Strawberry Classifier

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***Abstract*—**

***Index Terms*—**

I. Introduction

The vibrant red strawberry isn't merely a seasonal delight. In Malta, it has a distinct growing season, flourishing during the late winter and spring months. This unique window makes the arrival of Maltese strawberries a highly anticipated event for both residents and tourists. The popularity is further underscored by the success of the annual strawberry festival, a celebration where this delectable fruit takes center stage. From enjoying them fresh off the vine to incorporating them into innovative culinary creations, the festival showcases the versatility of the strawberry.

However, the journey from a humble seed to a juicy, edible berry is far from simple. Cultivating strawberries requires meticulous care and expertise. Unlike other fruits, they are delicate and susceptible to over-watering. Even seemingly beneficial rain can become detrimental if it exceeds the plant's needs [1]. This inherent fragility underscores the dedication and skill required by Maltese strawberry farmers.

The rise of technology has permeated every aspect of our lives, and agriculture is no exception. This study aims to leverage advancements in this field to address a crucial challenge in Maltese strawberry production identifying the optimal harvesting time. By implementing a machine learning-based solution to analyze various datasets, we propose a system that can accurately determine when a strawberry has reached its peak ripeness and is ready to be enjoyed by consumers.

Grounded in a pragmatic philosophy, this study emphasizes the practical application of research findings to address real-world challenges in strawberry production [2]. Employing a deductive approach, the study begins with a theoretical framework derived from existing literature and extends it to develop practical solutions for strawberry farming. The research strategy [2] incorporates both quantitative and qualitative methods, with quantitative analysis used for dataset construction and algorithm evaluation, while qualitative insights from experienced growers contribute to refining the system's recommendations, ensuring their anonymity. Various methodologies are employed, including data collection through image processing techniques and algorithm development using machine learning approaches. Operating within a limited time frame, the study focuses on the immediate application of findings to enhance strawberry production in Malta. Central to the study are cutting-edge techniques such as computer vision and machine learning, enabling the development of a sophisticated smart strawberry system [3] .

By traversing through the layers of the research onion, this study aims to provide a comprehensive understanding of strawberry growth stages and interventions, ultimately contributing to the advancement of agricultural technology and enhancing the sustainability of strawberry farming practices in Malta

This research proposes a "smart strawberry system" powered by computer vision. By analyzing digital details within strawberry images, the system goes beyond appearance to predict the ideal harvest window, minimizing waste and maximizing yield [3]. This early detection system also identifies potential diseases lurking beneath the surface, allowing farmers to take preventative measures and ensure healthy strawberries. Similar to how image processing aids pest management, this technology offers earlier disease detection, benefiting both farmers and consumers. In essence, the study aims to develop a system that detects strawberry growth stages and diseases using computer vision, offering recommendations based on these findings.

This study explores into the exploration of artificial intelligence (AI) techniques' viability in categorizing strawberry growth stages and proposing interventions to enhance growth. It hypothesizes that an AI-driven system can be fashioned to streamline this process, thereby enhancing the precision and efficiency of strawberry production. Specifically, the study endeavors to construct and assess a system proficient in automatically discerning diverse strawberry growth stages utilizing visual data and subsequently suggesting suitable interventions, including watering, nutrient application, and temperature adjustments, tailored to the identified growth stage. To fulfill these aims, the research questions are the following:

1) How can a robust and comprehensive dataset be constructed that accurately captures the visual characteristics of different strawberry maturity stages?
2) What AI algorithm is most effective for classifying the various growth stages of a strawberry plant?
3) How do the system's recommendations for growth interventions compare to the advice provided by experienced strawberry growers or established best practices?

II. Literature

A. YOLO & Roboflow: Empowering Agricultural Object Detection

YOLO (You Only Look Once) object identification models have emerged as a significant tool for real-time computer vision jobs in agriculture due to their speed and accuracy. However, training custom YOLO models can be difficult and time-consuming. Roboflow, a cloud-based platform, overcomes this constraint by giving user-friendly tools for data annotation, augmentation, and interaction with YOLO frameworks (Lippi, 2021).

Studies by Singh et al., 2023 [4] and Li et al., 2017 [5] demonstrate the importance of YOLO in agricultural object detection. Singh et al. gained a promising mAP (mean Average Precision) of 51% for fruit and vegetable recognition in a real-world market setting. Li et al. [5] achieved 90.42% accuracy in diagnosing apple leaf disease using a simulated dataset. These findings suggest that YOLO is suitable for real-time applications such as crop health monitoring, production estimation, and animal management.

Roboflow [6], a cloud-based online platform, automates procedures including data version management, experiment monitoring, and model deployment to simplify the process of building deep learning models. This streamlined technique has the potential to significantly decrease the time and energy needed training YOLO models for a variety of agricultural applications. Researchers and professionals can create and implement more efficient item identification models by combining YOLO's real-time capabilities with Roboflow's intuitive methodology, resulting in breakthroughs in agricultural technologies.

This combination of YOLO and Roboflow technologies not only shows the potential for advancement in agricultural item recognition, but it also highlights the importance of easily available and easy tools to encourage agricultural innovation.

B. Convolutional Neural Networks for Automated Disease Detection in Agriculture

Convolutional neural networks (CNNs) are transforming automated disease detection in agriculture. Yolo-Papaya is a unique approach presented by Al-Sagheer et al. (2022) [7] that identifies and classifies diseases in papaya fruit.

CNNs are a type of deep learning model that focuses on image recognition and classification. They accomplish this through a series of specialist layers: Convolutional layers use filters like tiny grids to look for specific patterns in an image. CNNs may use numerous filters to extract a wide range of information, from simple forms to complex textures. Pooling layers: Following feature extraction, pooling layers reduce data dimensionality by merging information from fewer areas. This helps to regulate model complexity and prevent overfitting.

Fully connected layers: Finally, the processed data is passed into these layers, which look like classic neural networks. They connect neurons across layers, allowing the network to learn more advanced features and make classifications based

Prediction \ Ground Truth	Papaya (Healthy fruit)	Anthracnose	Phytophthora Blight	Mechanic Damage	Chocolate Spot	Sticky_Disease	Physiologicalspot	Black spot	Scar
Papaya (Healthy fruit)	727								
Anthracnose		105		2	2				
Phytophthora Blight			20						1
Mechanic Damage		2		93					20
Chocolate Spot		4			220				
Sticky_Disease						16			
Physiological Spot							120	10	
Black spot							15	374	
Scar			1	12					340
False Negative	9				42	5	16	83	83
Total	736	111	21	107	264	21	151	467	444

Fig. 1. Confusion Matrix [7]

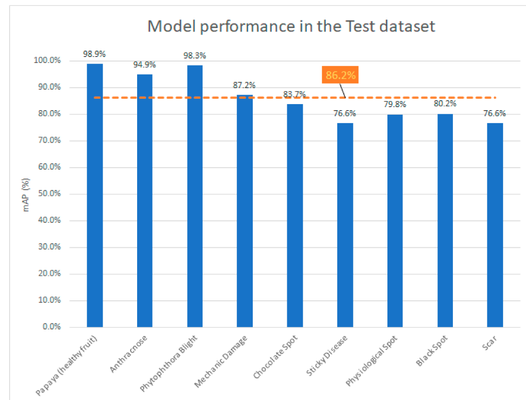

Fig. 2. Model Performace: A bar chart depicts class-specific model performance using mAP. A dashed line indicates the overall mean performance. [7]

on the retrieved data. The technique of feature extraction and hierarchical learning enables CNNs to recognise complicated patterns in images, making them perfect for disease diagnosis in agriculture. The Yolo-Papaya approach by Al-Sagheer et al. (2022) [7] exemplifies this. Precision agriculture researchers expanded on this notion by creating a new object detection system for quick and precise papaya fruit disease detection. This system makes use of YoloV7, a cutting-edge deep learning model noted for its speed and accuracy, and improves its performance with a Convolutional Block Attention Module (CBAM).

The combined technique produced remarkable results, with an overall mean average precision (mAP) of 86.2%. The algorithm achieved 98.9% accuracy in classifying healthy fruits and those affected with Phytophthora blight, as illustrated in Fig. 2. This demonstrates the system's ability to distinguish between healthy and infected papayas, with a particular strength in detecting Phytophthora blight, a deadly fungal disease.

C. Other Studies

Deep learning methods are transforming automated disease detection in agriculture. Al-Sagheer et al. (2022) [8] present a new CNN architecture for detecting and classifying the

Class	Accuracy	Precision	Recall	F1 Score
Healthy	96%	100%	84%	91%
Low	99%	96%	100%	98%
Medium	97%	89%	100%	94%
High	98%	96%	96%	96%

Fig. 3. Confusion matrices for all levels of different disease in citrus crops. [8]

Class	Healthy	Low	Medium	High
Healthy	21	0	0	0
Low	0	25	0	1
Medium	3	0	25	0
High	1	0	0	24

Fig. 4. The accuracy, precision, recall, and F1 score of the model. [8]

severity of citrus crop diseases [8]. Their model uses a pre-trained VGG16 network, which is a well-known architecture for image recognition [8]. This pre-trained model serves as the system's foundation, allowing it to learn from enormous image collections. The authors then improve the VGG16 architecture to better categorise citrus disorders. The system can identify and diagnose diseases in citrus fruits based on labelled datasets with disease severity levels ranging from mild to severe.

The system learns to distinguish between healthy and diseased fruit by analysing visual cues including colour fluctuations, texture alterations, and lesion patterns, and then uses these learned patterns to determine severity. This has various potential advantages, including early disease diagnosis for faster response, improved treatment procedures based on severity, and a reduction in reliance on physical inspection.

The model accurately predicts the low severity level of disease in citrus fruits with a precision of 100%, recall of 84%, and an F1 score of 91% figure 3, achieving an overall accuracy of 99%. When compared to other classes, Al-Sagheer et al. (2022) [8] model attained a 98% accuracy rate for diseases with high severity. Furthermore, the algorithm achieves 96% accuracy in detecting healthy states and 97% accuracy in identifying medium severity conditions figure 3. There are detailed accuracy, precision, recall, and F1 score data for each severity level of citrus crop disease as shown in the table 3.

De Moraes et al. (2023) [7] present Yolo-Papaya, a deep learning model for papaya diseases classification that uses the YoloV7 detector with CBAM augmentation [7]. Both studies show that CNNs are effective for disease diagnosis, although their approaches differ. Paper [8] focuses on disease severity categorization for citrus fruits using a pre-trained VGG16 model, which could provide valuable insights into targeted treatment choices [8]. Al-Sagheer et al. (2022) [7] focuses on papaya disease classification with YoloV7 and achieves high accuracy, particularly for Phytophthora blight detection.

Furthermore, existing research on automated disease identification must be critically evaluated for its strengths and weaknesses. While CNNs have demonstrated promising outcomes in this domain, issues such as dataset bias, model adaptability, and result interpretability remain major problems. Addressing these difficulties is critical to ensure the accuracy and usefulness of automated disease detection systems in agricultural practices.

III. Methodology

A. Automated Strawberry Maturity Classification with YOLOv8

The hypothesis of this study asserts that leveraging AI techniques enables the classification of strawberry growth stages and the recommendation of interventions for enhanced growth. The objective is to introduce an effective system capable of automatically detecting strawberry growth stages and determining watering and vitamin needs.

To achieve this, in accordance with the specified research questions presented in the introduction section, the study aims to construct a robust dataset for strawberry maturity stages by identifying key visual indicators like color, size, and texture. High-resolution images will be captured at various growth stages, covering eleven distinct categories of strawberry diseases, including Grey Mould, Angular Leafspot, Leaf Spot, Healthy Strawberries, Powdery Mildew fruit, Powdery Mildew fruit leaves, Healthy Leaves, Blossom Blight, Non-edible Strawberries, Anthracnose Fruit Rot, and Mulch.

Utilizing YOLOv8 with Roboflow offers an effective approach for classifying strawberry maturity stages. YOLOv8 is renowned for its speed and accuracy in instance segmentation, while Roboflow simplifies data preprocessing and model training.

Comparing system recommendations with grower advice involves evaluating their effectiveness in real-world agriculture. While systems rely on data insights, growers draw from their experience. Field trials play a crucial role in comparing both approaches, measuring metrics and gathering feedback to refine recommendations.

B. Model Training

In this studies, the development of a robust strawberry detection model involved the strategic application of cloud-based computing resources and specialized software. The YOLOv8 architecture, renowned for its precision and speed in instance segmentation applications, was chosen to train the model on a meticulously curated dataset. This dataset, constructed with the assistance of Roboflow, a platform specifically designed to streamline dataset creation and management, formed the critical foundation for the training process.

Initially, Google Colab, a cloud-based platform, was leveraged to facilitate efficient training sessions. By implementing code-driven integration between Roboflow and Google Colab, a seamless transition within the training pipeline was achieved.

```
!mkdir {HOME}/datasets
%cd {HOME}/datasets

# Install the roboflow library using pip
!pip install roboflow

# Import the Roboflow library
from roboflow import Roboflow

# Initialize a Roboflow object using your API key (replace with your actual key)
rf = Roboflow(api_key="bFVXmtlbtC5MLcrxJPaP")

# Specify the workspace and project names
project = rf.workspace("marstrawberry").project("strawberry-disease-uudgf")

# Download version 11 of the project's YOLOv8 dataset
dataset = project.version(11).download("yolov8")
```

Fig. 5. Roboflow to Google Colab

Parameter	Value
Epochs	100
Patience	50
Batch Size	16
Image Size (pixels)	640x640
Workers	8

Fig. 6. Training Parameters

This integration not only ensured the immediate availability of the strawberry dataset within the Colab environment but also served to optimize the training process by minimizing potential data handling errors.

As the training progressed to subsequent stages, Google Colab became the sole platform for model development. To ensure a smooth training pipeline and efficient data transfer, the following Figure 5 exemplifies the method employed for the direct export of the strawberry dataset from Roboflow to Google Colab.

The model trained for 100 epochs to learn complex patterns from the strawberry data. A patience of 50 epochs prevented overfitting. For efficiency, images were batched (size 16) and resized (640x640). Periodic saving (save=True) allowed performance evaluation, while disabled caching (cache=False) ensured data relevance. 8 worker threads accelerated training.A table in figure 6 is created with parameters and values used in the training as mentioned.

C. Phases in Developing a Strawberry Annotation, Detection, and Evaluation System

In developing a strawberry annotation, detection, and evaluation system, three distinct phases are outlined as shown in the pipeline diagram 7. Phase 01 involves collecting images of strawberries, annotating them using tools like Roboflow, and organizing the dataset into 11 classes representing various strawberry diseases and growth stages. Phase 02 focuses on strawberry detection, including the creation of a testing images folder, training a YOLO v8 model, and displaying predicted classes within images to identify strawberry diseases. Finally, Phase 03 evaluates the model's performance using manually annotated datasets, computing metrics such as confusion matrices, accuracy, recall, and precision.

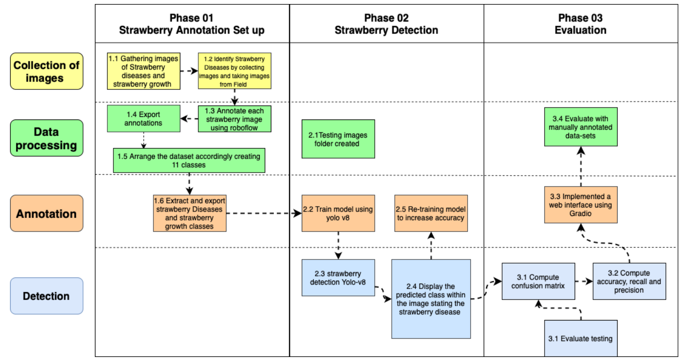

Fig. 7. Pipeline Diagram

D. GAI and LLM driven final recommend-er system

Developed a practical recommendation system for monitoring strawberry health which is constructed using Gradio, this system tailors recommendations based on analysis outcomes, harnessing advanced AI technologies to ensure a seamless user experience.

Central to this system is the Mistral-7B-Instruct-v0.2 API, facilitating the interpretation of user-provided descriptions of plant health, including symptoms and growth observations. This natural language processing (NLP) capability significantly enhances disease diagnosis, growth assessment, and comprehension of factors impacting strawberry health.

In order to enhance performance, various NLP tools underwent evaluation. Initial testing revealed redundant output, presenting both user queries and responses. This issue was promptly addressed, resulting in the display of only the response, thereby enhancing clarity and user satisfaction. Furthermore, the formulation of clear and concise user input messages further bolstered the system's efficacy by fostering improved comprehension and more informative responses. These optimizations collectively culminated in the development of a user-friendly and efficient recommendation system.

E. Conducting ground truth testing with a human expert

This section details an expert evaluation process for a strawberry disease detection model. The expert verified the model's ability to identify strawberry growth stages, diseases, and maturity levels. This involved testing the model with various images through a Gradio interface. The model successfully identified healthy strawberries, specific diseases like Gray Mold and Anthracnose, and even multiple elements in a single image. The model provided control suggestions for detected diseases. The expert observed some variation in the detail provided by the model's responses, suggesting potential for further development. Overall, the evaluation demonstrated the model's promise in accurately identifying these elements and its added value of recommending disease control methods.

F. Ethical considerations

This research prioritizes the quantitative analysis of strawberry growth, minimizing the need for personal data collection. Will only be required during ground truth testing, conducted with the assistance of an anonymous strawberry expert. Throughout the research process, participant safety is paramount, and no physical harm will be inflicted on any volunteers.

It's crucial to emphasize that this study is strictly academic in nature. There is no affiliation with, or benefit to, any specific commercial entity. The research findings will be publicly available upon completion. This commitment to open access ensures transparency and eliminates the possibility of any competitive advantage or disadvantage arising from the research. Ultimately, this research aims to promote healthy strawberry growth, offering valuable insights to benefit various stakeholders within the agricultural sector.

IV. FINDINGS&DISCUSSION OF RESULTS

V. CONCLUSION

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