IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 20, April 2026
Impact Factor: 8.2

Drone Based Multispectral Imaging for Agricultural Data Analysis

S. Kanadhasan, Divya. S, Naveen Kumar. A, Anand Kumar. A, Gayathri. M
Department of Electronics and Communication Engineering
Study World College of Engineering, Coimbatore, Tamilnadu, India
kannadhasan.ece@gmail.com, dvysk81@gmail.com, thangammahes05@gmail.com,
anandkumarcavin@gmail.com, gayumanikandan2307@gmail.com

Abstract: *Drones, or unmanned aerial vehicles (UAVs), provide a lot of advantages over traditional agricultural practices such as providing farmers with instant data and actionable insights. One of the main uses of drones in agriculture is to monitor and manage crops. Drones have high-resolution cameras and sensors that record comprehensive photos of crops, helping farmers to monitor plant health, identify pests and diseases and improve watering and fertilisation. This proactive strategy helps in timely interventions resulting to better production & quality of food. The employment of drone technology in the agriculture business has transformed conventional farming techniques by providing novel ways to counter numerous problems encountered ďy farmers globally. This report presents an extensive analysis of the use of drones in agriculture, emphasizing their effects on production, efficiency and sustainability. Drones have unique capabilities for data collecting, analysis and decision-making making them a transformational tool for modernising agriculture. Farmers may use drones to improve the allocation of resources, reduce risks, and eventually, help ensure global food security and sustainable development. With the recent development of improved sensors, data collecting platforms and data processing methodologies, the usage of unmanned aerial vehicle (UAV) or drone-based remote sensing has been brought into the spotlight of precision agriculture (PA) researchers. This requires large-scale data processing technologies, such as machine and deep learning approaches, to analyze the huge quantity of raw data acquired from such sensing systems. Therefore, a comprehensive review that integrates, classifies and analyzes the performance of various machine learning and deep learning algorithms for PA is relevant. Here, we summarize and synthesize previous efforts employing a generic pipeline of UAV-based remote sensing for precision agricultural research. We identify the numerous features collected from UAV data for different agriculture applications, explain the value of each feature for the performance of the crop model and demonstrate how the multiple feature fusion may increase the models' performance. Additionally, we examine and contrast the performances of several machine learning and deep learning models for three major agricultural trait estimates including yield prediction, disease detection and crop categorization. Furthermore, the paper briefly discusses current trends in UAV applications for PA in terms of their relevance and prospects.*

Keywords: Drone, UAV, Sensors, LADAR, RGB, IoT

I. INTRODUCTION

The employment of unmanned aircraft, sometimes known as drones, in the agriculture business has ushered in a new era of precision farming and resource management. With a growing need for more food production and reduced environmental effect, farmers are looking for breakthrough solutions to improve their operations as the global population grows. Drones are revolutionising traditional agricultural processes, giving a multi-faceted solution for real-time data collecting, analysis and actionable insights. The advent of improved sensors, data collecting platform and the internet has provided several opportunities, and problems for the improvement of agriculture. Furthermore, the

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 6, Issue 20, April 2026
Impact Factor: 8.2

enormous development of the usage of new technologies in agriculture has caused a huge volume of data or "Big-data". Agriculture data can be collected from various smart vehicles like field sensors, aerial vehicles, global positioning system (GPS), internet of things (IoT), cameras and intercommunicated for taking improved decisions for different smart farming activities such as crop planting, crop irrigation, soil management, disease detection, pest identification, etc. For successful management of such agricultural operations, the field (or agriculture) information such as crop water stress, crop vigour, crop height, soil moisture etc. has to be obtained. The crop information is gathered by regular scouting of the plant and organizing the farm operations appropriately, which is time intensive as well as hard in traditional way. Or, farm management using sensors, cameras, moving vehicles and global positioning systems (GPS) can generate a great quantity of data to help in data driven smart farming operations. Remote sensing is the most significant and frequently utilized technology for smart farming and precision agriculture. The effectiveness of remote sensing in precision agriculture largely depends on the factors such as the type of platforms (ground-based, airborne or satellite), sensors that detect the region of the electromagnetic spectrum (visible, infrared or thermal), resolutions (temporal and spatial) and energy source (active or passive source). In the past, information on crops at regional or global levels was obtained via remote sensing from air- or space-borne platforms equipped with different sensors, such as multispectral, hyperspectral, radio detection and ranging (RADAR) and Light Detection and Ranging (LiDAR). For example, evaluated the wheat and canola production in northeast Germany by employing satellite remote sensing data from six distinct optical sensors [1]-[5]. The study demonstrated that high-resolution photographs of satellites such as RapidEye and Sentinel-2 outperform low-resolution satellite photos using Landsat. But satellite-based remote sensing has three big drawbacks that make it not frequently the greatest solution for precision agriculture. Firstly, the satellites record the picture in spatial resolution in meters (for example Landsat has 30m and sentinel has 10m spatial resolution) which is frequently not enough for plant or plot level data analysis. The second, the return time of the satellite is not variable and frequently not accessible to take the photographs needed at the needed time. Third, the environmental factors, such as clouds, restrict the dependable quality of photographs [6]-[10]. This study discusses the development of drone technology in agriculture and its main uses and revolutionary influence on the sector. The purpose of this study is to review the pros and cons of the use of drones in order to emphasize the importance of drones as enablers of agricultural innovation and progress [11]-[15].

II. PROPOSED WORK

The traditional approach for broomrape control is based on large-scale use of chemicals which is expensive and can be detrimental to the environment and human health. Current herbicides are generally non-selective, impacting not just the broomrape but also beneficial species and neighboring crops. For example, the use of glyphosate and other systemic herbicides has been widespread but their efficiency is variable and typically needs large dosages, which can be damaging to the surrounding ecology. Furthermore, the use of chemical treatments emphasizes the need for more accurate and sustainable management systems. The use of pesticides such as sulfosulfuron and imazapic has demonstrated some success of broomrape control. However, these solutions can also damage non-target plant species and lead to the development of herbicide resistance. Environmental impact, coupled with the possibility for decreased efficacy over time, underlines the limits of traditional detection and control approaches. The most recent research suggests that customized treatments may be designed that efficiently reduce infestations and avoid the unneeded application of chemicals. Research is underway on new ways for early detection and integrated pest control (IPM) to lessen dependence on broad-spectrum pesticides. These techniques are aimed at a more sustainable balance whereby pesticides are used only when and where they are actually required, therefore saving the agricultural environment and decreasing the total ecological imprint of crop production. The increased interest in sophisticated remote sensing techniques for solving these difficulties. Studies have shown that hyperspectral and multispectral imaging throughout visible light, infrared and thermal bands can greatly improve the possibility of detecting physiological changes in plants due to illnesses or pests. These technologies are especially useful for detecting early indicators of broomrape infestation that is vital for prompt and focused treatment measures. The use of drones with multispectral sensors is a potential

ISSN: 2581-9429
Volume 6, Issue 20, April 2026
Impact Factor: 8.2

approach for accurate mapping of broomrape infestations within crop fields. They allow farmers to spray herbicide selectively rather than over entire fields, by detecting small variations in reflectance spectra from afflicted plants compared to healthy ones. Such a tailored method helps to save resources, reduce environmental impact and decrease the chance of herbicide resistance. Moreover, the complexity and quantity of data produced by these remote sensing technologies necessitate advanced analytical methodologies. Recent advances in machine learning and deep learning, particularly the use of Long Short-Term Memory (LSTM) networks, have been shown to be useful in simulating temporal changes in plant health that are critical in detection of infestations before they are visually visible. Moreover, researchers have used approaches like Synthetic Minority Over-sampling Technique (SMOTE) to address the data imbalance problem, where data of healthy plants are much more than those of ill ones . This technique balances the datasets and improves the accuracy of prediction models for recognizing the presence of illness.

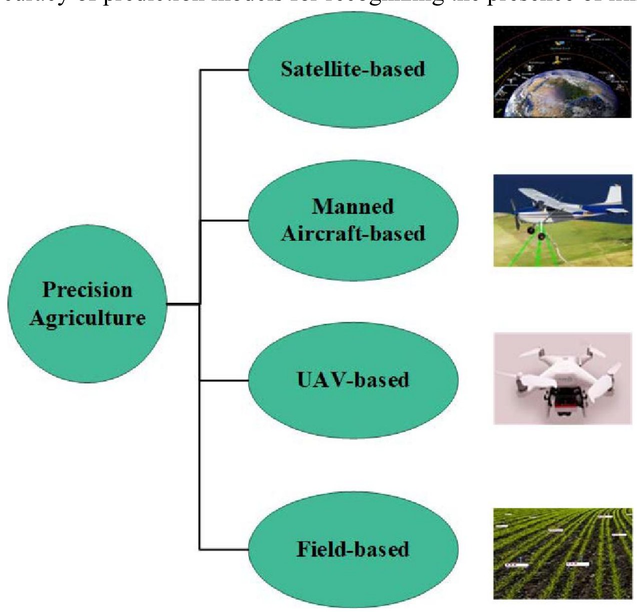

Figure.1. UAV based Sensor

Figure.2. Drone Image

This project aims to build a robust detection method for branching broomrape in tomato farms using multi-spectral images obtained by drones. We seek to achieve this by three primary goals: (1) to evaluate the ability of drone multispectral imagery to identify spectral changes to the canopy and leaves of tomato plants that may be indicative of broomrape infestation despite the predominantly subterranean nature of the parasite’s life cycle; (2) to identify the earliest growing degree day at which broomrape can be detected with acceptable Accuracy using our deep learning model; and (3) to assess the effect of using sequential data that represent different growth stages in a Long Short-Term Memory (LSTM) model on the Accuracy of broomrape detection. The UAV sensor is shown in Figure 1. The novel

DOI: 10.48175/IJARSCT-34675

technique aims to reduce the negative effect of broomrape on tomato productivity and to build a paradigm for sustainable pest control approaches in agriculture. This work aims to give practical insights to improve broomrape detection techniques' accuracy and efficiency by emphasizing the combination of technology and modeling. This research was conducted to address the problems of branching broomrape (Phelipanche ramosa) in California, a state with major tomato production. Broomrape has a hidden lifespan, causing serious harm from below ground level, and hence a new way to early identification was needed. By employing multispectral images collected by drones and LSTM networks with SMOTE data augmentation, we devised a technique for high-Accuracy detection of sick plants. Our results demonstrated the effectiveness of utilizing temporal data with balanced datasets, notably in Scenario 4, where we achieved an overall Accuracy of 88.37% and Recall of 95.37% in identifying broomrape, marking a considerable advancement towards early disease intervention. The results are consistent with our main goals, showing that multispectral imaging data are suitable for detecting spectral differences that may be used as an indicator of broomrape infestation. Furthermore, the earliest observable development stage with acceptable Accuracy was detected at 897 GDD, which shows the possibility for earlier intervention. Merging all development phases into the LSTM model resulted in a considerable increase in detection Accuracy, highlighting the advantages of sequential data analysis in this situation. The drone image is shown in Figure 2.However, the research also showed the inherent limits of synthetic data augmentation and the necessity for more complete real-world data to train and test the model. Going forward, large-scale data gathering from a range of farms and situations will be important to further enhance the model performance. Our study opens the path for future advances with the objective of converting our LSTM model into a robust and field-ready tool for farmers to manage and mitigate the impacts of broomrape in a more effective and sustainable manner. This focus on innovation in precision agriculture is a good omen for crop management and the future of tomato production in California and elsewhere.

The revised data were used for training and validating the model for the gathering of necessary information from the crop. The system was used in the field for problem analysis. It was noticed that the segmentation and illness detection ability of the system was enhanced. However, vegetation index performance has been degraded. The system performance may be increased with the use of different deep learning networks and better data labeling In the recent decade several noteworthy results have been derived in the crop monitoring study. Recently, a variety of crop condition-monitoring systems are created from remote sensing data. These crop condition monitoring approaches may be categorized as direct monitoring methods, picture classification methods and IoT based crop monitoring. IOT based technology uses several sorts of sensors for collecting agricultural data. These data are processed using a simulation model. This technology makes optimal use of resources, improves data collecting, saves time, and reduces human labor. This technology has various disadvantages including complexity, security and privacy.

III. CONCLUSION

The result is that the use of drones in precision agriculture has increased rapidly since 2017. The rise is largely due to the reduction in weight and cost of the UAVs and the improvement in payload capabilities. Drones are extensively employed for agricultural health monitoring and livestock identification, with the majority being multi-copter and fixed-wing kinds, while unmanned helicopters are utilized for pesticide and fertilizer spraying due to their greater payload capacity. Spot spraying using multi-copters is gaining popularity because of their greater flying stability. The drone cameras have changed dramatically in terms of weight, size and resolution from RGB to multispectral cameras for better feature extraction. The controllers have evolved from simple microcontrollers to artificial intelligence enabled boards like Arduino Uno, Raspberry Pi. Overall, the drone technology is progressing from semi-controlled systems to completely automated solutions, supported by advances in embedded systems, data transmission and data processing. The inclusion of machine learning has further empowered the farmer friendly solutions.

Multi-spectral photography and machine learning combined is a great tool for the issues of modern agriculture. Our solution provides real-time data-driven insights to improve decision making and encourage resource-efficient agricultural techniques. The system, however, is not perfect yet. A possible avenue is the use of hyperspectral cameras that collect much more comprehensive data over hundreds of spectral bands.

REFERENCES

[1]. Fang, Y.; Sun, H.; Yan, Y.; Ren, J.; Dong, D.; Chen, Z.; Yue, H.; Durrani, T. Wheat Growth Assessment for Satellite Remote Sensing Enabled Precision Agriculture. In Proceedings of the 8th International Conference on Communications, Signal Processing, and Systems, Urumqi, China, 20–22 July 2019; Lecture Notes in Electrical Engineering. Springer: Singapore, 2020; Volume 571.

[2]. Choroś, T.; Oberski, T.; Kogut, T. UAV Imaging at RGB for Crop Condition Monitoring. In Proceedings of the XXIV ISPRS Congress, the International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences—ISPRS Archives, Nice, France, 31 August–2 September 2020; Volume 43.

[3]. Guebsi, R.; Mami, S.; Chokmani, K. Drones in Precision Agriculture: A Comprehensive Review of Applications, Technologies, and Challenges. *Drones* 2024, *8*, 686.

[4]. Zhu, B.; Chen, S.; Xu, Z.; Ye, Y.; Han, C.; Lu, P.; Song, K. The Estimation of Maize Grain Protein Content and Yield by Assimilating LAI and LNA, Retrieved from Canopy Remote Sensing Data, into the DSSAT Model. *Remote Sens.* 2023, *15*, 2576.

[5]. Fu, H.; Lu, J.; Chen, J.; Wang, W.; Cui, G.; She, W. Influence of Structure and Texture Feature on Retrieval of Ramie Leaf Area Index. *Agronomy* 2023, *13*, 1690.

[6]. Su, X.; Nian, Y.; Yue, H.; Zhu, Y.; Li, J.; Wang, W.; Sheng, Y.; Ma, Q.; Liu, J.; Wang, W.; et al. Improving Wheat Leaf Nitrogen Concentration (LNC) Estimation across Multiple Growth Stages Using Feature Combination Indices (FCIs) from UAV Multispectral Imagery. *Agronomy* 2024, *14*, 1052.

[7]. Fu, Z.; Jiang, J.; Gao, Y.; Krienke, B.; Wang, M.; Zhong, K.; Cao, Q.; Tian, Y.; Zhu, Y.; Cao, W.; et al. Wheat Growth Monitoring and Yield Estimation Based on Multi-Rotor Unmanned Aerial Vehicle. *Remote Sens.* 2020, *12*, 508.

[8]. Zhang, J.; Cheng, T.; Shi, L.; Wang, W.; Niu, Z.; Guo, W.; Ma, X. Combining Spectral and Texture Features of UAV Hyperspectral Images for Leaf Nitrogen Content Monitoring in Winter Wheat. *Int. J. Remote Sens.* 2022, *43*, 2335–2356.

[9]. Fu, Z.; Yu, S.; Zhang, J.; Xi, H.; Gao, Y.; Lu, R.; Zheng, H.; Zhu, Y.; Cao, W.; Liu, X. Combining UAV Multispectral Imagery and Ecological Factors to Estimate Leaf Nitrogen and Grain Protein Content of Wheat. *Eur. J. Agron.* 2022, *132*, 126405.

[10]. Liao, Z.; Dai, Y.; Wang, H.; Ketterings, Q.M.; Lu, J.; Zhang, F.; Li, Z.; Fan, J. A Double-Layer Model for Improving the Estimation of Wheat Canopy Nitrogen Content from Unmanned Aerial Vehicle Multispectral Imagery. *J. Integr. Agric.* 2023, *22*, 2248–2270.

[11]. Larkin, R.P.; Griffin, T.S.; Honeycutt, C.W. Rotation and Cover Crop Effects on Soilborne Potato Diseases, Tuber Yield, and Soil Microbial Communities. *Plant Dis.* 2010, *94*, 1491–1502.

[12]. Nouri, A.; Lukas, S.; Singh, S.; Singh, S.; Machado, S. When Do Cover Crops Reduce Nitrate Leaching? A Global Meta-Analysis. *Glob. Change Biol.* 2022, *28*, 4736–4749.

[13]. Tahir, M.; Fernández, F.G.; Ricks, N.; Mulla, D.J. EPIC Model Prediction of Winter Rye Cover Crop Effects on Crop Yield and Nitrate-N Leaching in Minnesota. *Agron. J.* 2025, *117*, e70065.

[14]. Venkata Sai Chakradhar Reddy, D.; Sahoo, R.N.; Kondraju, T.; Rejith, R.G.; Ranjan, R.; Bhandari, A.; Moursy, A.; Tripathi, S.C.; Kumar, N. Drone-Based Multispectral Imaging for Precision Monitoring of Crop Growth Variables. *Biol. Life Sci. Forum* 2025, *41*, 10.

[15]. Caruso, G.; Tozzini, L.; Rallo, G.; Primicerio, J.; Moriondo, M.; Palai, G.; Gucci, R. Estimating Biophysical and Geometrical Parameters of Grapevine Canopies ('Sangiovese') by an Unmanned Aerial Vehicle (UAV) and VIS-NIR Cameras. *Vitis J. Grapevine Res.* 2017, *56*, 63–70.