using the YOLO architecture on a Raspberry Pi [19]. The system achieves a cumulative accuracy of 92.50% and a classification accuracy of 90.18%. This system shown potential in detecting flying insects; however, the restricted processing capacity of Raspberry Pi hampered its use in more computationally demanding applications. Arunabha M. Roy and Jayabrata Bhaduri developed an improved variant of YOLOv4, termed Dense-YOLOv4, by integrating DenseNet into its backbone to optimize feature transfer and reuse [20]. This model attained a remarkable mAP@0.5 score of 96.20% in detecting different stages of mango development within a complex orchard environment. Nonetheless, its substantial computing requirements provide obstacles for implementation on mobile devices. Despite attaining an amazing identification rate of 99.3% with an average processing time of 44 milliseconds, these models were exclusively tailored for a certain crop variety, hence limiting their wider usefulness.

In recent years, the YOLO algorithm family has seen substantial advancements to improve real-time object identification for lightweight and mobile-friendly apps. A YOLOv5-S model was created by Thanh-Nghi Doan for real-time insect detection and was incorporated into resource-limited mobile devices [21]. The model achieved a classification accuracy of 70.5% on the Insect10 dataset and 42.9% on the bigger IP102 dataset. The findings demonstrate that the model works well on smaller datasets but fails to attain the necessary accuracy for successful agricultural pest identification when the size and complexity of the pest dataset escalates. Furthermore, the upgraded iteration, YOLOv8, is extensively used owing to its enhanced speed and precision in real-time object recognition applications. Moreover, its design facilitates simple refining and customization to suit certain requirements. Yin Jian Jun improved the YOLOv8 model by optimizing its feature extraction process and decreasing the parameter count to create a lightweight design [22]. Utilizing advanced training methodologies, the model attained an impressive mAP@0.5 score of 97.3% for the detection of eight distinct species of rice pests. Despite the widespread use of YOLOv8 in several research, it has often been utilized to identify just a limited number of pest species, hence rendering its use less beneficial in more complex agricultural environments. Recently, the newest iterations in the YOLO series, including YOLOv9 and YOLOv10, have been released, including additional features that enhance performance while reducing computational overhead. YOLOv9 has innovations such as Generalized Efficient Layer Aggregation Network (GELAN) and Programmable Gradient Information (PGI), which underpin its increased detection performance [23]. Conversely, YOLOv10 has been created by researchers at Tsinghua University utilizing the Ultralytics Python package, presenting a novel approach to real-time detection by addressing post-processing challenges and deficiencies in model architecture found in earlier YOLO iterations [24]. By eliminating non-maximum suppression (NMS) and enhancing many components of the model architecture, YOLOv10 attains superior outcomes at a much reduced computational expense. Nonetheless, despite these developments, the actual use of both YOLOv9 and YOLOv10 in the detection of agricultural pests has yet to be realized.

Despite the significant advancements achieved in these investigations, some obstacles remain unresolved. The bulk of existing models can only identify a limited number of pest or item types. This constrains the use of these technologies across various agricultural contexts. Moreover, due to the limited size of their datasets and the reduced number of classes, their data preparation methodologies, including data augmentation and cleansing procedures, tend to be more straightforward and often neglected. This shortcoming may impede precise recognition when the number and diversity of classes expand. The real-time implementation of these models on mobile devices is often obstructed by hardware constraints. In several instances, the real-time detection capabilities are often constrained by the processing requirements of deep learning models [25]. Consequently, there is a significant need for a lightweight model to address these deficiencies. Despite the development and integration of some systems with smartphones, these systems lack the ability to provide real-time information and thorough pest identification across many categories. Furthermore, they lack a web-based platform for pest data monitoring and analysis.

METHODOLOGY

The suggested technique employs a systematic approach to create an efficient pest detection model for agricultural applications, as seen in Fig. 1. Initially, the researchers aggregated several pest picture databases and integrated them into a cohesive dataset by different preprocessing procedures, including data standardization. Data standardization is a method used to guarantee that datasets adhere to a uniform and defined format for the configuration of the YOLO format. Secondly, the researchers augmented the dataset by methods such as color modifications, picture translation, horizontal flipping, and scaling to increase its variety for training purposes. This stage is to compile a dataset suitable for training a resilient detection model that can generalize across various agricultural contexts. Subsequently, the photos were tagged using bounding boxes to precisely designate occurrences of pests. The researchers divided the dataset, assigning 80% for model training and 20% for model validation. Researchers then trained several YOLO object identification algorithms using the pest training dataset. The trained models were refined to enhance their efficacy across various YOLO versions. Subsequently, researchers verified and assessed the efficacy of each base and fine-tuned model using the common validation dataset. During validation, novel pest photos not used in training or fine-tuning were presented to evaluate the models' efficacy with unfamiliar data. The researchers included each model into the smartphone application to evaluate their real-time performance and analyze their capabilities in a realistic context. The ideal model for practical field adaption was established by comparative analysis of the data. This approach was subsequently used in a smartphone application to provide real-time insect identification in agricultural settings. A web-based monitoring system was ultimately designed to provide dynamic and real-time information on insect detection. This enables users, such as farmers, to oversee collected pest data and get actionable insights for efficient pest control.

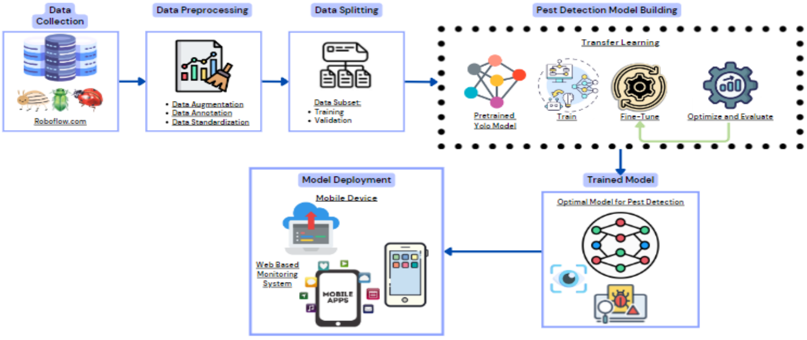

Fig. 1. Method to develop the pest detection system

Train a Dataset:

Please submit the dataset to the Roboflow platform. That will label our data. Multiple parameters may be configured for training. This involves selecting augmentation options, adjusting training settings, and implementing necessary modifications, along with designating the object detection model.

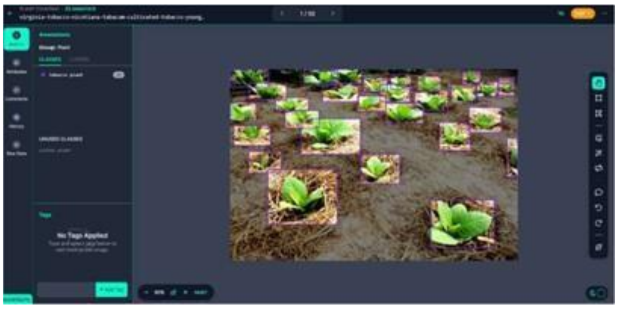

Fig 2 Train a Dataset

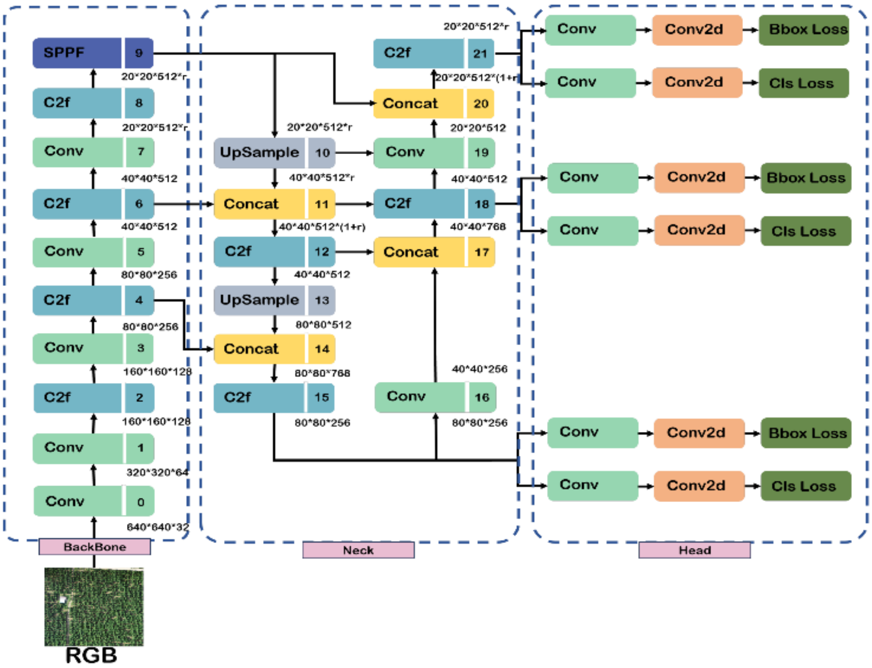

Fig. 3. Model architecture of YOLOv8 [18].

The architectural design has three primary components: Backbone, Neck, and Head [33]. The Backbone is used for extracting multi-scale characteristics to enable the model to comprehend inputs at various sizes. It comprises modules like Conv, C2f, and SPPF (Spatial Pyramid Pooling-Fast). In the Neck section, YOLOv8 amalgamates features without imposing uniform channel dimensions by including a route aggregation network and a feature pyramid network [34] [35]. This approach decreases both the parameter count and the total tensor dimensions. To streamline anchor box operations and mitigate displacement difficulties, YOLOv8 employs a decoupled head approach to differentiate between the detection and classification heads [36]. The Head component is tasked with bounding box regression, target categorization, and confidence evaluation in the prediction layers. It finally provides accurate detection outcomes via non-maximum suppression.

YOLO Algorithm for Detection:

The YOLO (You Only Look Once) approach is at the forefront of object recognition frameworks in computer vision research and has garnered considerable attention. This innovative method of object recognition distinguishes itself by attaining excellent accuracy and real-time performance in a single traversal of the neural network. Agricultural applications, especially in plant enumeration and identification, have gained significant advantages from the architectural advancements and concepts inherent in the YOLO algorithm. YOLO has diverged from the traditional two-stage detection framework, heralding a revolutionary phase for object detection. In contrast to conventional approaches that use region proposal techniques to identify probable object regions, YOLO predicts bounding boxes and class probabilities directly in a single pass through a neural network. This comprehensive technique has significantly improved the efficiency and accuracy of the detection procedure.

A fundamental characteristic of YOLO is the segmentation of photos into a grid, as shown by a 3x3 grid. Unlike the traditional method of identifying a single item per picture, YOLO enables the detection of one object inside each grid cell. This is accomplished by embedding a vector that describes each grid cell, hence enhancing the object identification process with more detail and efficiency.

Database Design:

Our system maintains a database for the storage of user data. It will retain critical information such names, contact data, sector area, and survey number of the agricultural land.

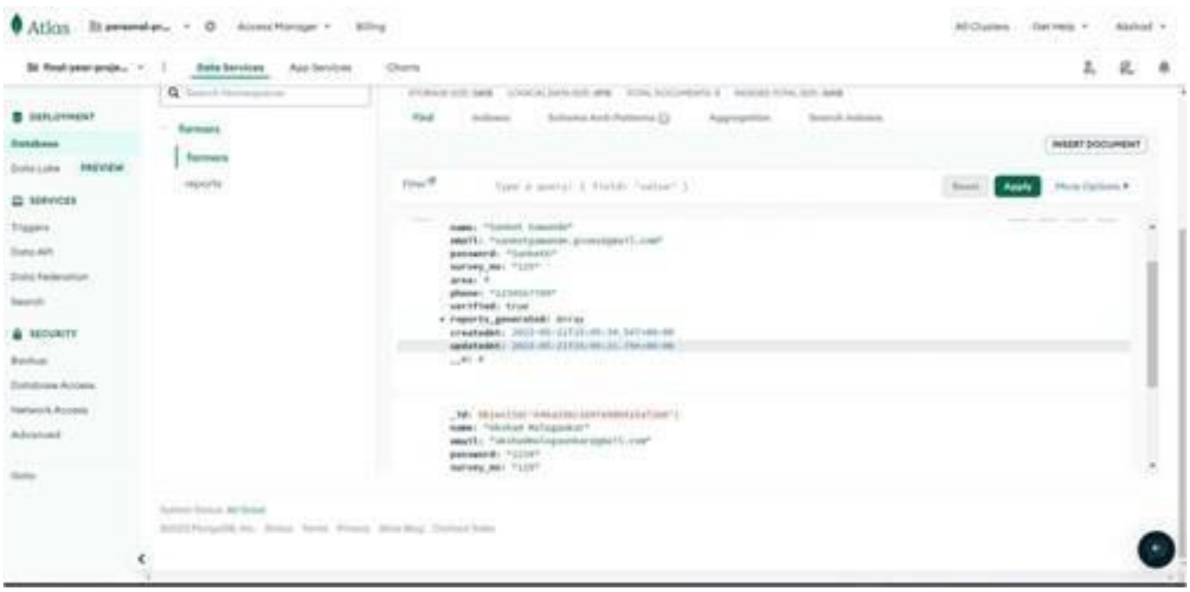

Fig 4: Database of User

The Plant Detection website has a user database to retain information on its region. It will maintain the database of reports, enabling users to print the data results.

System Design:

Fig 5: Database Report Generated

The plant recognition and counting system in agricultural regions using the YOLO algorithm has several benefits:

• Enhancing Crop Monitoring Efficiency: This initiative presents a comprehensive solution for the precise monitoring of crops, using automated systems to precisely identify and enumerate plants in agricultural areas. This program provides farmers with essential data regarding their crops' state and development, enabling informed decision-making and required modifications. This automated system is essential for delivering farmers timely and relevant information, enabling preventative steps and ongoing enhancements in crop management techniques.

• Prompt Identification of Agricultural Challenges: This program is crucial for the swift discovery of agricultural concerns, such insect infestations, illnesses, or nutritional inadequacies. The prompt recognition of these difficulties enables farmers to rapidly execute tailored treatments, therefore minimizing crop losses and improving total productivity.

• Enhanced Resource Utilization: Farmers may achieve improved resource management via accurate plant enumeration and identification. An accurate assessment of plant density on agricultural land enables farmers to optimize resource distribution, such as water, fertilizers, and pesticides. This information aids farmers in promoting efficient and sustainable methods, hence enhancing agricultural resource usage.

Plant enumeration is a technique for assessing agricultural output. Farmers may more effectively prepare for the storage, transportation, and selling of their food when they can accurately predict the potential yield based on the exact number of plants in a given agricultural area.

• Time Efficiency: The project significantly reduces time when contrasted with manual plant counting and detection methods. Extensive agricultural areas may be rapidly assessed, providing farmers with prompt data for decision-making and enabling them to use their time more effectively.

• Scalability: The project is versatile and applicable to several agricultural methods and crop types. It facilitates crop monitoring and management across many agricultural disciplines, including row crops, orchards, vineyards, and greenhouse cultivation.

• Data-Driven Insights: The research yields data-intensive insights about trends in crop distribution, density, and health. Decisions about future agricultural seasons may be informed by the longitudinal analysis of this data to ascertain optimal planting densities, identify suitable crop rotation methods, and gain valuable insights into enduring trends.

RESULT AND DISCUSSIONS

The architectural design has three primary components: Backbone, Neck, and Head [33]. The

Backbone is used for extracting multi-scale characteristics to enable the model to comprehend inputs at various sizes. It comprises modules like Conv, C2f, and SPPF (Spatial Pyramid Pooling-Fast). In the Neck section, YOLOv8 amalgamates features without imposing uniform channel dimensions by including a route aggregation network and a feature pyramid network [34] [35]. This approach decreases both the parameter count and the total tensor dimensions. To streamline anchor box operations and mitigate displacement difficulties, YOLOv8 employs a decoupled head approach to differentiate between the detection and classification heads [36]. The Head component is tasked with bounding box regression, target categorization, and confidence evaluation in the prediction layers. It finally provides accurate detection outcomes via non-maximum suppression.

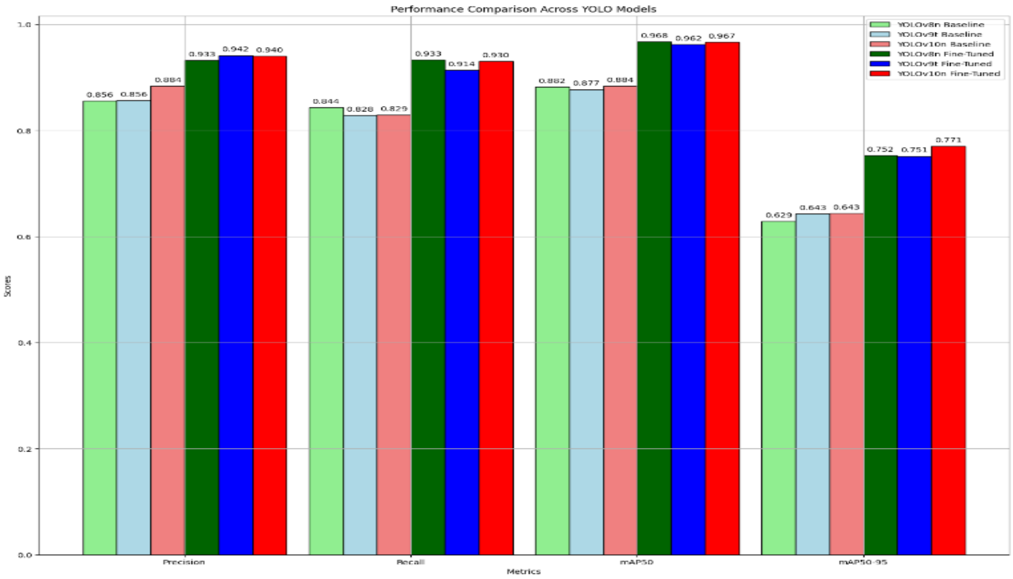

Fig. 6. Comparison of YOLOv8n, YOLOv9t, and YOLOv10-N on validation data during training.

Fig. 7. Sample predictions made byYOLOv8n

CONCLUSION

This article proposes a YOLO-based pest detection system coupled to a smartphone for real-time insect class identification and a dynamic web-based monitoring system for sustainable agriculture. The recommended system uses the YOLOv9t model for best computation efficiency, detection accuracy, and processing speed. Compared to similar systems, it can identify more pests with less processing power and good detection accuracy. The YOLOv9t model's lightweight construction may explain the improved results. It enables faster inference times for mobile pest species identification without losing accuracy. The numerical results show that the YOLOv9t model has a mAP@0.5 of 89.8%, a mAP@0.5:0.95 of 66.7%, a Precision of 87.4%, a Recall of 84.4%, and an inference time of 250.6 ms. The web-based software gives farmers real-time crop monitoring. This combination improves pest control by providing information into pest activity across industries. This technique improves functionality, computational efficiency, practicality, and real-time velocity detection.

If pests overlap or backgrounds, shapes, and colors are similar, detection failures may occur. Future upgrades will address these concerns. The researchers intend to add pest images from more complex ecosystems to the collection. This will improve the model's generalization in numerous real-world situations, especially those with different lighting, backgrounds, and perspectives. The researchers intend to use object tracking and motion filtering to improve the model's pest monitoring accuracy, particularly in overlap or rapid movement conditions. These adjustments would improve our pest detection model in complex agricultural settings by improving detection accuracy and robustness across pest management treatments.

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