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Integrating Machine Learning-based Fruit Disease Detection Algorithm for Satsuma Growers' Knowledge, Practices, and Technology Adoption

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Satsuma (Citrus unshiu) mandarin is a commercially valuable fruit susceptible to various diseases that impact production. This study assesses the need for the development of a machine learning model (ML) for Satsuma disease detection. A survey was administered to 196 growers in Malabing Valley in the Municipality of Kasibu of the Province of Nueva Vizcaya, Philippines, to identify the prevalent fruit diseases in the municipality, current practices, knowledge of disease management, technology adoption approaches, and resource assessments. The study identified Scab, Huanglongbing (Citrus Greening Disease), and Canker as the most prevalent diseases affecting Satsuma production in Malabing Valley. Despite moderate confidence in their knowledge of disease management and visual detection methods, Satsuma growers showed limited awareness of recent advancements and restricted access to training and information. There is a strong interest among growers in adopting new technological tools for disease detection, with high perceived usefulness, though current usage remains low. The study highlights the potential of machine learning, particularly convolutional neural networks (CNNs) like EfficientNet and ResNet, to enhance the accuracy and efficiency of disease detection. A proposed mobile and web-based application features, integrated with treatment recommendations and designed for disease detection and reporting, promises to reduce reliance on subjective visual inspections and improve overall disease management practices among growers.

Keywords: satsuma disease detection, fruit disease, machine learning, convolutional neural networks, agricultural technology adoption.

1. Introduction

The world citrus statistical data in 2021 and 2022 shows that the global production of citrus reached 158.5 million tons, and a few countries dominate the production, such as the People's Republic of China, the Federative Republic of Brazil, and the Republic of India, with a global output of 28%, 12%, and 9%, respectively, while the other 51% is produced in Asia [1].

Citrus fruit production in the Philippines has seen significant fluctuations in recent years, with a general upward trend observed from 1972 to 2021. In the year 2021, the amount produced was 152,382 tons [2]. Approximately 151,000 tons of citrus fruits were harvested in 2022, maintaining stability from the previous year. The rate of growth was highest in 2019, showing a significant rise of 7.5%, leading to output reaching its maximum volume of 167,000 tons.

While rice, corn, vegetable, and root crops are major crops, citrus production has significantly increased since the early 1980s. The favorable climate, temperature, fertile soils, and abundant forests in the Municipality of Kasibu, Nueva Vizcaya, with a total area of 31,880 hectares and agricultural region of 22,340.99 hectares, provide the perfect conditions for farming a diverse range of citrus varieties spanning about 656 hectares shows in Table 1. Cultivating citrus crops has become the primary source of income for the 866 growers, resulting in notable community improvements.

Table 1. Different commodities in the Municipality of Kasibu with its total area and estimated number of growers.

No.	Commodities	Estimated Number of Farmers	Area (Ha)
1	Rice – Irrigated	4,897	2,534
	Rice – Upland	235	145
2	Corn	1,525	473
3	Livestock (Large & small Ruminant, Swine)	2,433	1,693
4	Poultry (Chicken, Duck, Goose, Turkey)	4,143	115
5	Vegetable & Root Crops	5,520	4,187
6	Citrus (Mandarin, Oranges, Pummelo)	839	656
7	Banana	1,269	721
8	Coffee	181	129
Total		**21,042**	**10,653**

Source: Submitted Agricultural Data or Statistics in the Municipality of Kasibu to the Department of Agriculture Regional Office on May 30, 2022

Satsuma, a kind of mandarin citrus fruit, dominates citrus production, accounting for 80% of the total output. It is predominantly grown in the Malabing Valley of Kasibu Municipality, located in Nueva Vizcaya Province. And dubbed as the "Citrus Capital of Luzon" with Administrative Order No. 18, Series of 2022 [3].

Citrus fruits are well-known for their rich nutritional content as they include an abundance of bioactive compounds and phytochemicals such as minerals, vitamins, flavonoids, and carotenoids, which are beneficial for the human body. Phytochemicals may function as antioxidants, enhanclipids andivity of defensive enzymes in the liver, counteracting the oxidation of genetic material by lipids, and enhancing the immune system [4].

During the harvest season, which runs from June to October, the average production volume and average harvest per hectare are 9,571.90 metric tons and 34 metric tons, respectively. With these numbers, it is evident that there is a positive contribution in the economy of the country.

Despite all the positive data and honor indicated, the country is still encountering various challenges and risks in citrus farming, including fruit diseases that can significantly impact crop yield and quality.

The prevalent fruit diseases that can be found in the municipality are scab, huanglongbing, canker, black spot, sooty mold, and Alternaria rot, shown in Table 2. This has caused significant low production, particularly affecting the Satsuma variety.

With these diseases, technological advancements like machine learning (ML) have become powerful tools in agriculture, offering precise detection, improved accuracy, and cost-effective solutions for citrus growers. According to a comprehensive review on computer vision and artificial intelligence in the food industry, these technologies enhance the ability to identify and manage crop diseases efficiently, thus improving overall productivity and reducing economic losses for farmers [5].

Table 2. The most prevalent Satsuma fruit diseases in Malabing Valley.

Image	**Fruit Disease**	**Other Common Name**	**Scientific Name**
	Scab	Sour orange scab	*Elsinoe fawcettii*
	Huanglongbing	Greening, yellow shoot, yellow dragon	*Candidatus Liberibacter*
	Canker	Asiatic citrus canker	*Xanthomonas campestris*
	Black Spot	CBS	*Xanthomonas alfalfae*
	Sooty Mold	Black mold	*Capnodium citri*
	Alternaria	Alternaria brown spot (ABS), alternaria brown spot of mandarins, brown spot	*lternaria alternata*

Additionally, a detailed review of machine learning applications in agriculture highlights the significant advancements and diverse applications of ML, further supporting its role in modernizing agricultural practices and providing scalable solutions for various agricultural challenges, including those faced by citrus growers [6].

ML algorithms can be used to analyze the citrus fruit visual data captured through image processing, identifying subtle signs of disease that are invisible to the naked eye. This enhanced precision leads to more targeted treatment applications, reducing unnecessary fungicide use and environmental impact. ML-based tools can be deployed on mobile devices, providing growers with accessible and affordable disease detection solutions. This allows for intervention, minimizing crop production losses and maximizing yield [7]. However, challenges such as detection accuracy, possible treatment suggestion management, and lack of reporting of diseases to agriculture authorities.

Research and development efforts are continuously addressing these challenges, paving the way for improved detection accuracy, treatment suggestions, and fruit disease reporting solutions for citrus fruit disease detection. A systematic literature review on image acquisition, preprocessing, and classification of citrus fruit diseases highlights the advancements and ongoing efforts in this area, emphasizing the importance of accurate disease identification for effective crop management [8]. Furthermore, a systematic review of citrus disease perceptions and fruit grading using machine vision illustrates the practical benefits of machine learning in improving the precision and efficiency of disease detection and fruit grading processes [9].

By bridging the gap between technology and agriculture, machine learning has the potential to revolutionize crop protection strategies, contributing to a more sustainable and productive future for the agricultural sector. These integrated approaches not only support growers in managing their crops more effectively but also promote sustainability by reducing the reliance on chemical treatments and minimizing crop losses.

Table 2. Identified diseases by the growers and ranked according to the frequency.

Rank	Disease	Frequency
1	Scab	178
2	Huanglongbing (Citrus Greening Disease)	103
3	Canker	63
4	Black Spot	37
5	Alternaria	32
6	Sooty Mold	30

For this reason, the government has taken steps to improve the production of the citrus industry, as studies show it significantly contributes to the Philippines' local economic growth [10]. This study aims to assess Satsuma growers' knowledge and current practices in disease management, assess their readiness and acceptance of adopting technology, and collect foundational data for the development of a disease detection system integrated with machine learning. By integrating advanced technology for more effective disease identification and management, this study aims to enhance Satsuma production in Malabing Valley, ultimately improving crop yields and growers' livelihoods.

2. Methodology

This needs assessment aims to enhance Satsuma fruit production in Malabing Valley, Nueva Vizcaya, Philippines, through the development of a machine learning model for fruit disease detection.

The target population for this study was Satsuma citrus growers within the Malabing Valley of Municipality of Kasibu in the Province of Nueva Vizcaya, Philippines. Malabing Valley was composed of five (5) barangays, namely: Papaya, Malabing, Binogawan, Tadji, Capisaan, and Wangal. A random sampling technique was employed to ensure the chance of being chosen. Out of a total of 399 Satsuma growers, a sample size of 196 was determined using a 95% confidence level and a 5% margin of error. This sample size is considered adequate to represent the target population.

A five-domain questionnaire was developed as shown in Table 3 to gather data on the needs and perceptions of Satsuma growers and content validated by five (5) agriculture experts. The content validity done was the extent of a measurement tool represents the measured construct and it is considered as essential evidence to support the validity of a measurement tool such as a questionnaire for research [11].

The survey was administered through in-person interviews conducted with Satsuma growers between the months of March and May 2024, in Malabing Valley. Prior to the survey, an approved letter request was taken from the Municipal Mayor's Office to conduct research within the municipality and informed consent was obtained from each participant identified by the barangay council. They were informed about the purpose of the research and their right to withdraw at any time. The confidentiality of all collected data was maintained. No participant names or identifying information was linked to the results.

Table 3. The five domains of the survey questionnaire.

Domain	**Description**
Demographic Profile	This domain provides a comprehensive picture of the citrus growers, including their background and the characteristics of their farms.
Encountered Satsuma Fruit Diseases	This domain aims to identify the possible Satsuma fruit diseases encountered by citrus growers.
Knowledge of Farming	This domain assesses Satsuma growers' knowledge, access to information, and confidence regarding disease detection and management practices
Technology Adoption in Farming	This domain measures the attitudes and behaviours of Satsuma growers in Malabing Valley towards adopting technological tools for disease detection and management in their farms.
Resources in Farming	This domain assesses Satsuma growers' perceptions of their access to financial resources, skilled labor, infrastructure, and their belief in the importance of these resources for effective disease detection and management.

The survey was conducted in English language and translated to Filipino and was checked by a grammarian and Filipino major academician, to ensure clear communication and accurate responses.

Descriptive statistics, including frequencies and percentages, were used to summarize responses for the domains.

3. Results and Discussion

Prevalence of Satsuma Fruit Diseases in Malabing Valley

The survey data revealed valuable insights into the most prevalent diseases affecting Satsuma fruit production in Malabing Valley. Table 4 shows the breakdown of the identified diseases ranked by their frequency.

Table 4. Identified diseases by the growers and ranked according to the frequency

Rank	Disease	Frequency
1	Scab	178
2	Huanglongbing (Citrus Greening Disease)	103
3	Canker	63
4	Black Spot	37
5	Alternaria	32
6	Sooty Mold	30

The table revealed Scab as the dominant disease threat with 178 frequencies, highlighting its significant impact on Satsuma production in Malabing Valley. Another major concern is Huanglongbing with 103 frequencies, underlining the need for the machine learning model to effectively detect this serious disease. Fungal diseases like Canker, Black Spot, and Alternaria also pose challenges with their notable presence among the survey results. While less frequent, Sooty Mold should also be included in the model's detection capabilities to provide growers with the most comprehensive disease management support possible.

Satsuma Disease Detection and Practices

The survey provided valuable insights into current disease detection practices and the specific challenges faced by Satsuma growers.

Table 5. Knowledge level and practices of Satsuma growers.

Aspect	Mean Score	Interpretation
Knowledge of Diseases	3.86	Moderate confidence
Importance of Detection and Management	4.14	Recognized importance
Access to Training and Information	3.81	Limited access to resources
Confidence in Visual Detection	3.73	Moderate confidence in visual methods
Knowledge of Latest Research	2.94	Limited awareness of recent advancements

Table 5 paints a picture of Satsuma growers in Malabing Valley who recognize the importance of disease management but face limitations in their current practices. While growers reported moderate confidence in their general knowledge of diseases with a mean score of 3.86 and acknowledged the importance of detection and management with a mean score of 4.14, there seems to be a gap in acquiring necessary resources and staying updated on advancements. Limited access to training and information with a mean score of 3.81 suggests a need for educational programs or resources to improve their understanding of diseases and best practices. This is further emphasized by the low score for knowledge of the latest research with a mean score of 2.94. Despite growers' moderate confidence in visual detection methods with a mean score of 3.73, this reliance on subjective visual inspection highlights the potential for inaccuracies and the value of a more objective tool.

Acceptance Level of Technology Adoption

The survey results regarding technology adoption for disease detection reveal a promising contradiction as shown in table 6. On one hand, Satsuma growers in Malabing Valley hold a strongly positive perception of technology in this area. They see its value and effectiveness in disease management with a mean score of above 4.1, express high interest in adopting new tools with a mean score of 4.52 and have a strong belief in its potential to improve practices with a mean score of 4.08. However, despite this positive outlook, the current use of technology for disease detection remains low with a mean score of 2.69. This disconnect highlights a potential gap between growers' positive attitudes and their actual practices. There might be a lack of awareness about existing tools, or current options could be complex and user-unfriendly, leading to the moderate satisfaction score of a mean score of 3.48 with existing technology.

Table 6. Acceptance level of technology adoption.

Aspect	**Mean Score**	**Interpretation**
Perceived Usefulness of Technology	4.1	Strongly agree technology is effective and valuable
Interest in Adopting New Technologies	4.52	High interest in exploring new disease detection tools
Belief in Technology's Role	4.08	Strong belief technology can improve disease management
Satisfaction with Current Tools	3.48	Moderate satisfaction, suggesting room for improvement
Current Technology Use	2.69	Low current use of technology for disease detection

Proposed Fruit Disease Detection System

Architecture of the Fruit Disease Detection System

Fig. 1 shows the proposed fruit disease detection system leverages a mobile or web app interface for user convenience. The user captures an image of the fruit, which then undergoes preprocessing to prepare it for analysis. This pre-processed image is fed into a machine learning model which serves as the core of the system. Presumably trained on a vast dataset of unhealthy (with disease) and healthy fruit images, the model can classify the disease in the uploaded image or predict if the fruit is healthy. The user receives the results seamlessly, either through the app displaying the disease classification or a downloadable report from the web app. This user-friendly system offers the potential for offline functionality, especially on the mobile app, allowing growers in areas with limited internet connectivity to utilize the disease detection tool in their orchards. Furthermore, integration with a treatment recommendation for the identified diseases via a mobile-based application and a web-based application for disease reporting to municipal agriculture authority are also considered.

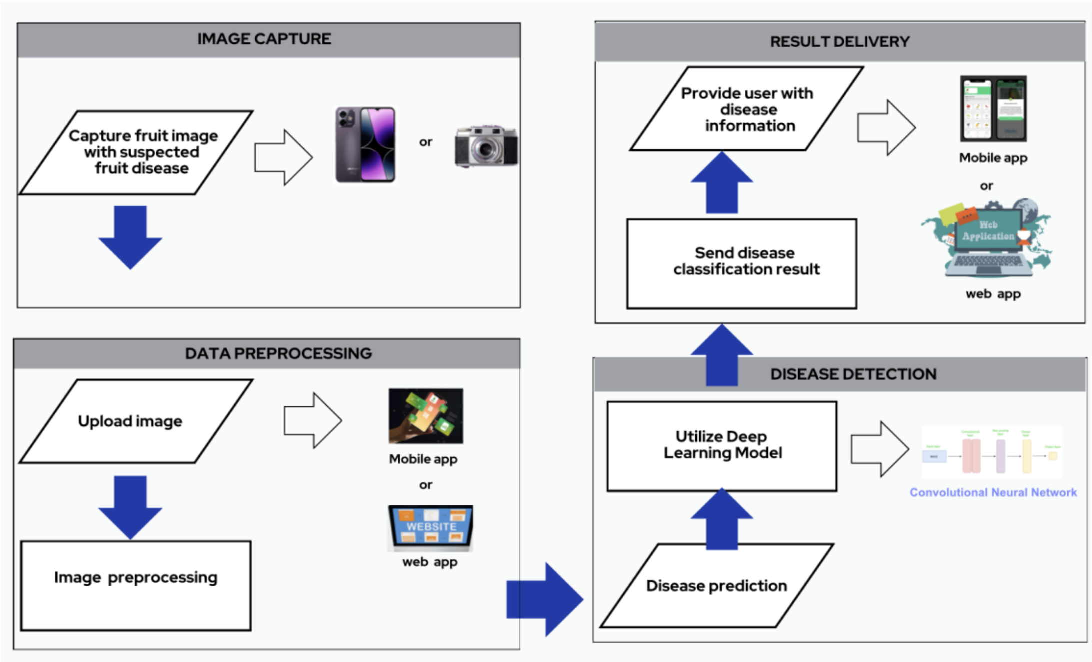

Fig. 1. Proposed architecture of the fruit disease detection system.

Fruit Disease Detection Process

The process in Fig. 2 starts with growers capturing an image of the fruit suspected to have a disease using the mobile app. The captured image is then uploaded to the system, likely to a cloud-based server. Once uploaded, the image undergoes preprocessing steps. This involves preparing the image for analysis by the machine learning model, potentially including resizing, color format conversion, or background noise removal. The pre-processed image is then fed into a deep learning model, which is the core of the disease detection system. This model is likely trained on a vast dataset of images containing various fruit diseases. By analyzing the image features and comparing them to the information stored within the model, the deep learning model predicts the presence or absence of a disease. It can potentially identify the specific disease if present. Finally, the user receives the results seamlessly through the mobile app. This might include the predicted disease type or a simple classification of healthy or diseased fruit.

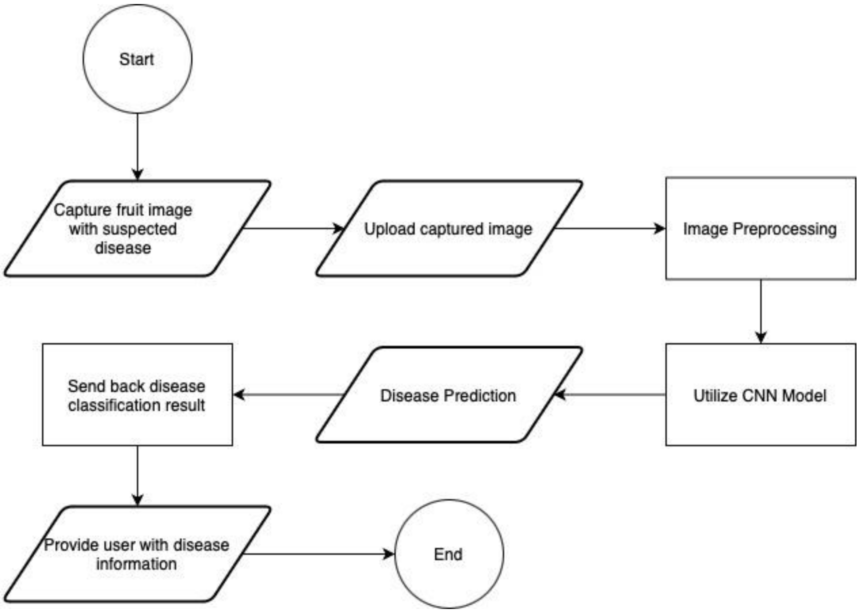

Fig. 2. Proposed fruit disease detection process.

Machine Learning Integration in Fruit Disease Detection

Convolutional Neural Network (CNN) integration

Integrating convolutional neural networks (CNNs) into fruit disease detection represents a significant advancement in agricultural technology, promising enhanced accuracy and efficiency in identifying and managing plant diseases. Below is a discussion on the key aspects and benefits of this integration, along with reliable sources.

CNNs have shown remarkable success in various image recognition tasks, and their application to fruit disease detection is no exception. The ability of CNNs to automatically learn and extract features from images makes them particularly suited for this task [12].

Integrating CNNs into fruit disease detection allows for real-time monitoring of crops [13]. Early detection of diseases can prevent the spread of infections and minimize crop losses, ensuring better yield and quality.

Utilizing CNNs for disease detection can reduce the need for expensive laboratory tests and expert consultations [14]. With the widespread availability of smartphones and inexpensive imaging devices, farmers can easily access CNN-based diagnostic tools.

CNNs have demonstrated exceptional performance in image recognition tasks, including the detection of fruit diseases. Their capacity to automatically learn and extract features from images makes them highly effective for this application. Integrating CNNs into fruit disease detection enables real-time crop monitoring, facilitating early disease detection that can prevent the spread of infections and reduce crop losses, thereby ensuring better yields and quality. Furthermore, the use of CNNs can minimize the reliance on costly laboratory tests and expert consultations. With the widespread availability of smartphones and affordable imaging devices, CNN-based diagnostic tools are becoming increasingly accessible to growers.

Likewise, offers a promising avenue for enhancing agricultural productivity and sustainability.

Target CNN model

The development of accurate and efficient disease detection models for crops has become increasingly crucial in recent years, as the global population continues to grow, and the demand for food production rises accordingly. Traditionally, the identification of crop diseases has relied heavily on the expertise of human experts, which can be both time-consuming and costly. To address this challenge, researchers have focused their efforts on developing automated, image-based disease detection systems that leverage advanced techniques in computer vision and machine learning [15].

In the context of satsuma fruit disease detection, this paper proposes a target model that combines image processing and machine learning algorithms to accurately identify and classify disease symptoms. EfficientNet and Resnet architectures [16] have shown promising results in the field of crop disease detection and will serve as the foundation for the proposed model. EfficientNet is a lightweight and efficient convolutional neural network that has demonstrated high accuracy in various image classification tasks [16]. Resnet, on the other hand, is a deep neural network architecture that can effectively extract and learn hierarchical features from complex disease patterns [17].

The proposed model will leverage transfer learning techniques to fine-tune these pre-trained models on a comprehensive dataset of satsuma fruit images, encompassing both healthy and diseased samples. Transfer learning has been successfully applied in previous studies to address the challenge of limited dataset sizes, a common issue in the agricultural domain [18]. The experiment results presented in related works [17,18,19,20] indicate that transfer learning-based models can achieve significantly higher disease identification accuracy compared to traditional CNN architectures.

4. Conclusion

This study demonstrates the significant potential of integrating convolutional neural networks (CNNs) into the detection and management of diseases in Satsuma mandarins. Through advanced machine learning techniques, particularly CNN architectures such as EfficientNet and ResNet, the proposed model has shown promise in accurately identifying and classifying disease symptoms from images. The application of transfer learning further enhances the model's performance, addressing the common challenge of limited datasets in the agricultural domain.

The assessment of Satsuma growers' readiness for technology adoption revealed a positive inclination towards implementing machine learning-based solutions for disease management. The survey results underscore the necessity for a robust, image-based disease detection system that not only identifies diseases but also provides treatment recommendations through a mobile and web-based application interface. This technological intervention is anticipated to improve early disease detection, reduce dependency on expert consultations, and ultimately enhance agricultural productivity and sustainability.

In conclusion, the integration of CNNs into fruit disease detection systems presents a viable and efficient solution for modern agricultural challenges. This approach not only supports farmers in managing crop diseases more effectively but also contributes to global food security by ensuring better yield and quality of produce.

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