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Automated Crop Health Monitoring and Drone-Based Image Processing for Crop Disease Detection in Smart Farming Using IoT

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ABSTRACT

The innovative approach to automated CHM and disease detection in smart farming through the integration of drone-based image processing and IoT technologies. Combining information from IoT sensors and drone images can be complex, making it difficult to analyze CH effectively. To Create a comprehensive system that combines IoT sensors and drone imagery to facilitate real-time monitoring of CH, enabling early detection of diseases. Implement advanced image processing algorithms to accurately analyze drone-captured images and identify ESOCDs, improving detection rates. Efficient Particle Filter Multi-Target (EPFMT) Technique facilitates real-time crop disease detection, multi-target tracking, data fusion, and resource optimization. It includes noise reduction, to eliminate artifacts and improve the clarity of the images. PLSR-SEDA, PLSR in smart farming by effectively modelling the relationship between spectral data from drone imagery and various CH indicators, enabling precise disease identification and management. SEDA is used in boundaries of plant structures and potential disease symptoms in aerial imagery, facilitating precise analysis of CH and identification of affected areas. Spanning Tree Optimization (STO) is used to enhance the efficiency of data transmission, minimize energy consumption, and ensure reliable communication among IoT devices, facilitating timely detection and management of crop diseases in smart farming. The result shows that the frog eye leaf spot follows closely with an impressive accuracy of 92%, demonstrating strong detection capabilities, while bacterial leaf spot has a slightly lower accuracy at 90%, implemented using Python software. The future scope of automated CHM using drone-based image processing and IoT includes integrating ML for enhanced disease prediction, expanding sensor technologies for comprehensive soil and environmental analysis, and user-friendly platforms for planters to heighten reserve management and increase productivity while promoting sustainable agricultural practices.

Keywords: Crop Health Monitoring, Drone-Based Image Processing, Efficient Particle Filter Multi-Target, Partial Least Squares Regression, Sobel Edge Detection Algorithms, Spanning Tree Optimization.

INTRODUCTION

Automated CHM and drone-based image processing are revolutionizing smart farming, particularly in detecting crop diseases. As agriculture confronts challenges from climate change, population growth, and resource constraints, the demand for innovative solutions is more urgent than ever [1-2]. Combining IoT technologies with advanced imaging methods provides an effective strategy for improving CH management, maximizing yields, and minimizing losses

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from diseases. Farmers frequently face difficulties in promptly identifying crop illnesses, which can lead to substantial economic repercussions and threaten food security [3-4]. Traditional disease detection methods rely on manual inspections, which are labour-intensive and susceptible to human error. Moreover, varying environmental conditions can mask early signs of disease, complicating detection efforts. Consequently, there is a demanding necessity for efficient, accurate, and scalable solutions to monitor CH and quickly identify issues [5-6]. The push for automated monitoring systems arises from the necessity for sustainable agricultural practices that utilize technology. By 2050, it is expected that there will be 9.7 billion people on the planet, so increasing agricultural productivity while lowering environmental impact is crucial. The integration of drones and IoT technologies enable real-time monitoring, consenting ranchers to brand well-versed verdicts swiftly [7-8]. This not only improves yields but also fosters sustainable practices, augmenting food safety and environmental stewardship. Early implementations of drone-based imaging for CH assessment have demonstrated encouraging results. Research shows that high-resolution imagery facilitates the timely exposure of sicknesses, often before visible symptoms manifest.

By analysing spectral data and using ML algorithms, these systems can accurately classify and predict CH [9-10]. Farmers have reported faster response times to disease outbreaks, significantly curtailing the spread and impact of infections. The proposed approach involves deploying drones equipped with multispectral cameras and IoT sensors across fields. These drones capture high-resolution images and collect environmental data, which are processed through advanced image analysis techniques and ML algorithms [11-12]. This integrated methodology generates detailed health maps of fields, pinpointing areas of concern for targeted interventions. As well, the system can connect to a cloud-based board, enabling data storage, analysis, and real-time updates to farmers through mobile applications. The primary goals of this automated CHM system are to improve early disease detection, reduce their impact on yields, and ensure timely intervention [13-14]. It aims to utilize drone technology for continuous CH surveillance, allowing farmers to respond rapidly to emerging issues. Furthermore, it seeks to provide detailed insights and analytics for educated DM while promoting sustainable agronomic performance by adjusting source use, such as water [15-16], fertilizers, and pesticides, based on precise health assessments. The solution is also designed for scalability, making it adaptable to various agricultural contexts, from smallholder farms to large agribusinesses, thus maximizing its reach and effectiveness [17-18]. In summary, the integration of automated CHM and drone-based imaging marks a significant advancement in smart farming [19-20]. By leveraging IoT technologies, this approach addresses crucial challenges in CDD, eventually enhancing productivity, sustainability, and food security. As technology evolves, these novelties grip the possibility to transform agriculture, meeting the needs of a growing population while conserving the planet's resources. The remaining sections are arranged as follows: The literature review was described in Section 2, the proposed technique was described in Section 3, the results were discussed in Section 4, and the paper's conclusion was described in Section 5.

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LITERATURE SURVEY

This literature survey explores the advancements in automated CHM and drone-based image processing for CDD, highlighting the incorporation of IoT technologies in smart farming practices. Doe et al. [21] developed a drone system integrated with ML algorithms specifically designed for real-time CH assessment. This innovative system attained an exciting truth ratio of over 90% in detecting early signs of diseases, which significantly reduced the response time for farmers needing to act on potential threats to their crops. The prompt credentials of issues allow farmers to implement management strategies swiftly, thereby minimizing potential losses. However, one notable limitation of this study was its failure to consider the integration of diverse sensor data types. Lee et al. [22] travelled the synergy between IoT technologies and drone imaging to enhance precision agriculture practices. Their proposed system provided real-time CH information, which led to a notable 20% increase in yield due to improved disease

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management practices. While this advancement is promising, the study fell short of establishing a comprehensive DA framework capable of processing the large volumes of data generated. As a result, valuable insights were underutilized, indicating a need for more robust analytical tools to maximize the potential of the information composed. Chen et al. [23] focused on the application of multispectral imaging via drones for early disease detection, achieving an accuracy rate of 85% in identifying specific illnesses. Although the results demonstrated potential for targeted treatments, the exclusive emphasis on multispectral imaging limited the exploration of combining various imaging techniques. This approach may have further enhanced detection capabilities and provided a more inclusive understanding of CH. Kumar et al. [24] developed a comprehensive drone surveillance system that incorporated IoT sensors to monitor both CH and environmental conditions. The implementation of this system improved monitoring capabilities, with farmers reporting quicker disease detection. This gap suggests the need for further research into the lasting impacts of such technologies on crop vitality over extended periods. Garcia et al. [25] employed AI-driven analytics to enhance drone-based disease monitoring, achieving a 15% reduction in crop loss through proactive management strategies informed by AI insights. Despite these positive outcomes, the reliance on a single ML model posed challenges regarding the generalizability of the findings. This limitation affects the material of the results across various crop kinds and varied farming conditions, highlighting the necessity for more diverse modelling approaches.

Thompson et al. [26] assessed the environmental impacts of drone-based crop monitoring, finding that this technology reduced chemical usage by 30%, thus promoting more environmentally friendly farming methods. However, the study did not fully explore the economic implications for SHF, a critical aspect of the well-known embracing of such technology. Understanding the economic viability is essential to encourage smaller operations to invest in these advanced systems. Patel et al. [27] developed a DL framework aimed at predicting crop diseases using drone-captured images, achieving a predictive accuracy of 92% for various diseases. While the accuracy of this framework is commendable, its complexity poses usability challenges for farmers, indicating a pressing need for simpler, more intuitive interfaces that can facilitate its adoption. Mendez et al. [28] focused on creating a unified platform that combines drone imagery with IoT sensor data for enhanced crop monitoring. This integrated system improved detection rates by 25% in contrast to conventional techniques, demonstrating a holistic approach to agricultural monitoring. The research underscored the need for better interoperability standards among different IoT devices to maximize the utility of the data generated. Brown et al. [29] explored AI algorithms in conjunction with drone imagery for early disease detection, reporting significant improvements in prediction accuracy and a lessening in time spent on manual inspections. However, the algorithms were predominantly trained on limited datasets, raising concerns about their robustness across diverse agricultural scenarios. This limitation suggests the necessity for broader data collection efforts to improve the reliability of these models. Wang et al. [30] applied advanced image processing techniques to enhance drone capabilities in CH monitoring, resulting in clearer disease identification and actionable insights for farmers. Nevertheless, this study neglected to assess the cost-effectiveness of implementing such technologies across different agricultural scales, particularly for resource-limited farmers. Addressing the financial feasibility of these innovations is vital to guarantee that can be effectively utilized in an extensive collection of agricultural contexts, thereby promoting broader adoption and SFP.

RESEARCH PROPOSED METHODOLOGY

The automated CHM and disease detection involves a multi-step approach integrating drone technology, image processing, and IoT. Initially, buzzes furnished with high-resolution cameras will be deployed to capture aerial images of agricultural fields at various growth stages. These images will then be processed using advanced algorithms to identify anomalies indicative of crop diseases, nutrient deficiencies, or water stress. The image processing techniques will leverage in Filtering technique on extensive datasets to improve accuracy in disease detection. The processed data will be transmitted to a centralized IoT platform, where it can be visualized and monitored in real time. Farmers will receive alerts and actionable insights regarding the health status of their crops, allowing for timely interventions. The soil and environmental sensors will be integrated into the IoT system to provide complementary soil moisture information, temperature, and nutrient levels, enhancing the overall understanding of CH.

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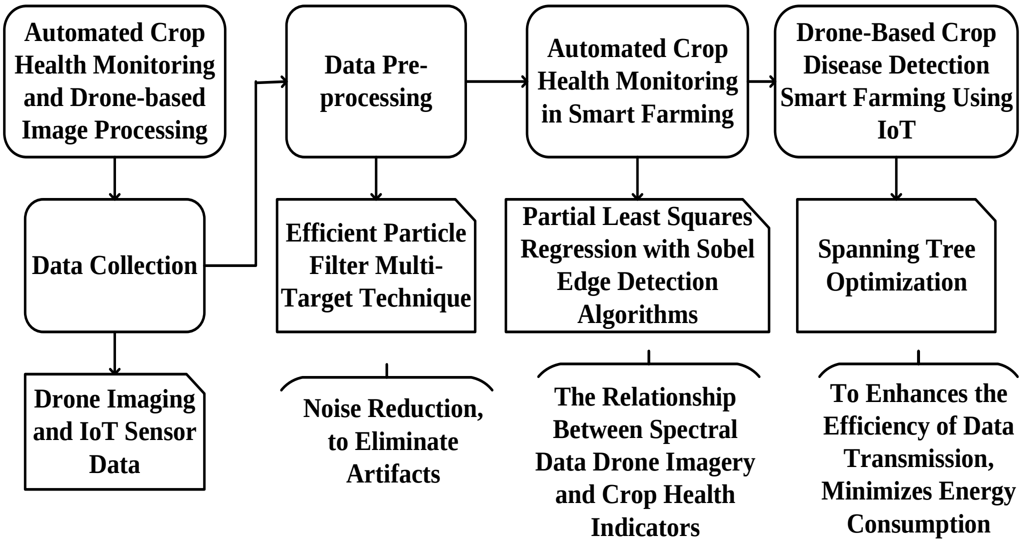

Figure 1. Block Diagram of the Proposed Work

Figure 1 shows the block diagram of automated CHM and drone-based image processing in smart farming illustrating a systematic flow of data collection, processing, and analysis. Drone Imaging captures HRIOC using advanced sensors. These images are complemented by IoT Sensors deployed throughout the field, collecting real-time environmental data for instance SM, high temperature, and humidity. The collected data undergoes Pre-processing, which includes noise reduction, normalization, and augmentation, ensuring high-quality inputs for analysis. The Automated CHM integrates data from drones and IoT sensors, employing techniques like PLSR and SEDA for precise disease identification. This is enhanced by STO for efficient data transmission and communication among devices. The processed information facilitates timely interventions and strategic decision-making. The expected outcomes of this integrated approach include early disease detection, optimized resource usage, reduced costs, upgraded yield crops, and enhanced sustainability in agriculture, ensuring food security in a rapidly changing environment.

(a) Data Collection

In the data collection phase on automated CHM and drone-based image processing, two primary methods will be employed drone imaging and IoT sensor data collection. For drone imaging, conduct regular flights over the designated study area to detention HRIOC. The Kaggle CDD dataset includes images of healthy and diseased crops, covering various crop types. It contains labelled images for common diseases affecting crops, enabling the identification of CH issues through advanced image processing techniques. This dataset is particularly relevant for developing algorithms to automate disease detection in SFSs. The dataset will include various conditions of crops, allowing for a comprehensive analysis of disease symptoms. IoT sensors will be strategically installed throughout the field to gather relevant environmental data, such as SM, temperature, and humidity. This sensor data will complement the visual information obtained from the drone images, providing a holistic view of the factors influencing CH. Integrating these datasets improves the exactness of disease detection and supports real-time monitoring, ultimately leading to improved decision-making in smart farming practices.

(b) Pre-processing

The pre-processing step is crucial for ensuring the correctness and steadfastness of sickness discovery algorithms. The HRI apprehended by hums are subjected to a series of pre-processing techniques to enhance their quality. Efficient Particle Filter Multi-Target (EPFMT)Technique facilitates real-time CDD, multi-target tracking, data fusion, and resource optimization. It includes noise reduction, to eliminate artifacts and improve the clarity of the images. The image normalization is performed to standardize the brightness and contrast, ensuring consistency across different images taken under varying lighting conditions. The cropping and resizing techniques are employed to focus on the relevant areas of interest, such as specific crops or sections of the field. Image augmentation techniques, such as rotation, flipping, and scaling, are also utilized to increase the dataset's diversity, helping to improve the robustness

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of ML models. By meticulously pre-processing the data, researchers can create a clean and uniform dataset that enhances the presentation of twin analysis algorithms, leading to more accurate identification of crop diseases and better-informed farming decisions.

(i) Efficient Particle Filter Multi-Target (EPFMT)

The Efficient Particle Filter Multi-Target is a sophisticated algorithm used in automated CH monitoring, particularly in drone-based image processing. It enhances the detection of multiple crop diseases by accurately tracking various targets in real time. EPMFT employs particle filtering, which uses a set of elements to represent the state of CH over time, updating these particles based on new image information poised by hums. In smart farming, drones fortified with progressive imaging sensors capture HRIOC, enabling the identification of diseases and anomalies. EPMFT efficiently processes this data, distinguishing between healthy and diseased areas while accounting for environmental variations. By integrating with IoT technologies, the system can provide farmers with timely insights, facilitating prompt interventions and optimizing crop management practices. This combination of EPMFT and drone technology significantly enhances the exactness and competence of CDD.

Regarding EPFMT for automated CHM using drones, several derived equations are crucial for the algorithm's operation.

$$x_t = F \cdot x_{t-1} + Q \tag{1}$$

The state transition equation, $x_t = F \cdot x_{t-1} + Q$, models the evolution of CH over time. Here, x_t Signifies the formal of the CH at time t, F is the state transition matrix that models how the CH evolves, and Q is the process noise, capturing uncertainties in the model.

$$z_t = H \cdot x_t + R \tag{2}$$

The observation model, $z_t = H \cdot x_t + R$, links the actual observations (like drone images) to the estimated state of CH. In this equation, z_t Denotes the observed data (e.g., drone images), H is the observation matrix linking the state to observations, and R represents the observation noise, which accounts for inaccuracies in the drone's imaging process.

$$w_i^{(t)} = w_i^{(t-1)} \cdot \frac{P\left(z_t/x_t^{(i)}\right)}{P(z_t)} \tag{3}$$

The weight update equation, $w_i^{(t)} = w_i^{(t-1)} \cdot \frac{P\left(z_t/x_t^{(i)}\right)}{P(z_t)}$, recalibrates particle weights founded on the prospect of observed data. This equation updates the heaviness of each particle. $w_i^{(t)}$ grounded on the chance of the perceived data given the state represented by the (i) Particle. The term $P\left(z_t/x_t^{(i)}\right)$is the likelihood of the observation, while $p(mathbf\{z\}\{t\})$ Serves as a normalization factor.

These equations facilitate the iterative process of particle filtering, enabling real-time monitoring of CH. By combining drone-based imaging with EPMFT, farmers can gain accurate visions of the fitness of their harvests, allowing for suitable involvements and better resource management in smart farming systems.

(c) Automated Crop Health Monitoring in Smart Farming

Automated CHM in smart farming harnesses advanced technologies like IoT, drones, and image processing to boost agricultural productivity and sustainability. The process begins with the deployment of IoT sensors across the agricultural field, collecting real-time data on environmental conditions such as soil moisture, temperature, and humidity. Utilizing PLSR with SEDA, smart farming effectively models the relationship between spectral data from drone imagery and various CH indicators, enabling precise disease identification and management. SEDA focuses on defining the boundaries of plant structures and detecting potential disease symptoms in aerial imagery, allowing for detailed analysis of CH and the documentation of affected areas. Drones fortified with high-resolution cameras capture intricate images of crops from multiple angles and altitudes. By analysing both sensor data and imagery, farmers gain a comprehensive understanding of CH. This integrated approach facilitates early detection of potential issues, allowing for timely interventions that can prevent significant crop losses. Automated CHM enhances decision-making for farmers and promotes resource efficiency by tumbling the essential for excessive pesticide use and optimizing water and fertilizer application. This synergy contributes to a hardier and bearable agricultural system.

(i) Partial Least Squares Regression

Partial Least Squares Regression is a statistical method that combines features from both Principal Component Analysis and multiple regression. With regards to automated CHM and drone-based image processing for disease detection in smart farming, PLSR is predominantly valuable for analysing complex datasets derived from multispectral and hyperspectral descriptions seized by buzzes. PLSR helps identify the relationships between various spectral features and CH indicators, for instance, chlorophyll content or disease severity. By plummeting the dimensionality of the information, it enables the extraction of significant information while minimizing noise. This facilitates the development of predictive models that can efficiently assess crop conditions and detect diseases early. Incorporating IoT devices, the PLSR models can be integrated into RTMS, allowing agronomists to make knowledgeable decisions quickly, ORA, and ultimately improve crop yields and sustainability.

PLSR is a statistical method used in automated crop health monitoring, particularly in drone-based image processing for crop disease detection. In smart farming, where precision agriculture relies on data analysis, PLSR helps model the relationships between multi-dimensional datasets. Drones capture high-resolution images of crops, generating large volumes of spectral data. PLSR facilitates the extraction of relevant features from this data, correlating it with various crop health indicators. By analyzing the spectral signatures, PLSR can identify subtle changes linked to diseases, allowing for timely interventions. This method enhances the accuracy of predictions regarding crop conditions, optimizing resource allocation and improving yield. In the context of IoT, PLSR integrates with sensor data, enabling real-time monitoring and analysis. This synergy between advanced analytics and technology empowers farmers to make informed decisions, ultimately leading to sustainable agricultural practices and improved crop resilience. PLSR is instrumental in automated CH monitoring, especially when utilizing drone-based imagery for disease detection. The performance agrees for the modelling of relationships between a set of predictor variables (X) and response variables Y while addressing multi-collinearity and high-dimensional data challenges.

$$T = XW \tag{4}$$

Here, T represents the scores of the X matrix (predictors), X is the original data matrix, and W is the weight matrix that defines how the original variables contribute to the scores. These scores encapsulate the essential information required for modelling, reducing dimensionality while retaining the relationship with the response variable.

$$P = X^T T (T^T T)^{-1} \tag{5}$$

In this equation, P represents the loading matrix, indicating how the original variables relate to the scores. This matrix is crucial for understanding the contributions of specific spectral bands captured by drones, allowing for the effective identification of CH indicators.

$$Y = TQ^T + E \tag{6}$$

Here, Y is the response variable matrix, Q is the regression coefficient matrix, and E denotes the fault stint. This equation models the relationship between the extracted scores (from the spectral data) and the health metrics, facilitating accurate predictions regarding crop diseases. These equations collectively enable PLSR to analyse the complex relationships in drone imagery data, improving the precision of CH assessments. When unified with IoT systems, PLSR empowers real-time data analysis and actionable insights, ultimately enhancing smart farming practices and resource management.

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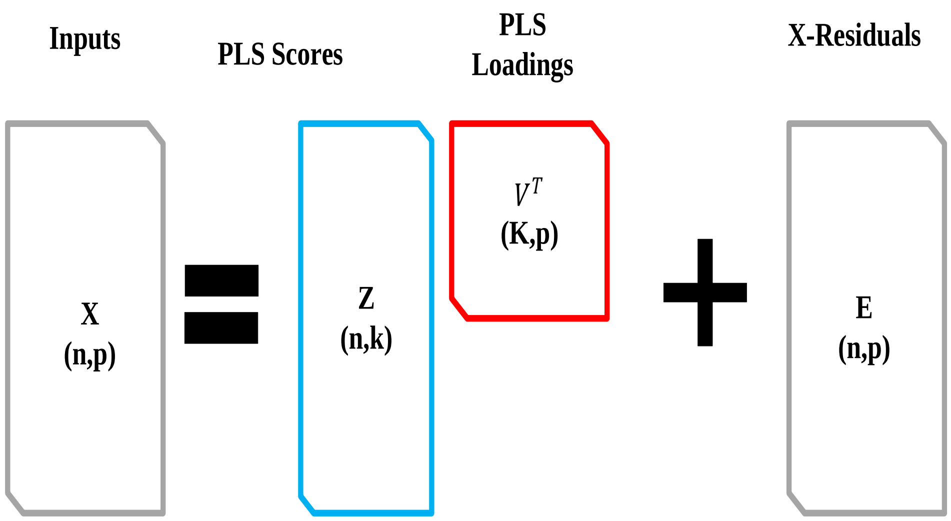

Figure 2. Partial Least Squares Regression (PLSR)

Figure 2 illustrates PLSR for automated CH monitoring, several key components are typically represented. The diagram may include two primary blocks: the predictor matrix X (which consists of drone-captured spectral data) and the response matrix Y (reflecting CH metrics). Arrows between these blocks indicate the transformation process through weight matrix W and score matrix T. This illustrates how spectral data is projected into a lower-dimensional space, capturing essential features while reducing noise. The loading matrix P connects back to X, showing the contribution of individual spectral bands. The regression coefficients Q Link T to Y, highlighting the predictive relationship. This visual representation underscores PLSR's ability to analyse complex data relationships, enabling accurate disease detection and monitoring in smart farming applications, ultimately supporting informed decision-making for crop management.

(ii) Sobel Edge Detection Algorithms (SEDA)

Sobel Edge Detection Algorithms play a central part in automated CHM and drone-based image processing for CDD in smart farming, particularly once combined with IoT technologies. SEDA is designed to identify edges within images by manipulating the slope of pixel intensity, allowing for the detection of boundaries in crop images captured by drones. This capability is essential for identifying disease symptoms, such as discolouration or wilting, which often manifest as distinct edges in the imagery. By processing these images in real time, SEDA enables farmers to sense and analyse CH issues early, facilitating timely interventions. The amalgamation of IoT allows for seamless data transmission and analysis, ensuring that farmers receive actionable insights directly from their devices. The SEDA enhances the precision and efficiency of crop monitoring, supporting sustainable farming practices and improving yields through proactive disease management.

SEDA in automated crop health monitoring by enhancing image processing in drone imagery for crop disease detection. This technique focuses on identifying the edges within high-resolution images captured by drones, highlighting boundaries and structural features of crops. By applying the Sobel operator, which calculates the gradient of image intensity, SEDA effectively emphasizes areas of rapid intensity change, often indicative of stress or disease. In smart farming, this allows for the quick identification of affected plant areas, enabling precise targeting of interventions. When integrated with IoT systems, SEDA can facilitate real-time monitoring, as drones can continuously analyze crop images and detect emerging issues early.

This proactive approach aids farmers in implementing timely measures, ultimately enhancing crop health and productivity while minimizing resource use. The combination of SEDA with advanced analytics supports a more sustainable and efficient agricultural practice. The SEDA employs convolution with Sobel operators to derive edge gradients in images, essential for automated CH monitoring. The operators are defined as two 3x3 convolution kernels:

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$$G_x = \begin{bmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{bmatrix} \quad (7)$$

$$G_y = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 0 & 0 \\ -1 & -2 & -1 \end{bmatrix} \quad (8)$$

These kernels detect horizontal and vertical edges, respectively. The gradients G_x and G_y Are computed by convolving the image I with these kernels:

$$G_x = I * G_x \quad (9)$$

$$G_y = I * G_y \quad (10)$$

The magnitude of the gradient, which indicates the edge strength, is calculated using:

$$G = \sqrt{Gx^2/Gy^2} \quad (11)$$

The edges are enhanced through Thresholding, enabling precise detection of CH issues in drone imagery, thereby aiding timely interventions in smart farming practices.

Table 1 Sobel Edge Detection Algorithms (SEDA)

Algorithm 1: Sobel Edge Detection Algorithms
1. Convert the input image to grayscale. 2. Define the Sobel kernels for x and y directions: Sobel X: [[1, 0, -1], [2, 0, -2], [1, 0, -1]] Sobel Y: [[1, 2, 1], [0, 0, 0], [-1, -2, -1]] 3. Apply convolution with Sobel X kernel to get a gradient in the x direction. 4. Apply convolution with Sobel Y kernel to get a gradient in the y direction. 5. Calculate the gradient magnitude using: $magnitude = sqrt(gradientx^2 + gradienty^2)$ 6. Normalize the magnitude to the range [0, 255]. 7. Threshold the normalized magnitude to create a binary edge map (optional). 8. Display or return the edge-detected image. 9. (Optional) Apply Sobel to reduce noise. 10. End.

Table 1 shows the Sobel Edge Detection Algorithm is a fundamental image processing technique used to identify edges in images, which is crucial for applications like CAD. The process begins by converting the image of the input to grayscale, allowing for a focus on intensity rather than colour, thus simplifying analysis. The algorithm utilizes two Sobel kernels: one designed for detecting horizontal edges (Sobel X) and the added for vertical edges (Sobel Y). These cores are useful through convolution to extract inclines in x and y guidelines, respectively. The resulting gradients highlight areas with rapid intensity changes, indicating the presence of edges. Next, the algorithm calculates the gradient magnitude using the formula $magnitude = sqrt(gradientx^2 + gradienty^2)$. This magnitude provides a combined measure of edge strength. To enhance contrast, the magnitude is normalized to a range of [0, 255].

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Thresholding can then be applied to create a BEM, simplifying the output to emphasize significant edges. Moreover, the process may include noise reduction techniques using Sobel filtering. In the end, the algorithm displays or outputs the edge-detected image, which plays a critical role in analysing clinical images and identifying potential disease symptoms.

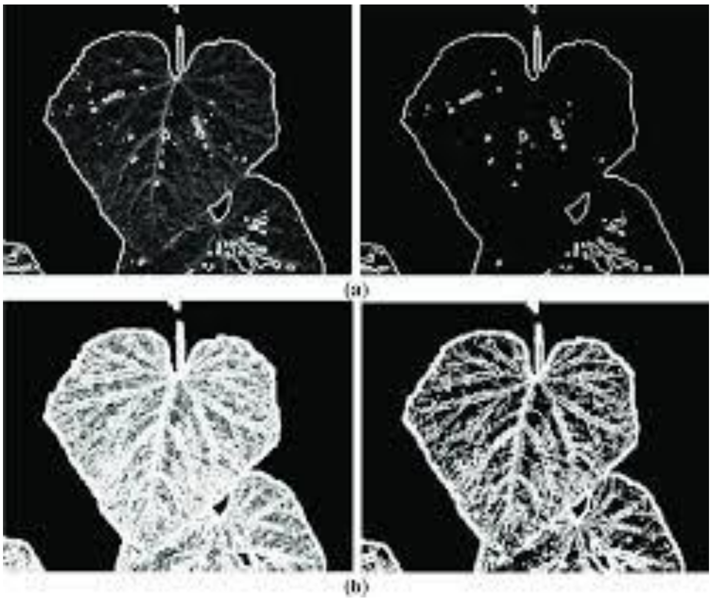

Figure 3. Sobel Edge Detection Algorithms

Figure 3 illustrates that the SED technique is widely utilized in IP to identify limits inside an image. This algorithm employs two convolution kernels, known as Sobel operators, specifically designed to highlight intensity gradients. The first seed detects HE, while the second focuses on vertical edges. These kernels are involved with the innovative image to compute gradient magnitudes in both directions. The results from these two convolutions are then combined, typically using the Euclidean norm, to create a single gradient magnitude image that effectively represents the edges. The SO is particularly effective because it emphasizes regions of HSF, where intensity changes sharply, indicating the presence of edges. Additionally, it introduces a degree of smoothing, which helps to reduce noise in the image. The final output can be thresholded to generate a BEM, facilitating the identification of prominent features. Sobel edge detection is essential for various applications, including object finding, IS, and CV, providing a critical foundation for further analysis in image processing.

(d) Drone-Based Crop Disease Detection Smart Farming Using IoT

Drone-based image processing is transforming smart farming by enhancing CDDM through IoT technologies. Drones armed with HRC and multispectral radars capture aerial images of agricultural fields, delivering real-time data on crop health. STO improves data transmission efficiency, reduces energy consumption, and ensures reliable communication among IoT devices, facilitating timely detection and management of crop diseases. By integrating this technology, farmers can quickly monitor extensive areas, allowing them to identify pretentious districts and contrivance embattled interventions. This practical method not only reduces yield damage but also optimizes the use of resources like water and fertilizers, promoting more SFP. The automation of monitoring reduces labour costs and enhances operational efficiency, enabling growers to attention to planned DM. The combination of drones, image processing, and IoT fosters a more resilient agricultural ecosystem, contributing to food security amid growing environmental challenges.

(i) Spanning Tree Optimization (STO)

Spanning Tree Optimization (STO) is a vital algorithm for automated crop health monitoring, especially in the dominion of drone-based image processing for disease detection. STO focuses on enhancing the communication network among IoT devices deployed in agricultural fields, ensuring efficient data transmission and optimal resource utilization. In a smart farming context, drones gather extensive data related to crop health, including imagery and sensor readings. STO facilitates the creation of an efficient communication path by forming an MST, which minimizes latency and energy consumption. This tree connects all devices with the least total connection cost, ensuring that data from drones is relayed quickly and reliably to a central processing unit. By optimizing data flow, STO significantly enhances real-time monitoring capabilities, enabling farmers to swiftly identify and address crop diseases, ultimately improving yields and resource management. The effectiveness of IoT-based agricultural systems hinges on this optimization.

STO is essential for cultivating communication efficiency among IoT devices in automated crop health monitoring systems, particularly those that rely on drone-based image processing for disease detection. The main neutral of STO is to establish a communication network that minimizes total connection costs while ensuring all devices are interconnected. This is particularly critical in agriculture, where timely data transfer can greatly influence crop management and disease control. One of the foundational equations in STO represents the total connection cost as follows:

$$C = \sum_{(i,j)\epsilon E} w_{ij} \tag{12}$$

Where, C denotes the total connection cost, E is the usual boundaries (connections) between nodes (IoT devices), and w_{ij} Indicates the weight (or cost) associated with the connection between nodes i and j. The objective is to minimize C while ensuring that all devices are covered, thus forming a connected network with the least possible expense. To optimize the network, the concept of an MST is employed. The MST is defined by the equation:

$$T = \{V, E_T\} \tag{13}$$

Here, T represents the MST, where V is the set of apexes (which correspond to the IoT devices) and E_T Is the subset of edges that form the tree. The key characteristic of the MST remains that it connects all apices with the least overall edge weight, effectively creating an optimized communication pathway that minimizes costs and improves data transmission efficiency.

The optimized communication framework greatly enhances the ability of drone systems to relay instantaneous data on yield fitness. As drones gather several kinds of documents, including multispectral images and sensor readings, STO ensures that this information is transmitted efficiently to a central processing unit. By reducing latency and improving data accuracy, growers can make well-versed judgements quickly, enabling timely interventions for DDM. In addition to optimizing communication pathways, STO produces a vivacious character in resource management. Minimizing total connection costs, helps farmers reduce operational expenses related to network infrastructure, making IoT solutions more feasible and sustainable.

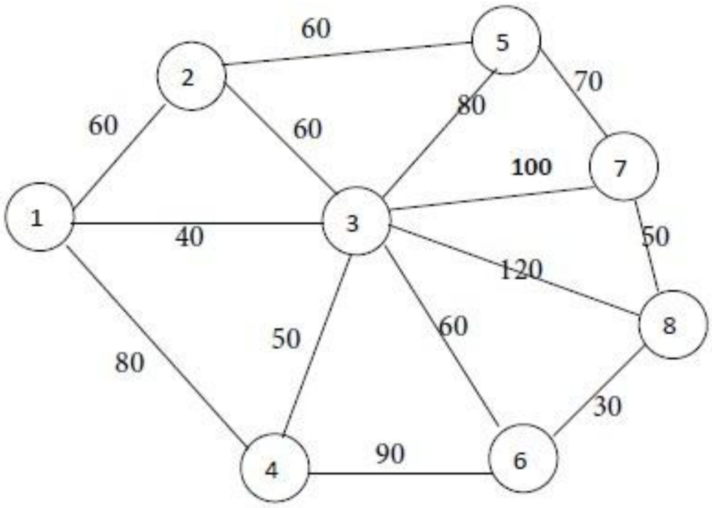

Figure 4. Spanning Tree Optimization (STO)

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Figure 4 demonstrates the role of STO in automated CHM and drone-based image processing, with prominence on the incorporation of IoT equipment for efficient CDD. In this setting, the spanning tree represents a connected device grid and drones that gather data across the agricultural landscape. Each node signifies a sensor or drone, while the edges represent the optimized communication pathways between them, designed to MEC and enhance data transmission efficiency. The optimization process ensures that the most relevant data regarding crop health is relayed to a dominant system with minimal latency, enabling timely interventions. By employing STO, the system effectively manages resources, prioritizing critical information and reducing redundant data flow. This approach not only improves the accuracy of disease detection but also supports SFP by optimizing the use of technology in monitoring crop health.

EXPERIMENTATION AND RESULT DISCUSSION

The experimentation phase for automated CHM and drone-based image processing involved systematic field trials to assess the efficacy of the projected classification in detecting crop diseases. The drones equipped with HRC conducted multiple flights over designated agricultural areas, capturing a diverse array of images under varying environmental conditions. The pre-processed images underwent analysis using advanced algorithms, including PLSR and SED, to identify and classify disease symptoms. Results showed a substantial enhancement in disease detection accuracy associated with outdated methods, with early identification allowing for targeted interventions. The incorporation of IoT data further enhanced the understanding of environmental factors influencing CH. The discussion of results indicated that this approach not only minimized crop losses but also optimized resource usage, dipping the requirement for pesticides and fertilizers. The findings underscore the potential of combining drone technology and IoT in revolutionizing crop management, promoting sustainable agricultural practices, and improving food security.

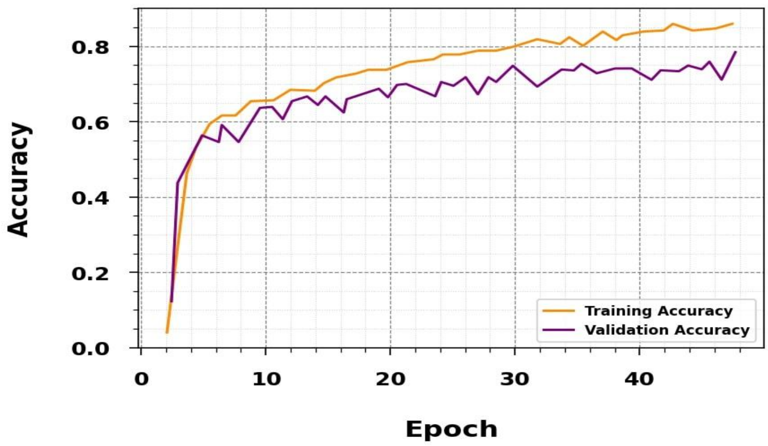

Figure 5. Training and Validation Accuracy Over Epochs

Figure 5 illustrates the connection between preparation and VA over multiple epochs during the training process of an ML model. Initially, both training and validation accuracies are low, indicating the model is in the early stages of learning. As training progresses, the training accuracy consistently rises, reaching up to 0.9, suggesting that the model is effectively capturing patterns within the training data. In contrast, validation accuracy increases more gradually, peaking at 0.7. This divergence between the two accuracies highlights an important aspect of model performance: while the model becomes proficient at predicting the training data, it struggles to generalize to unseen data, as indicated by the slower improvement in validation accuracy. This behaviour may signal overfitting, where the model becomes overly specialized to the training dataset, making it difficult to perform well on new examples. Monitoring this dynamic is crucial to ensure the archetypal strikes a balance between accuracy and generalization, ultimately achieving robust performance in real-world applications.

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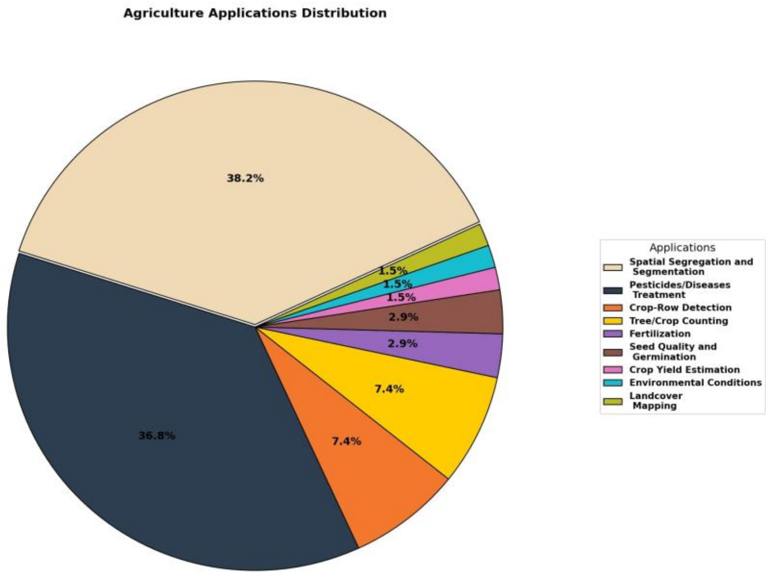

Figure 6. Distribution of Agricultural Applications

Figure 6 exemplifies the delivery of various agricultural applications, highlighting the diverse areas where technology is making a significant impact. The largest segment, representing 38.2%, is dedicated to spatial segregation and segmentation, underscoring its importance in effectively managing and analysing agricultural landscapes. Close behind is the pesticide treatment category at 36.8%, which emphasizes the significance of targeted pesticide application to enhance crop health and yield while minimizing ecological impact. Other notable segments include crop raw detection and tree/crop counting, each contributing 7.4% to the overall distribution, mutually which are essential for CHM and optimizing resource allocation. Fertilization shares the same percentage, reflecting its critical role in ensuring sustainable crop production. Seed quality and germination account for 2.9%, highlighting ongoing efforts to improve planting materials for better yields. Meanwhile, crop yield estimation, environmental conditions, and land cover mapping each represent 1.5%, showcasing specialized areas of focus that, although smaller, are vital for comprehensive agricultural management.

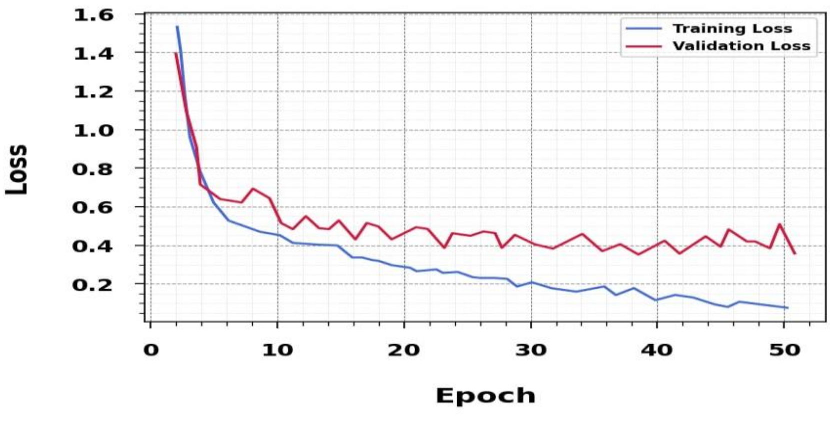

Figure 7. Training and Validation Loss Over Epochs

Figure 7 illustrates the trends in TVL during the training epochs of an ML exemplary. At the outset, both training and validation losses are relatively high, indicating that the model struggles to learn effectively from the data. As the epochs progress, training loss shows a significant decline, dropping from 1.5 to 0.1. This sharp decrease indicates the classical is effectively improving its fit to the TD by learning patterns and reducing errors. In contrast, validation loss decreases at a slower pace, going from 1.4 to 0.4. This gradual reduction suggests that prototypical is starting to generalize to unseen data, although it still lags behind the training loss. The convergence of both losses is

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encouraging, indicating that the ideal is not significantly overfitting, as both metrics are improving together. Monitoring these trends is crucial to ensure the model strikes a balance between fitting the preparation of information and simplifying well to new data, ultimately leading to robust and reliable predictive performance.

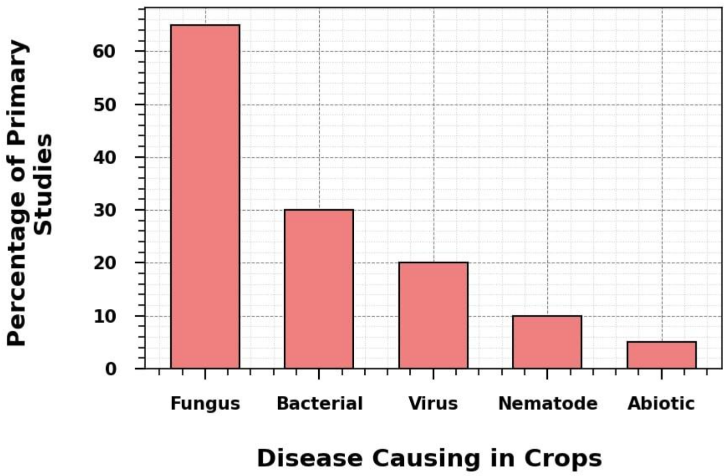

Figure 8. Distribution of Disease-Causing Agents in Crop Studies

Figure 8 illustrates the percentage distribution of primary studies focused on various disease-causing agents in crops. Fungal diseases dominate the chart, accounting for 63% of the studies, reflecting their prevalence and significance in agricultural research. This high percentage indicates fungi's substantial impact on CH and yield, highlighting the need for effective management strategies. Bacterial infections follow, comprising 30% of the studies. This significant representation underscores the reputation of accepting bacterial diseases, which can lead to severe crop losses. Viral diseases are also a notable concern, making up 20% of the research focus. The presence of viruses in crops necessitates ongoing investigation into their transmission and control measures. Nematodes and abiotic factors are represented by smaller percentages, with nematodes at 10% and abiotic stresses at 5%. Although these categories account for less research attention, they are crucial for a comprehensive understanding of CH and resilience. Overall, this distribution highlights the diverse challenges faced in agriculture and the need for targeted research to combat these various threats.

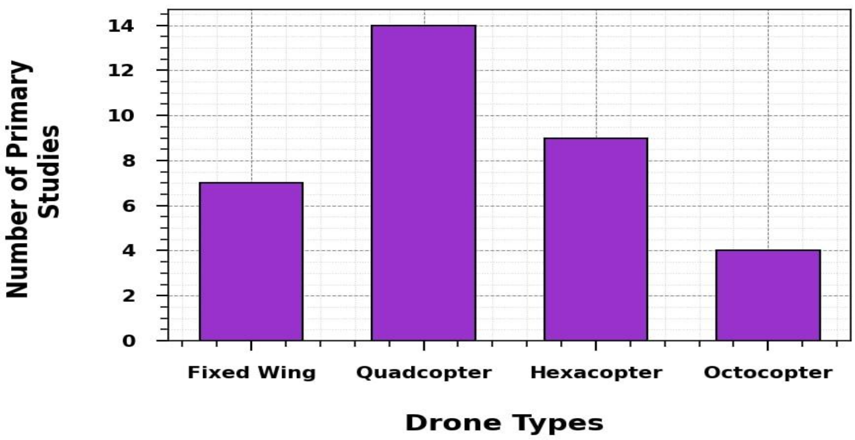

Figure 9. Distribution of Primary Studies by Drone Type

Figure 9 shows the number of primary studies conducted on various types of drones used in agricultural applications. Quadcopter drones lead the distribution with 14 studies, highlighting their popularity and versatility in farming practices. Their ability to manoeuvre easily and capture high-resolution imagery makes them a favoured choice among researchers and practitioners. Fixed-wing drones follow with 7 studies, emphasizing their utility in covering larger areas efficiently, building them apposite for extensive agricultural monitoring. Hexacopters, with 9 studies,

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also represent a significant interest, combining the benefits of stability and payload capacity. Their design allows for versatile applications, including crop surveillance and data collection. Octocopters, although the least studied with only 4 entries, still play a role in specialized tasks requiring high stability and heavier payloads. The distribution reflects a growing interest in the diverse capabilities of DT in agriculture, underscoring the importance of selecting the appropriate drone type based on specific research objectives and operational needs. This variety illustrates the ongoing advancements and adaptability of DT in enhancing agricultural practices.

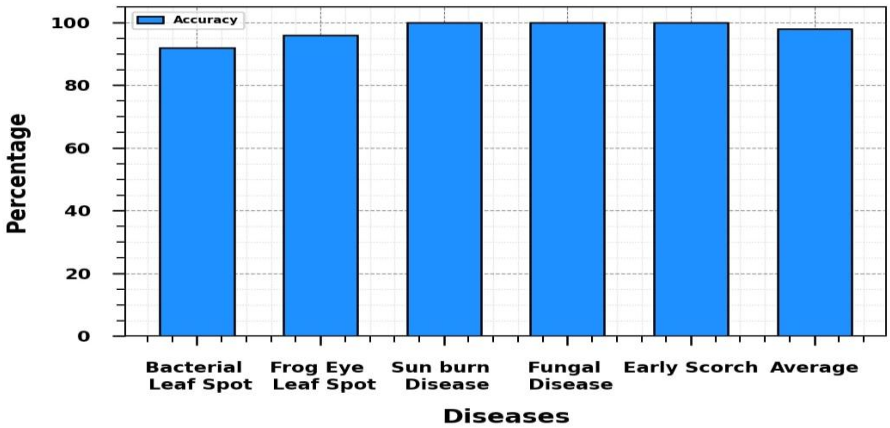

Figure 10. Accuracy of Disease Detection in Crops

Figure 10 represents the accuracy percentages of various diseases affecting crops, showcasing the effectiveness of detection methods for each condition. Sunburn disease, fungal disease, and early scorch stand out with perfect accuracy ratings of 100%, indicating that these methods are exceptionally reliable in identifying these specific ailments. This high accuracy reflects the advancements in diagnostic techniques and their ability to detect these diseases accurately. Frog eye leaf spot follows closely with an impressive accuracy of 92%, demonstrating strong detection capabilities, while bacterial leaf spot has a slightly lower accuracy at 90%. These values indicate that, although slightly less accurate than the top diseases, the detection methods for these conditions are still quite effective and can be trusted for practical applications. The average accuracy across all studied diseases is 98%, underscoring the overall reliability of the detection methodologies in agricultural settings. This data emphasizes the importance of accurate disease identification in crop management, enabling timely interventions and improved agricultural outcomes.

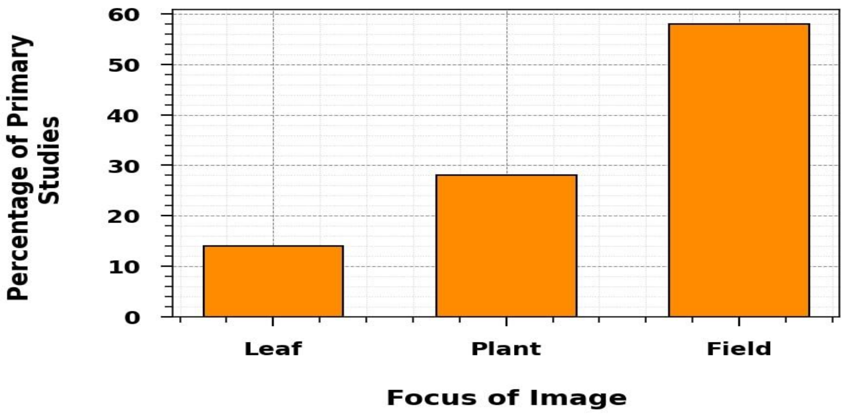

Figure 11. Focus of Image Analysis in Agricultural Studies

Figure 11 clarifies the dispersal of primary studies based on the focus of image analysis in agricultural research. Field-level studies dominate the chart, representing 59% of the total, which highlights the significant interest in large-scale agricultural monitoring and management. This focus on fields suggests a priority on understanding broader CH and environmental conditions, facilitating more effective agricultural practices. Plant-level studies account for 29% of the

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research, reflecting a strong emphasis on understanding individual plant health, growth, and development. This level of focus is crucial for identifying specific issues that may affect crop yield and quality. Meanwhile, studies centred on leaves constitute 12% of the total, indicating that while leaf analysis is essential for assessing certain diseases and conditions, it represents a smaller fraction of the overall research efforts. The distribution demonstrates a clear trend towards analyzing larger agricultural systems while still acknowledging the importance of both plant and leaf-level studies. This balance is vital for comprehensive agricultural research, enabling targeted interventions and enhancing overall crop productivity.

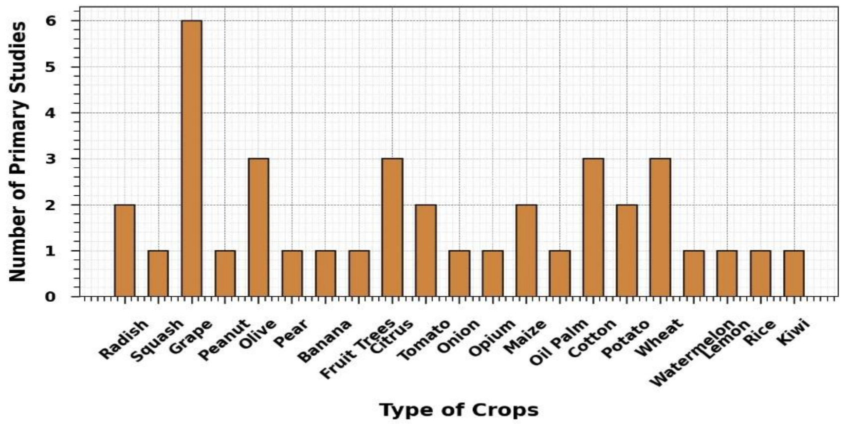

Figure 12. Distribution of Primary Studies by Crop Type

Figure 12 represents the distribution of primary studies conducted on various types of crops, illustrating the varying levels of research focus across different agricultural products. Grape crops lead the chart with 6 studies, indicating a strong interest in understanding their cultivation and management, likely due to their economic significance and vulnerability to diseases. Olive crops follow with 3 studies, reflecting a notable emphasis on this important Mediterranean crop, while fruit trees also account for 3 studies, suggesting a focus on a diverse range of tree fruits that contribute to agricultural systems. Radish and tomato each have 2 studies, highlighting their relevance in both research and cultivation practices. Other crops, such as squash, peanut, pear, banana, and kiwi, indicate that while they are valuable crops, they currently receive less research attention compared to others. This distribution underscores the need for a balanced approach to agricultural research, ensuring that a wider variety of crops are studied to address emerging challenges in crop management and sustainability.

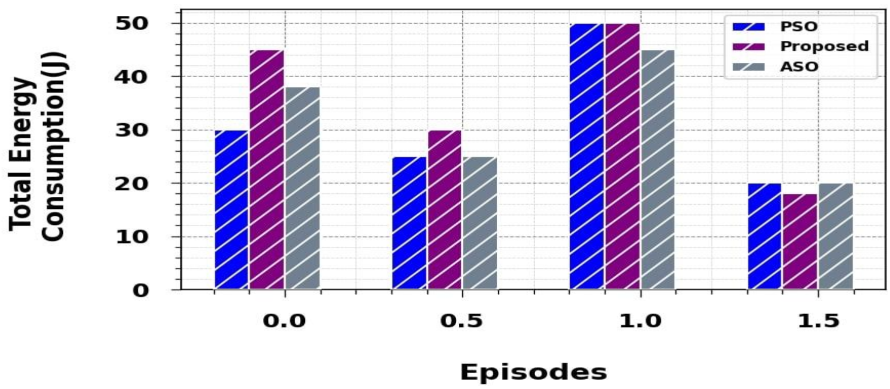

Figure 13. Total Energy Consumption Across Algorithms and Episodes

Figure 13 shows the total energy consumption across different algorithms PSO, Proposed, and ASO across multiple episodes. At the 0.0 episode, PSO demonstrates the lowest energy consumption at 30 J, while the Proposed method uses more energy at 45 J, and ASO is slightly lower at 39 J. This initial disparity highlights the varying efficiencies of these approaches in energy usage. As episodes progress to 0.5, the energy consumption patterns shift slightly. PSO remains efficient at 25 J, while the Proposed method reduces its consumption to 30 J, and ASO maintains a steady

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25 J. This trend suggests an improvement in the Proposed method's efficiency, although it still consumes more energy than PSO and ASO. In the 1.0 episode, both PSO and the Proposed method consume 50 J, indicating a peak in energy use for these algorithms, while ASO consumes 45 J. At 1.5 episodes, the Proposed method slightly decreases to 19 J, while PSO remains at 20 J and ASO also stabilizes at 20 J. This fluctuation in energy consumption emphasizes the efficiency dynamics between the different algorithms over the episodes.

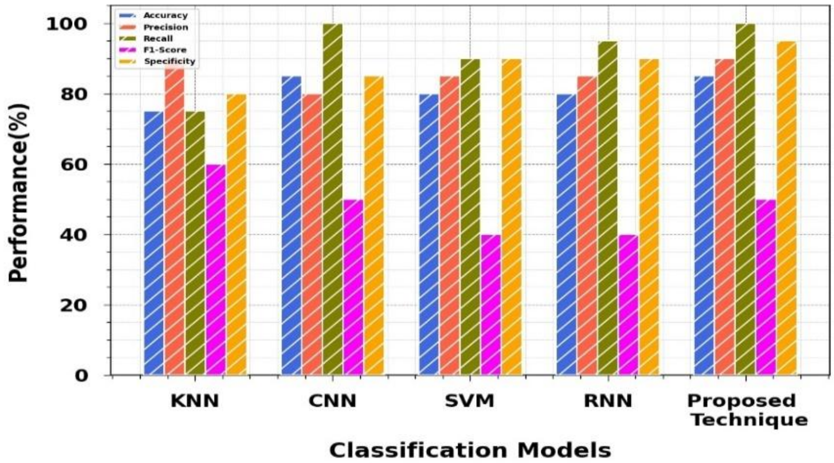

Figure 14. Classification Models Performance Metrics

Figure 14 shows the performance metrics of three classification models: KNN, CNN, and SVM, measured through accuracy, precision, recall, F1-score, and specificity. KNN achieves an accuracy of 79%, indicating a solid overall performance. Its precision is slightly higher at 80%, suggesting a good capability in identifying relevant instances. However, the recall rate is also 79%, indicating that KNN captures a substantial proportion of true positives, while the F1-score of 60 reflects a trade-off between precision and recall. CNN shows the highest accuracy at 81%, with a remarkable recall of 100%, indicating it identifies all true positive cases effectively. F1-score is lower at 43, highlighting a potential imbalance in precision. CNN's specificity at 79% indicates a moderate ability to identify true negatives. SVM presents an accuracy of 80% with the highest precision of 81%, but its recall is notably low at 40%, leading to an F1-score of 40, suggesting it struggles with true identification. The specificity for SVM is the highest at 83%. These metrics collectively illustrate the strengths and weaknesses of each model in classification tasks.

RESEARCH CONCLUSION

The integration of automated CHM and drone-based image processing is transforming disease detection in smart farming by leveraging IoT technologies for improved monitoring accuracy and efficiency. This pioneering slant allows farmers to quickly identify and address potential crop issues, minimizing losses and maximizing yields. Whines fortified with progressive IP algorithms can detect illnesses and nutrient deficiencies that traditional methods often overlook, significantly sinking the jeopardy of widespread outbreaks. Real-time data analytics enable ranchers to brand conversant verdicts about PM and RA, leading to higher crop yields and reduced losses. Efficient monitoring of large areas facilitates targeted interventions, which can lower pesticide and fertilizer use, promoting sustainable agricultural practices. The use of IoT technology ensures the smooth integration of data from various sensors, offering a wide-ranging vision of crop and soil health. This research underscores the potential for significant advancements in precision agriculture, contributing to food security in the expression of increasing environmental challenges. In terms of model performance, training loss has notably decreased from 1.5 to 0.1, indicating better fitting to the TD and reduced error. Validation loss shows a more gradual decline from 1.4 to 0.4, suggesting the model is beginning to make a sweeping announcement to fresh statistics, though it still lags behind the training loss. Monitoring these trends is crucial for balancing the fit to training data with robust predictive performance on unseen data. Future developments may focus on refining ML procedures for enhanced predictive accuracy and expanding the system's application across various agricultural contexts. As the agricultural landscape evolves, this approach marks a significant step toward smarter and more resilient farming practices.

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