© April 2025| IJIRT | Volume 11 Issue 11 | ISSN: 2349-6002

Crop Anaysis using Drone Technology (IOT Based, Agriculture)

Mr. Kushal R Borkar[1], Ms. Pallavi Chaple[2], Mr. Yashnil Jagnit[3], Mr. Harish BhajiKhaye[4], Prof. Mrunalini Moon[5], Dr. Anil Warbhe[6]

[1,2,3,4]Student, Department of Information Technology, Nagpur Institute of Technology, Rashtrasant Tukadoji Maharaj Nagpur University, Mahurzari, Katol Road Nagpur-441501

[5]Guide, Assistant Professor, Department of Information Technology, Nagpur Institute of Technology, Rashtrasant Tukadoji Maharaj Nagpur University, Mahurzari, Katol Road Nagpur-441501

[6]Associate Professor, Department of Information Technology, Nagpur Institute of Technology, Rashtrasant Tukadoji Maharaj Nagpur University, Mahurzari, Katol Road Nagpur-441501

1. INTRODUCTION

In the context of increasing global population and climate change, modern agriculture must enhance production efficiency. Vegetables production is crucial for human nutrition and has a significant environmental impact. To address this challenge, the agricultural sector needs to modernize and utilize advanced technologies such as drones to increase productivity, improve quality, and reduce resource consumption. These devices, known as Unmanned Aerial Vehicles (UAV), with their agility and versatility play a crucial role in monitoring and spraying operations. They significantly contribute to enhancing the efficacy of precision farming. The aim of this review is to examine the critical role of drones as innovative tools to enhance management and yield of vegetable crops cultivation. This review was carried out using the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) framework and involved the analysis of a wide range of research published from 2018 to 2023. According to the phases of Identification, Screening, and Eligibility, 132 papers were selected and analysed. These papers were categorized based on the types of drone applications in vegetable crop production, providing an overview of how these tools fit into the field of Precision Farming. Technological developments of these tools and data processing methods were then explored, examining the contributions of Machine and Deep Learning and Artificial Intelligence. Final considerations were presented regarding practical implementation and future technical and scientific challenges to fully harness the potential of drones in precision agriculture and vegetable crop production. The review pointed out the significance of drone applications in vegetable crops and the immense potential of these tools in enhancing cultivation efficiency. Drone utilization enables the reduction of input quantities such as herbicides, fertilizers, pesticides, and water but also the prevention of damages through early diagnosis of various stress types. These input savings can yield environmental benefits, positioning these technologies as potential solutions for the environmental sustainability of vegetable crops.

2. LITERATURE SURVEY

Table 1. Summary of the discussed related work.

Ref	Methodology	Pros	Cons
M. Istiak *et al.* (Istiak et al., 2023) (2023)	Determination of the impact of imaging modalities and imagery datasets in relation to agricultural applications, categorical evaluation of UAV configuration, and the feasibility assessment of UAVs in precision agriculture. In addition, the worldwide taxonomy of crops for which unmanned aerial vehicles are used is documented.	Perform a meta-analysis of recent studies on the use of UAVs for applications based on visual imagery in agriculture.	NA
Qin *et al.* (Qin et al., 2023) (2013)	They examine the impact of downwash airflow produced by a plant protection drone's flight altitude on the powdery mildew spores' horizontal, vertical, and ground distribution in wheat. Spore traps are used to track the evolving dynamics of airborne powdery mildew conidia.	The study offers a basis for scientific and reasonable spraying and control by agricultural drones, as well as for more in-depth research on the dissemination of powdery mildew spores and enhanced pest management.	The impact of airflow disturbance is closely linked to the release of powdery mildew pathogen spore numbers. The drone's rotor airflow has less of an impact on spore release in the early stages, when spore release is minimal.
Torres-Sanchez *et al.* (Torres-Sá et al., 2015) (2015)	An inventive Otsu-based thresholding Object-based Image Analysis (OBIA) algorithm was used to find vegetation in remotely sensed photos that were taken.	The classification error decreased as the object size increased until an optimal value was attained.	Once the ideal value was reached, increasing the size of the object led to larger errors, while the other parameters, like shape and compactness had little bearing on the classification accuracy.
Wang *et al.* (Wang et al., 2020) (2020)	To improve the prediction of grain yield, structural and spectral data taken from UAV-based images during the rice growing season is used.	Improving the accuracy of grain yield predictions and gaining effective crop growth monitoring.	NA
L. Li *et al.* (Li et al., 2018) (2018)	The half-Gaussian fitting method for FVC estimation (HAGFVC) is a novel approach for breaking down the Gaussian mixture strategy and estimating FVC.	The outcomes show that the HAGFVC approach can be applied correctly and effectively.	The prevalence of mixed pixels in LARS images, particularly at high altitudes above ground level or in the case of moderate vegetation coverage, caused other methods they tested to perform poorly.
J. Enciso *et al.* (Enciso et al., 2019) (2019)	A method for utilizing UAV data to measure crop height, canopy cover, and NDVI values in relation to time and space for three different tomato varieties during the growing season.	There was no discernible difference between the estimated UAV and manually measured crop heights, according to the computed paired t-test statistic.	Enhancements should be made to UAV crop growth and NDVI monitoring.
D. Stroppiana *et al.* (Stroppiana et al., 2018) (2018)	An unsupervised clustering algorithm was used to classify a multispectral orthomosaic that was created from images.	The most appropriate inputs were spectral indices, and SAVI and GSAVI produced the best results, with OA exceeding 94%.	NA
M. Der Yang *et al.* (Yang et al., 2017) (2017)	A thorough and effective UAV image classification method for agricultural areas. Image-based modeling and texture analysis yielded the digital surface model and texture information of the images in addition to spectral information.	A useful tool for evaluating rice lodging is their suggested hybrid image classification strategy, which combines spectral and spatial aspects.	NA
S. Malek *et al.* (Malek et al., 2014) (2014)	One suggested approach is to combine an active contour method based on Level Sets (LSs) with the keypoints of the ELM classifier to capture the shape of each tree.	The promising capabilities of their proposed framework were confirmed by the results of the experiments.	NA
R. Chew *et al.* (Chew et al., 2020) (2020)	A model pretrains using the publicly available ImageNet dataset and the VGG16 architecture, utilizing developments in deep convolutional neural networks and transfer learning.	At this scale, crops like maize and bananas can be categorized with great accuracy.	Legume crops, which are used in intercropping, can be challenging to reliably identify.
J. Rebetez *et al.* (Rebetez et al., 2016) (2016)	A hybrid CNN-HistNN deep neural network that can effectively classify a wide range of crops by utilizing both color distribution and texture patterns.	An enhancement in the performance of classification.	Many model parameters, like the number of layers and filters in the CNN, were absent from their analysis.
Q. Yang Rebetez *et al.* (Yang et al., 2020b) (2020)	A novel approach that uses RGB images to directly identify the main stages of rice growth.	The outcomes demonstrated the recommended deep learning method's outstanding performance in yield time estimation and phenology discovery in almost real time.	Early phenology is particularly difficult to distinguish because available data only spans a small portion of the growing season.
Bah *et al.* (Bah et al., 2018) (2018)	A novel fully automatic learning method for finding weed from UAV images that combines convolutional neural networks with an unsupervised training dataset.	The outcomes show performance that is comparable to supervised data classification.	NA
Fan *et al.* (Fan et al., 2018) (2018)	A novel deep neural network-based method is presented for identifying tobacco plants in UAV-captured images.	It performs well in accurately identifying and estimating the quantity of tobacco plants in UAV photos.	NA
Bah *et al.* (Bah et al., 2020) (2020)	A new method called CRowNet recognizes crops in UAV-captured images by using a convolutional neural network, the Hough transform, and a model created with S-SegNet.	The performance showed the best and most robust result when compared quantitatively with traditional approaches.	
Field data and superpixel standardization are not required for CRowNet.	NA		

3.PROBLEM STATEMENT

Agricultural drones can help farmers solve many problems, including:

- Irrigation problems
- Soil variation
- Pest and fungal infestations
- Crop and growth monitoring
- Yield estimation
- Water stress assessment
- Weeds, pest, and disease detection
- Soil health scans

Planning irrigation schedules.

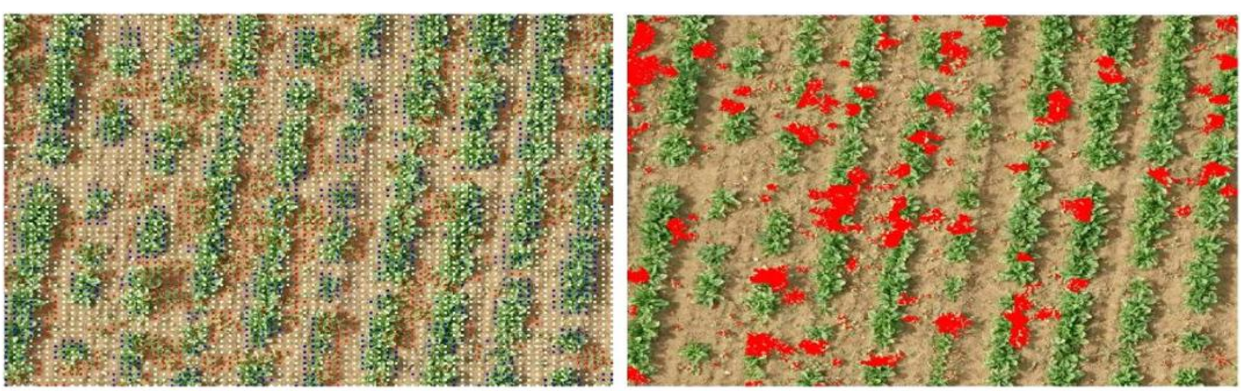
Drones in agriculture Drones are currently one of the most representative technologies in the evolution of precision agriculture in the scientific and productive world. However, their history began in other fields of application. The drone, in fact, originated as a tool to be employed in the military sector, aiming to safeguard the integrity of human personnel in reconnaissance and surveillance missions. Over time, their use has extended well beyond the military context, finding applications in various sectors, including entertainment, transportation, security, photography, and environmental exploration. The most common designation is "Unmanned Aerial Vehicles" (UAV). They can also be defined by other acronyms, many of which are of Anglo-Saxon origin: in addition to "Remotely Piloted Aircraft System" (RPAS), they may be referred to as "Unmanned Aerial System" (UAS), "Aerial Robot" or simply "Drone".

These terms refer to a complex system consisting of the aerial platform, one or more components and/or sensors making up the payload, and a ground station in communication with the flight controller of the platform. Within the flight controller, components dedicated to the orientation and movement of UAVs are present, including gyroscopes, magnetic compass, GNSS module, pressure sensor, and triaxial accelerometer.

UAVs are generally categorized based on various attributes, including aircraft types, wing types, take off/landing direction, payloads, flying altitude, etc.

According to the classification by Watt et al., they can be distinguished as MAV (Micro (or Miniature) or NAV (Nano Air Vehicles), VTOL (Vertical Take-Off & Landing), LASE (Low Altitude, Short-Endurance), LALE (Low Altitude, Long Endurance), MALE (Medium Altitude, Long Endurance), HALE (High Altitude, Long Endurance). The most used platforms in precision agriculture fall into the LASE class and are fixed-wing systems or multirotors, such as helicopters, quadcopters, hexacopters, octocopters, etc.

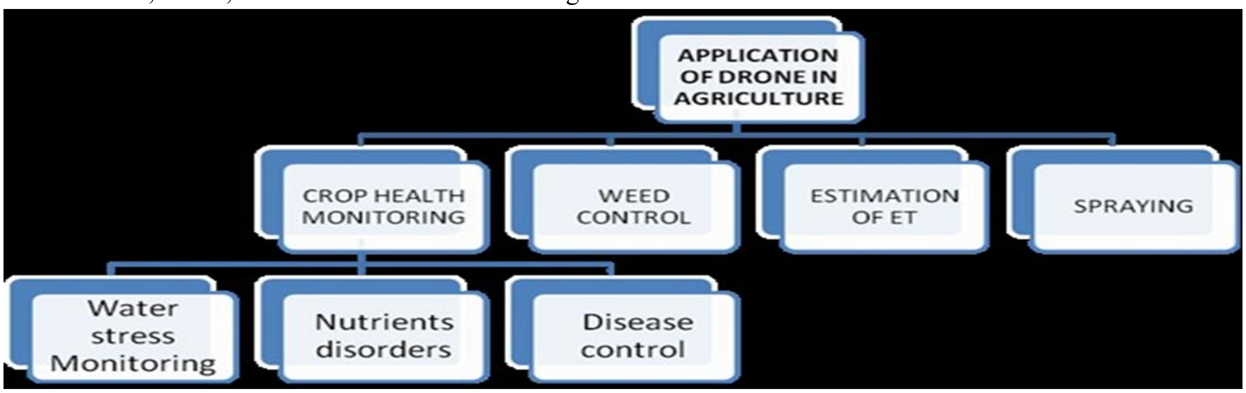
4. PROPOSED APPROACH



(a) (b)

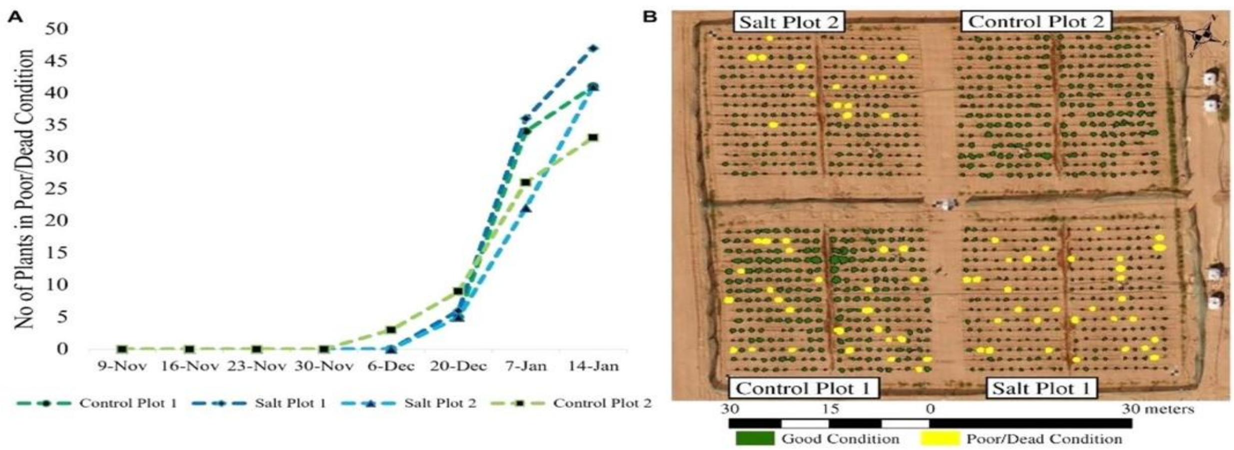
In vegetables cultivations, one of the fields where drone usage has become more established and widespread is the accurate and geospatial assessment of plant health and stress levels (Table 5). This practice has proven to be one of the most common and rooted applications in vegetable cultivation [120] and today it can be carried out with various methodologies and using different sensors. For instance, in potato cultivation, Th´eau et al. [102] employed a thermal infrared sensor for stress scouting and calculated the Temperature Vegetation Dryness Index (TVDI), resulting in accurate scouting maps. Meivel and Maheswari [103] used a multispectral camera and calculated various vegetation indices, including

Normalized Difference Vegetation Index (NDVI). Meanwhile, Butte et al. [104] proposed a deep learning algorithm named Retina- Unet Ag, capable of detecting healthy and diseased plants, with an average Dice Score Coefficient (DSC) of 0.74. The scientific community has increasingly recognized the solid connections between measurable parameters through these platforms and the degree of plant health. Many recent studies, in fact, use UAVs as tools for evaluating and quantifying plant responses to specific treatments. For instance, crop's response to different irrigation treatments was evaluated by Garcia- Garcia et al. [115] in tomato cultivation; they used NDVI to estimate the dynamics of Canopy Cover (CC) with varying water supply, while Fullana- Peric`as et al. [116] tested NDVI, Simple Ratio Index (SR), and Green Normalized Difference Vegetation Index.

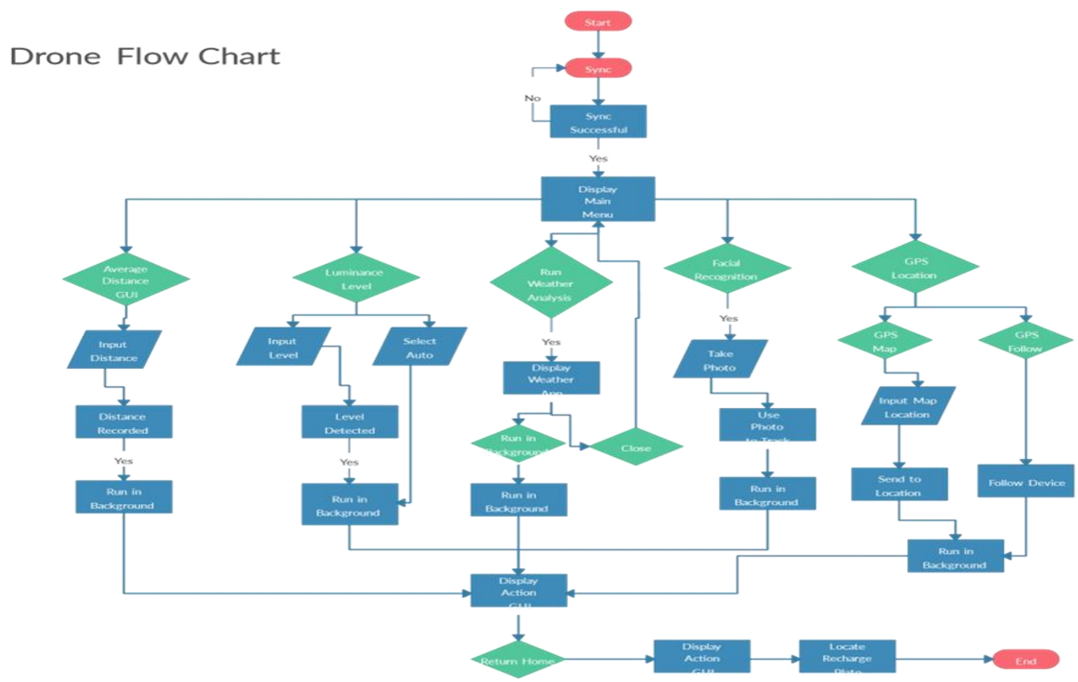


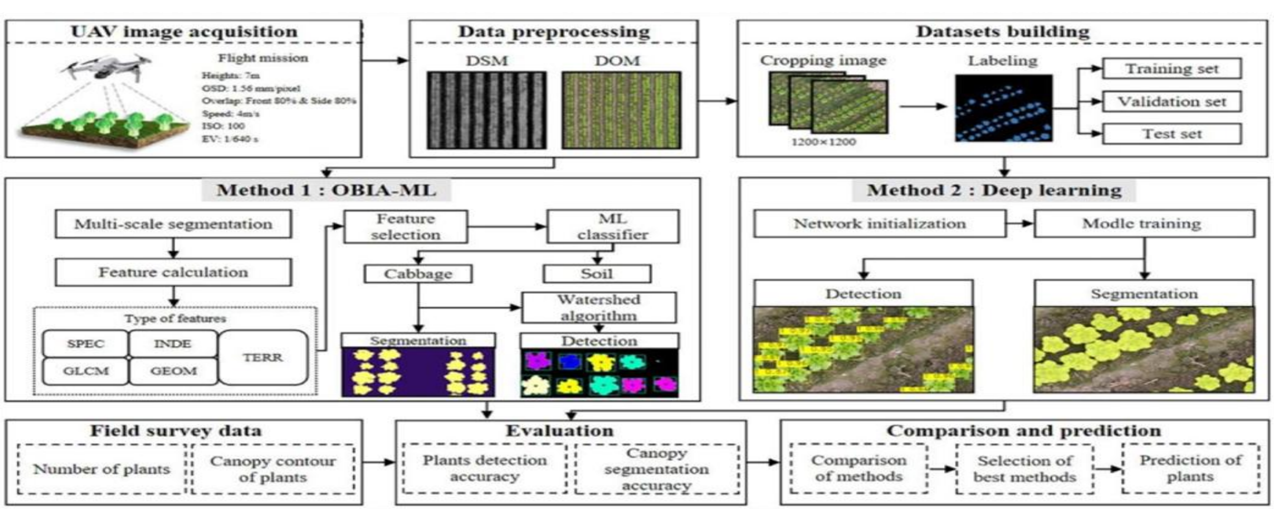
5. METHODOLOGY

Nutrient status and deficiency monitoring:
Plants need the appropriate levels of nutrients in order to thrive and produce a strong yield. The appropriate levels of nitrogen will ensure strong growth of vegetation and foliage, appropriate levels of phosphorous are required for strong root and stem growth and appropriate levels of potassium are necessary for improving of the resistance to disease and also to ensure a better quality of crop. If soil lacks any of these nutrients, the plant will become stressed and will struggle to thrive. NDVI Index mosaics offer the possibility to identify exactly which areas of the crops are stressed or struggling and to target directly these areas. The NIR/multispectral imagery provided by the UAVs can identify these management zones long before the problem become visible to the naked eye. This means that these management zones can be targeted before crop development and yield is affected.
Currently, the most common way to determine the nutritional status is visually, by means of plant colour guides that do not allow quantitatively rigorous assessments [26]. More accurate evaluations require laboratorial leaf analyses, which are time consuming and require the application of specific methods for a correct interpretation of the data [27]. There are some indirect alternatives available for some nutrients, such as the chlorophyll meter (Soil-plant analyses development (SPAD) for nitrogen predictions [28], but this is a time consuming process [29] and the estimates are not always accurate [30]. Thus, considerable effort has been dedicated to the development of new methods for the detection and estimation of nutritional problems in plants [31].
Nitrogen is, by far, the most studied nutrient due to its connection to biomass and yield. Potassium and sodium [32] have also received some attention. Multispectral images have been the predominant choice for the extraction of meaningful features and indices [33, 34], but RGB [35] and hyper spectral images [33] are also frequently adopted. Data fusion combining two or even three types of sensors (multispectral, RGB, and thermal) has also been investigated [35].
The vast majority of the studies found in the literature extracts vegetation indices (VI) from the images and relates them with nutrient content using a regression model (usually linear). Although less common, other types of variables have also been used to feed the regression models, such as the average reflectance spectra [32], selected spectral bands [34], colour features [36], and principal components [37]. All of these are calculated from hyper spectral images, except the colour features, which are calculated from RGB images.


A
No of Plants in Poor/Dead Condition
0
5
10
15
20
25
30
35
40
45
50
9-Nov 16-Nov 23-Nov 30-Nov 6-Dec 20-Dec 7-Jan 14-Jan
Control Plot 1
Salt Plot 1
Salt Plot 2
Control Plot 2
B
Salt Plot 2
Control Plot 2
Control Plot 1
Salt Plot 1
30 15 0 30 meters
Good Condition
Poor/Dead Condition

6.FLOWCHART


Drone Flow Chart
Start
Sync
No
Sync Successful
Yes
Display Main Menu
Average Distance GUI
Luminance Level
Run Weather Analysis
Facial Recognition
GPS Location
Input Distance
Input Level
Select Auto
Yes
Display Weather App
Close
Yes
Take Photo
GPS Map
GPS Follow
Input Map Location
Distance Recorded
Level Detected
Run in Background
Use Photo
Send to Location
Follow Device
Yes
Run in Background
Display Action GUI
Return Home
Display Action GUI
Locate Recharge
End


UAV image acquisition
Flight mission
Heights: 7m
GSD: 1.56 mm/pixel
Overlap: Front 80% & Side 80%
Speed: 4m/s
ISO: 100
EV: 1/640 s
Data preprocessing
DSM
DOM
Datasets building
Cropping image
Labeling
1200×1200
Training set
Validation set
Test set
Method 1 : OBIA-ML
Multi-scale segmentation
Feature calculation
Type of features
SPEC
INDE
TERR
GLCM
GEOM
Feature selection
ML classifier
Cabbage
Soil
Watershed algorithm
Segmentation
Detection
Method 2 : Deep learning
Network initialization
Modle training
Detection
Segmentation
Field survey data
Number of plants
Canopy contour of plants
Evaluation
Plants detection accuracy
Canopy segmentation accuracy
Comparison and prediction
Comparison of methods
Selection of best methods
Prediction of plants

7.TOOLS FOR DEVELOPMENT

Hardware Requirement:
UAV : DJI Mavic Air 2
Radio Transmitter: DJI N2
VR Box : JIO Dive

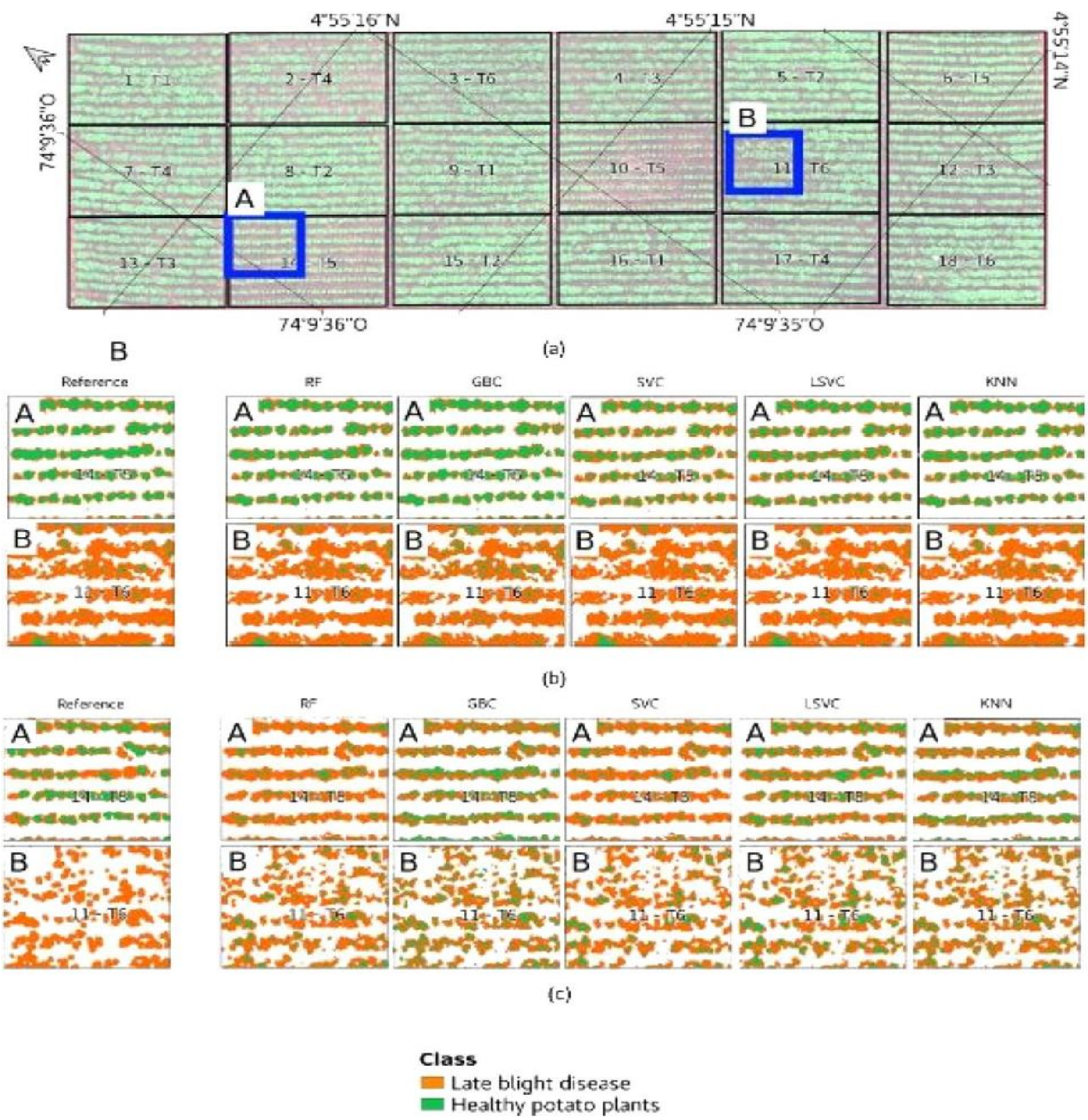
Software Requirement: DJI Fly, Digi Sky, Litchi, Air Data UAV, UAV Forecast. OS Platform

- Android.
- Coding Language: C++, Python, DJI Software Development Kit (SDK).
- Back End: Litchi Apk.
- protocol: OcuSync transmission Protocol.

Technology Used
UAV & FPV (A.R)

- IOT(Internet of Things): It is use to create a live project
- Jio 5G Network
- Jio Dive
- Auto Pilot & Obstacle Avoidance.

8.EXPECTED OUTCOME



REFERENCE

[1] I. FAO, The State of Food Security and Nutrition in the World 2023: Urbanization, agrifood systems transformation and healthy diets across the rural–urban continuum, FAO, IFAD, UNICEF, WFP, WHO, Rome, Italy (2023), https://doi.org/10.4060/cc3017en.

[2] S. Chakraborty, A.C. Newton, Climate change, plant diseases and food security: an overview, Plant Pathol. 60 (2011) 2–14, https://doi.org/10.1111/j.1365- 3059.2010.02411.x.

[3] J.S. Dias, Nutritional Quality and Health Benefits of Vegetables: A Review, Food and Nutrition Sciences 3 (2012) 1354–1374, https://doi.org/10.4236/fns.2012.310179.

[4] D. Aune, E. Giovannucci, P. Boffetta, L.T. Fadnes, N. Keum, T. Norat, D. C. Greenwood, E. Riboli, L.J. Vatten, S. Tonstad, Fruit and vegetable intake and the risk of cardiovascular disease, total cancer and all-cause mortality— A systematic review and dose-response meta-analysis of prospective studies, Int. J. Epidemiol. 46 (2017) 1029– 1056, https://doi.org/10.1093/ije/dyw319.

[5] R. Finger, S.M. Swinton, N. El Benni, A. Walter, Precision Farming at the Nexus of Agricultural Production and the Environment, Annual Review of Resource Economics 11 (2019) 313–335, https://doi.org/10.1146/annurevresource- 100518-093929.

[6] I. Kutyauripo, M. Rushambwa, L. Chiwazi, Artificial intelligence applications in the agrifood sectors, J. Agric. Food Res. 11 (2023) 100502, https://doi.org/ 10.1016/j.jafr.2023.100502.

[7] P. Radoglou-Grammatikis, P. Sarigiannidis, T. Lagkas, I. Moscholios, A compilation of UAV applications for precision agriculture, Comput. Netw. Chem. Lab. Symp. 172 (2020) 107148, https://doi.org/10.1016/j. comnet.2020.107148.

[8] P. Catania, E. Roma, S. Orlando, M. Vallone, Evaluation of Multispectral Data Acquired from UAV Platform in Olive Orchard, Horticulturae 9 (2023) 133, https://doi.org/10.3390/horticulturae9020133.

[9] M.V. Ferro, P. Catania, D. Miccich`e, A. Pisciotta, M. Vallone, S. Orlando, Assessment of vineyard vigour and yield spatio-temporal variability based on UAV high resolution multispectral images, Biosystems Eng. 231 (2023) 36–56, https://doi.org/10.1016/j.biosystemseng.2023.06.001.

[10] V. Gonzalez-Dugo, P. Zarco-Tejada, E. Nicol´as, P.A. Nortes, J.J. Alarc´on, D. S. Intrigliolo, E. Fereres, Using high resolution UAV thermal imagery to assess the variability in the water status of five fruit tree species within a commercial orchard, Precis. Agric. 14 (2013) 660–678, https://doi.org/10.1007/s11119-013- 9322-9.

[11] G. Messina, S. Pratic`o, G. Badagliacca, S. Di Fazio, M. Monti, G. Modica, Monitoring Onion Crop “Cipolla Rossa di Tropea Calabria IGP” Growth and Yield Response to Varying Nitrogen Fertilizer Application Rates Using UAV Imagery, Drones 5 (2021) 61, https://doi.org/10.3390/drones5030061.

[12] E. Roma, V.A. Laudicina, M. Vallone, P. Catania, Application of Precision Agriculture for the Sustainable Management of Fertilization in Olive Groves, Agronomy 13 (2023) 324, https://doi.org/10.3390/agronomy13020324.

[13] J. Torres-S´anchez, J.M. Pe˜na, A.I. de Castro, F. L´opez-Granados, Multi-temporal mapping of the vegetation fraction in early-season wheat fields using images from UAV, Comput. Electron. Agric. 103 (2014) 104–113, https://doi.org/10.1016/j. compag.2014.02.009