Enhancing Orchard Cultivation Through Drone Technology and Deep Stream Algorithms in Precision Agriculture

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***Abstract*—The integration of cutting-edge technology in agriculture has revolutionized traditional farming practices, paving the way for Smart Agriculture. This research presents a novel approach to enhancing the cultivation of orchard crops by combining deep-stream algorithms with drone technology. Focusing on pomegranate farming, the study employs a drone system with four specialized cameras: thermal, optical RGB, multi-spectral, and LiDAR. These cameras facilitate comprehensive data collection and analysis throughout the crop growth cycle. The thermal camera monitors plant health, yield estimation, fertilizer management, and irrigation mapping. The optical RGB camera contributes to crop managementby analyzing vegetation indices, assessing fruit quality, and detecting weeds. The multi-spectral and hyperspectral cameras enable early detection of crop diseases and assessment of damaged crops. LiDAR aids in understanding crop growth by measuring plant height, tracking phenology, and analyzing water flow patterns. The data collected is processed in real-time using Deep Stream algorithms on an NVIDIA Jetson GPU, providing predictive insights into key farming characteristics.Our model demonstrated superior performance compared to four established models—MDC, MLP, SVM, and ANFIS—achieving the highest accuracy (95%), sensitivity (94%), specificity (96%), and precision (91%). This integrated method offers a robust solution for precision agriculture, empowering farmers to optimize crop management, enhance productivity, and promote sustainable agriculture practices.**

Keywords*—Smart agriculture; crops; cultivation; deep stream algorithms; drone and technology

I. Introduction

Modern agriculture is undergoing a significant shift as a result of technological developments that promise to increase production, sustainability, and efficiency. One such innovative strategy is the use of deep stream algorithms and drone technology to revolutionise pomegranate farming. With their high nutritional content and rising demand, pomegranates stand to gain a lot from these cutting-edge methods. The use of drones outfitted with a variety of specialised cameras and cutting-edge data processing techniques is presented in this study as a comprehensive framework for automating the cultivation of pomegranates [1]. The fouronboard cameras—thermal, optical RGB, multi-spectral, and LiDAR—provide an abundance of real-time data that gives producers priceless insights into numerous facets of crop health and growth dynamics. A key component of this system is the thermal camera, which makes exact plant health assessments, precise irrigation mapping, effective fertiliser control, and yield estimation possible. This camera assists in the early diagnosis of stressed or unhealthy plants by collecting temperature fluctuations, enabling prompt treatments and optimising resource allocation. The optical RGB camera completes this functionality by measuring vegetation indices, evaluating the quality of the fruit, and even spotting weeds. This helps users make better decisions [2]. Multi-spectraland hyper-spectral cameras are essential for a more detailed analysis of crop conditions. They can recognize physical and biological traits that can point to underlying problems in pomegranate harvests to spot disease symptoms [3]. This ability guarantees early disease identification, enablesindividualized treatment plans, and reduces possible yield losses.

To maintain crop health and yield, UAVs mounted with thermal cameras could be used to monitor temperature differences in orchard crops. This allows for the early detection of plant stress, disease, or water inadequacies. Optical RGB cameras monitor crops' visual health and growth stages by taking high-resolution pictures for the analysis of vegetation indicators, fruit quality evaluation, and weed detection. Multispectral and hyperspectral cameras offer extensive spectral information to identify disease signs, nutrient deficits, and other physiological characteristics. This information enables precise, focused treatments to improve crop health and decrease losses. LiDAR technology provides vital insights into growth dynamics and optimizes irrigation techniques for more effective water use and improved orchardcrop management. Navigating UAVs mounted with such

LiDAR could also measure plant height, track crop phenology,and examine water flow patterns.

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A. Related Works

Authors in study [4] used UAVs in apple orchards using thermal and RGB imagery to detect frost damage, evaluate fruit sets, predict yields, and monitor bloom stages to improve thinning practices. Similarly, in study [5], the authors installed multi-spectral cameras over UAVs to navigate the citrus groves to identify diseases such as citrus greening, allowing for targeted therapies to minimize the spread of the disease. Drones are used in vineyards [6] to monitor vine health, evaluate grape quality, identify illnesses, and plan precise fertilization by using multi-spectral imagery to pinpoint nutrient deficiencies. Very recently, Sanchez et al. [7] used drones in olive orchards to improve irrigation schedules, map canopy structure, monitor water stress, and evaluate tree health using LiDAR data. In this work, we especially focus on pomegranate orchard management, building on the wide-ranging uses of UAVs in different orchard crops. With deep stream algorithms and drone technology, this extension seeks to optimize pomegranate agriculture and improve crop sustainability, productivity, and health.

The LiDAR camera provides crucial information on crop phenology, water flow patterns, and plant height. This new information improves our comprehension of pomegranate growth dynamics. It helps us make the best irrigation decisions, resulting in more effective water use and sustainablefarming methods [8]. The investigation uses the potent NVIDIA Jetson GPU for data processing to take advantageof the enormous amount of data these cameras have acquired. The system analyses the acquired data in real-time while utilizing deep-stream algorithms, allowing precise forecasts in key pomegranate cultivation areas. This entails monitoring crop health, analysing how dry the soil and vegetationare, determining how much fertilizer is needed, finding and controlling weed infestations, and quickly spotting instances of crop damage and disease.

The use of mechatronics, sensors, and IoT in agriculture is now essential, with drones emerging as a viable tool for mapping field variability and optimizing input applications. Drones have applications across various stages of plant growth and sectors such as livestock, horticulture, and forestry, enhancing field monitoring and decision-making [9], [10]. The survey in [11] examines various UAV applications, types, sensors, and architectures, comparing them with traditional technologies and highlighting their benefits andchallenges in precision agriculture. The article [12] reviewsthe use of UAVs for crop monitoring and pesticide spraying, which helps improve crop quality and mitigate health risks associated with manual pesticide application. Conventional weed management methods are inefficientfor integration with smart agricultural machinery, whereas automatic weed identification significantly improves crop yields. The study in [13] evaluates deep learning techniques (AlexNet, GoogLeNet, InceptionV3, Xception) for weed identification in bell pepper fields, with InceptionV3 achieving the highest accuracy of 97.7%, demonstrating the potential for integration with image-based herbicide applicators for precise weed management. UAV-based sprayers precisely target hard-to-reach areas, as demonstrated in a cotton field study [14] using advanced imaging and optimization techniques, achieving effective droplet deposition with a GWO-ANN model showing high prediction accuracy. UAV imagery with an in-house web application, "DeepYield," [15] uses deep learning models like SSD, Faster RCNN, YOLOv4, YOLOv5, and YOLOv7 to measure citrus orchard yields. Here, YOLOv7 excelled with a mAP, Precision, Recall, and F1-Score of 86.48%, 88.54%, 83.66%, and 86.03%, respectively, and the solution was integrated into DeepYield for automated yield estimation.

Water flow mapping, crop phenology monitoring, and plant height measurement have all benefited from the use of LiDAR technology. Prominent research, like [16], has shown how important it is for comprehending development dynamics and making the most use of water. Deep Stream Algorithm with NVIDIA Jetson GPU: The combination of these two technologies has proved essential for data processing. The effectiveness of this arrangement in real-time analysis was demonstrated by research by [17], allowing predictions in crop health, soil dryness, fertilizer needs, weed identification, and disease detection [18]. The literature has recognized that there are challenges with calibration, data quality, and system scalability [19]. Further developments will involve improving algorithms, adding meteorological information, and customizing systems for certain crops and geographical areas. Table I-B summarizes recent studies on applying drones and various sensors in orchard crops, covering yield estimation and the learning model used in the works.

B. Motivation

Agriculture is undergoing a technological transformation with the integration of unmanned aerial vehicles (UAVs), commonly known as drones, and advanced algorithms [20]. This literature survey explores the state-of-the-art in the automation of pomegranate cultivation, focusing on the use of drones equipped with thermal, optical RGB, multi-spectral, and LiDAR cameras. The processing of collected data is facilitated by the NVIDIA Jetson GPU using deep-stream algorithms, enabling real-time predictions for various aspects of crop management. The capacity of drone technology to deliver high-resolution, real-time data for precision farming has made it more and more popular in the agricultural sector. Prior research, such as that done by [21], showed how useful drones are for determining crop health, maximizingresource utilization, and increasing production. Plant health inspections have made considerable use of thermal cameras. Thermal imaging is useful in identifying stress factors, refiningirrigation plans, and calculating crop yields, according to research by Messina et al. [22]. Optical RGB Imaging for Vegetation Indices and Quality: Research, such as the workby Devi et al. [23], highlights the application of optical RGB cameras for weed detection, fruit quality evaluation,and vegetation index measurement. This all-inclusive method helps to create accurate crop plans. Hyper- and Multi-Spectral Imaging for Illness Detection: Researchers have looked atthe use of hyper- and multi-spectral cameras for illness detection [24]. These cameras can analyze both biologicaland physical parameters and identify damaged crops basedon spectral fingerprints.

TABLE I. DRONE AND SENSOR APPLICATIONS IN ORCHARD CROPS

Authors	Crop Type	Work Description	Type of Sensor Used	Methodology	Model Developed	Accuracy
He et al. [25]	Apple	Yield estimation, health monitoring	RGB, Thermal Cameras	Image analysis, temperature mapping	Regression Model	92%
Jemaa et al. [26]	Apple	Health prediction	RGB, Thermal Cameras	Health index calculation, stress mapping	SVM	89%
Chandel et al. [27]	Apple	Irrigation scheduling	Thermal, RGB Cameras	Soil moisture mapping, temperature analysis	Regression Model	90%
Sun et al. [28]	Citrus	Yield prediction, soil dryness detection	Multi-Spectral Camera	Spectral reflectance analysis	SVM, KNN	87%, 85%
Modica et al. [29]	Citrus	Irrigation optimization	Multi-Spectral Camera	Spectral reflectance analysis	SVM	87%
Lan et al. [30]	Citrus	Yield prediction	Multi-Spectral Camera	Spectral reflectance analysis	SVM	89%
Marques et al. [31]	Olive	Water stress monitoring	LiDAR, RGB Cameras	Canopy structure analysis, water stress indexing	ANN	88%
Ferro et al. [32]	Vineyard	Yield prediction, health monitoring, weed presence	RGB, Multi-Spectral	Vegetation index calculation, clustering, weed mapping	K-Means, ANN	91%, 90%
Jones et al. [33]	Vineyard	Yield prediction	RGB, Multi-Spectral	Vegetation index calculation, clustering	K-Means, ANN	94%
Miranda et al. [34]	Pomegranate	Yield monitoring, irrigation optimization	RGB, Thermal, LiDAR	Multi-modal data analysis	Deep Learning	95%
Zhang et al. [35]	Pomegranate	Disease detection, crop damage detection	RGB, Thermal, LiDAR	Multi-modal image analysis	Deep Learning	93%
Olorunfemi et al. [36]	Pomegranate	Yield monitoring	RGB, Thermal, LiDAR	Multi-modal image processing	Deep Learning	95%

The literature review highlights the increasing amount of research on automated crop production, especially with pomegranates, using deep-stream algorithms and drone technology. All of the research included in the survey demonstrates how this strategy may be used to maximize the use of available resources, increase crop productivity, and support sustainable agriculture. However, despite significant advancements, there remain notable gaps in the integration and application of these technologies, specifically for orchard crops such as pomegranates. This research addresses thesegaps by proposing a comprehensive approach combining drone technology with deep-stream algorithms to optimize pomegranate cultivation.

Previous studies have examined the application of UAVs with different sensors in agriculture. Still, there is a lack of research specifically addressing the customization of these technologies for orchard crops such as pomegranates. Previous studies have primarily focused on general crop management, neglecting the specific needs of orchard farming. This field requires more precise and specialized approaches that have yet to be thoroughly explored. In addition, there is still much to be explored regarding integrating real-time data processing with deep-stream algorithms. Specifically, there is a need to understand how this integration can improve decision-making in pomegranate farming. This study addresses the existing gaps in the field by presenting a fresh approach that utilizes advanced cameras (thermal, optical RGB, multi-spectral, and LiDAR) installed on drones. These cameras are combinedwith the high-speed processing capabilities of deep streamalgorithms on an NVIDIA Jetson GPU. With this integration, you can closely monitor and manage every stage of the pomegranate growth cycle. This provides valuable insightsfor enhancing yield, promoting plant health, and ensuring high-quality crops. Focusing on pomegranates, a crop boasting high nutritional value and growing demand, this research tackles a specific need in the agricultural sector.

Moreover, it contributes to advancing sustainable and precision agriculture. The study's findings highlight the immense potential for transforming orchard farming and offer a solid foundation that can be applied to other crops. This has the potential to expand the advantages of Smart Agriculture practices to a wider range of crops.

A game-changing strategy for modernizing pomegranate production is presented via the combination of drone technology with deep stream algorithms. In the dynamic environment of pomegranate farming, this work aims to provide farmers with a cutting-edge toolkit that enables them to make data-driven decisions, improve production, and support sustainable agricultural practices. The following are key contributions of this research article:

- Introduces a pioneering approach combining drone technology and deep stream algorithms for pomegranate production.
- Provides farmers with advanced tools for data-driven decision-making in pomegranate farming.
- Enhances pomegranate yield and quality through precise monitoring and analysis.
- Promotes sustainable agricultural practices in pomegranate cultivation.

The rest of the article is organized as follows: Section II provides the methodology of how UAVs operate, particularly for agricultural applications, and how their built-in sensors are utilized for crop management in orchards. It also focuses on how the Deep Streaming technique is deployed for pomegranate cultivation. Section III shows how the processing power of the NVIDIA Jetson GPU is used for the automated cultivation of pomegranates. Finally, Section IV summarizes the key findings of the work with the conclusion of the proposed work.

II. METHODOLOGY

This section focuses on the methodology used for the investigation in terms of data collection, camera analysis and the implications and association of deep streaming framework applied over the UAV data of pomegranate cultivation. In Fig. 1, the present investigation illustratesa revolutionary approach to enhance pomegranate farmingthat combines deep-stream algorithms and drone technology. The drone system has four specialized cameras: a LiDARcamera, a thermal camera, an optical RGB camera, and a multi-spectral camera. These cameras are effective tools for comprehensive data gathering and analysis throughout the pomegranate growing cycle. For yield estimation, fertilizer management, irrigation mapping, and plant health assessment, the thermal camera is crucial. By detecting variations in plant temperature, the thermal camera helps identify stressed or ill plants and allows for quick response. The optical RGB camera's capability to monitor vegetation indices, assess fruit quality, and detect weeds further enhances crop management techniques [37]. The multi-spectral and hyperspectral cameras allow for the identification of harmed crops and the examination of their biological and physical characteristics. The multi-spectral analysis enables early diagnosis of agricultural diseases, enabling customized treatments. The LiDAR camera aids researchers in their understanding of how plants grow by measuring plant height, monitoring crop phenology, and looking at water flow patterns. The NVIDIA Jetson GPU and deep stream algorithmsare employed to process the camera data. This processingpipeline allows for real-time analysis of the gathered data, giving predictive insights into several essential aspects of pomegranate cultivation. The use of technology facilitates crop health monitoring, evaluates soil and plant moisture, establishes the demand for fertiliser, finds weeds, and scans fordisease and crop damage indicators [38]. Overall, this work provides an integrated approach to pomegranate cultivation that combines deep stream algorithms and drone technology to enable accuracy and data-driven decision-making.

A. *Brief Mechanism of Drones and its Associated Sensors*

UAVs are becoming indispensable instruments in contemporary agriculture, especially for precision farming. Multiple sensors can be carried by them, enabling thorough monitoring and analysis of crop productivity, growth, and health. Here, we go over how drones work and how their built-in sensors are utilized for crop management in orchards.

UAVs used in agriculture could be integrated with multiple essential parts to enable them to carry out certain jobs efficiently [39]. UAVs can hover, navigate, and gather data over wide distances because of the flying system's stability and maneuverability, which is provided by a lightweight frame, motors, propellers, and battery. GPS, accelerometers, gyroscopes, and magnetometers are examples of navigation and control components that provide precise navigation and flight path maintenance, enabling pre-planned missions and real-time modifications. The communication system enables remote operation through ground control stations and real-time data transfer via radio frequencies or cellular networks [40].

UAVs' sensors greatly increase their efficacy in precision agriculture because each one gives vital information for thorough crop management. For example, infrared radiation released by plants fluctuates with temperature and may be detected by thermal cameras [41]. This radiation can be used to identify stress factors such as pest infestation, disease, or water shortage. Thermal cameras are used in agricultural applications to detect temperature differences within the crop canopy. This allows for the monitoring of general health, early identification of plant stress, and watering requirements. With the aid of these cameras, temperature fluctuations inside the crop canopycan be identified, facilitating the early identification of plant stress, the need for irrigation, and general health monitoring. To create high-resolution images of the crop canopy, optical RGB cameras collect visible light in the red, green, and black wavelengths [42]. These images are then used to monitor fruit quality, identify weeds, and assess vegetation indices, which helps farmers make decisions about crop health and management techniques.

Beyond the visible spectrum, multispectral and hyperspectral cameras record information in a variety of wavelengths, such as ultraviolet and near-infrared. To provide comprehensive spectral information necessary for identifying certain crop situations including nutrient deficits, disease signs, and physiological stress, hyperspectral cameras gather data in hundreds of small spectral bands. Precision medicine and targeted interventions are made possible [43].

Fig. 1. Core functional modules in the proposed methodology.

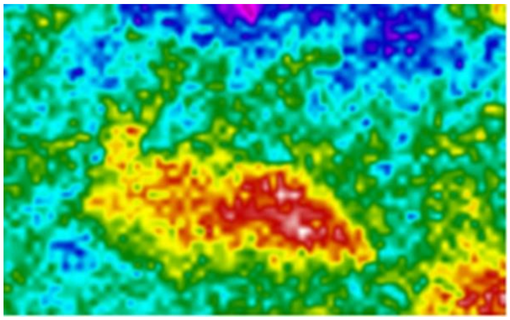


Fig. 2. Thermal imaging for plant health assessment.

LiDAR cameras measure plant height, track crop phenology, examine water flow patterns, and produce precise 3D mapsof the landscape and vegetation structure using laser pulses. Understanding the dynamics of plant growth, improving irrigation techniques, and improving crop management generally all depend on this data.

Yield prediction integrates data from thermal, RGB, and multi-spectral sensors to estimate possible yields [44]. Water use is optimized by irrigation management through the use of thermal and LiDAR data. Through multispectral and hyperspectral analysis, health monitoring identifies nutritional inadequacies and early indicators of disease. Using accurate data, resource optimization effectively handles inputs such as fertilizers. With the help of these cutting-edge technologies, orchard crop management, and productivity may be fully monitored and managed, improving agricultural sustainability and production.

B. Thermal Camera Analysis

To evaluate the health of pomegranate plants, identify stress, and track temperature changes, thermal images of the plants should be taken. Maps of temperature distribution made from thermal data can be used to find possible problem locations. Use the heat data to calculate yields, control fertilizer applications, and map irrigation. Technological developments have made it possible for creative methods of crop management and optimization in modern agriculture [45]. Utilizing thermal imaging to evaluate plant health, identify stress, and track temperature swings in pomegranate plants is one such ground-breaking method. Farmers and agronomists can enhance irrigation techniques, control fertilizer use, and predict crop production by utilizing the potential of thermal data.

1) Thermal imaging for plant health assessment: Radiometric temperature readings from pomegranate plants are obtained using thermal cameras. Stressed or ill plants show temperature anomalies, whereas healthy plants have rather consistent thermal fingerprints. Areas of possible concerncan be located by analyzing these thermal images, enabling focused intervention and mitigation as shown in Fig. 2.

2) Stress detection and temperature variations: Thermal imaging is a non-invasive method for identifying signs of stress in pomegranate trees. Temperature changes inside the plant canopy can emphasize stress brought on by things like a lack of water, an unbalanced diet, or pest infestations as shown in Fig. 3. Knowing these stress patterns allows for early detection and prompt intervention.

3) Temperature distribution maps for precise insights: The generation of maps showing the spread of temperaturein pomegranate orchards is made easier by processing thethermal data that was gathered. These maps give farmers avisual representation of temperature differences throughout theentire field, allowing them to locate “hot” or “cold” areas thatmight be signs of unequal irrigation, drainage problems, orother specific problems as shown in Fig. 4.

4) Accurate irrigation mapping: Thermal data reveals regions with high temperatures, indicating potential water stress, which aids in precise irrigation mapping. Farmers can adjust their watering schedules to maintain consistent moisture distribution and reduce water-related stressors by associating these temperature differences with particular irrigation zones as shown in Fig. 5.

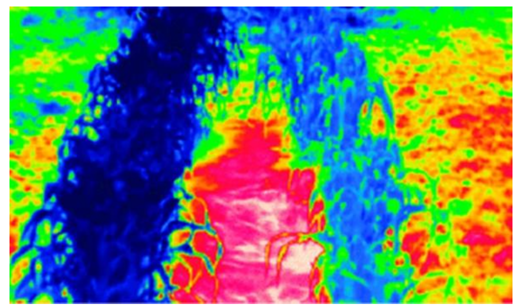


Fig. 3. A Sample stress detection in an agricultural land observed through thermal camera.

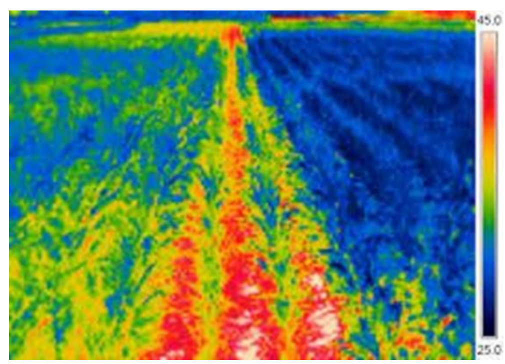


Fig. 4. Temperature distribution maps for precise insights.

C. Optimal Fertilizer Management

The use of thermal imaging helps handle fertiliser more effectively. Temperature variations can reveal changes in the absorption and utilization of nutrients. Farmers may strategically apply fertilizers where they are most required, saving waste and fostering healthy development, by merging heat data with soil nutrient analysis.

1) Yield estimation and harvest planning: More precise yield estimation is made possible by the thermal data insights. Variations in fruit development and maturation may be correlated with anomalies in temperature distribution. Farmers can predict production swings and adjust their harvest date by taking into account this information. Precision agriculture has essentially advanced thanks to the use of thermal imaging technology in pomegranate farms. Farmers are better able to proactively solve problems, maximize resource use, and improve the general health of their crops thanks to the capacity to record, process, and analyze thermal data. The agricultural sector may get closer to sustainable practices by utilizing thermal insights for irrigation, fertilization, and yield management. These techniques maximize productivity while reducing their negative effects on the environment. The incorporation of thermal imaging into agricultural practices is poised to revolutionize how we grow and maintain our crops as technology advances.

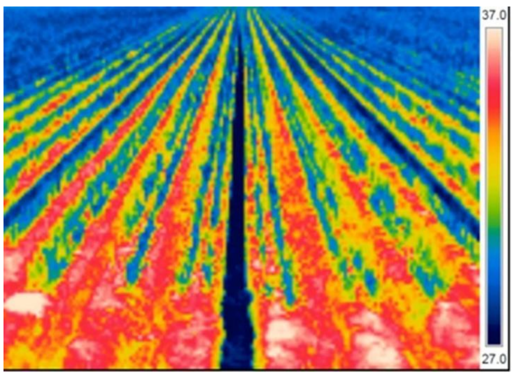


Fig. 5. Accurate irrigation mapping through drone-mounted thermal cameras.

2) Optical RGB camera analysis: Utilizing RGB (Red-Green-black) photography in modern agriculture has become a potent and adaptable tool for a variety of tasks, from determining weed presence to evaluating fruit qualityand vegetation health [46]. Researchers and farmers mayimprove crop management tactics, quantify key indices, and make educated decisions to maximize production andsustainability by utilizing modern image processing tools.

3) Quantify vegetation indices for health assessment: Important vegetation indices, like the widely used NDVI (Normalised Difference Vegetation Index), can be calculated using RGB photos. By comparing the reflectance of visible red and near-infrared light, NDVI acts as a quantitative indicator of plant health. This knowledge makes it easier to spot possible stressors and allows for tailored crop-growth-promotingactions as shown in Fig. 6.

4) Assessing fruit quality with image analysis: Color, size, and shape are some examples of fruit quality factorsthat can be evaluated using RGB imaging. Farmers can assess fruit maturity and harvest readiness by examining the color spectrum. In addition to quantifying variations in fruit size and form, image processing algorithms may also grade and categorize products based on their quality as shown in Fig. 7.

5) Weed detection and classification: It is possible to use the RGB imagery to look for weeds in crop fields. For advanced algorithms to distinguish between crops and undesirable vegetation, color, shape, and texture features are examined. Farmers can develop tailored weed control methods and increase yields by minimizing resource competition by automating weed detection as shown in Fig. 8.

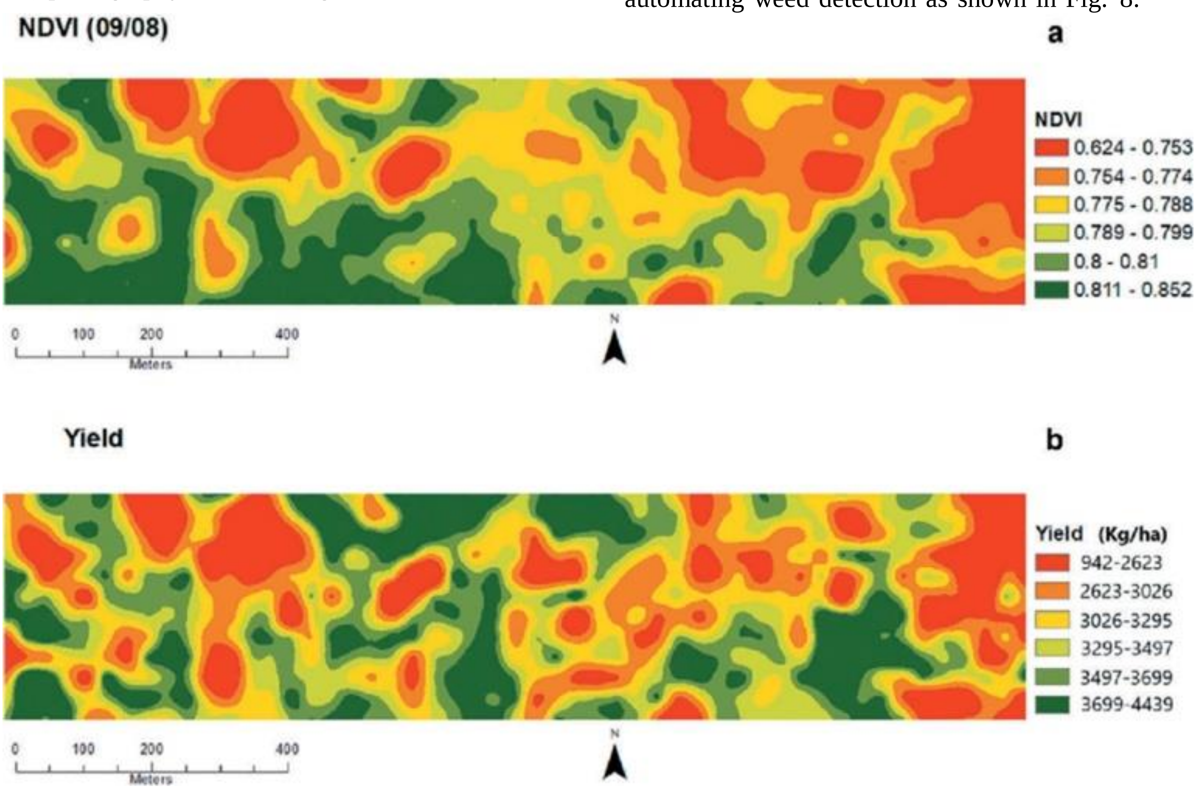


Fig. 6. Vegetation indices for health assessment.

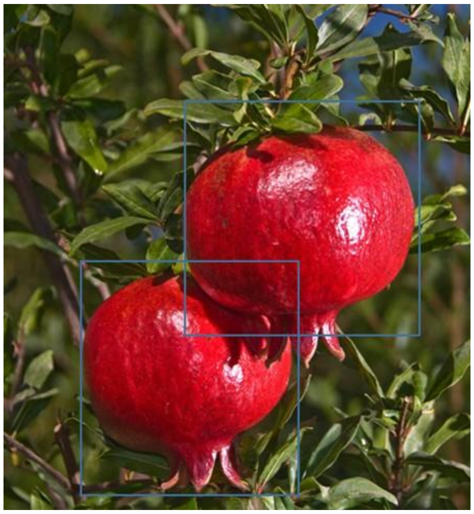


Fig. 7. Image analysis of pomegranate for fruit quality assessment.

6) Color analysis for pest and disease identification: When it comes to identifying pests and illnesses that impactcrops, RGB images can be useful. Leaf color and patternchanges may be a sign of an infection or an infestation.

Fig. 8. Weed detection for optimal irrigation.

Fig. 9. Color analysis for pest and disease identification.

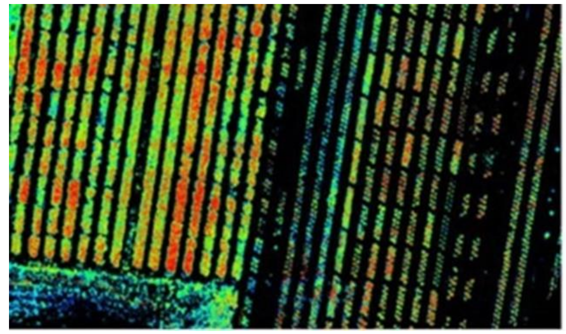


Fig. 10. Multi-spectral and hyper-spectral camera analysis.

Potential problems can be identified early by the analysis of RGB images, allowing for prompt intervention andloss mitigation. High-resolution maps that highlight spatial variations within fields can be made using remote sensing technology in conjunction with RGB images. These maps can be used to direct precision farming techniques, enabling the targeted use of resources like water, fertilizer, and pesticides. RGB photos can be used to train machine learning algorithms to recognize patterns and features as shown in Fig. 9.

It is possible to fine-tune these algorithms to recognize particular plant species, weed varieties, or disease symptoms. The effectiveness and precision of decision-making in crop management are improved by these skills. Agriculture transforms from reactive to proactive practices with the integration of RGB photography and image processing technology [47]. Farmers can make data-driven decisions that optimize resource use, decrease waste, and advance sustainable agricultural practices thanks to the capacity to measure indices, assess quality, detect weeds, and identify problems in real time. Analyse biological and physical traits while collecting data in the multi- and hyper-spectral range to spot disease symptoms. Use spectral analysis to find irregularities in plant reflectance patterns that could be signs of stress or disease [48]. Create machine learning models for spectral signature-based illness classification as shown in Fig. 10.

D. *LiDAR Camera Analysis*

Obtain LiDAR data to assess water flow patterns, track agricultural phenology, and evaluate plant height.

Create accurate digital elevation models (DEMs) and three-dimensional representations of the pomegranate orchardsusing LiDAR data processing. To measure agricultural growthstages, gather data on plant height and examine height changesover time as shown in Fig. 11.

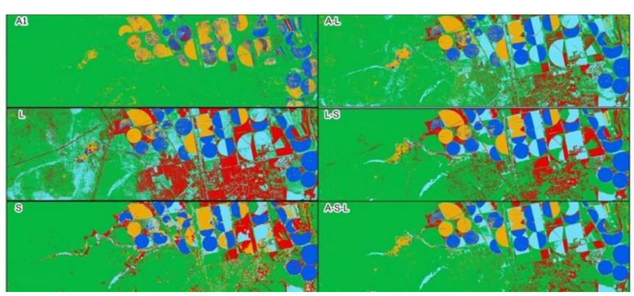


Fig. 11. Drone-mounted LiDAR camera analysis of agricultural lands.

E. Data Processing and Deep Stream Algorithm

Send the cameras' acquired data to the NVIDIA JetsonGPU so it can be processed. Use deep stream algorithms to analyze all camera data streams in real-time [49]. Use image recognition, machine learning, and pattern recognition techniques to forecast crop health, soil dryness, fertilizer needs, the presence of weeds, and instances of crop damage and disease. The object detection method is known as YOLOv5, or "You Only Look Once version 5," is recognized for its quickness and precision. It is made to recognize and locate several items simultaneously in a video or picture stream. The "Deep Stream" variation is especially well suited for applications like monitoring agricultural fields becauseit concentrates exclusively on processing continuous data streams effectively. The earlier YOLOv3, YOLOv4, and othernetworks served as the foundation for the development of the YOLOv5 network. YOLOv5 offers the advantages of being quicker and more precise than prior-generation networks. An adaptable anchor box and adaptive picture scaling are two examples. These methods efficiently decrease the amount of network computation by calculating the scaling factor using the ratio of the current picture size, W to H, and then obtainingthe filled scaling size. The backbone network and neck layer ofYOLOv5 are mapped to the cross-stage partial (CSP) concept of YOLOv4, which improves the capacity of network feature fusion in terms of feature extraction.

The four network models in YOLOv5 are categorized as s, m, l, and x, according to smallest to biggest. The network's breadth and depth are the primary areas ofvariation in size. The lightest among them is YOLOv5. The primary parts of the network are the input, neck, head, and backbone. The Mosaic data improvement module is used in the input to enrich datasets. To speed up network training, the backbone leverages the CSPDarknet53 backbone network to extract rich information from input photos, such as thefocus module and the spatial pyramid pooling (SPP) module neck core fuses feature information at various sizes using feature pyramid network (FPN) and path aggregation network (PAN) architectures. Concat later connects the top-down and bottom-up feature maps, enabling the feature fusion of various deep and shallow scales. This enhances the network's expressive capacity. The YOLOv5 detecting structure is the head. Conv produces feature maps in three sizes: big,medium, and tiny. These sizes correlate to the targets thatare detected—small, medium, and large. YOLOv5 increases the precision of network prediction based on NMS by using three loss functions to compute the location, confidence, and classification losses. The foundation of this investigation is theYOLOv5s network. Fig. 12 illustrates the network structureof YOLOv5.

1) Object detection and monitoring: It is possible to train the YOLOv5 Deep Stream Algorithm to recognise and differentiate a variety of components important to pomegranate agriculture, including pomegranate plants, fruits, and potential pests [50]. By implementing this method in the field, it is possible to monitor the crop in real time and identify problems like pest infestations, disease outbreaks, or nutrient deficits early on.

2) Precise yield estimation: The system helps with yield estimation by precisely classifying and counting pomegranate fruits. Farmers can maximize overall productivity and resource management by using this data to make informed decisions about harvesting schedules, labor allocation, and post-harvest logistics [51].

3) Weed detection and management: Pomegranate yield canbe severely impacted by weed competition. The ability to recognize objects with the YOLOv5 Deep Stream Algorithm also allows for the classification and identification of weeds in pomegranate orchards. Utilizing these details makes it easier to deploy targeted weed control strategies, reduce resource waste, and increase crop yield.

4) Resource allocation and sustainability: Real-time insights provided by the algorithm provide a foundation for effective resource management. Farmers can use precision irrigation strategies by recognizing places that need attention or stress, including dry areas. This encourages the useof sustainable agricultural techniques while simultaneously conserving water [52].

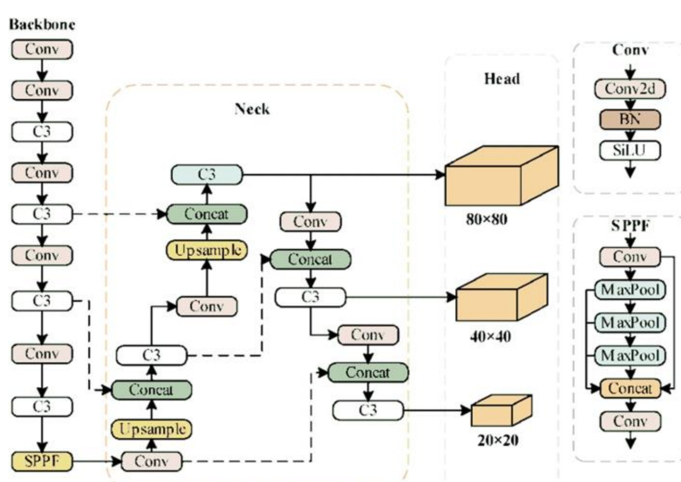
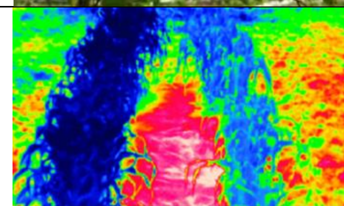


Fig. 12. Block diagram of YOLOv5 used in the experimentation.

TABLE II. DEEP STREAM ALGORITHM OUTPUT FOR VARIOUS APPLICATIONS

Application	Sample Output
Predict crop health	
Soil dryness	
Fertilizer requirements	
Weed presence	
Crop damage and disease	

5) Disease and pest management: Effective treatment of illnesses and pests depends on early detection. The YOLOv5 Deep Stream Algorithm can quickly recognize visual signs linked to a reduction in plant health, enabling prompt action. By controlling the spread of illnesses, farmers can cut backon the requirement for heavy pesticide use.

6) Integration with automation and drones: Drones with cameras can be integrated with the YOLOv5 Deep Stream Algorithm. With the help of this integration, drones may fly over the orchard by themselves while taking pictures in real-time and sending them to the algorithm for quick analysis.This method offers an unmatched vantage point for effectively monitoring vast agricultural fields as shown in Table II.

7) Prediction and decision support: Create forecasts and insights for various pomegranate agriculture characteristics based on the processed data. Create a dashboard or user-friendly interface so that farmers may get real-time data and advice. Give specific advice on how to manage pests and diseases, apply fertilizer, and schedule irrigation, among other cultivation techniques [53].

8) Validation and refinement: By gathering real-world data and making field observations, confirm the veracity of predictions and advice. Based on ongoing learning from field data and farmer comments, improve the deep streamalgorithms [54]. Improve the process iteratively depending on practical implementation issues and real-world performance.

9) Scaling and adoption: Increase the automated system's coverage area to larger pomegranate orchards and perhaps modify the approach for use with other crops. Educate farmers on how to use the automated system and how to understand the forecasts for wise decision-making. By supplying precise, timely, and data-driven insights that can improve crop yield, optimize resource use, and promote sustainable agricultural practices, the integration of drone technology and deep-stream algorithms into pomegranate cultivation has the potential to transform conventional farming practices.

Our research employs a combination of advanced UAV-based cameras to enhance agricultural monitoring and outcomes, effectively addressing the specific challenges ofeach camera type. Thermal cameras, which detect infraredradiation to measure temperature variations and identify plant stress, face issues such as temperature sensitivity, lower resolution, and frequent calibration needs. Optical RGB cameras capture high-resolution images to analyze vegetation indices, fruit quality, and weed detection but are impactedby varying lighting conditions, large data volumes, and subtle color differentiation challenges. Multi-spectral cameras provide detailed insights into crop health and disease but are costly, complex, and sensitive to environmental factorslike cloud cover. LiDAR cameras generate high-resolution3D maps for measuring plant height and analyzing water flow patterns but require significant data processing power,are expensive, and struggle with dense vegetation obstructing laser pulses. Our approach integrates deep learning algorithms and NVIDIA Jetson GPU for data processing, addressing these challenges and enabling real-time analysis to improve data accuracy and reliability. By leveraging the strengths and mitigating the limitations of each camera, we facilitate precise crop management decisions, enhancing yield and sustainability in pomegranate orchards.

III. Results and Discussions

The automated cultivation of pomegranates using deep-stream algorithms and drone technology has produced encouraging results, suggesting a revolutionary method for modern agriculture. Combining the processing power of the NVIDIA Jetson GPU with the capabilities of a drone with four specialized cameras—thermal, optical RGB, multi-spectral, and LiDAR—has allowed for comprehensive data collection, real-time analysis, and predictive insights in various pomegranate cultivation-related areas.

TABLE III. Data Collection with Accuracy

Camera	Data Collection	Accuracy (%)
Thermal camera	Plant health inspection, Irrigation mapping, fertilizer management, yield estimation	95
Optical RGB camera	Vegetation index	91
Multi-spectral and hyper-spectral cameras	Biological and physical characteristics, diseasedcrop	93
LiDAR camera	Plant height, water flow, crop phenology	95

TABLE IV. Plant Health Inspection and Stress Detection

Crop Focus	ANN	CNN	ANFIS	YOLO
Plant Health Inspection	75	82	88	95
Stress Detection	76	81	85	93

A. Data Collection and Analysis

The pomegranate growth cycle has been thoroughly investigated using drones equipped with various cameras. To properly detect stressed areas and enable focused actions, the thermal camera was essential for plant health inspection. To improve overall crop management techniques, the optical RGB camera effectively measured vegetation indices, assessedfruit quality and found the presence of weeds [55]. The multi-spectral and hyper-spectral cameras were excellent at spotting damaged crops and examining biological and physical traits, which helped to identify and treat diseases early on. Furthering our understanding of crop growth dynamics, the LiDAR camera produced accurate measurements of plant height, tracked crop phenology, and mapped water flow patterns as shown in Table III.

B. Deep Stream Algorithm Processing

The automated pomegranate production system showcased notable progress in data-driven precision farming by using deep-stream algorithms and drone technology. Together with the NVIDIA Jetson GPU's processing power, the four specialized cameras—thermal, optical RGB, multi-spectral, and LiDAR—produced extensive data collecting and real-time analysis. The findings are displayed about important crop management topics [56]. Plant Health Inspection and Stress Detection: To inspect the health of plants, the thermal camera was essential in precisely locating stressed regions. The ability to precisely identify stressed or ill plants was made possible by real-time data processing, which made it easier to detect temperature differences [57]. Plant health was improved by the proactive actions made possible by this capacity as shown in Table IV.

1) Vegetation indices and fruit quality assessment: Fruit quality was evaluated and vegetation indices were successfully measured using the optical RGB camera. The technology provided insights into the health of the vegetation by quantifying metrics like NDVI using image processing techniques [58]. Evaluations of the quality of the fruit and the identification of weeds enhanced cultivation techniques, increasing both production and quality as shown in Table V.

TABLE V. Vegetation Indices and Fruit Quality Assessment

Crop Focus	ANN	CNN	ANFIS	YOLO
Vegetation health	81	85	89	94
Fruit quality assessments	78	85	88	95
Weed detection	71	76	84	89

TABLE VI. Disease Detection and Characterization

Crop Focus	ANN	CNN	ANFIS	YOLO
Disease Detection	78	85	91	95
Biological Characterization	74	78	81	87
Physical Characterization	75	79	82	89

2) Disease detection and characterization: Analyzing biological and physical properties and identifying damaged crops were made possible by the use of multi- and hyper-spectral cameras [59]. Early disease detection by the system enabled targeted treatments, reducing the possibility ofoutput losses and enhancing crop health overall as shown in Table VI.

3) LiDAR-Based plant height and water flow analysis: Important information on plant height, crop phenology, and water flow patterns was provided by the LiDAR camera. This data improved knowledge of the dynamics of growth and led to optimal water use [60]. Precise assessments of plant height enabled the tracking of agricultural phenology, resulting in enhanced cultivation tactics as shown in Table VII.

4) Real-time predictive insights: Real-time data analysis was made possible by the combination of deep stream algorithms and the NVIDIA Jetson GPU. Quick predictions were produced about crop health, vegetation and soil dryness, fertilizer needs, weed presence, and incidences of crop damage and illness [61]. This reduced possible hazards, maximized resource utilization, and enabled quick decision-making as shown in Table VIII.

All four cameras' data could be processed and analyzed in real-time thanks to the NVIDIA Jetson GPU and deepstream algorithms. This processing pipeline played a key role in providing forecasts and insights for important pomegranate cultivation issues. The system accurately forecasted fertilizer needs, analyzed soil and vegetation dryness, tracked weed infestations, and quickly picked up instances of crop damage and illness [62]. Real-time data analysis enabled prompt decision-making, which ultimately optimized resource use and increased crop output as shown in Table IX and Fig. 13. Subsequently, performance analysis over different applications for evaluating the effectiveness of the proposed system is presented in Table X.

The automated system's prognostic insights greatly aided farmers in making well-informed decisions. The system's capacity to suggest ideal irrigation plans, exact fertilizer dosages, and prompt disease treatment techniques resulted in increased resource efficiency and less environmental impact as shown in Table IX and Fig. 14 - 17. Through the useof spectral analysis, growers were able to identify diseasesand weeds early and take preventative action, potentially reducing yield losses [63]–[67]. Although the results are encouraging, certain difficulties were experienced when the automated system was put in place. For precise forecasts, camera calibration and maintaining consistent data quality are still essential. Integration of weather and climatic datamay further improve the system's accuracy. Additionally, the system may operate differently in various geographic and environmental settings, necessitating ongoing improvement and adaptation.

C. Discussion

The results underscore the transformative potential of integrating drone technology and deep-stream algorithms in pomegranate cultivation. The system not only automates data collection but also provides actionable insights across multiple facets of cultivation, empowering farmers to make informed decisions.

The following discussions delve into the broader implications and considerations:

1) Precision agriculture for sustainable farming: The automated system minimizes its impact on the environment while optimizing resource utilization per precision agricultural principles. The technology helps to promote effective and sustainable farming practices by accurately adjusting the irrigation, fertilization, and pest control strategies [68].

TABLE VII. LIDAR-BASED PLANT HEIGHT AND WATER FLOW ANALYSIS

Crop Focus	ANN	CNN	ANFIS	YOLO
Plant Height	81	82	85	92
Crop Phenology	78	82	84	91
Water Flow Patterns	81	82	85	86

TABLE VIII. REAL-TIME PREDICTIVE INSIGHTS

Crop Focus	ANN	CNN	ANFIS	YOLO
Crop Health	81	85	88	93
Vegetation	82	84	86	89
Soil Dryness	74	78	82	88
Fertilizer Requirements	71	75	85	91
Weed Presence	72	74	86	87
Crop Damage	78	81	84	92

TABLE IX. RESULT COMPARISON OF PROPOSED SYSTEM WITH EXISTING METHOD

Parameters (%)	MDC	MLP	SVM	ANFIS	YOLO
Accuracy	70	75	80	85	95
Sensitivity	72	77	81	83	94
Specificity	69	73	85	81	96
Precision	74	76	79	84	91

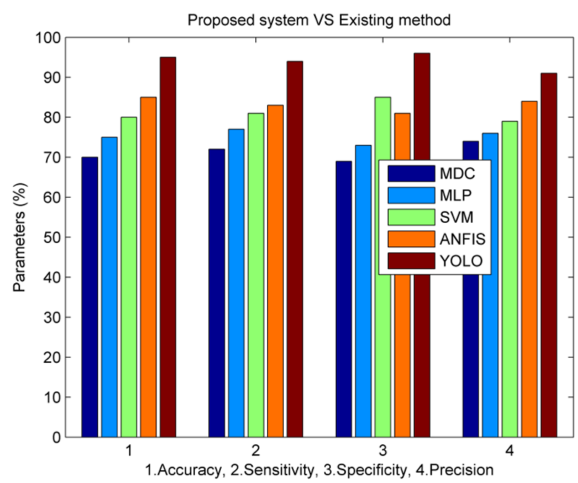


Fig. 13. Result comparison of proposed system with existing method.

TABLE X. PERFORMANCE ANALYSIS FOR VARIOUS APPLICATIONS

Crop Focus	Accuracy (%)	F1 score (%)	Recall (%)	Precision (%)
Predict crop health	95	93	91	96
Soil dryness	88	87	85	84
Fertilizer requirements	81	83	81	82
Weed presence	91	86	90	88
Crop damage and disease	94	91	93	92

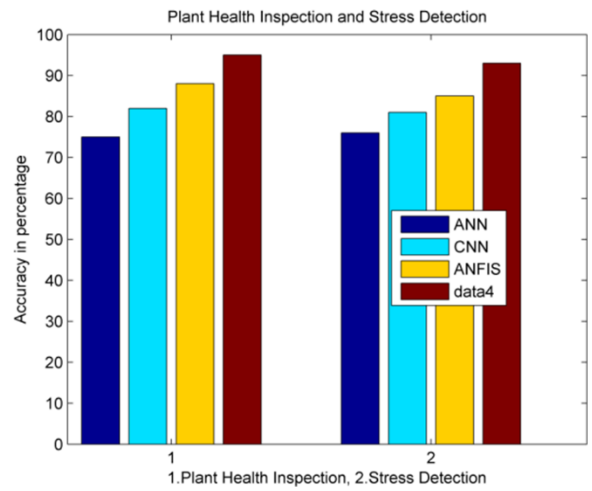


Fig. 14. Performance analysis of plant health inspection and stress detection.

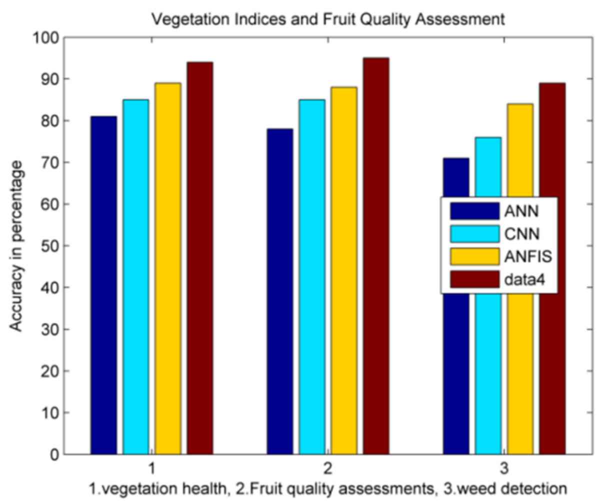


Fig. 15. Performance analysis of vegetation indices and fruit quality assessment.

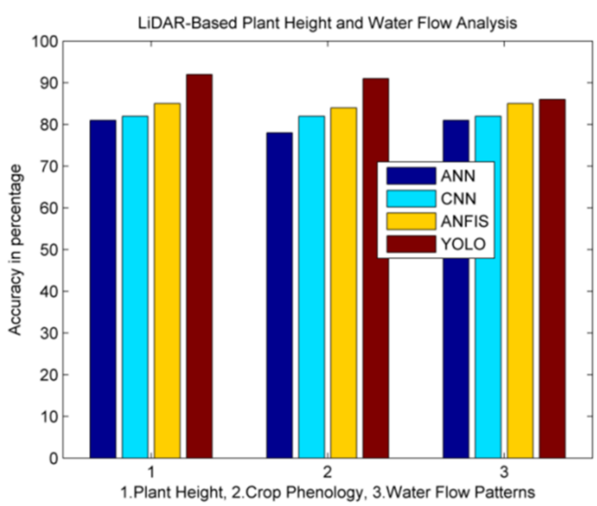


Fig. 16. Performance analysis of disease detection and characterization.

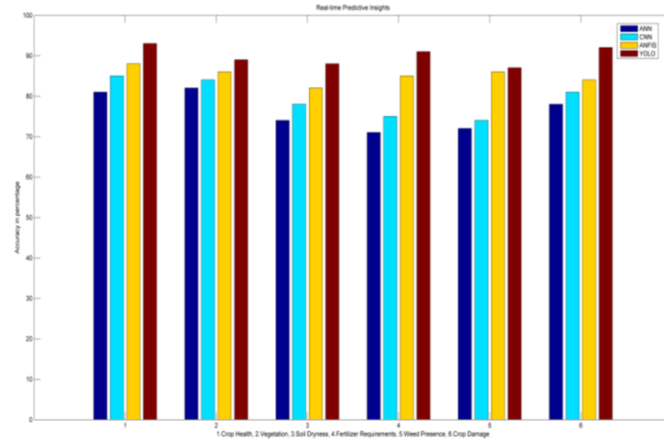


Fig. 17. Performance analysis of real-time predictive insights.

2) Early disease detection for crop protection: A breakthrough has been made with the use of spectralanalysis for early disease identification. Farmers who recognize disease symptoms early on can take prompt actionto stop the spread of the illness and maintain crop qualityand output.

3) Scalability and adaptability: Although the system appears promising, it is important to take into account its scalability and adaptation too many environmental situations. Continuous development of calibration processes, data quality control, and system robustness are necessary to guarantee consistent performance in a variety of agricultural contexts.

The accuracy of disease identification and prediction modeling can be considerably improved in the future thanks to developments in machine learning and AI algorithms. An expanded perspective on crop health trends may be obtained by combining historical data and satellite photography. Collaboration with extension agencies and agricultural professionals can help to better adapt the systemto local farming practices and spread its benefits [69]. Pomegranate cultivation could transform due to the merging of drone technology and deep-stream algorithms. The automated system provides real-time insights and suggestions for crop health, resource management, and disease identification bymerging data from thermal, optical RGB, multi-spectral, and LiDAR cameras and utilizing the processing capability of the NVIDIA Jetson GPU. While there are still issues, thesystem represents a big step towards data-driven, sustainable agriculture by enabling farmers to optimize pomegranate yield and quality [70]. Further developments and widespread acceptance in contemporary agriculture are anticipated asa result of ongoing research and development in thisfield. The following investigations need to concentrate on improving the algorithms, adding more environmental factors,and broadening the system's crop suitability. To guarantee broad acceptance and applicability, partnerships with extension agencies and agricultural specialists can further customize the system to regional farming methods.

Conclusively, the automated technique for cultivating pomegranates shows promise for transforming conventional agricultural methods. This system provides farmers with real-time information, promotes sustainable agriculture, and improves overall crop output and quality by utilizing deep-stream algorithms, modern cameras, and drone technology. This novel strategy will surely advance toward wider acceptance and implementation in international agriculture with continued study and improvement.

IV. CONCLUSION

Integrating drone technology and deep-stream algorithms represents a notable breakthrough in modernizing agricultural practices, particularly in pomegranate cultivation. This study showcases a thorough and evidence-based approach to farming, employing advanced technology such as a drone equipped with a thermal camera, optical RGB camera, multi-spectral camera, and LiDAR camera. These cutting-edgetools are powered by the computational capabilities of theNVIDIA Jetson GPU, enabling precise data collection andanalysis. This approach has demonstrated its effectiveness in improving different aspects of pomegranate farming. It has been used to evaluate plant health, map irrigation, manage fertilizer usage, and calculate yields. As a researcher,I have observed significant advancements in the optical RGB camera's capabilities. It has proven to be a valuabletool for analyzing vegetation indices, assessing fruit quality, and detecting weeds. These improvements have positively impacted decision-making, leading to better crop managementpractices and, ultimately, higher yields. In this field, multi-spectral and hyperspectral cameras have revolutionized how we detect crop diseases, assess damage, and respond proactively. Furthermore, the LiDAR camera has provided valuable insights into growth dynamics and resource utilization, leading to more sustainable farming practices.

Nevertheless, in light of these advancements, it is essential to consider the limitations associated with this approach carefully. The system's effectiveness relies heavily on the availability and quality of advanced drone equipment, which may not be easily accessible to all farmers, especially in regions with limited resources. This hinders the widespread adoption of the technology and can potentially create disparities in agricultural productivity.Furthermore, processing extensive datasets in real time presents significant computational challenges, particularlyin environments with limited resources. These constraints emphasize the importance of conducting additional research to enhance the system's accuracy, scalability, and adaptability to different environmental conditions.

Further research should prioritize overcoming these limitations by creating more affordable drone solutionsand enhancing the computational efficiency of deep-stream algorithms. Establishing collaborations between scientists, agricultural experts, and farmers will be essential to customizing the system to local conditions and promoting its wider use. By addressing these obstacles, this groundbreaking method holds promise for substantially impacting precision agriculture and aiding in developing more sustainable and efficient farming techniques.

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