INTERNATIONAL JOURNAL OF INTEGRATED ENGINEERING
ISSN: 2229-838X e-ISSN: 2600-7916

IJIE

Vol. 17 No. 2 (2025) 290-300
https://publisher.uthm.edu.my/ojs/index.php/ijie

# Smart Agribot: Advanced CNN-Based Disease Detection in Green Beans with EfficientDet & Auto-Spraying

**Froilan G. Destreza[1]*, Romeo Concepcion Jr.[1], Jomari A. Alano[1], Joven J. De Padua[1], Ken J. Butiong[1]**

[1] *College of Engineering & Technology,*
*Batangas State University, The NEU ARASOF-Nasugbu Campus, Batangas, PHILIPPINES*

*Corresponding Author: froilan@g.batstate-u.edu.ph
DOI: https://doi.org/10.30880/ijie.2025.17.02.024

**Article Info**

Received: 28 March 2025
Accepted: 15 July 2025
Available online: 8 August 2025

**Keywords**

CNN, image processing, disease detection

**Abstract**

The Smart Agribot is a cutting-edge robotic system developed to improve how green beans are grown in the Philippines. It combines advanced technology like Convolutional Neural Networks (CNNs) for disease detection, automated spraying, and efficient crop transportation. This project aims to make farming more productive, reduce waste, and improve plant health. The Agribot's physical design uses common, affordable parts like Arduino Uno, Raspberry Pi, metal frames, and wooden supports, creating a sturdy yet cost-effective machine. Its brain is a CNN model trained on a large set of images showing healthy and diseased green bean plants. This training allows the Agribot to accurately identify different plant diseases. Extensive testing confirmed that the system can reliably detect diseases, with especially high accuracy in spotting Rust, a common issue in bean crops. The Agribot's automatic sprayer further reduces the amount of chemicals needed by only spraying plants that truly need it, which lowers costs and lessens environmental harm. Additionally, the built-in crop transporter makes harvesting faster and more efficient without significantly affecting crop yields. Together, these features make the Smart Agribot a promising tool for modern farming. It can help farmers save time, reduce costs, and improve overall productivity. As the Agribot continues to be improved, it has the potential to work with other crops and farming systems, supporting more sustainable agriculture in the future.

## 1. Introduction

### 1.1 Research Background

The Philippines boasts a substantial land area of 30 million hectares, with nearly half of it dedicated to agriculture. This nation is renowned for cultivating major crops such as rice, coconuts, corn, sugarcane, bananas, pineapples, mangoes, and beans, including the notable sitao. Sitao, as a year-round crop, holds economic and nutritional significance, with a life cycle of around 14 weeks, influenced by soil conditions as mentioned in the previous source [1–3].

Despite its agricultural potential, the Philippines faces challenges in sustaining agricultural growth. While the sector grew by 0.5% in Q2 2020 due to increased agriculture and fishery output, Q3 2021 witnessed a 2.6% decline, attributed to various factors, including labor shortages. Almario [4] highlighted the alarming 1% annual reduction in agricultural personnel, forewarning an impending shortage of farmers, as mentioned in the article.

This impending scarcity is reinforced by data indicating a drop in agricultural employment rates from 53% to 1.39% between 2013 and 2015, as mentioned in this article [5].

Factors such as globalization, trade, climate change, and production vulnerabilities have facilitated the spread of transboundary plant pests and diseases, as noted by the Food and Agriculture Organization (FAO) of the United Nations in this article [6–7]. Plant viruses have emerged as a significant obstacle, affecting crop yield and production. Technology has responded with innovations like automated sprayers, which reduce labor costs and environmental impact. Advanced agricultural robots capable of tasks such as transportation, spraying, and disease identification have also been developed, as mentioned in this article [7–8].

## 2. Literature Review

During the research and design process, insights from various studies were incorporated to enhance the feasibility and efficacy of the project. Potter et al. [9] works with the HMMER web server. Hussain et al. [10] highlighted the Smart variable rate sprayer (SVRD) concept, and Shetty et al. [11] ESP32 module application for image capture provided valuable input, as taken from those previous studies. Prakash et al. [12] Android application connected to a robot system via Bluetooth, Mique and Palaoag [13], CNN-based rice pest detection, and [14] image processing techniques contributed to the project's development, as drawn from the previous studies [12–14]. Collaboration between human pickers and crop-transporting robots from Seyyedhasani et al. [15] research and methodologies from other studies further shaped the project [15–17]. The project aimed to use CNN for disease detection, drawing on various sources to create a comprehensive Smart Agribot for green bean cultivation with disease detection, automated spraying, and crop transportation. For object detection, the study employs the EfficientDet model, as mentioned in the previous studies [18], which is renowned for its effectiveness and accuracy in computer vision. With new technologies like BiFPN and compound scaling, it improves object identification.

EfficientNet is a family of image classification models from Google AI that trains relatively quickly on little quantities of data, making the most of scarce datasets. EfficientDet is an improvement on EfficientNet. The EfficientDet-D7 variant uses fewer parameters and FLOPs than earlier detectors to attain an exceptional AP score of 55.1 on the COCO test-dev. According to a study by Victor Dibia, EfficientDet models provide the best overall performance with a mean average precision (MAP) of 51.2 for EfficientDet D6, while MobileNet SSD V2 used to be the state of the art in terms of speed 1. Therefore, we used EfficientDet as it provides better accuracy than SSD MobileNet V2 while maintaining competitive inference speeds.

The Smart Agribot is an advanced farming robot designed to help farmers grow green beans more efficiently in the Philippines. It combines disease detection, automated spraying, and crop transportation into a single system, making it a valuable tool for modern agriculture.

One of the main advantages of Smart Agribot is its use of EfficientDet-Lite0 for disease detection. This is a special type of computer model designed to identify objects, like diseased leaves, quickly and accurately, even on small devices like the Raspberry Pi. This makes it more practical for real-world farming, where power and processing speed are often limited. In comparison, other systems like the one by [20] use simpler CNN models, which can be less accurate and harder to run on smaller devices. Another example is [22], who developed a rice pest detection system using basic CNNs, but without the speed and efficiency that EfficientDet provides.

The physical design of the Smart Agribot also stands out. It uses affordable, easy-to-find parts like Arduino Uno, Raspberry Pi 4, metal frames, and wooden supports, making it less expensive to build and maintain. This is ideal for small farms, where budgets are tight. In contrast, robots like the one built by [8] are often larger and more industrial, which can be too bulky for smaller crops like green beans. Smart Agribot also includes a crop transporter, which helps with harvesting, reducing the need for manual labor – a feature that many single-purpose robots do not offer.

Another major advantage of Smart Agribot is its data approach. It was trained using over 4,000 high-quality images of real green bean plants, including common diseases like Rust, Mosaic, and Leaf Mold. This makes it more accurate in the field compared to systems that rely on more generic, publicly available datasets.

Finally, the Smart Agribot system focuses on sustainability. It uses precise, automated spraying, which reduces chemical use and limits environmental harm. This is important for farmers looking to lower costs and protect their land. Many other agribots prioritize performance over environmental impact, which can be a drawback in the long run.

In summary, the **Smart Agribot** is a powerful tool for modern farming, offering a combination of smart disease detection, efficient spraying, and practical crop transportation. It stands out for its affordability, real-world data, and focus on sustainability, making it an excellent choice for small-scale farmers

## 2.1 Objectives

The primary objective was to develop a Smart Agribot: Advanced CNN-Based Disease Detection in Green Beans with EfficientDet & Auto-Spraying, incorporating automatic spraying. Specific objectives included creating a comprehensive robotic system, training a CNN for disease detection, and evaluating system efficiency in disease detection, spraying, and crop transportation. The study aimed to gauge the Smart Agribot's overall effectiveness through optimal integration and performance of its components.

## 2.2 Research Gap and Contribution of Study

This study addresses a critical research gap in agricultural technology by introducing Smart Agribot for early-stage disease detection in green beans (string beans). The Smart Agribot combines disease detection, crop transportation, and pesticide application through automation [19], filling a void in comprehensive agricultural solutions. It offers a practical application of deep learning algorithms in agriculture, potentially increasing crop yields, while its rechargeable battery power source promotes sustainability. The study's real-world experimental data, though limited to daytime use, provides valuable insights for future research. Moreover, it enriches farmers' knowledge by sharing modern farming techniques and disease identification methods, making a significant contribution to the agricultural sector's efficiency and sustainability. This research serves as a reference for future studies, inspiring further innovations in agricultural technology.

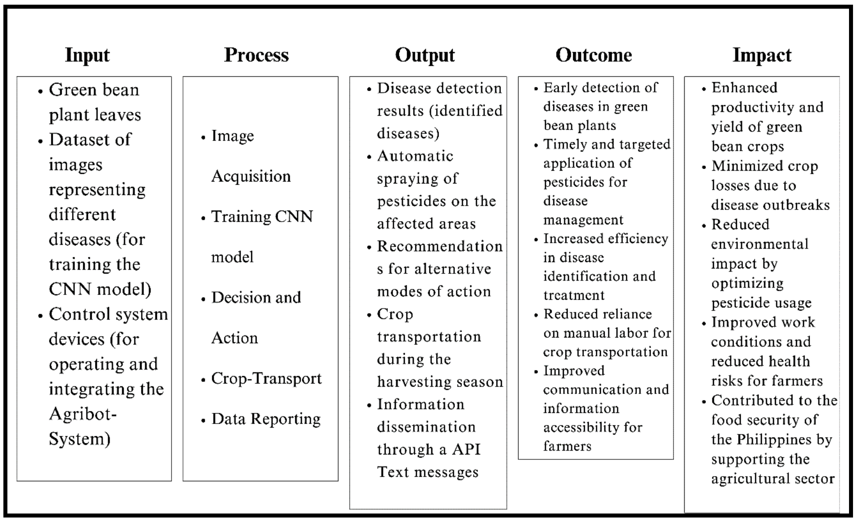
# 3. Methodology

## 3.1 Conceptual Framework

The Smart Agribot: Advanced CNN-Based Disease Detection in Green Beans with EfficientDet & Auto-Spraying project is framed within a comprehensive conceptual framework that progresses through the stages of input, process, output, outcome, and impact. This framework elucidates the project's flow from its initial components to its profound effects on agriculture and sustainability.

## 3.2 Smart Agribot Design

The final project design comprises distinct components. The robot's body, crafted from wood and metal, is divided into back and front sections. The rear houses the gallon, while the front accommodates microprocessors, batteries, and vital gear. A steel chassis supports DC motors and wheels, while a black crane with dual servomotors acts as the arm, moving laterally and vertically. The crane holds a Pi Camera, hose, and sprayer nozzle. Micro-limit switches regulate motion - one shifts the crane and the other halts movement. A crop transporter enhances harvest efficiency, boasting a platform with an affixed basket. This tool simplifies bean collection, reducing trips for farmers. Circuit diagrams, formulated using Fritzing, depict the interconnected components. The setup involves two microcontrollers in serial communication [13]. The Raspberry Pi 4 functions as the brain, linked to an LCD, relay, and camera. The relay controls the water pump via a 12V battery. Gear motors are managed by an Arduino Uno and motor driver, while two servos and limit switches are incorporated for precision and control.



| Input | Process | Output | Outcome | Impact |
|---|---|---|---|---|
| • Green bean plant leaves<br>• Dataset of images representing different diseases (for training the CNN model)<br>• Control system devices (for operating and integrating the Agribot-System) | • Image Acquisition<br>• Training CNN model<br>• Decision and Action<br>• Crop-Transport<br>• Data Reporting | • Disease detection results (identified diseases)<br>• Automatic spraying of pesticides on the affected areas<br>• Recommendations for alternative modes of action<br>• Crop transportation during the harvesting season<br>• Information dissemination through a API Text messages | • Early detection of diseases in green bean plants<br>• Timely and targeted application of pesticides for disease management<br>• Increased efficiency in disease identification and treatment<br>• Reduced reliance on manual labor for crop transportation<br>• Improved communication and information accessibility for farmers | • Enhanced productivity and yield of green bean crops<br>• Minimized crop losses due to disease outbreaks<br>• Reduced environmental impact by optimizing pesticide usage<br>• Improved work conditions and reduced health risks for farmers<br>• Contributed to the food security of the Philippines by supporting the agricultural sector |

**Fig. 1** *Conceptual framework of the proposed project design*

The study leveraged the Engineering Design Process, inspired by the National Aeronautics and Space Administration (NASA) [20], to construct the robot. Fig. 1 provides an isometric view of the final project design, featuring various components. The robot's body comprises rectangular wood and metal sheets, divided into back and front sections - the backside accommodates the gallon, while the front houses microprocessors, batteries, and essential equipment. The bottom of the chassis is constructed from steel and welded to support DC motors and wheels. The black crane, featuring two servomotors, functions as the robot's arm, with left-right and up-down movement capabilities. The Pi Camera, hose, and sprayer nozzle are attached to the upper part of the swinging arm (Fig. 2). Additionally, two micro-limit switches are programmed to control the Agri-Bot's movement, with the left switch controlling lateral movement and the right switch serving as a stop mechanism.

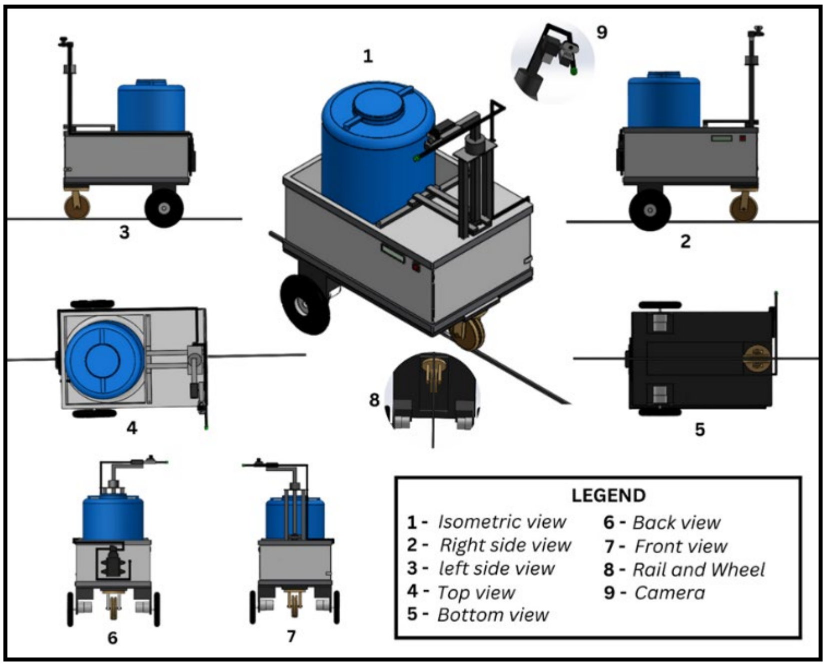


**Fig. 2** *Agribot for disease detection and automatic sprayer*

Fig. 3 showcases an isometric view of the crop transporter, featuring a rectangular platform with an attached basket. This crop transporter aims to facilitate harvesting activities, allowing farmers to conveniently place their harvested green beans into the basket when their hands become full. This innovative tool provides a practical solution for farmers by streamlining the collection process and reducing the need for multiple trips to unload the harvested crop. With the inclusion of the basket on the rectangular platform, the crop transporter enhances efficiency and productivity during the harvesting phase.

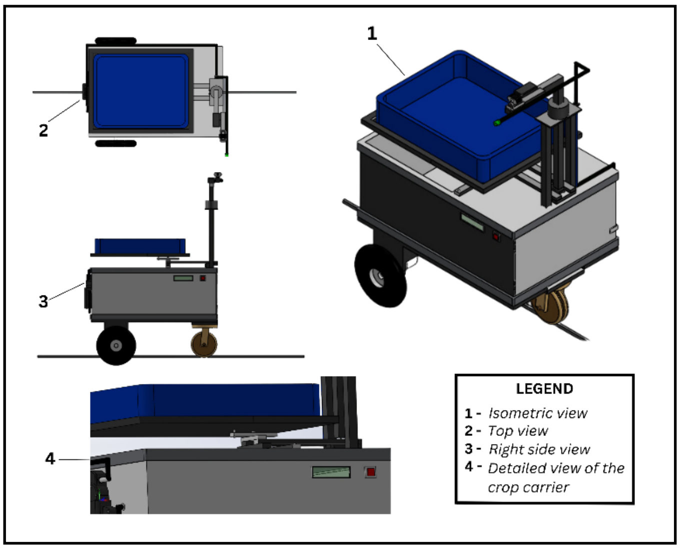


**Fig. 3** *Agribot for crop-transporter*

Fig. 4 depicts the circuit diagrams of the developed project, illustrating the interconnection of components that form the circuitry framework. The circuit diagrams were designed using Fritzing software. The system circuitry consists of two microcontrollers operating in serial communication. The design incorporates the

Raspberry Pi 4 as the main brain of the system, responsible for the detection process. The Raspberry Pi is connected to an LCD, a relay, and a camera. The relay serves to control the on and off states of the water pump, which in turn was connected to a 12V lead-acid battery [21]. Additionally, two gear motors were controlled using a motor driver (L298N), which is connected to an Arduino Uno. Two servo motors are also connected to the Arduino. Furthermore, two limit switches were integrated with the Arduino, allowing control over one servo motor and enabling the stopping of the motors when necessary.

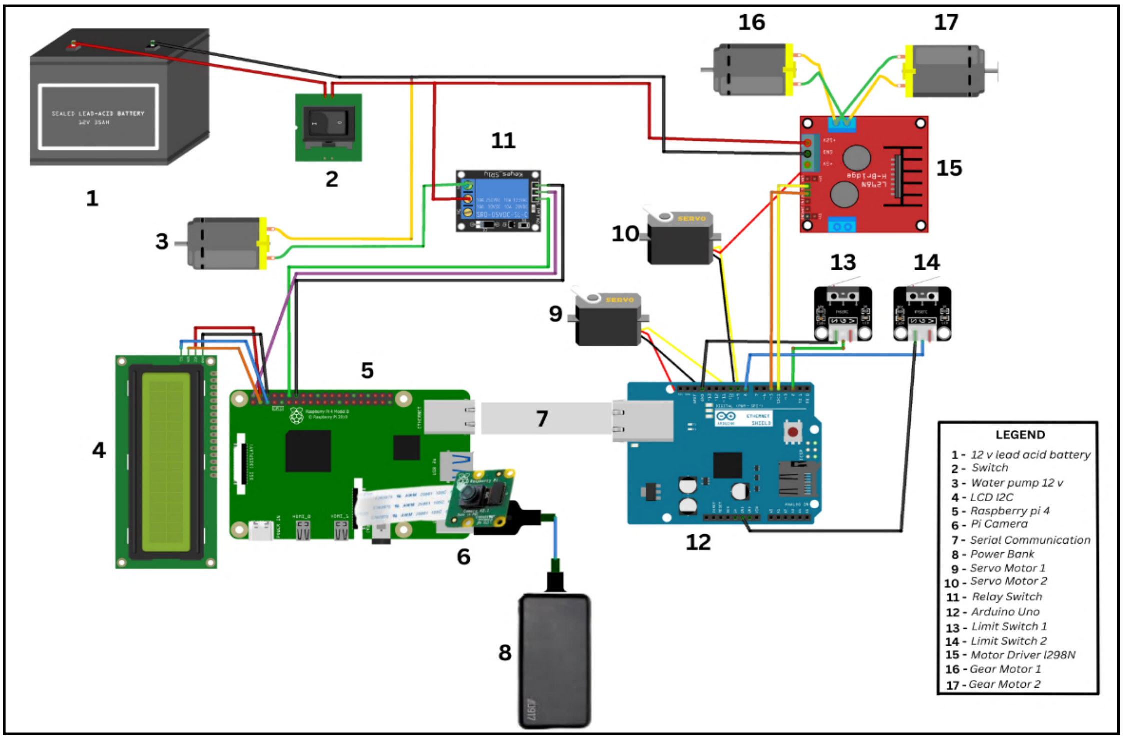


**Fig. 4** *Circuit diagrams*

## 3.3 Train Image Dataset

A total of 4,000 images were captured of green bean plants. For each class, 1,000 images were used, out of which 800 were green bean plants, to train the dataset. Ten percent of the images from each class, which amounts to 100 images for each class, were used for validation shown in Table 1. Similarly, ten percent of the images were allocated for testing purposes across all classes. The image was privately owned, captured, and not obtained from online sources. These images were captured directly on the farm, from various heights and angles relative to the ground level. All images in the dataset were captured at a high resolution of 3468x4624 pixels, ensuring exceptional clarity and detail for disease identification. Each image in the dataset is approximately 4 megabytes (MB) in size, contributing to the dataset's comprehensive and detailed nature. To train the convolutional neural network using the acquired image data set. First, images were gathered for training the object detection model. The data is then preprocessed by converting each image into a .xml data annotation file. This requires manually annotating the objects in the image by drawing bounding boxes around them and assigning them a class label. This consisted of 1000 images per class. Once the images were gathered and labeled, there was a folder full of images and a corresponding .xml data annotation file for each image.

**Table 1** *Four classes of string bean plant images were taken*

| Class Name | Total Images (Training) | Total Images (Validation) | Total Images (Testing) |
|---|---|---|---|
| Healthy | 800 | 100 | 100 |
| Rust | 800 | 100 | 100 |
| Mosaic | 800 | 100 | 100 |
| Leaf Mold | 800 | 100 | 100 |

After selecting an appropriate model architecture, namely EfficientDet-Lite0, which belongs to a family of mobile/IoT-friendly object detection models derived from the EfficientDet architecture, the TensorFlow model was trained using the provided training data. The training process involved utilizing the command "batch size=64, train whole model = True, epochs=10" to optimize the model's performance and accuracy.

The images (Fig. 5) were classified according to the health status of the bean plant. Rust, Mosaic, and Leaf Mold are the common diseases of the said bean plant [22–23].

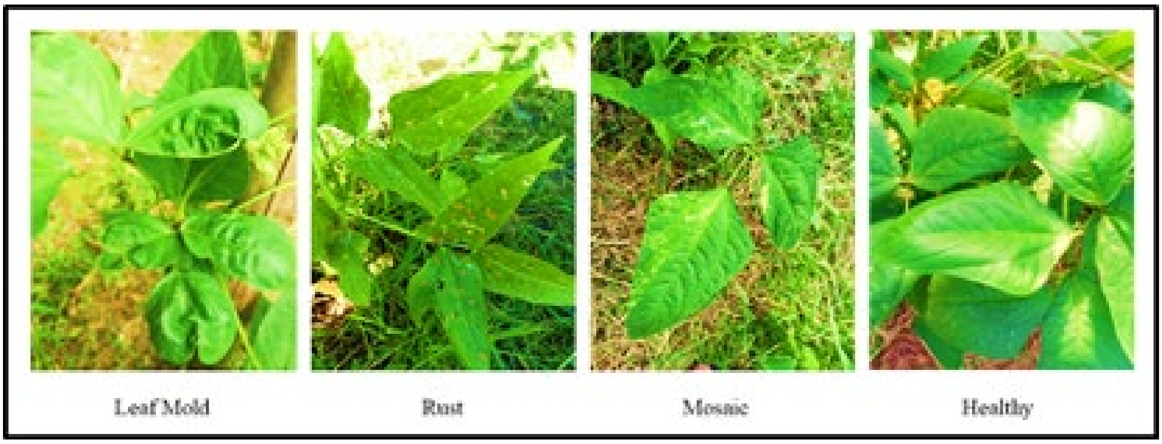


**Fig. 5** *Sample leaf images of 4 different categories used in the study*

## 3.4 Discussion of Performance Evaluation

Imagine walking through a field of green beans under the bright sun. While the plants look healthy at first glance, diseases might be quietly affecting them, threatening the crop. In the past, farmers would need to check each plant by hand, a time-consuming and tiring task. But what if there was a faster, easier way to spot these diseases right away, without needing expensive equipment or too much work?

This is where technology comes in. A recent study focuses on detecting plant diseases in green beans using artificial intelligence (AI) combined with an affordable, small computer. The system uses a model called EfficientDet-Lite0, which is a special type of AI designed to find problems, like diseases, in images. What makes this system unique is that it doesn't rely on big, expensive computers; it works on a Raspberry Pi 4, a small, cheap device that can be easily used in the field.

The study looks at two versions of this model. The first is the original version, which runs on a normal computer or laptop. The second is a version that's been changed to work on the Raspberry Pi, using TensorFlow Lite, which is a special tool that helps run AI models on small devices. This means the disease detection system can work right where the crops are grown, with real-time results.

To measure how well the system works, the researchers use something called Mean Average Precision (mAP), which helps evaluate how accurately the model detects and locates diseases in the plants. They also use a Confusion Matrix, which helps them see where the model might make mistakes, such as wrongly identifying healthy plants as diseased or missing a disease that's actually present.

The ultimate goal of this technology isn't just to spot diseases, but to make the entire process of farming more efficient. Once the system detects a disease, a precision sprayer comes into play. This tool only sprays the affected areas of the plant, saving both time and resources. This reduces the amount of chemicals used and makes the process more environmentally friendly.

The idea of automation goes even further. In the future, robots might be used to harvest crops, replacing human workers. These robots could work together with disease detection systems to make the entire process—from planting to harvesting—more efficient and automated.

One of the most exciting innovations is the Smart Agribot, a robotic system that combines disease detection, precise spraying, and even transportation of harvested crops. This all-in-one machine could completely change farming, making it smarter, faster, and more sustainable. By reducing human labor and using AI to make decisions, the farming process becomes more efficient and less reliant on resources.

In the big picture, this research could transform the way we think about farming. With AI and automation, farmers can monitor their crops more accurately and respond more quickly to problems. This means better crop yields, less waste, and a more sustainable approach to farming. In the end, this could lead to a future where farming is not only more productive but also better for the environment.

## 3.5 Performance Evaluation

The Smart Agribot’s performance was carefully tested to see how well it can detect plant diseases and respond to them in real time. To do this, the researchers used two versions of their computer model: the original version that runs on a regular computer, and a lighter version designed for a small, low-cost device called a Raspberry Pi 4. This smaller version is important because it allows the robot to work directly in the field without needing expensive or powerful machines.

To check how well each version of the model performed, the researchers used a method called Mean Average Precision (mAP). This method measures how accurately the robot can detect and identify diseases in the green bean plants. A higher mAP means better performance. The original model had a mAP of 0.667, while the Raspberry Pi version had a slightly lower score of 0.643. This small difference shows that although there was a little drop in accuracy, the smaller model still worked very well. This is impressive, especially since the Raspberry Pi is a much simpler and cheaper device than a full computer.

The study looked at more detailed scores, such as AP50 and AP75, which show how well the robot performs when the match between the predicted and actual disease is at least 50% or 75% accurate. Again, both models performed well, and the differences were small. For example, the AP50 for the original model was 0.830, and for the Raspberry Pi version, it was 0.810—a difference of just 0.02.

The study checked how well the robot could recognize each type of plant condition—Healthy, Rust, Mosaic, and Leaf Mold—it was found that the original model was slightly better in all categories. However, the Raspberry Pi version still performed strongly, especially in detecting Rust and Leaf Mold, which are common and harmful diseases for green beans. Even with its smaller size and simpler processing power, the Raspberry Pi version of the model was able to detect these diseases with a high level of accuracy.

To better understand where the model made mistakes, the researchers also used a confusion matrix, which is like a chart showing how often the robot correctly or incorrectly identified each disease. For example, in most cases, the robot correctly identified healthy plants and the various diseases, but there were a few cases where it got confused—like identifying a Mosaic-infected plant as healthy. Even so, the number of mistakes was small, which means the robot’s predictions were mostly reliable.

## 3.6 Mean Average Precision (*mAP*)

In table 2, we analyze the validation results of two models: the original TensorFlow model and the exported TFLite model, both designed for classifying green bean plants. These models are evaluated based on various metrics, including mAP (mean Average Precision), AP50, AP75, and class-specific AP scores for Healthy, Leaf Mold, Rust, and Mosaic.

**Table 2** *Convolutional neural network validation results for the classification of green bean plants with the TensorFlow framework*

| Model | Map | AP50 | AP75 | AP_/Healthy | AP_/Leaf Mold | AP_/Rust | AP_/Mosaic |
|---|---|---|---|---|---|---|---|
| Original TensorFlow | 0.667 | 0.830 | 0.787 | 0.691 | 0.677 | 0.725 | 0.575 |
| Exported TFLite | 0.643 | 0.810 | 0.768 | 0.680 | 0.665 | 0.719 | 0.508 |

The original TensorFlow model achieved a higher mAP of 0.667 compared to the exported TFLite model, which achieved a slightly lower mAP of 0.643. This difference in mAP indicates that there was some loss of accuracy during the model export process.

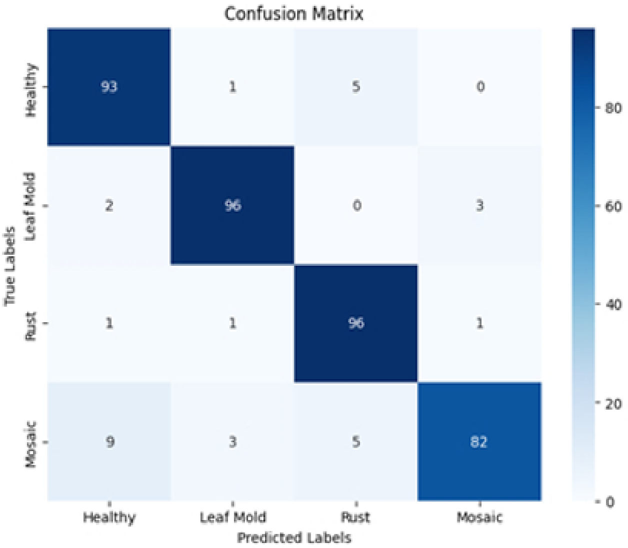
However, it's worth noting that the AP50 score of the exported TFLite model is only marginally lower than that of the original TensorFlow model, with a difference of approximately 0.02. This suggests that the TFLite model is still quite proficient at detecting objects with a relatively high level of accuracy. The AP75 score of the TFLite model is about 0.018 lower than that of the original TensorFlow model.

When looking at the per-class AP scores, it becomes evident that the original TensorFlow model consistently outperforms the TFLite model for all four classes: Healthy, Leaf Mold, Rust, and Mosaic. The differences in AP scores range from 0.013 to 0.167, highlighting the original model's superior performance in detecting these specific object classes compared to the TFLite model.

The difference in accuracy between the two models is expected due to the TFLite model's quantization process and the use of global NMS (Non-Maximum Suppression) instead of per-class NMS. Despite these differences, the exported TFLite model still achieves relatively high accuracy, especially in terms of AP50. This makes it a viable choice for deployment on devices with limited computational resources, such as the Raspberry Pi, where resource efficiency is critical.

## 3.7 Confusion Matrix

Fig. 6 shows a 4x4 matrix that represents the performance of a classification model of the exported TFLite model with four classes. Each row of the matrix corresponds to the actual classes, while each column represents the predicted classes. The values within the matrix indicate the number of instances that belong to a true class but were predicted as the corresponding predicted class. Interpreting the matrix, in the first row, the model correctly predicted 93 instances as Healthy, misclassified 1 instance as Leaf Mold, misclassified 5 instances as Rust, and made no misclassifications for the Mosaic class. Moving on to the second row, the model correctly predicted 96 instances as Leaf Mold, misclassified 2 instances as Healthy, made no misclassifications for Rust, and misclassified 3 instances as Mosaic. Similarly, in the third row, the model accurately predicted 96 instances as Rust, misclassified 1 instance as Healthy, misclassified 1 instance as Leaf Mold, and misclassified 1 instance as Mosaic. Lastly, in the fourth row, the model correctly predicted 82 instances as Mosaic, misclassified 9 instances as Healthy, misclassified 3 instances as Leaf Mold, and misclassified 5 instances as Rust.



| | Healthy | Leaf Mold | Rust | Mosaic |
|---|---|---|---|---|
| Healthy | 93 | 1 | 5 | 0 |
| Leaf Mold | 2 | 96 | 0 | 3 |
| Rust | 1 | 1 | 96 | 1 |
| Mosaic | 9 | 3 | 5 | 82 |

**Fig. 6** *The performance of a classification model*

## 3.8 Disease Detection Performance and Potential

One of the strongest features of the Smart Agribot is its ability to detect plant diseases with a high level of accuracy, especially in identifying common problems like Mosaic disease. The robot uses a special computer program called EfficientDet-Lite0, which helps it recognize signs of illness in green bean plants by analyzing pictures of the leaves. This early detection allows farmers to take action quickly, helping to protect crops and avoid bigger problems later.

The researchers trained the system using thousands of high-quality images taken from real farms. This helps the robot understand what diseased and healthy plants really look like in actual farm conditions—not just in ideal lab settings. What makes this even more impressive is that the robot can do all of this using a small, affordable computer called a Raspberry Pi, making it useful even in places with limited technology or internet access.

While the system still has some room to improve in detecting less obvious diseases like Rust or Leaf Mold, it already shows strong potential as a helpful tool for farmers. With more training and updates, its accuracy can get even better over time.

## 3.9 Efficiency and Environmental Impact of The Automatic Sprayer

The automatic sprayer in the Smart Agribot is designed to help farmers use chemicals like pesticides more wisely. Instead of spraying the entire field, the robot only sprays the plants that are actually sick. It first checks each plant using its camera and disease detection system. If it finds signs of a disease, it uses a small sprayer to treat just that plant.

This method is much better than traditional spraying, where farmers often spray all their crops—even the healthy ones. By targeting only the plants that need help, the Smart Agribot saves chemicals, which helps farmers save money. It also protects healthy plants from being sprayed unnecessarily.

Another big benefit is that using fewer chemicals is better for the environment. It helps keep the soil and water cleaner and is safer for people working on the farm. This makes the Smart Agribot not just smart in how it works, but also responsible. It supports more eco-friendly farming and helps protect both people and nature while still keeping crops healthy.

## 3.10 Crop Transportation and Harvesting Efficiency

The crop transporter is another useful feature of the Smart Agribot that helps make the harvesting process faster and more organized. During harvest time, farmers often have to bend, carry, and walk back and forth many times to collect crops and move them to storage. This can be tiring and time-consuming, especially when done by hand. The crop transporter helps solve this problem by carrying the harvested green beans for the farmer.

The robot includes a platform with a basket where farmers can place the harvested beans. Once the basket is full, the Agribot can move the crops to a different location without the farmer needing to make multiple trips. This not only saves time and energy but also makes the process more efficient and less physically demanding.

While the crop transporter doesn’t directly increase the number of beans harvested, it improves the overall workflow of the harvest. By reducing the number of trips and simplifying the movement of crops, farmers can finish harvesting more quickly and with less effort. This can be especially helpful on larger farms or when there are fewer workers available.

Even though the tests showed that this feature doesn’t significantly change the crop yield, it still adds value by making the job easier and more productive. In the long run, having a robot that can carry harvested crops can help farmers manage their time better and reduce stress during busy harvest seasons.

## 3.11 The Smart Agribot’s Role in Enhancing Agriculture Practices

The Smart Agribot presents a promising solution for enhancing agricultural practices. With its disease detection capabilities, efficient agrochemical application, and improved harvesting processes, it offers potential benefits for the agricultural sector in the country. The accurate and timely identification of plant diseases provided by the Smart Agribot can greatly assist Filipino farmers in managing and mitigating crop diseases, leading to improved crop yields and reduced losses. The optimized use of agrochemicals through targeted spraying helps minimize waste and reduce the environmental impact, aligning with the country's goals for sustainable agriculture. Streamlined and secure transportation of crops facilitated by the Smart Agribot can enhance the efficiency of harvesting processes in the Philippines. This can contribute to reducing post-harvest losses, ensuring the freshness and quality of produce, and ultimately improving the overall productivity of the agricultural industry.

The study introduced a novel approach to addressing agricultural challenges in the Philippines through the development of the Smart Agribot—a robotic system that integrates artificial intelligence, automated spraying, and crop transportation. This innovation is both timely and significant, particularly as the nation grapples with a steady decline in agricultural labor and the growing threat of crop diseases. By leveraging deep learning, particularly the EfficientDet-Lite0 model, the researchers aim to detect common green bean diseases such as Rust, Mosaic, and Leaf Mold with precision and deploy real-time responses through targeted pesticide spraying.

One of the strengths of this study lies in its commitment to accessibility and sustainability. The Smart Agribot is built using low-cost and readily available materials, including an Arduino Uno, Raspberry Pi 4, and a wood-and-metal frame. This cost-conscious design makes it a realistic solution for small- to medium-sized farms, which often operate under strict budget constraints. The robot’s multifunctionality—disease detection, spraying, and crop transportation—sets it apart from other single-purpose agricultural robots and increases its practical value in the field.

Another aspect is the use of a real-world, self-curated dataset. Unlike many studies that rely on online databases, the researchers collected over 4,000 high-resolution images directly from local farms. This approach enhances the ecological validity of the model and increases the likelihood of robust field performance. The choice of EfficientDet-Lite0, optimized for use on low-powered devices like the Raspberry Pi, aligns well with the goal of creating a field-ready, mobile AI solution.

The evaluation of the Smart Agribot was thoughtfully conducted under controlled daytime conditions, providing a solid foundation for assessing its core functionalities in a stable environment. This initial testing environment ensured consistent and reliable data collection, which is essential for model benchmarking. As the project advances, there are exciting opportunities to extend performance assessments to more variable real-world scenarios—such as low-light conditions, uneven terrain, and diverse weather situations—to further demonstrate the robot’s adaptability and resilience in dynamic farm settings.

The study acknowledges a slight drop in performance during the conversion of the model to TensorFlow Lite, the fact that the model still maintained high accuracy on resource-constrained hardware like the Raspberry Pi 4 is a strong testament to the robustness of the implementation. Future studies may explore techniques such as data augmentation or adaptive quantization to enhance performance even further, potentially unlocking even greater efficiencies on edge devices.

The Smart Agribot shows great potential as a transformative tool for agriculture in developing countries. By combining disease identification, precise agrochemical application, and crop transport, it not only addresses the issue of labor scarcity but also promotes environmental sustainability through reduced chemical usage. As farming increasingly turns to automation and AI, this project stands as a compelling example of how advanced technologies can be tailored to fit the specific needs and limitations of local agricultural systems.

## 4. Conclusion

In conclusion, this research study has successfully achieved its stated objectives.

Firstly, the development and evaluation of the Smart Agribot, a sophisticated robotic system designed specifically for green bean cultivation, aligns with the first objective outlined in this study.

The system's disease identification component, utilizing the state-of-the-art EfficientDet-Lite0 model, excelled in accuracy, particularly in the recognition of diseases like Rust. The system's ability to promptly and accurately identify plant diseases is in harmony with the second research objective, which aimed to train a Convolutional Neural Network (CNN) model for disease recognition, even though there is still room for improvement in the detection of specific diseases.

The third research objective was also met by the study, which supported the effectiveness and sustainability of the Smart Agribot, particularly in its automated spraying component, which reduces pesticide waste while minimizing adverse effects on healthy plants and the environment. Although the optimization of crop transportation had a minimal impact on crop productivity, it enhanced harvesting efficiency, fulfilling the fourth research objective.

Collectively, the Smart Agribot represents a promising development in agricultural practices and aptly addresses the research's fifth objective by combining the ability to detect diseases using the EfficientDet-Lite0 model, resource-efficient agrochemical application, and streamlined harvesting processes. It is expected to benefit the agricultural sector by increasing crop yields, lowering losses, and promoting sustainability in farming practices. The Smart Agribot's capacity to fundamentally alter agriculture holds great promise as it develops and goes through practical application, paving the way for a more sustainable and prosperous farming future in the Philippines and elsewhere.

## Acknowledgement

The authors deeply appreciate the Batangas State University the National Engineering University ARASOF-Nasugbu, for its invaluable support and guidance throughout this project. The university's unwavering commitment to fostering innovation, research, and excellence has been instrumental in the successful completion of this endeavor.

## Conflict of Interest

The authors declare that there is no conflict of interest regarding the publication of the paper.

## Author Contribution

*The authors confirm contribution to the paper as follows:* ***study conception and design:*** *Froilan G. Destreza, Jomari A. Alano;* ***data collection:*** *Joven J. De Padua, Ken J. Butiong;* ***analysis and interpretation of results:*** *Froilan G. Destreza, Romeo Concepcion Jr., Jomari A. Alano;* ***draft manuscript preparation:*** *Jomari A. Alano, Froilan G. Destreza. All authors reviewed the results and approved the final version of the manuscript.*

## References

[1] Atilano, C. (2017). *Asia 21 alumni series: On Agriculture.* Asia Society. https://asiasociety.org/philippines/asia-21-alumni-series-agriculture

[2] Shead, B. (2017). *Biomass industry in the Philippines.* ASEAN Briefing https://www.aseanbriefing.com/news/biomass-industry-philippines/

[3] Shetty, S., Bhosale, R., Naik, R., Mane, R., Lokare, R., & Patil, S. (2021). Agribot-System for Plant Disease Detection and Pesticide Sprinkling. Proceedings of the 4th International Conference on Advances in Science & Technology (ICAST2021), https://doi.org/10.2139/ssrn.3867160

[4] Almario, M. F. "Why Philippines agriculture lags behind." *Philippine Daily Inquirer* (2011)

[5] "Employment by economic sector in the Philippines 2019," Statista, (2022)

[6] Guest, "The Impact of Plant Disease on Food Security," MDPI.

[7] O'Malley, G. F., & O'Malley, R. (2022). *Iron Poisoning.* MSD. https://www.msdmanuals.com/home/injuries-and-poisoning/poisoning/insecticide-poisoning

[8] Gollakota, A., & Srinivas, M. B. (2011, 16-18 Dec. 2011). Agribot — A multipurpose agricultural robot. In *2011 Annual IEEE India Conference* (pp. 1-4). https://doi.org/10.1109/INDCON.2011.6139624

[9] Potter, S. C., Luciani, A., Eddy, S. R., Park, Y., Lopez, R., & Finn, R. D. (2018). HMMER web server: 2018 update. *Nucleic Acids Res,* 46(W1), W200-w204. https://doi.org/10.1093/nar/gky448

[10] Hussain, N., Farooque, A. A., Schumann, A. W., McKenzie-Gopsill, A., Esau, T., Abbas, F., Acharya, B., & Zaman, Q. (2020). Design and development of a smart variable rate sprayer using deep learning. *Remote Sensing,* 12(24), 4091. https://www.mdpi.com/2072-4292/12/24/4091

[11] Shetty, S., Bhosale, R., Naik, R., Mane, R., Lokare, R., & Patil, S. (2021). Agribot-System for Plant Disease Detection and Pesticide Sprinkling. Proceedings of the 4th International Conference on Advances in Science & Technology (ICAST2021), https://doi.org/10.2139/ssrn.3867160

[12] Prakash, N., Udayakumar, E., & Kumareshan, N. (2020, 23-24 July 2020). Design and development of android based plant disease detection using Arduino. In *2020 7th International Conference on Smart Structures and Systems (ICSSS)*. https://doi.org/10.1109/ICSSS49621.2020.9202278

[13] Mique, E. L., & Palaoag, T. D. (2018). Rice pest and disease detection using convolutional neural network. In *Proceedings of the 1st International Conference on Information Science and Systems* (pp. 147–151) https://doi.org/10.1145/3209914.3209945

[14] Tm, P., Pranathi, A. , SaiAshritha, K. , Chittaragi, N. B., and Koolagudi, S.G. (2018). Tomato leaf disease detection using convolutional neural networks. In 2018 eleventh international conference on contemporary computing (IC3) (pp. 1-5). IEEE. https://doi.org/10.1109/IC3.2018.8530532

[15] Seyyedhasani, H., Peng, C., Jang, W.-j., & Vougioukas, S. G. (2020). Collaboration of human pickers and crop-transporting robots during harvesting – Part II: Simulator evaluation and robot-scheduling case-study. *Computers and Electronics in Agriculture,* 172, 105323. https://doi.org/https://doi.org/10.1016/j.compag.2020.105323

[16] Parashar, D., & Agrawal, D. (2020). Automated classification of glaucoma using retinal fundus images. In *2020 First IEEE International Conference on Measurement, Instrumentation, Control and Automation (ICMICA)* (pp. 1-6). https://doi.org/10.1109/ICMICA48462.2020.9242702

[17] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)* (pp. 770-778). https://doi.org/10.1109/CVPR.2016.90

[18] Tan, M., Pang, R., & Le, Q. V. (2020). EfficientDet: scalable and efficient object detection. In *2020 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR*) (pp. 10778-10787). https://doi.org/10.1109/CVPR42600.2020.01079

[19] Remigio, R. V., Andreotti, G., Sandler, D. P., Erickson, P. A., Koutros, S., Albert, P. S., Hurwitz, L. M., Parks, C. G., Lubin, J. H., Hofmann, J. N., Beane Freeman, L. E. (2024). An updated evaluation of atrazine–cancer incidence associations among pesticide applicators in the Agricultural Health Study cohort. *Environmental Health Perspectives*, 132(2), 027010. https://doi.org/10.1289/EHP13684

[20] Remigio, R. V., Andreotti, G., Sandler, D. P., Erickson, P. A., Koutros, S., Albert, P. S., Hurwitz, L. M., Parks, C. G., Lubin, J. H., Hofmann, J. N., Beane Freeman, L. E. (2024). An updated evaluation of atrazine–cancer incidence associations among pesticide applicators in the Agricultural Health Study cohort. *Environmental Health Perspectives*, 132(2), 027010. https://doi.org/10.1289/EHP13684

[21] Honsberg, C. B. and Bowden, S. .G. (2019). Photovoltaics Education Website. https://www.pveducation.org/.

[22] Imbriani, K. (2009). Green Bean Diseases. Garden Guides. https://www.gardenguides.com/12218898-green-bean-diseases.html

[23] Isleib, J. (2012). Signs and symptoms of plant disease: Is it fungal, viral, or bacterial? MSU Extension. https://www.canr.msu.edu/news/signs_and_symptoms_of_plant_disease_is_it_fungal_viral_or_bacterial