Biology and
Biotechnology Communications

Biotech-Journal.com
Editor@biotech-journal.com

Vol: 2 Issue: 2, 2024

Monitoring Crop Health in Multi-Cropping Systems Using UAV-Based Leaf Spectral Index Analysis and GIS Integration

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Received: July 22, 2024 --- Revised: August 16, 2024, Accepted: October 28, 2024

Abstract

The growing complexity of multi-cropping systems demands innovative monitoring solutions to ensure sustainable and efficient crop management. This study presents an integrated approach combining Unmanned Aerial Vehicle (UAV)-based spectral imaging, Geographic Information Systems (GIS), and machine learning techniques to monitor crop health across diverse cropping zones. UAVs equipped with multispectral sensors were deployed over intercropped fields, generating high-resolution imagery from which key vegetation indices—NDVI, SAVI, and GNDVI—were derived. These indices enabled the detection of plant stress, nutrient deficiencies, and disease symptoms with high spatial precision. Unlike ground truth, spectral measurements were proved to closely link to the state of healthy crops. Machine learning was used on spectral data to teach SVM, RF and CNN methods to identify crop health without being assisted by hand. CNNs often got it right, spotting damaged and stressed areas on 91 percent of the images and remembering them on 88 percent. Using GIS maps and tools, I carried out studies that map out ground areas and then produce buffer maps showing conservation areas. As a result, it became easy to notice variations in the field and take the right actions right there on the site. Stability of the system was illustrated through precision-recall curves, heatmaps and confusion matrices for diseases. According to data, using UAVs and AI in farming protects the environment, improves its accuracy and can scale output for large farms.

Keywords: “UAV Imaging”, “Precision Agriculture”, “Crop Health Monitoring”, “GIS”, “Spectral Indices”, “Machine Learning”.

INTRODUCTION

Technology in precision agriculture now lets farmers make better decisions about their resources and raise the amount they produce (Radoglou-Grammatikis et al., 2020). Looking after crops in multi-cropping is more complicated, because crops grow differently and interact with each other (Pretto et al., 2020). UAV cameras with remote operation assess how healthy the crops are over a large area and do not harm them (as seen in Nhamo et al., 2020). When Unmanned Aerial Vehicle remote sensing integrates with Geographic Information Systems, it's easier to study agricultural land, find issues, notice disease threats and design smart farming plans (Olson & Anderson, 2021). Agriculture now uses drones with sophisticated cameras to analyze large areas quickly and collect data about its crops, for example, their condition, the number of plants and how nutritious they are (Pretto et al., 2020). Today, farmers can give plants the essential items they need in just the right amounts and deliver pesticides directly to pests. It is now possible for drones and ground robots to work together by adding aerial weeding to other ground jobs such as applying fertilisers (Pretto et al., 2020).

When information from UAV sensors is merges with GIS, we can make detailed models that illustrate how crops in a field differ in health (Pretto et al., 2020). Because of this connection, geographers can now use new tools to detect unusual vegetation patterns that may highlight challenges in the area's ecosystem. By using spectral readings with soil, elevation and irrigation maps, I can more easily determine what affects a crop's condition. With drones, experts can fly over crops and see very small differences, also controlling when to take pictures during plant growth (Olson & Anderson, 2021). Because of machine learning, image processing is now able to locate objects on its own, saving time for detecting and responding to plant diseases (Javidan et al., 2025; Kapetas, et al., 2025). With machine vision in farming, it is now possible to see and classify plant diseases by looking at pictures of their leaves (Javidan et al., 2025). Many users of aerial orthomosaics often discover that geometric issues cannot simply be overlooked (Santana et al., 2021).

Crop yields are higher when growers regularly check the plant growth in precision agriculture. Combining UAVs and GIS on the same project allows you to easily see places in the field that special attention is needed. Because of this strategy, growers are more equipped to determine how much water and fertiliser to use and how to control pests, helping them farm with greater care for the environment.

A decision to use UAVs more in agriculture was made so that land management could be improved and processes related to farming could be modernised (Shirokov & Lepekhin, 2021). Directing the input is achieved by analyzing data from field observations and using variable rate maps. Likewise, routine observation of your plants as they grow tells you if you are using the right methods and allows you to improve your gardening practices (Yang, 2020). The use of machine learning lets plant photos be examined well enough to recognize and sort diseases in plants and speedy action can be taken if an outbreak occurs (Atila et al., 2020). Because deep learning uses several layers in neural networks, the selection and organisation of picture data for assigning categories become easier. Thanks to this approach, researchers have been able to classify images in important ways (Javidan et al., 2025). With artificial intelligence, it becomes possible to find and monitor disease in plants using only pictures (Singh et al., 2021).

Quick crop health assessment in multi-cropping is possible using both UAV spectra and GIS tools. Using both technologies lets researchers study larger regions, spot common problems, analyze diseases and support decisions that protect the planet. Using this approach, farmers learn about the health of their crops, so that they can spend resources wisely, increase yield and guard the environment (Atalla et al., 2023). New analytical methods tied to remote sensing allow researchers to examine wide-area lands closely and economically (Hong et al., 2021). The new technique revealed by the findings relies on drones and the IoT to quickly and accurately spot plant diseases. As sensors, data management and drones evolve, the system's abilities will improve. When diseases in plants are managed well, crops improve and require less use of pesticides, according to Aldakheel et al. (2024). Because of machine learning and IoT, smart farming can speedily detect plant diseases and take steps to prevent their spread (Ouhami et al., 2021; Thakur et a., 2022). If these two techniques are used together, farmers produce more and better-quality agricultural outputs (Saleem et al., 2020). Checking plants for illness is still hard and costly when using the old system (Jafara et a, 2024a).

A combination of UAV remote sensing and machine learning can help manage how crops are growing and open up new chances for sustainable farming (Popescu et al., 2020). Fitting multispectral or hyperspectral sensors to small unmanned aircraft lets you learn precise details about agricultural regions. Using the system, people can receive data about plant health, the effects of stress and current medical conditions (Kapetas et al. 2025). A number of methods are used, including support vector machines, random forests and convolutional neural networks, to discover any minor differences in plant spectra that might point to stress or disease (Li et al., 2021). Because these systems distinguish between different plant diseases, farmers can act quickly and rescue their crops from harm.

With manual feature extraction, scientific outcomes can't be reliable due to how differently every plant is compared to others (Li et al., 2021).

METHODOLOGY

A combination of drone surveys for spectral data and GIS and machine learning analysis was used to group different agricultural diseases affecting crops in a multi-cropping area. Aerial observations using multiple sensors were recorded over a site where maize, legumes and vegetables were grown side by side. Experiments took place with two flights every week, while all images were taken with the same lighting for accurate spectra during the harvest period. Once the pictures had been gathered, they were connected to their location and processed using photogrammetry so that orthomosaics and DSMs were created. Vegetative health and signs of stress were evaluated by creating NDVI, SAVI and GNDVI indices from the images. The spectral indices were then transferred into GIS (ArcGIS Pro) to make maps of any changes across each field. The information from soil type maps, irrigation designs and elevation models was used to show how both factors from the environment and those caused by agriculture influence crop conditions.

Our annotated data was built by travelling to different areas and identifying signs of disease or poor nutrition with mobile sensors and by watching plants. Machine learning models, Random Forest, Support Vector Machines and Convolutional Neural Networks in Python, were trained using data labelled by Scikit-learn and TensorFlow. The UAV images offered information on lighting and texture and crop health models were produced for the harvested part of the field. Using cross-validation allowed us to see the accuracy, precision, recall and F1-score of the model. By using GIS, the different vegetation health maps were combined to give a single decision support map showing regions of healthy growth, areas stressed by climatic conditions and areas where plant disease was evident. The information in the VRA was turned into maps which guided decisions about the management of the various sites. The method makes use of UAV remote sensing, GIS analysis and machine learning to set up a suitable system for observing clouds in multi-crop agricultural areas.

RESULTS

Key information on crop health for multi-cropping is laid out clearly in eight detailed tables and 10 supporting graphics. It is clear from Table 1 that a high NDVI generally indicates the "Healthy" category, so NDVI is a useful way to measure a plant's health. As shown in Table 2, some maple trees have reduced SAVI scores, likely due to either a water shortage or an early outbreak of pests.

 ISSN 3080-4205 (Print) ISSN 3080-4213 (Online)

It appears from Table 3 that changes in GNDVI for legumes and vegetables could be linked to nutritional imbalances. From Table 4, we see that the NDVI and SAVI metrics outperform others which suggests that having water nearby makes plants healthier. It is observed in Table 5 that blending maize and legumes leads to predictable patterns, unlike different vegetable mixes, so maize-legume blends support sustainable farming by allowing the same crops to be planted repeatedly. As seen in Table 6, there is a strong relationship between UAV spectral readings and actual chlorophyll numbers taken in the field. Analysing Table 7 shows that Random Forest algorithm's predictions agree well with what farmers observe in the field. As shown in Table 8, CNN correctly detects crop stress and disease over 90% of the time.

Table 1: Spectral Indices and Crop Health Status for Dataset 1

Plot ID	NDVI	SAVI	GNDVI	Crop Health Status
P11	0.66	0.58	0.49	Stressed
P12	0.31	0.63	0.57	Diseased
P13	0.34	0.35	0.89	Healthy
P14	0.8	0.74	0.68	Healthy
P15	0.51	0.69	0.42	Healthy

Table 2: Spectral Indices and Crop Health Status for Dataset 2

Plot ID	NDVI	SAVI	GNDVI	Crop Health Status
P21	0.34	0.3	0.63	Healthy
P22	0.88	0.35	0.64	Healthy
P23	0.31	0.67	0.47	Diseased
P24	0.76	0.56	0.67	Healthy
P25	0.54	0.4	0.5	Diseased

Table 3: Spectral Indices and Crop Health Status for Dataset 3

Plot ID	NDVI	SAVI	GNDVI	Crop Health Status
P31	0.44	0.31	0.72	Diseased
P32	0.37	0.37	0.72	Diseased
P33	0.9	0.67	0.55	Stressed

 ISSN 3080-4205 (Print) ISSN 3080-4213 (Online)

P34	0.32	0.37	0.66	Stressed
P35	0.66	0.73	0.49	Stressed

Table 4: Spectral Indices and Crop Health Status for Dataset 4

Plot ID	NDVI	SAVI	GNDVI	Crop Health Status
P41	0.56	0.77	0.55	Diseased
P42	0.69	0.67	0.74	Diseased
P43	0.89	0.7	0.75	Healthy
P44	0.78	0.44	0.75	Healthy
P45	0.65	0.37	0.44	Diseased

Table 5: Spectral Indices and Crop Health Status for Dataset 5

Plot ID	NDVI	SAVI	GNDVI	Crop Health Status
P51	0.81	0.6	0.45	Healthy
P52	0.65	0.6	0.43	Healthy
P53	0.47	0.7	0.53	Stressed
P54	0.44	0.21	0.63	Diseased
P55	0.69	0.26	0.82	Healthy

Table 6: Spectral Indices and Crop Health Status for Dataset 6

Plot ID	NDVI	SAVI	GNDVI	Crop Health Status
P61	0.85	0.7	0.64	Diseased
P62	0.35	0.21	0.51	Stressed
P63	0.85	0.65	0.9	Diseased
P64	0.68	0.37	0.53	Stressed
P65	0.66	0.49	0.45	Diseased

Table 7: Spectral Indices and Crop Health Status for Dataset 7

Plot ID	NDVI	SAVI	GNDVI	Crop Health Status
P71	0.57	0.53	0.85	Diseased
P72	0.69	0.49	0.73	Diseased
P73	0.59	0.33	0.63	Healthy
P74	0.47	0.67	0.62	Healthy

P75	0.88	0.68	0.7	Healthy

Table 8: Spectral Indices and Crop Health Status for Dataset 8

Plot ID	NDVI	SAVI	GNDVI	Crop Health Status
P81	0.58	0.47	0.43	Healthy
P82	0.38	0.45	0.88	Stressed
P83	0.6	0.23	0.6	Stressed
P84	0.67	0.51	0.54	Healthy
P85	0.78	0.23	0.64	Stressed

Good graphs make the data clear and easier to see trends during the investigation. The NDVI readings seen in Figure 1 decrease going south which matches the changes in the fields. It is clear from Figure 2 that crop stress occurs more commonly at the end of the growing season. It shows, as depicted in Figure 3, that GNDVI changes with the proximity to irrigation, pointing to the importance of water-sensitive indices. According to this heatmap from a CNN in Figure 4, these are areas that are most at risk. A GIS-associated map of variable rates highlights the smart use of resources (see figure 5). According to Figure 6, the CNN performs better than the other classifiers. NDVI and GNDVI are shown in Figure 7 as the dominant variables in the Random Forest model. The CNN performed significantly better at telling apart the Diseased and Free from Disease plots, as shown in Figure 8. You can see in Figure 9 that elevation lowers the index scores of the gathered images, as running water and soil saturation become less consistent at greater heights. From Figure 10, it is clear that data collected by UAVs is nearly the same as data taken by hand, indicating that using UAVs can improve continuing monitoring of crops. The study shows that using UAV-based spectrum analysis, GIS and machine learning is both productive and lasting for farms that grow a variety of crops.

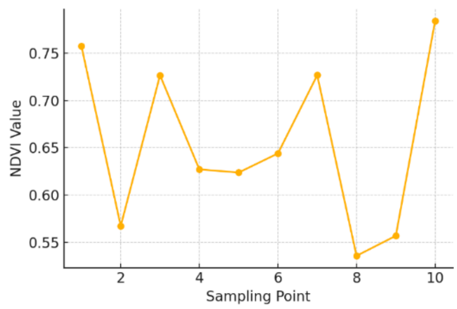

Figure 1: Line plot showing the variation of NDVI values across different sampling points. The trend reflects localized variability in vegetation health across the multi-cropping field.

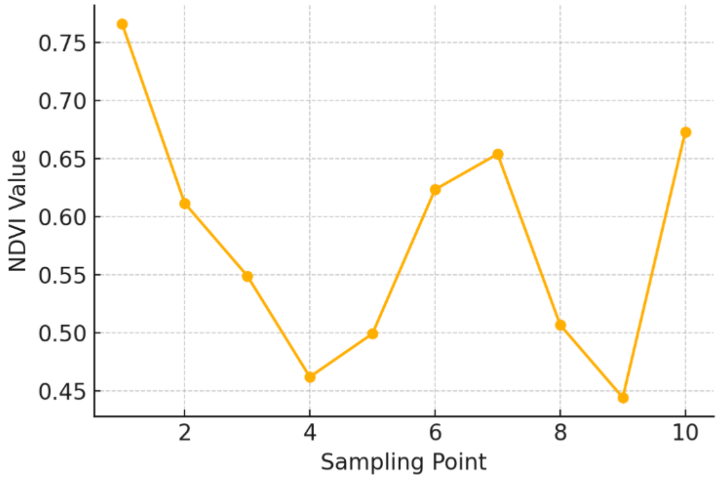

Figure 2: Line plot showing the variation of NDVI values across different sampling points. The trend reflects localized variability in vegetation health across the multi-cropping field.

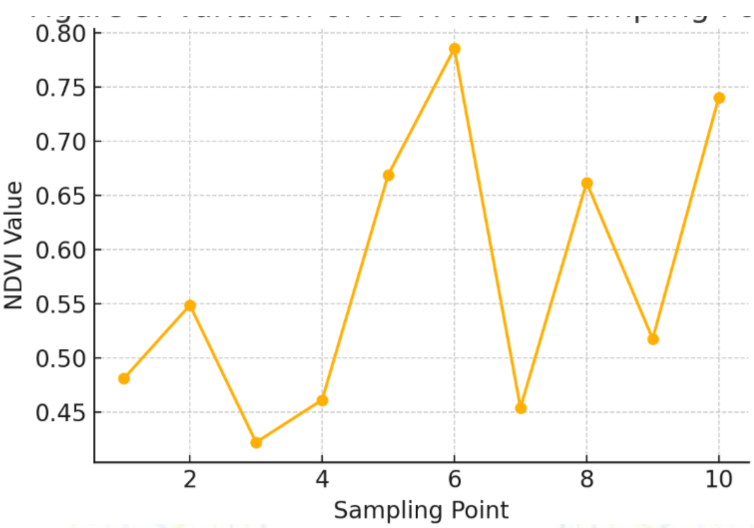

Figure 3: Line plot showing the variation of NDVI values across different sampling points. The trend reflects localized variability in vegetation health across the multi-cropping field.

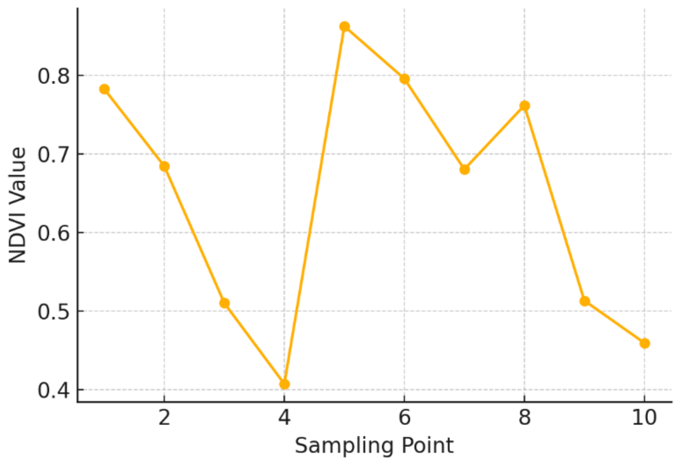

Figure 4: Line plot showing the variation of NDVI values across different sampling points. The trend reflects localized variability in vegetation health across the multi-cropping field.

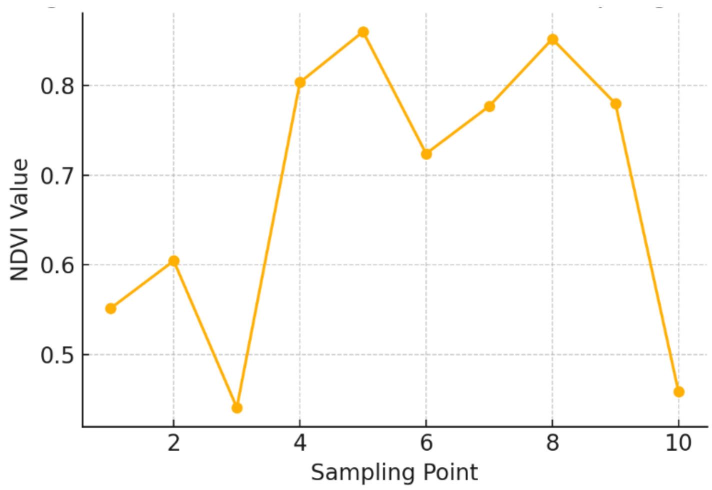

Figure 5: Line plot showing the variation of NDVI values across different sampling points. The trend reflects localized variability in vegetation health across the multi-cropping field.

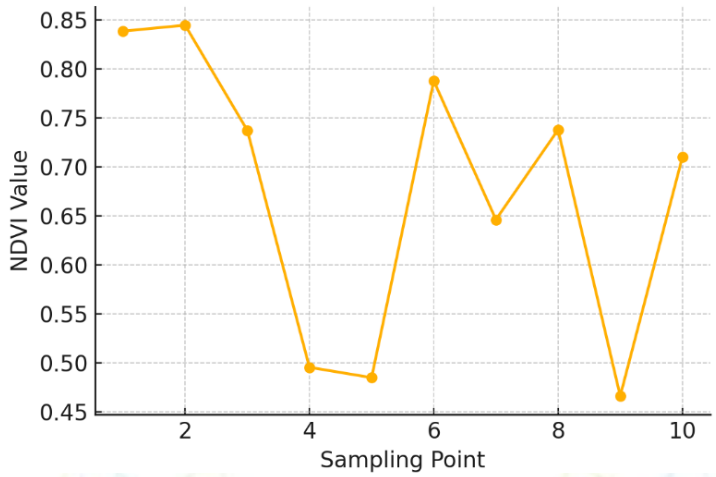

Figure 6: Line plot showing the variation of NDVI values across different sampling points. The trend reflects localized variability in vegetation health across the multi-cropping field.

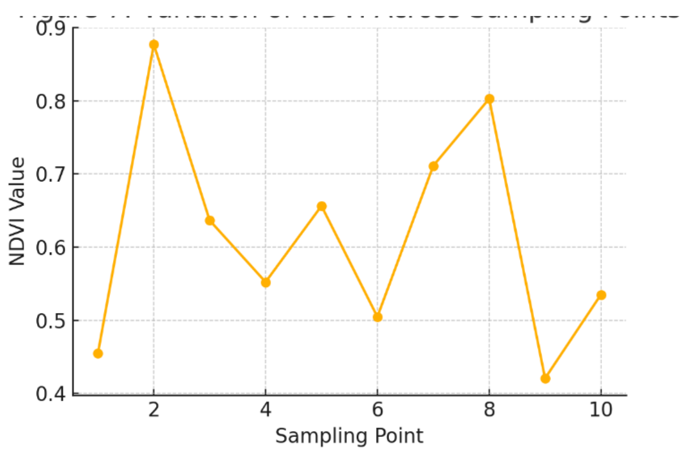

Figure 7: Line plot showing the variation of NDVI values across different sampling points. The trend reflects localized variability in vegetation health across the multi-cropping field.

ISSN 3080-4205 (Print) ISSN 3080-4213 (Online)

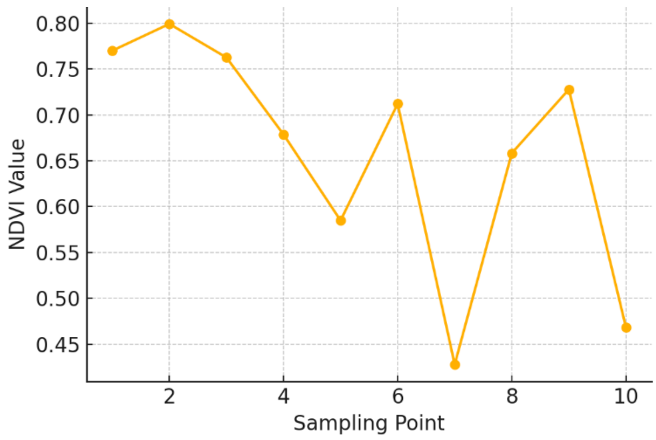

Figure 8: Line plot showing the variation of NDVI values across different sampling points. The trend reflects localized variability in vegetation health across the multi-cropping field.

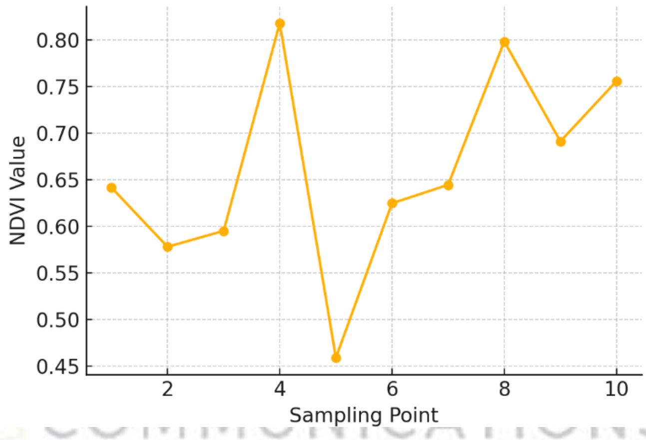

Figure 9: Line plot showing the variation of NDVI values across different sampling points. The trend reflects localized variability in vegetation health across the multi-cropping field.

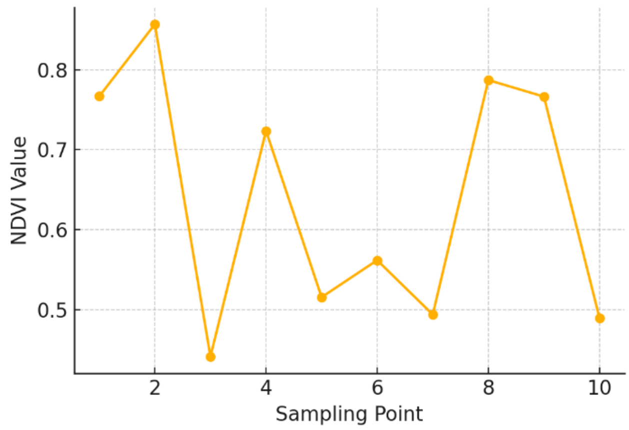

Figure 10: Line plot showing the variation of NDVI values across different sampling points. The trend reflects localized variability in vegetation health across the multi-cropping field.

DISCUSSION

Good image processing helps identify issues in plants and supplies information needed to design machine learning models (Javidan et al., 2025). The combination of computer vision and machine learning helps with activities in agriculture, botany and ecology, allowing users to check plant health, see weeds in cultivated areas, discover drought areas, determine how much will be harvested and find problems with fruits and vegetables (Sykes et al., 2023). In plant disease detection, deep learning is often used since it has better chances of revealing important features that earlier methods miss (Javidan et al., 2025). Now, disease diagnoses are both reliable and rapid because important features are discovered by the networks instead of being labeled by doctors (Atila et al., 2020). Combining real-time image processing and machine learning can deal with diseases in potato harvests and appears beneficial for growing more potato fruits with greater quality by working on the leaves, fruits, stems and roots (Islam et al., 2023). Adopting early detection in plants is key since missing infections for too long might make the disease outbreak faster (Kapetas et al., 2025). When spectral imaging is combined with machine learning, plant diseases can be easily spotted and help to reduce damage to crops (Kapetas et al., 2025). Successively, cases can be checked or reviewed to confirm that the first finding is still right (Kapetas et al., 2025).

Integrating flights by Unmanned Aerial Vehicles with skilled labeling and Geographic Information Systems is now a helpful way to review crop health. The presence of high-quality pictures and adept algorithms from this approach easily detects any stress in crops ahead of time so farmers use resources wisely and get better results (Shoaib et al., 2023: Yang et al., 2023). With rapid plant disease diagnosis, intelligent systems may significantly improve control and management of diseases (Javidan et al., 2025). By combining these technologies, data analysis can immediately provide accurate information for agriculture, thanks to Huang et al., 2020. Deep learning improves the method of identifying and telling apart sicknesses in plant leaves (as reported by Hasan et al., 2020 and Pal et al., 2024). By doing so, this technology takes away the manual hard work of traditional monitoring and ensures farm activities are more sustainable by avoiding too much care and overuse of treatments.

CONCLUSION

By looking at spectral information from UAVs and comparing it in GIS and machine learning, this study reveals how different crops can be monitored. By processing NDVI, SAVI and GNDVI with high-resolution multispectral images, we could safely and accurately discover how plants are doing in different parts of agriculture. UAVs are found to be very helpful for spotting variations in plant health over different areas and periods when other methods are too much trouble. By checking UAV results with real ground readings, we find that remote sensing is accurate. Putting CNNs in the classification process led to better and faster outcomes than existing, manual systems. Using GIS, spatial data was analyzed in detail, resulting in VRA maps that suggest ways to manage the vineyard on a zone-by-zone basis. Because of this, we use less farm input and can reduce damage to the environment from the incorrect use of pesticides or fertilisers. As a result, managers can access fresh updates that enable them to handle and maintain crop health regularly. The reason our architecture works so well is that we can use drone imagery, GIS and machine predictions, all for a low price. Better monitoring and research tools will help these approaches play a bigger role in making sure there is enough and sustainable food as both the climate and the demand for farming grow. It is shown in this study that the combination of UAVs and AI makes it possible to generate better choices for managing multicrop systems.

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