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Plant Disease Detection

Exploring Applications in Hyperspectral Imaging and Machine Learning for Agriculture

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Abstract

The threat of crop disease on food security and agriculture is projected to escalate, leading to reduced crop yields, global economic loss, and endangered food availability to vulnerable populations. Early identification of plant disease is crucial to combatting the crisis but traditional manual methods for disease detection are laborious and may miss early signs of infection. The proposed solution suggests equipping a drone with a hyperspectral camera to collect images and analyzing the data with neural networks trained to flag and classify infected plants. This approach offers a faster, more accurate, and potentially more cost-effective alternative to current practices. While the expensive and complex nature of hyperspectral imaging (HSI) may be an obstacle to the adoption of the drone, rapidly advancing technologies compounded with rental-based usage may make these tools simpler, cheaper, and more accessible to a wider audience. The research further discusses the potential for automated flight paths and the expansion of disease detection to a broader range of crops.

Introduction

Problem and Context

Global plant disease outbreaks have been increasing in frequency and are projected to become even more severe, threatening food availability to vulnerable populations and harming farmer livelihoods (Ristaino et al., 2021). Not only do plant diseases lead to lower yields, but it also causes a loss of species diversity (Savary et al., 2019). The ongoing climate crisis, coupled with increased bacterial tolerance to chemical pesticides and globalization, is also expected to increase plant diseases. The economic effects of disease are substantial and can strain farmers' livelihoods. Worldwide, the food production chain loses over $1 billion yearly due to bacterial plant diseases (Martins et al., 2018), and $100-200 billion from fungal pathogen diseases in crops ("Food Security: How Do Crop Plants Combat Pathogens?: USDA ARS", n.d.), costing the global economy around $220 billion ("Researchers Helping Protect Crops From Pests — National Institute of Food and Agriculture", 2023).

To detect diseased crops, farmers typically hand check crops individually to look for visible manifestations of fungus, bacteria, or illness of the crop. One of the problems with such manual detection is that it relies on symptoms being clearly visible, which often only occurs at later stages of disease development. In addition, this practice is labor-intensive, time consuming, costly, and may miss signs that are not readily visible to the human eye. As a result, farmers frequently err on the side of caution when dealing with diseases and resort to spraying chemicals on the entire plant instead of specific areas, leading to a waste of resources and unnecessary expenses (Nevo, 2023).

Proposed Solution

To improve current crop disease detection methods, the following research suggests the use of visual imaging techniques together with drones to identify the plant's affliction through the use of machine learning (ML) algorithms. Current common disease detection methods generally include manually observing crops, and/or sending physical plant samples to conduct lab tests on. Both practices are generally inefficient. Through the proposed method, detection will be accurate enough to target diseased portions directly, saving farmers time, money, and resources.

When a plant is attacked by an offender, be it a fungus, bacteria, or general pest, it enters a state of stress. In this state, certain chemical properties (such as chlorophyll levels) change resulting in different light frequencies being reflected off the plant. This change is very subtle but can be picked up by modern hyperspectral imaging techniques. In addition to the sensor, a vehicle to carry it is necessary. As such, the solution suggests using a quadcopter mounted with a hyperspectral camera. Quadcopters are very maneuverable and can move with extreme precision. The proposed drones (section Drone and Hardware subsection Proposed Models) are capable of extremely precise and efficient movements, allowing imaging of plants at a high rate. This data can then be promptly analyzed by machine learning algorithms to flag and classify diseases.

Plant Disease

The proposed drone can be used to detect diseases in agriculture that appear visually on the plant such as on the leaves or other foliage. Every disease manifests visually in different areas; two diseases which affect different sections of crops are explored below.

The Fusarium Head Blight (FHB) is a serious wheat disease that causes yield loss, low seed germination, and grain contamination. FHB lessens the yield of wheat, while also producing mycotoxins that can blight the grain. FHB shows through discoloration on the kernels of the wheat, including premature bleaching, shriveled appearances, and ranges of color from pink and gray. Applications of machine learning to detect FHB have been studied and are explored in section Data Processing subsection Machine Learning.

While the FHB disease appears on the head of the plant, other diseases will show in different areas. An example of a common plant disease that appears on leaves include leaf rust which can be found on corn ("Signs and symptoms of plant disease", 2012). This fungal disease is caused by the Puccinia Sorghi Fungus, and mainly occurs in the United States Corn Belt. Leaf rust manifests as orange-light-brown lesions and small dark-reddish-brown pustules over the top and bottom of the leaf. The drone can be trained on data on varying types of diseases such as the ones listed above, to detect warning signs of disease and classify them for farmer's use. For example, the proposed drone should recognize the disease on kernels of wheat, while for the fungus, the drone would recognize the stalk of the corn. Thus, maintaining full view when taking images is highly important.

Data Collection

Hyperspectral Imaging (HSI)

The drone utilizes hyperspectral imaging to collect visual data of the crops. Hyperspectral imaging, which analyzes a much greater spectrum of light than strictly red-green-blue (RGB) values, was chosen due to its high success rate with previous plant and agricultural applications, and its unique ability to identify specific diseases (Mahlein, 2016). The range of light that the hyperspectral camera captures can vary, so selecting the right range is key. For plants and vegetation, the most optimal range appears to be one that combines the visible and near infrared range which can capture changes in the leaf pigmentation (400–700 nm) and mesophyll cell structure (700–1300 nm) (Lowe et al., 2017). There are also different ways hyperspectral cameras physically work, including push broom, snapshot, filter wheel, and liquid crystal tunable filters which all have different advantages and disadvantages depending on their application. Push broom devices have been one of the most popular types used in research, and work by scanning a space line by line and then stacking said lines to construct a 2D image. This method, though effective, can be time consuming due to its line-by-line technique. A popular alternative is the snapshot approach, which takes the photo at once, reducing time and post-processing complexity. At its current form, snapshot cameras' spatial and spectral resolutions are limited, but the technology is still evolving (Sousa et al., 2022).

Although hyperspectral imaging can provide very large amounts of useful data, there are many factors that can contribute to inaccurate and noisy data. Such causes include external illumination from sources like the sun, which can suffer from atmospheric effects like absorption and scattering of light, and shadows projected by clouds and the time of day. A potential solution to combat this would be providing a controlled source of illumination during the night. Nonetheless, this concept also possesses drawbacks, including the possibility of uneven illumination.

Color Imaging

While the proposed solution mainly supports using hyperspectral cameras, the size and complexity of its data can make it impractical for most farmers. For that reason, using color (RGB) cameras–as most drones are already equipped with–can be much cheaper and more accessible to non-researchers. Though not as effective, color imaging can provide enough data to detect plant diseases that manifest on leaf patterns, and has significant research already established; for example, the previously mentioned disease Fusarium Head Blights (FHB) has been studied and detected using color imaging with machine learning. The use of ML on FHB is explored in section Data Processing subsection Machine Learning. Despite its advantages in accessibility and cost, color imaging faces the same issues of uneven lighting as HSI and may catch signs in later stages than HSI.

Data Processing

Data Analysis

Hyperspectral imaging results in large numerical datasets. The most sensible way to analyze these elaborate datasets is by considering only a small number of positions in the wavelength range. By focusing on this, ML algorithms can hone in on changes across conditions at key points. One of the most popular existing metrics for vegetation is the NDVI (Normalized Difference Vegetation Index), which measures the difference between red light and near-infrared reflectance of vegetation, often used in remote sensing with plant cover. An alternative approach is focusing specifically on the “red edge” of images which refers to the distinct change in reflectance of vegetation and is observed where the visible spectrum ends and the near infrared range starts (specifically, 690–740 nm) on the electromagnetic spectrum as seen in Figure 1.

Varying levels of light can result in inconsistencies in recorded data. To combat this, multiple light spectrums can be merged, and the ratio between them recorded minimizing the effect of such differing lighting (Lowe et al., 2017).

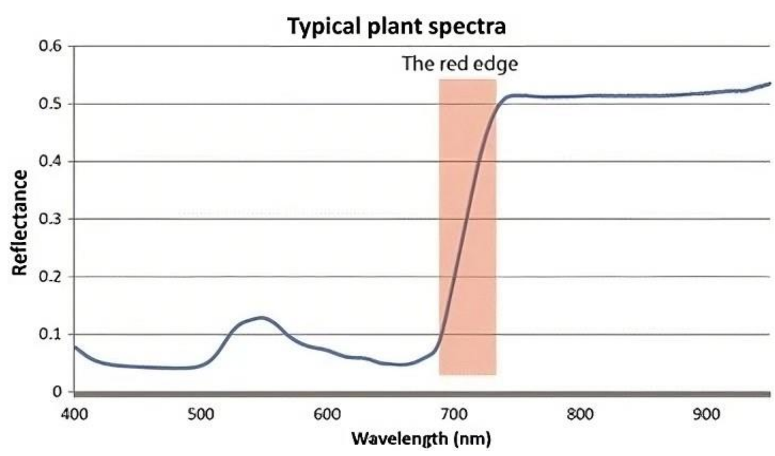


Figure 1. The “red edge” of images refers to the distinct change in reflectance of vegetation and is observed where the visible spectrum ends and the near infrared range starts (Lowe et al., 2017).

Machine Learning

Deep learning is a powerful tool that can be used to parse large amounts of unstructured data. The network architecture most commonly used for visual tasks involving pixel data are convolutional neural networks (CNN) illustrated in Figure 2. CNNs are able to effectively detect edges, shapes, and colors thanks to the convolutional layer. In this layer, small filters called kernels are applied to the input data in small sections. The results are summed to produce a feature map which could contain things such as edges and corners. Following the convolutional layer, a max pooling layer is used to down-sample the image into smaller subsets by taking the maximum values in small regions of the image. This effectively drops less important features. The final layers of the CNN are fully connected. In this stage of the CNN, the information is processed, and predictions are made.

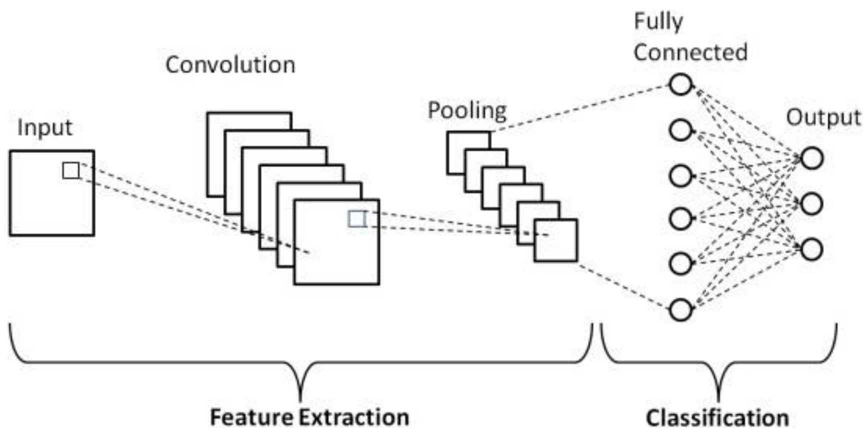


Figure 2. A simplified diagram of a CNN (Phung & Rhee, 2019).

The use of CNN on plant disease detection has been previously tested with color imaging. In a 2016 study aimed at using deep learning for image-based detection, the best performing model demonstrated extremely high accuracy on a held-out test set using photos taken on phone cameras (Mohanty et al., 2016). However, it's important to note that these results held up only in controlled environments where disease was explicitly visible. When photos were not taken in ideal conditions, the accuracy went down substantially, demonstrating how current technology would likely fare in real-world conditions.

Nonetheless, deep CNN has been taken out of controlled conditions and applied to field studies; one instance of this was with the previously mentioned fungal disease Fusarium Head Blights (FHB). In a study, a CNN model was trained to analyze the color of the plants' spikes. A crucial factor found in the study was the importance of timing. Researchers concluded the best time for image capture is when max disease severity was reached before the decay of the plant starts (Qiu et al., 2019). The importance of timing is likely true for most color imaging tasks due to the invisible nature of early disease and is a facet where hyperspectral imaging may have an advantage.

Applying hyperspectral imaging to plant disease detection is less studied, but presents certain advantages due to having a broader light spectrum than RGB imaging. Since it has a larger dataset, it's possible for machine learning models to detect disease not visible to the human eye (and thus, can catch signs earlier). CNN applications on hyperspectral imaging are actively evolving due to continuous research in the field, but one of the largest obstacles for applying CNN to hyperspectral data is the lack of data for training. HSI also requires higher processing time and power when analyzed. Regardless, the results point to the feasibility of using CNN for disease detection in agricultural applications using color imaging. Though hyperspectral imaging's practicality for most farmers may be called into question, rapid technological advances give researchers hope in its use in the future.

Drone and Hardware

Drone Criteria

Quadcopter drones were favored over UAVs because of their maneuverability and flexibility. Several drone options were evaluated and compared. The evaluation process narrowed down drones using four key criteria: weight, range, stability, and flight duration. Six drones were examined, and assessed using the criteria above, along with cost and ability to withstand environmental factors.

Ideally, the drone must be compact and portable and able to maintain a flight time of over half an hour. To carry the necessary equipment, it should be able to carry at least 500 grams while maintaining a safe height and relative stability. The drone's camera also must be capable of being swapped out in order to equip hyperspectral cameras (especially one designed for the targeted wavelength).

Proposed Models

The objective of exploring the following proposed drone models was to find features that were deemed important for the drone to be optimal in data collection. The first drone that was looked at was the RHEA 160 Hexacopter. This drone held a large advantage over other drones because of its stability but it required high maintenance and had limited flight time. The DJI M210 RTK and DJI M300 were also explored. Both models offered two cameras and stability but were deemed unsuitable due to their weight and cost. The DJI Inspire 2, made for aerial photography, was cut due to its limited flight duration.

The two remaining drone candidates–the Impossible US-1 and the DJI Mavic 2 Enterprise–demonstrated advantages in either efficiency or range. Both drones offer ideal designs for the suggested solution due

to their lightweight nature and ability to maintain stability. Though the DJI Mavic-2 Enterprise possesses good range and portability, it's important to note that its model has been discontinued. The Impossible US-1 has a high battery efficiency and flight time and is capable of a load of 1300g, sufficient to carry multiple cameras and extra equipment.

Using the blueprints of the DJI Mavic 2 Enterprise and the Impossible US-1, our 3D artist was able to create a drone model in Blender shown in Figures 3 and 4. The design for our drone was chosen based on the criteria of the ideal drone type outlined above. In a real-world situation, the drone would fly above crops and collect images with its hyperspectral camera as shown in Figure 5.

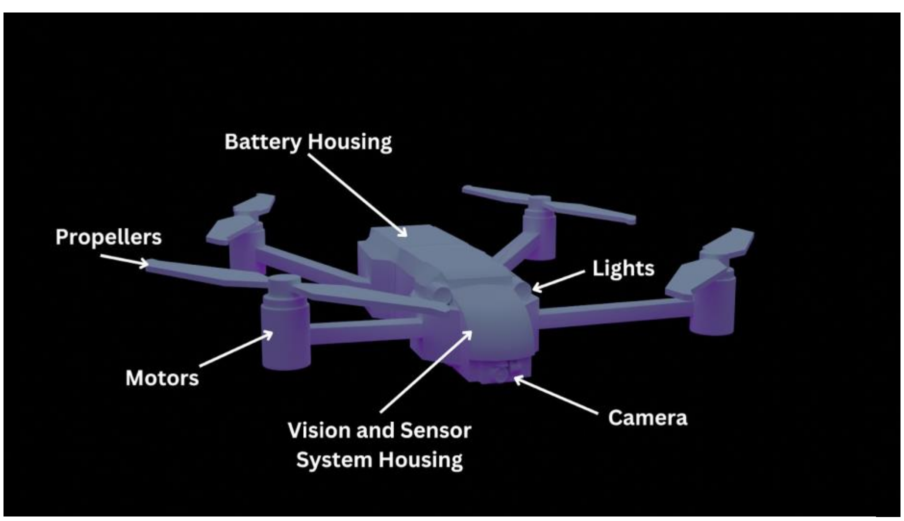
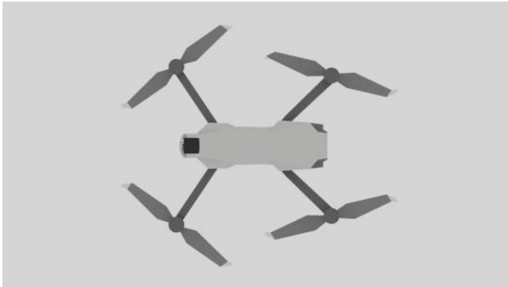
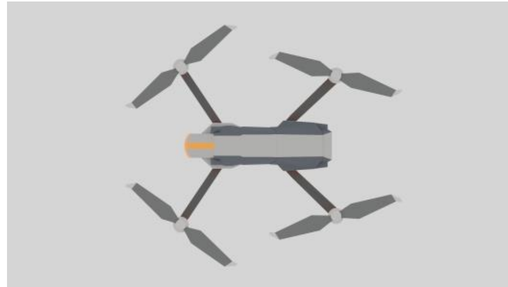


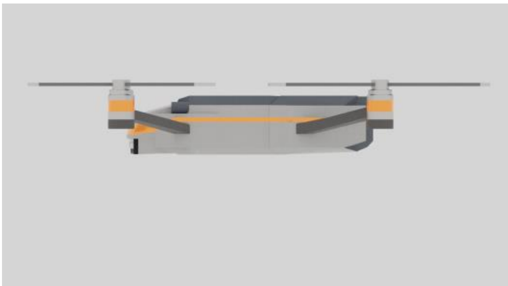
Figure 3. 3D Rendering of an ideal drone and its components.



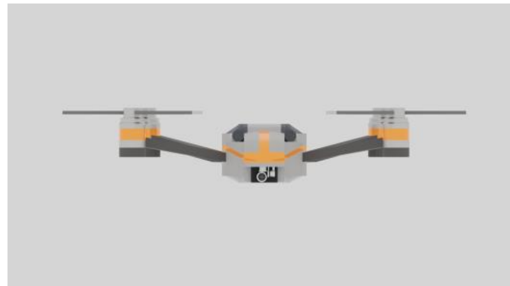
(a) Bottom view of model



(b) Top view of model



(c) Side view of model



(d) Front view of model

Figure 4. Drone model from different perspectives

Figure 5. 3D render of modeled drone flying over field.

Practicality

Cost

Currently, the total cost of acquiring the hardware of the presented drone is estimated to be $42,396. In order to ballpark the proposed model's expenses, the costs of the proposed drones were analyzed. The DJI Mavic 2 Enterprise costs a total of $6,500 but has been discontinued by the manufacturer. The Impossible Aerospace US-1 drone, previously mentioned in drones and hardware, is a similar alternative that costs around $7,000 without any accessories. The Pika L hyperspectral camera ($35,076), comes equipped with GPS and numerous software such as georectification, post-processing, and analytical software. However another alternative can be the BlackBird V2 ($36,720.09) which provides the same features, at a higher cost.

Feasibility

Californian farmers typically make between $44,000 and $66,000 a year, making purchasing the pro- posed technology often infeasible (Salary.com, n.d.). Additionally, even if cost did not pose a problem to select farmers, hyperspectral cameras provide complex data when compared to typical RGB cameras due to their analysis of a much wider spectrum of light. Both the expense and the data complexity pose serious barriers for most farmers to buy and operate the drone on their own. Despite these challenges, there are several options that would allow farmers to realistically employ this tool.

To address cost and complexity, the drone can be rented out for individual farmers to use. This would relieve the farmers from the technical issues and provide a cheaper way for them to benefit from the drones. By keeping technical professionals in control of some operation responsibilities, farmers are relieved from the burden of dealing with hardware maintenance, software issues, and confusing data. This approach widens the possibility of using real-world cases as more training data to both fine-tune and further the scope of the drone's ability to accurately detect diseases.

One alternate proposal is shifting the target consumer demographic to a more commercial scale. Since some individual farmers might not be able to afford the product, even through rental, corpora- tions which employ farmers may be able to solve the cost constraints. These companies could invest in drones and systematically implement them in their employees' farms in order to increase crop yield margins.

Although the drone may pose cost and complexity issues currently, hyperspectral drones present a feasible solution through service-based usage.

Future Implications

The next steps of this research would be to look into automated flight paths and varying diseases across a broader spectrum of plants. Currently, the drone is best equipped to detect diseases that manifest on the foliage of the plants, but future uses include detecting diseases in plant stems and roots. Additionally, a more economically friendly version of the drone could be proposed using color cameras, eliminating the cost of expensive hyperspectral cameras.

Automated Paths

Present day solutions require drones to be controlled manually but potentially, pre-planned flight paths for the drones could be implemented. Unfortunately, current FAA Regulations do not allow autonomous drone operation but in the event the restrictions are relaxed or lifted, future research could potentially acquire the use of third party software to create automated paths. A mobile device could be incorporated into the process, and drones could communicate with the device through radio frequencies or Wi-Fi, allowing farmers greater flexibility.

Broader Spectrum of Plants

An important focus for improvement would be in the accuracy and scope of disease detection. Signs of infection can manifest in many different areas of the plant, and it's important for these areas to be captured through imaging techniques and factored into machine learning algorithms. Additionally, also a broader range of diseases able to be detected would be ideal, which would be achieved mainly through more extensive training data.

RGB Cameras

With greater development, the drone could easily become more accessible to the public by replacing the hyperspectral camera with regular RGB cameras. A good color camera costs a fraction of hyperspectral cameras and is much more familiar to most demographics than his. The use of color cameras in plant disease detection has already been studied and has demonstrated impressive results, pointing toward their feasibility. RGB cameras provide a more accessible option for farmers who don't want to deal with the complexity and/or cost of hyperspectral imaging.

Conclusion

Various issues, such as the ongoing climate crisis and the growing bacterial tolerance to chemical preventatives, are anticipated to lead to a significant worldwide increase in plant disease. Moreover, globalization continues to play a role in the rapid spreading of diseases across continents, highlighting the importance of detecting these diseases at an early stage.

The report suggests the use of a drone equipped with a hyperspectral camera to efficiently collect data, followed by analysis using neural networks trained to detect and categorize infected plants. This approach aims to enhance speed, efficiency, and effectiveness in plant disease detection. Although complexity and cost of hyperspectral cameras may present initial challenges to widespread drone adoption, exploring business models such as rent-based business practices can increase accessibility. Color cameras and automated paths may also be utilized in the future as today's technology rapidly advances. Ultimately, through the novel combination of drones, hyperspectral imaging, and machine learning, the proposed solution offers an ambitious solution to combat the escalating threat of crop diseases.

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