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Detecting Sugarcane Pests and Diseases Using CNNs for Precision Crop Detection and Management

April Joy A. Palmares, MIT[1]**; Patrick D. Cerna,** DIT[2]

[1]State University of Northern Negros, Philippines
[1] ajpalmares@sunn.edu.ph

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Abstract: Effective disease management is essential for sustaining sugarcane yield and quality, and traditional methods, such as visual inspection and chemical analysis, are often costly and time-consuming. This study proposes an innovative solution that leverages artificial intelligence (AI) through Convolutional Neural Networks (CNNs) for advanced crop detection and management in sugarcane farming. The AI precision system aims to automate the detection of sugarcane pests and diseases by analyzing collected imagery using machine learning algorithms. This system processes various image parameters, including leaf color, pest types, damage areas, and texture, to accurately identify diseases. By integrating machine learning with image processing techniques, the system provides farmers with rapid and precise diagnoses, enhancing their ability to manage crops effectively and efficiently. The study employs a descriptive developmental approach, emphasizing the AI-driven system's design, development, and evaluation. The objectives include creating a CNN-based system to capture and analyze sugarcane imagery, facilitating timely pest and disease detection, and assessing the system's quality and usability. Integrating AI in sugarcane agriculture promises significant advancements in crop monitoring and management. This research aims to contribute to precision agriculture, enabling farmers to optimize sugarcane cultivation, reduce losses, and enhance productivity. The proposed system offers a scalable solution for real-time monitoring of extensive crop fields, promoting sustainable agricultural practices and supporting economic stability.

Keywords: Convolutional Neural Networks (CNNs), Sugarcane Pest and Disease Detection, Precision Agriculture

I. Introduction

Sugarcane cultivation is successful based on several key factors, including sugarcane disease management. Therefore, disease identification becomes the key to minimizing losses in sugarcane yield (Corsiga et al., 2018). The proposed method for plant disease detection in sugarcane cultivation includes image processing and machine learning algorithms for detecting sugarcane diseases. This analysis is premised on different image parameters or features such as leaf color to detect type of pest, damage area, and texture to show high accuracy in identifying diseases.

Different machine-learning, feature-extraction, picture-segmentation, processing, and acquisition techniques for automatic sugarcane disease detection systems in precision agriculture provide farmers with faster and more appropriate disease diagnoses. Automating the sugarcane disease detection system is very important in hastening disease diagnosis (Zamani et al., 2022).

Conventionally, nowadays, inspections require a manual visual inspection of leaves or an obsolete chemical procedure conducted by experts. Such processing methods need several experts to inspect plants continuously, which adds the cost of inspection to its already astronomical cost in the case of larger farms.

On the other hand, the objective of the descriptive developmental approach in this study is to develop a system for detecting pests and diseases in sugarcane using CNNs for precision crop detection and management. The development of Advance Crop Detection and Management for Sugarcane will generally mean using artificial intelligence, particularly convolutional neural networks (CNNs), to analyze the images collected for detecting and subsequently monitoring and managing sugarcane crops.

Moreover, the suggested method for detecting plant diseases in sugarcane cultivation is less computationally expensive and takes less time to predict than other deep learning approaches. Thus, utilizing statistical machine learning and image processing algorithms would provide a better platform to detect and manage diseases accurately in sugarcane. The slightly offbeat approach offers a cheap yet viable alternative for field monitoring in crop production.

II. LITERATURE REVIEW

Thirteen genera of plant-parasitic nematodes—Pratylenchus, Helicotylenchus, Tylenchorhynchus, Xiphinema, Rotylenchulus, Meloidogyne, Hoplolaimus, Paratylenchus, Longidorus, Criconemoides, Scutellonema, Trichodorus, and Hemicycliophora—were discovered linked to sugarcane in the Philippine province of Negros Occidental. Pratylenchus was the most prevalent of these (Gargantiel et al., 1973). Pests and plant diseases pose serious challenges to crop output globally, resulting in considerable financial losses and food shortages. Management and control of plant disease and insect pest problems firmly depend on their early detection and diagnosis. Detection and diagnosis in the traditional sense can be quite time-consuming and labor-intensive, necessitating some specialist knowledge in the field. Very recently, the use of deep-learning techniques for establishing fully automated and user-friendly systems for effectively detecting plant diseases and pests has gained prominence. Deep learning methods promise increasing precision and efficacy in plant disease and pest identification (Mohanty et al., 2016). AI techniques are integrated into smart agriculture to improve crop health monitoring and nutrient management. Applying AI methods and algorithms makes agricultural practices more sustainable and efficient. AI has applications in predictive modeling for nutrient management and early detection of crop diseases and pests. Remote sensing combined with imaging technologies plays a critical role in real-time monitoring, facilitating immediate decision-making. The work of (Iftikhar et al., 2024) details an effort in deep learning approaches to disease diagnosis manifested in a convolutional neural network for disease detection and classification. The work focuses on potatoes, demonstrating the significance of data augmentation while performing an extensive hyperparameter optimization for plant disease identification. The experimental results indicated that the model under study outperformed with a 98% success rate. The work of (Khan et al., 2024) instead shows the use of UAV (uncrewed aerial vehicle) technology to monitor crops and detect pests in the fight against crop diseases and pest infestation in agriculture. The optimized model proposed aims to enable effective detection and classification of pests using UAV-based methods. The model combines enhanced CSP networks with sophisticated attention modules and improved multiscale feature extraction through the YOLOv5s model. The model was tested rigorously against five agricultural pests in a medium-scale dataset and demonstrated remarkably high mean average precision (mAP) scores of 95.0%, average recall of 93.0%, and average precision of 96.0%. This shows great potential in enhancing agricultural production in a drone-based ecosystem. Computer vision-based and deep-learning techniques have been employed to select and plant healthy sugarcane billets (Alencastre-Miranda et al., 2021). This led to an increase in plant count per hectare and higher crop productivity. The results were generalized to different sugarcane varieties by applying convolutional neural network architectures and a two-stage transfer learning approach. It was found that the best trade-off regarding time and accuracy was given by AlexNet, leading to consequent yield increments of 33-80% depending upon the variety. Plant diseases threaten crop production and food supply in general, especially for sugar-cane cultivation in Brazil, India, and China. To counter this, (Hemalatha et al., 2022) seeks to propose a deep neural network architecture trained on some 3000 images to detect diseases such as rust spot, yellow leaf disease, Helminthosporium leaf spot, Cercospora leaf spot, and red rot, achieving 96% accuracy. An Android application was designed to allow farmers to take and upload pictures for real-time disease prediction, thus facilitating timely precaution measures. (Komol et al., 2023) Propose that it is conceivable to apply the YOLO version 8 algorithm method for an early diagnosis and treatment of three classes of sugar-cane diseases, attaining an accuracy of 96.67%. With such a deep learning technique and robotics working together, automatic monitoring and treatment of sugarcane fields could happen in real-time, improving the control of these diseases, therefore lessening their effect on the world sugarcane market. Such impacts can be mitigated through early detection with deep learning, specifically CNN architectures. In diagnosing sugarcane diseases, the study of (Militante et al., 2019) applies several CNN models such as StridedNet, LeNet, and VGGNet. With VGGNet, the highest accuracy rate of 95 was reached. This study (Upadhye et al., 2023) analyzes CNN applications learning for the early detection and classification of four sugarcane diseases in India, attaining 98.69% accuracy-and presents a web application for real-time disease detection, thus establishing the feasibility of such use of CNNs by classifying sugarcane images into healthy and diseased images. Besides, it proposes several avenues for future research to enhance agricultural productivity and price forecasting on AI platforms. Sugarcane, a genus of the Poaceae family high in sucrose, produces white sugar, jaggery, molasses, and bagasse. However, damaged plants cannot be used, and it is essential to identify them quickly. The feature extractors such as Inception v3, VGG-16, and VGG-19 were tested against various classifiers and compared in identifying damaged sugarcane plants through an innovative deep learning framework, as discussed in (Srivastava et al., 2020). The study involves the analysis of leaves, stems, and color of the plants, and while statistical parameters were calculated, including accuracy, precision, specificity, AUC, and sensitivity using Orange software, the best-combined results produced were 90.2% AUC using VGG-16 and SVM. Pests, diseases, nutrient deficiencies, and malnutrition account for significant sugarcane production losses in India. Oftentimes, the timely identification and treatment required go outside the capabilities of local experts. To diagnose diseases such as eyespot, leaf scaling, yellow leaf, and pokkah boeng, the authors in (Atheeswaran et al., 2023) proposed an intelligent farming system for sugarcane growers in India using machine learning-based IoT tools, image processing, and soft computing. The system will assess color, shape, and texture features using ANN, Neuro-Fuzzy, and Case-Based Reasoning algorithms.

In agriculture, especially sugarcane farming, the application of deep learning and AI technologies facilitates the detection and management of plant diseases and pests. The presence of thirteen genera of plant-parasitic nematodes associated with sugarcane in Negros Occidental, a province in the Philippines, of which the most common was Pratylenchus, shows a global challenge concerning crop losses attributed to pests and diseases. While conventional methods of diagnosis remain slow, tedious, and require specialist knowledge, the recent advancements in AI provide a promising avenue for solutions. Studies indicate that more than any other approach, deep learning via Convolutional Neural Networks (CNNs) significantly improved disease and pest detection accuracy and performance speed. Uncrewed aerial vehicle (UAV) technology combined with model optimizations in pest detection, such as YOLOv5s with high accuracy, has improved crop monitoring. Likewise, in sugarcane, deep learning models like AlexNet and VGGNet were sufficiently accurate for distinguishing healthy plants from plants showing various disease symptoms, helping to improve yield and disease management. An integrated mobile application for the real-time prediction of diseases provides further impetus to mobilize timely interventions. All these advancements in AI are indeed making agriculture more sustainable and efficient, thus promoting crop health, high yield, and economic stability in areas largely dependent on crops like sugarcane.

Therefore, the real pioneer in this system becomes the application of AI to merge real-time crop monitoring, early disease detection, and pest control in sugarcane into an integrated system. It does not solely rely on manual inspection or operate merely on a given pest, such as plant-parasitic nematodes. AI models, including Convolutional Neural Networks (CNNs), are utilized to detect various crop stressors in line with the earlier detection capabilities with better accuracy and efficiency. Monitoring via this innovation is continuous, scalable, and can occur across different environmental conditions. Timely information is provided to the farmer by complementary integration of the AI-based prediction models with mobile apps for in-field disease diagnosis, thereby reducing the dependency on specialized knowledge and labor. Enhanced production, resulting from these interventions, creates an instance of sustainability via optimized input utilization and reduced crop losses.

III. METHODOLOGY

The researcher employed the descriptive development methodology, which entails systematic studies involving design, development, and thorough evaluations of instructional programs, processes, and products that must comply with specified standards or criteria. Within drone technology and CNNs being utilized for precision crop detection and management in sugar cane agriculture, model development-cum-testing-cum-validation denotes the feedback loop iterated many times, which is critical in ensuring the developed model's fitness for accuracy, reliability, and functionality. Each iteration consists of multiple stages of gradually improving the model by collecting feedback and applying it to the next iteration.

This study applied an advanced technique of Convolutional Neural Networks (CNNs), a type of machine learning that exists under a true deep learning paradigm. In simple words, deep learning is a type of machine learning that learns the hierarchical representation of images by the involvement of multiple layers of interconnected neurons. Using CNNs, the authors can train a dataset from various sugarcane fields and develop a viable crop detection and management model.

The researcher adopted Roboflow to create an image classification model. This research uses stratified sampling. The researcher divides the dataset into different strata based on specific characteristics (like object classes, sugarcane image, and pests). Then, they sample proportionately from each stratum so that all subgroups are duly represented.

The data collected from the Research and Extension Center of SRA and other images taken manually in the sugar cane field with the help of field personnel were comprehensive. The data gathered include the pictures of healthy sugar cane plants with uniform color and growth. Images showing various sugar cane diseases, such as smut, downy mildew, yellow spot, leaf scorch, and pookah being. The images indicate nutrient deficiencies (e.g., nitrogen, phosphorus, potassium) with corresponding symptoms like yellowing or stunted growth. The researcher also gathers images capturing common pests such as the green aphids, wooly aphids, army worms (taquitos), migratory locusts (apan), stem borers (damask), and rat and images showing the effects of pest infestations, such as holes in leaves, damaged stems, and wilting.

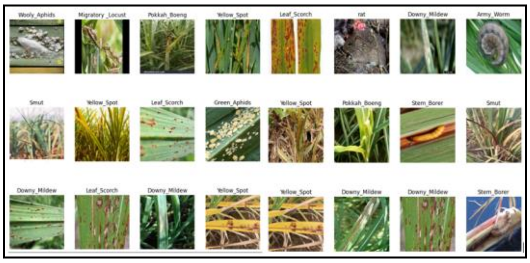

Figure 1.0: Sugarcane Pest and Diseases

Various images of sugarcane pests and diseases are shown in Figure 1.0, illustrating the various visual characteristics of diseases and pests and the extent to which these impact the crop's health. Each image showcases the facets involved in recognizing and combating these agricultural threats.

The researcher will upload the named database to Roboflow based on the collected data. Each image will be labeled into its appropriate class, and eventually, the datasets will be split into training (80%), validation (10%), and testing (10%) sets to accurately establish the model's accuracy and generalizability, assuring consistent performance for pest and disease detection in sugarcane fields.

Another step in the process is preprocessing, where the images will be standardized for the best performance of the model. The researcher resizes all images to a fixed dimension, such as 224 by 224 pixels, which is much suited when working with models such as MobileNet. The other option is to convert images to grayscale if necessary, along with auto-correcting the orientation to remove any misaligned rotation in all images to ensure consistency across the dataset with orientation.

The researcher will practice augmentation techniques to optimize the model's generalization performance. Random flips, rotations, and cropping will be performed to introduce variability in image orientation and composition. Additional real-world variations will be created through various other effects, such as blur and brightness adjustments and added noise. These collectively make the models increasingly robust against becoming weighted down in their predictions under highly variable ambient conditions.

Modeling on the training output would involve selecting a model type, for example, MS COCO. Upon commencement of training, valuable insight will be gained regarding loss and accuracy graphs to measure performance and a confusion matrix to analyze class predictions in order to have an optimally trained model for deployment.

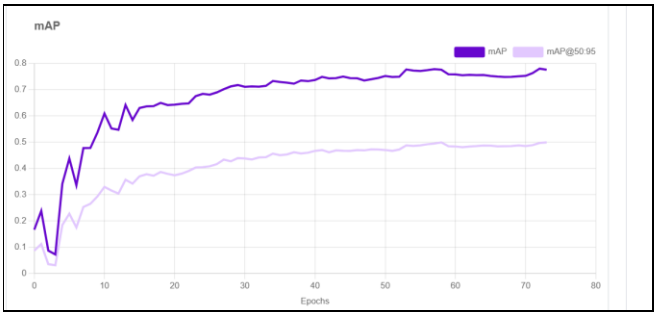

Figure 2.0: Graphs to Track Performance

Figure 2.0 illustrates the higher Mean Average Precision (mAP) values indicate better model performance in detecting objects.

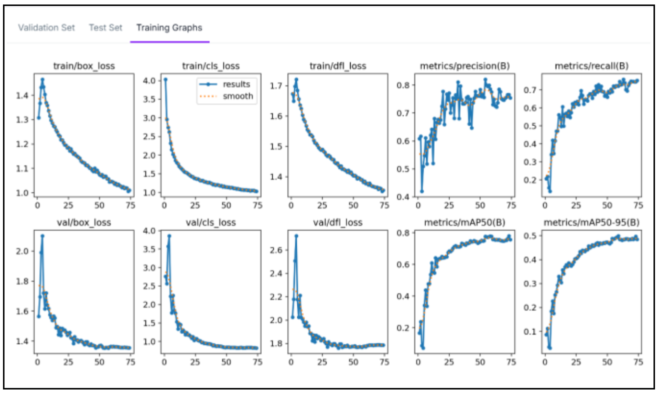

Figure 3.0: Training Graphs

Figure 3.0 illustrates the training performance of the model, showcasing key evaluation metrics, including precision and recall. These metrics provide valuable insights into the model's effectiveness in distinguishing between classes. Precision describes the ratio of accurate positive classifications over all predicted positive classifications, reflecting accuracy in classification. In contrast, recall describes the capability of the model to make actual positive classifications in all cases, thus highlighting its sensitivity. The graph illustrates the interrelationship among these metrics for observing the model's learning curve and performance variance over time.

Figure 4.0: Model Performance

Figure 4.0 shows that the model performed excellently at an mAP of 93.9%, a precision of 94.8%, and a recall of 92.5%. This means that the model can detect positive instances in a very high percentage without compromising on the sensitivity towards an actual positive instance.

To estimate the accuracy of the model, we first calculate the F1-score, which balances Precision and Recall. The formula for the F1-score is:

$$\mathrm{F1} = 2\,x + \frac{Precision\ x\ Recall}{Precision + Recall}$$

Using the given Precision of 94.8% and Recall of 92.5%, the F1-score is approximately 93.64%. Once we have this value, we can approximate the accuracy using the formula:

$$\mathrm{Accuracy} = \frac{Precision + Recall}{2}$$

Applying the given values, the estimated accuracy is 93.65%. This suggests that the model performs reliably in detecting sugarcane pests and diseases, closely aligning with expert assessments. The well-balanced Precision and Recall indicate that the model effectively identifies affected areas while minimizing false detections, making it a valuable tool for precision agriculture.

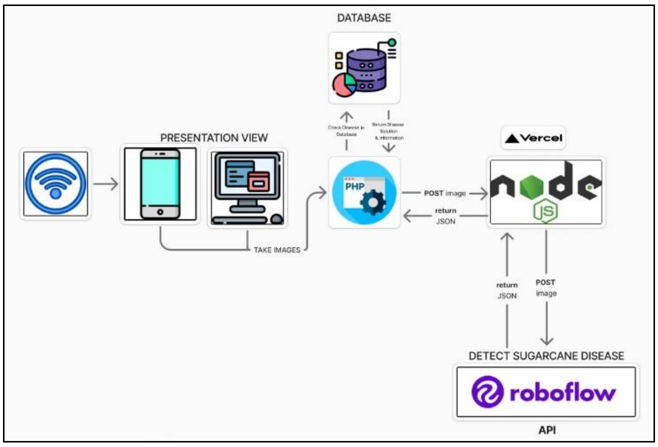

Figure 5.0: System Architecture

Figure 5.0 shows of how the different components (frontend, PHP, Node.js, and Roboflow API) interact in an object detection system. It outlines the data flow, API communications, and role of each technology in processing and handling images for object detection.

In utilizing the system, an internet connection is required while running Roboflow API since it is an online service. The interface presentation, either on a mobile or desktop, takes a snap and forwards it to PHP, after which PHP manages everything to do with the database-from data retrieval to data storage. The other function of PHP is to process the image and perform an API POST request to the Node.js server hosted on Vercel. Thereafter, once the object detection is complete, PHP receives the JSON response returned by Node.js for further processing and data management.

API interaction is performed using Axios on Node.js deployed on Vercel. Then the server forwards the POST requests received from PHP to Roboflow API to start processing of that image. After Roboflow has processed the image, it returns a JSON response of detected objects to PHP. While Roboflow allows you to train models, after the training, you would be granted a unique API key and endpoint to invoke the trained model for inference. This kind of integration allows for smooth flow for object detection and data management across the system.

IV. RESULTS AND DISCUSSION

In this study, CNN methodology was suggested for the automated identification of pests and diseases affecting sugarcane crops in fine-tuned crop detection and management. Experimental results indicate the promise of using CNN-based approaches for this application while necessitating further research and development.

General Model Performance

With an overall accuracy of 93.65% in the recognition of pests and diseases affecting the different classes of sugarcane, including healthy sugarcane, the model performance was evaluated by precision and recall on a total of 3895 images. This further corroborates the ability of this model to discriminate healthy from infected sugarcane and pinpointing specific types of infestation.

Comparison with Other Techniques for Pest Targeted Approaches

The application of CNNs for the detection of pests and diseases in sugarcane has great implications on precision crop management:

Early Detection and Intervention: Associate automation in pest detection with early identification so that timely intervention could be done to prevent wide-scale crop loss.

Focused Treatment: Farmers can be helped to specifically treat the actual pest or disease, thus they would not have to waste broad spectrum use of pesticides or poisonous effects on the environment.

Optimal Utilization of Resources: Real-time monitoring and assessment optimize water and fertilizer supply in getting improved health and yield of crops.

Better Decision Power: This information generated from the CNN could be put into a decision system with actionable items given to the farmer for him to make the use of them for effective management of crops.

Limitations and Future Research

However, even with the promise shown by these results, several areas of limitation were highlighted in this study:

Limited Data: Steps to increase the size and diversity of the dataset would require introducing several more sugarcane varieties, environmental condition, and disease stage variations.

Generalizability: The models may perform differently when evaluated in different locations or telecrop regions because of the crop, pest, and disease prevalences varying among these different regions.

Real-time Implementation: Further investigation is needed to tune the model for real-time deployment on mobile or drone platforms to be able to monitor in-field conditions.

Future research directions encompass:

Data augmentation; This will include data augmentation methodologies in a bid to increase the size and diversity of the training data.

Model optimization: Testing several architectures of CNNs with different optimization methods to enhance the accuracy and performance of the model.

Integration with Drone Imagery: Modification of the CNN model to adapt to imagery from drones for large scale monitoring of sugarcane fields.

An advanced decision-making tool: A straightforwardly usable decision support system integrating the CNN model with other data sources to give complete recommendations to farmers regarding the management of their crops.

Conclusion

This study has evidentially illustrated the prospects of the application of CNNs in effective and accurate detection of pests and diseases associated with sugarcane. From the observation, it can be concluded that it could be a technique for timely interventions and targeted treatment measures, and more efficient resource utilization for sustainable and productive sugarcane cultivation. Nevertheless, it requires more research and developmental training to work around the limitations and to their full potential convert the capabilities of CNNs towards precision management of sugarcane and other staple crops.

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