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Smart Agriculture Utilizing Computer Vision for Precision Farming

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ABSTRACT:

Computer vision integration has enabled farming by allowing automation and intelligent decision-making in numerous aspects of crop production. From weed detection to fruit classification, efficiency, accuracy, and sustainability are all factors in modern agricultural practices. Nevertheless, this is one of the biggest roadblocks-availability of high-quality public image datasets for developing and validation of machine learning algorithms in agricultural applications. The paper reviews publicly available datasets collected under real-world field conditions, which are categorized as follows: weed control, fruit detection, and others of agricultural operation. We refer to the key attributes in the dataset, the importance of these attributes in the algorithm development process, and the challenges related to dataset generation and accessibility. This review provides a useful guide for selecting right datasets for researchers and emphasizes that the need to develop more datasets to advance precision agriculture.

Keywords: Crop Monitoring, Precision Agriculture, Image Dataset, Computer Vision, Deep learning, Smart agriculture, GIS, drones, remote sensing. Image analysis, RGB

I. INTRODUCTION

Precision agriculture is transforming farming by using modern technology to improve productivity while reducing waste and environmental impact. One of the most powerful tools in this field is computer vision, which helps analyze images to monitor crops, detect weeds, and guide automated machines. By using digital images, computer vision provides accurate and real-time information about crops and their surroundings. Different imaging techniques support various farming tasks. RGB (red-green-blue) imaging works like human vision to inspect crops, while near-infrared (NIR) and multispectral imaging help detect plant health issues that are not visible to the naked eye. These technologies allow farmers to monitor crops, assess growth stages, and identify diseases early. With the rise of artificial intelligence and robotics, computer vision is playing a key role in automating farming tasks. Robots equipped with cameras and AI can recognize and remove weeds, pick fruits at the right time, and analyze soil conditions. Autonomous farming machines can also navigate fields, reducing the need for human labor and improving efficiency. The main goal of computer vision in precision agriculture is to identify and differentiate between crops, weeds, and other objects to optimize farming operations. As technology advances, its applications continue to grow, making farming smarter and more sustainable. By improving decision-making, reducing costs, and increasing yields, computer vision is set to revolutionize modern agriculture, helping farmers meet the growing demand for food while using fewer resources.

II. Literature Review

Singh, A. K.., Precision agriculture (PA) is transforming Indian farming by integrating advanced technologies like AI, IoT, and remote sensing to enhance productivity and sustainability. The paper highlights how PA can optimize resource use, reduce costs, and improve crop yields through data-driven decision-making. One of the key advantages is efficient water and fertilizer management, which minimizes waste and environmental harm. However, the adoption of PA in India faces challenges such as high initial costs, lack of awareness, and limited digital infrastructure in rural areas. Small landholdings further complicate large-scale implementation. Additionally, data management remains a major hurdle due to the complexity of handling vast agricultural datasets. The paper evaluates PA's effectiveness using metrics like crop yield improvement, cost reduction, and resource efficiency. While PA offers immense benefits, government support, including subsidies and farmer training, is crucial for wider adoption. Addressing these challenges can unlock the full potential of PA in Indian agriculture. Ultimately, precision agriculture can pave the way for a more efficient, profitable, and sustainable farming future

Chandra A.L., The paper by Chandra et al. (2020) provides a comprehensive survey on the use of computer vision and deep learning for plant phenotyping in agriculture. The main objective is to explore how AI-driven techniques can improve the accuracy and efficiency of plant trait analysis, helping researchers and farmers monitor crop growth, detect diseases, and enhance yield prediction. One of the key advantages of deep learning in plant phenotyping is its ability to analyzed large-scale image datasets, enabling automated and precise trait identification. It also reduces manual labor, enhances disease detection, and optimizes breeding processes. However, the study highlights several limitations, such as the need for extensive labelled datasets, high computational requirements, and challenges in adapting models to varying environmental conditions. The performance of deep learning models in plant phenotyping is evaluated using metrics like classification accuracy, F1-score, and mean average precision (MAP) to assess detection and segmentation quality. The methods discussed in the paper include convolutional neural networks (CNNs) for feature extraction, transfer learning to improve model generalization, and data augmentation techniques to enhance training robustness. The research also emphasizes the need for explainable AI models to improve transparency and trust in automated phenotyping. Despite challenges, the integration of deep learning with computer vision is revolutionizing plant phenotyping, enabling scalable and efficient crop analysis. Future advancements should focus on improving model interpretability, expanding labelled datasets, and optimizing computational efficiency for real-world agricultural applications. This study serves as a valuable resource for researchers aiming to advance AI-driven precision agriculture.

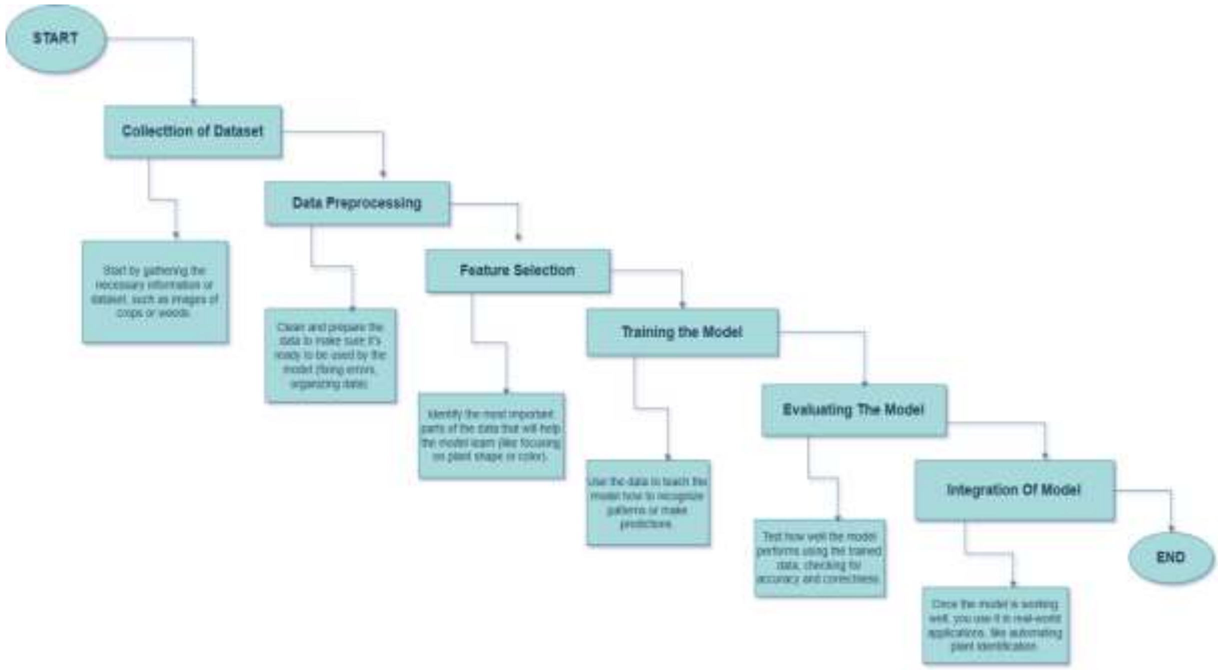
Haug, S., & Ostermann., The paper by Haug and Ostermann (2021) introduces a publicly available dataset designed for evaluating computer vision models in precision agriculture, particularly for crop and weed detection. The main objective is to provide high-quality field images that can help train and test machine learning algorithms for automated weed identification and crop monitoring. This dataset offers several advantages, such as improving AI-based weed detection, enhancing crop management, and supporting deep learning research for agricultural automation. However, it also has some limitations, including restricted crop variety, environmental variability affecting image consistency, and the need for extensive annotation for accurate training. The performance of models using this dataset is evaluated through key metrics like classification accuracy, precision-recall, F1-score, and Intersection over Union (IOU) for object detection. The dataset was created using real-world field images, which were processed, labelled, and tested on various deep learning models for benchmarking. The study emphasizes the importance of AI in reducing manual labor in agriculture, making farming more efficient and sustainable. Despite challenges like dataset scalability and annotation complexity, this research provides a strong foundation for developing smart farming solutions. By leveraging computer vision, farmers can achieve better weed control, optimize resource usage, and increase crop yields. Future advancements could focus on expanding the dataset to include more crop varieties and improving model generalization across diverse farming conditions. Overall, this work contributes significantly to the field of precision agriculture, enabling automation and improved decision-making in farming practices.

Hemming, J., & Rath., The paper by Hemming and Rath (2020) explores the use of computer vision for weed identification in precision agriculture under controlled lighting conditions. The main objective is to develop and evaluate a vision-based system that accurately distinguishes weeds from crops in real-world field conditions. One of the key advantages of this approach is its ability to automate weed detection, reducing the need for herbicides and manual labor. The system also enhances efficiency by enabling targeted weed control, minimizing crop damage, and improving overall farm productivity. However, the study highlights several limitations, including the dependency on controlled lighting, which may not be practical in large-scale outdoor farming. Environmental factors like shadows and varying light intensity can also affect detection accuracy. The performance of the system is assessed using metrics such as classification accuracy, precision-recall scores, and segmentation quality. The methods used involve image preprocessing techniques like contrast enhancement, edge detection, and machine learning algorithms for weed classification. Deep learning models, such as convolutional neural networks (CNNs), were employed to improve detection accuracy. The research emphasizes the importance of robust dataset collection and annotation to enhance model performance. Despite challenges, computer vision-based weed identification holds great potential for precision agriculture by optimizing weed control and reducing environmental impact. Future advancements should focus on making the system adaptable to diverse lighting conditions and improving real-time processing capabilities. This study contributes significantly to the development of AI-driven agricultural solutions, paving the way for more sustainable and efficient farming practices.

Ganatra, N., The paper by Ganatra and Patel (2021) explores the role of deep learning in precision agriculture, focusing on its applications in crop monitoring, disease detection, and yield prediction. The main objective is to analyze

various deep learning techniques and their effectiveness in automating agricultural tasks to improve productivity and sustainability. One of the key advantages of deep learning in agriculture is its ability to process large-scale image datasets, enabling accurate plant disease detection, weed classification, and soil health assessment. These AI-driven solutions reduce manual labor, optimize resource usage, and enhance decision-making for farmers. However, the study also highlights several limitations, including high computational costs, the need for extensive labelled datasets, and difficulties in adapting models to different environmental conditions. The performance of deep learning models is evaluated using metrics such as accuracy, precision-recall scores, F1-score, and mean squared error (MSE) for predictive tasks. The methods discussed in the paper include convolutional neural networks (CNNs) for image-based analysis, recurrent neural networks (RNNs) for time-series predictions, and transfer learning to improve model adaptability with limited data. The paper also explores data augmentation techniques to enhance training efficiency and reduce overfitting. Despite challenges, deep learning has shown significant potential in transforming modern agriculture by enabling smart farming solutions. Future research should focus on developing more interpretable AI models, reducing computational requirements, and expanding datasets to improve model robustness. This study provides valuable insights into the impact of AI in precision agriculture, emphasizing the need for further advancements in deep learning applications.

3. Methodology



1.Collection of Dataset:

Collect images of crops, weeds, or soil using drones, satellites, or cameras. These images serve as the data for training the model to perform tasks like detecting diseases, weeds, or assessing crop growth.

2. Data Preprocessing:

The raw data collected often requires cleaning or transforming before it can be used for modeling. This can involve tasks such as noise removal, normalization, or image augmentation.

3. Feature Selection:

Identify the key features from the images, such as the shape, color, or texture of plants or soil that can help differentiate between healthy crops and diseased ones, crops and weeds, or wet and dry soil areas.

4.Training the Model:

Use machine learning algorithms to train the model on the selected features from the images. The model learns to recognize patterns, such as the appearance of pests or the growth stage of plants.

5.Evaluating the Model:

Test the trained model using a separate set of images to check how accurately it can detect weeds, diseases, or estimate yields. Evaluation ensures the model's predictions are reliable.

6.Integration of Model:

Once the model performs well, integrate it into a field management system. The model can now analyze new images from the farm and provide real-time insights or recommendations, like identifying areas that need more water or less pesticide.

Paper-1:

1. **Data Collection:**

Data Collection Platforms: The methodology uses various data sources, including: Ground-based sensors and cameras: These collect close-up, detailed images of plants. Aerial drones (UAVs): Capture broader, high-resolution images from above, which are useful for monitoring larger field sections. Drones equipped with RGB, thermal, or multispectral cameras capture larger areas at high resolutions. UAVs (Unmanned aerial vehicle) are used for crop health monitoring, weed detection, and yield prediction. Satellite Imagery: This enables extensive field monitoring but is limited by resolution and cloud cover.

2.Pre-processing and Image Segmentation:

Adjustments like lens correction, color balancing, and segmentation of image regions (e.g., plant vs. soil) are done to make the images clearer and ready for analysis. Image Correction: Techniques like lens distortion correction, white balance adjustments, and noise filtering are applied to improve image quality.

Segmentation Techniques: Use Thresholding and K-means clustering for basic segmentation, separating plant from background. For complex segmentations (e.g., separating leaves, stems), apply U-Net or Mask R-CNN models to achieve pixel-wise segmentation.

Data Collection Platforms:

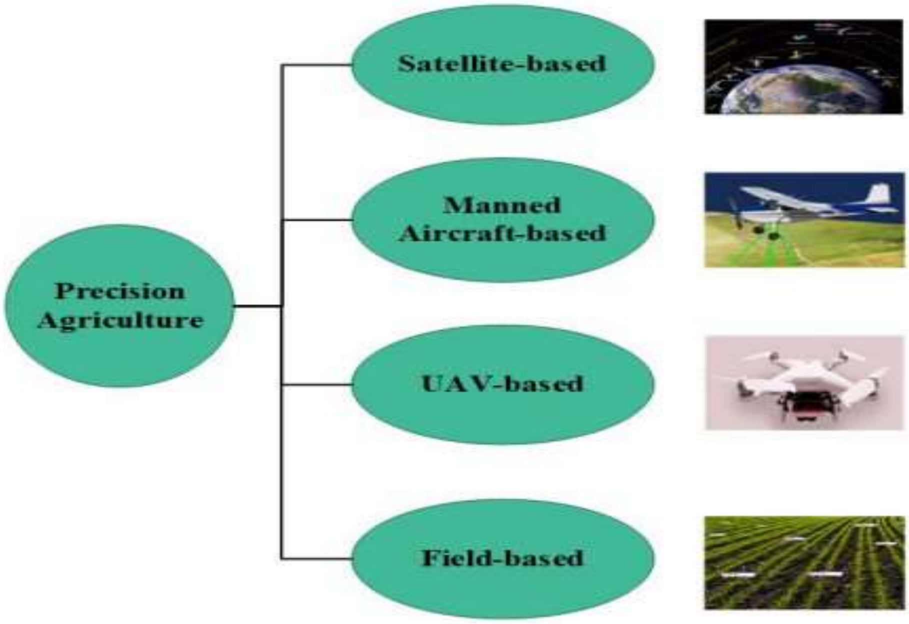


Fig.1.1: Data Collection Platforms

Architecture Design:

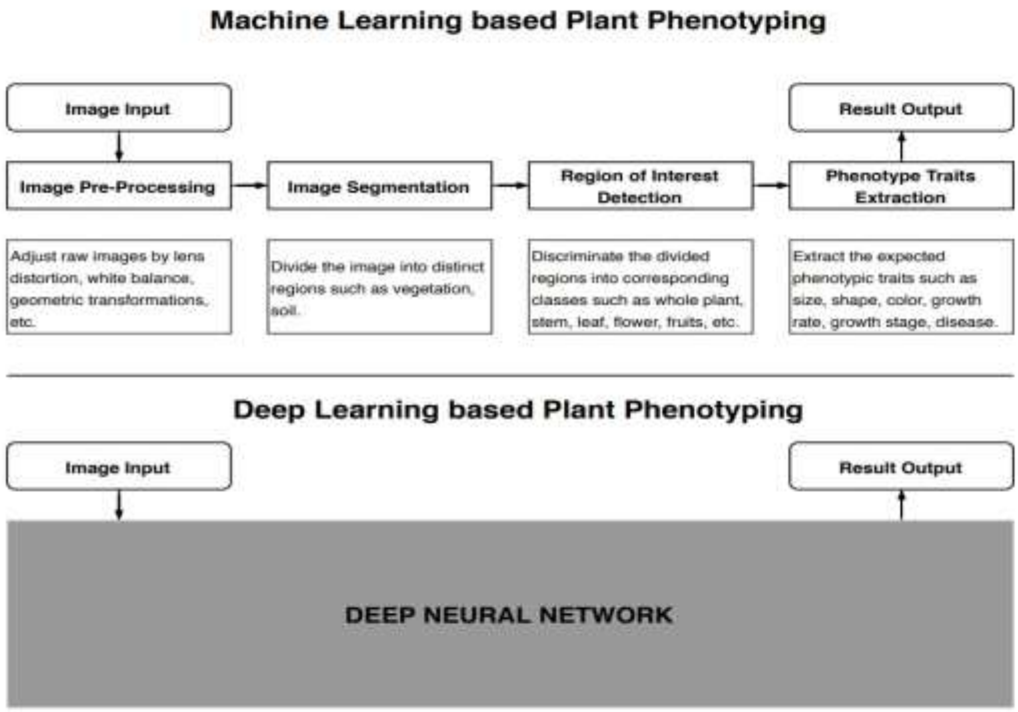


Fig.1:2: Architecture Design

3.Machine Learning and Deep Learning Models:

1.Convolutional Neural Networks (CNNs): A convolutional neural network (CNN) is a type of artificial neural network used primarily for image recognition and processing, due to its ability to recognize patterns in images. A CNN is a powerful tool but requires millions of labelled data points for training. CNNs used for tasks such as plant disease recognition, crop classification, and segmentation. CNNs are highlighted for their convolutional and pooling layers, which process spatial hierarchies in imagery, essential for recognizing features in complex agricultural images. Within Deep Learning, a Convolutional Neural Network or CNN is a type of artificial neural network, which is widely used for image/object recognition and classification. CNNs are used in tasks like image classification, object detection, and segmentation, where they help in identifying objects, shapes, and textures. CNNs require millions of labeled data points for training, and high-power processors like a GPU or NPU to produce results quickly. CNNs use relatively little pre-processing compared to other image classification algorithms. They also learn to optimize filters through automated learning, instead of having filters hand-engineered. Key layers: Convolutional Layer: Detects simple patterns in images (like edges). Pooling Layer: Reduces data size while retaining important information. Fully Connected Layer: Combines features to make final decisions (e.g., classifying the object in an image). The below fig 1.3 describing the workflow of the model using CNN algorithm.

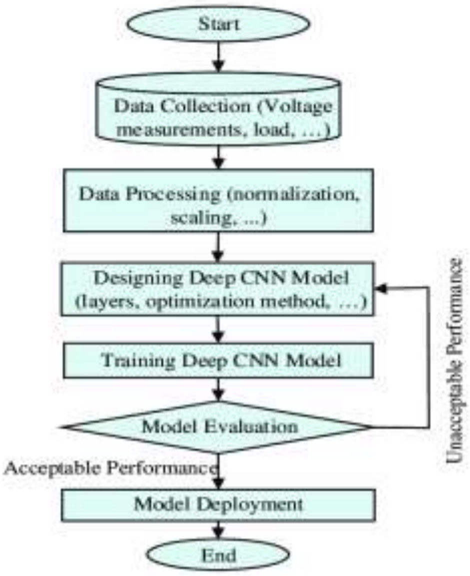


Fig.1.3: Convolutional Neural Network

2.Reinforcement Learning (RL): Reinforcement Learning is a type of machine learning algorithm that learns to solve a multi-level problem by trial and error. Reinforcement Learning (RL) -Sometimes combined with CNNs for autonomous tasks such as weed identification and crop monitoring, where decision-making is crucial for real-time applications. Reinforcement Learning (RL) is a machine learning technique where an algorithm learns by interacting with an environment, making decisions, and receiving rewards or penalties as feedback to improve over time. In this paper, although specific RL algorithms aren't implemented, RL is suggested as a valuable approach for potential use in precision agriculture. RL could be applied in areas such as automated crop management, weed control, or resource allocation (e.g., watering, pesticide application) by enabling models to make real-time decisions and improve based on field conditions. For example, an RL model could learn the best timing and quantity for watering crops by receiving feedback based on soil moisture and plant health, continually refining its approach for optimized crop growth and efficient resource use. Fig 1.4 describing about the workflow of the model using Reinforcement Learning and Fig 1.5 describing about the typical RL scenario.

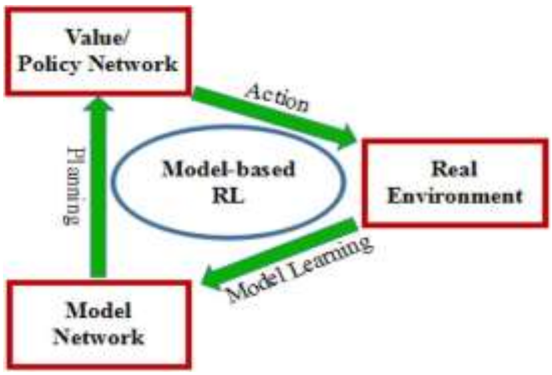
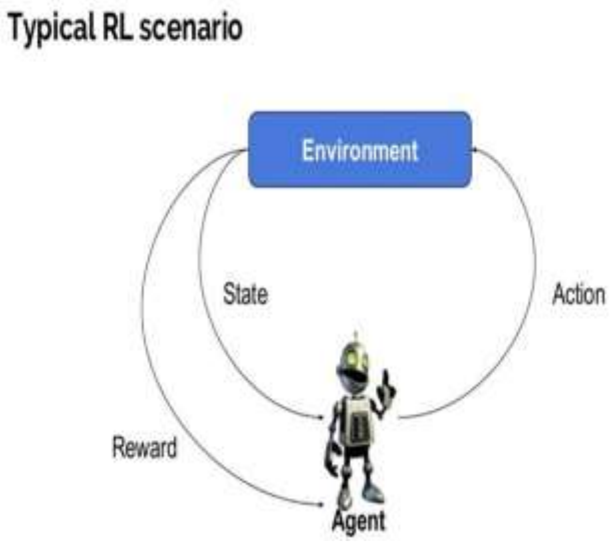


Fig.1.4: Reinforcement Learning



3.Generative Adversarial Networks (GANs):

Generative Adversarial Networks (GANs) are a class of machine learning frameworks designed for generating new data samples that resemble a given dataset. GANs consist of two neural networks, a **generator** and a **discriminator**, that compete against each other in a zero-sum game.

The generator creates fake data from random noise. Its goal is to generate data so realistic that the discriminator cannot distinguish it from real data. Input: Random noise (latent vector). Output: Fake data sample (e.g., an image, audio signal). The discriminator evaluates whether a given sample is real (from the training dataset) or fake (generated by the generator). Its goal is to correctly classify real and fake data. Input: A data sample. Output: A probability indicating whether the input is real or fake.

Precision Agriculture: Synthetic Data Generation for Crop/Weed Classification: GANs can augment datasets like CWFID by generating synthetic images of crops and weeds, helping balance the dataset and improving model performance. deep learning architecture used for generating new, synthetic data samples that resemble a given training dataset. Introduced by Ian Goodfellow in 2014, GANs have two neural networks competing against each other in a game-like setting. The discriminator tries to improve at identifying fake data. The below fig 1.6 describing the workflow of the model using Generative Adversarial Networks algorithm.

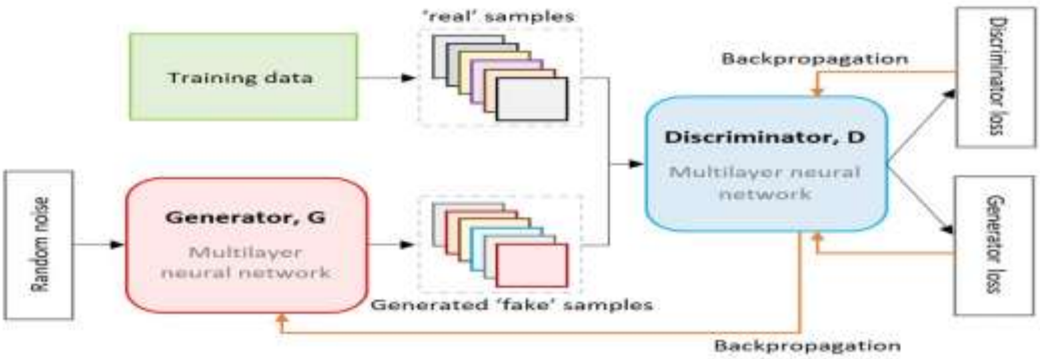


Fig.1.6: Generative Adversarial Networks

Paper-2:

1.Dataset Collection and Classification:

The authors compile and evaluate publicly available datasets used in agricultural research, like Plant Village, CWFID, and Leaf snap. These datasets are categorized by their contents (e.g., plant species, disease types) to understand which datasets are most suited to specific tasks in agriculture. The paper also identifies gaps in available datasets. They evaluate datasets based on factors like image quality, number of classes, and specific application use cases (e.g., identifying plant diseases or detecting weeds). Fig 2.1 describing about the workflow of the model using Dataset Collection and Classification and Fig 2.2 describing about the typical Architecture Design.

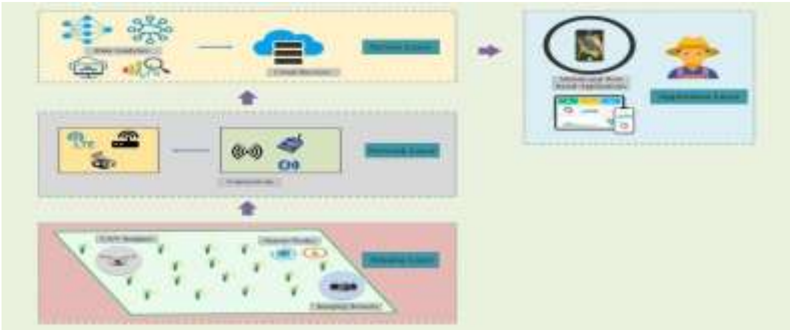


Fig.2.1: Dataset Collection and Classification

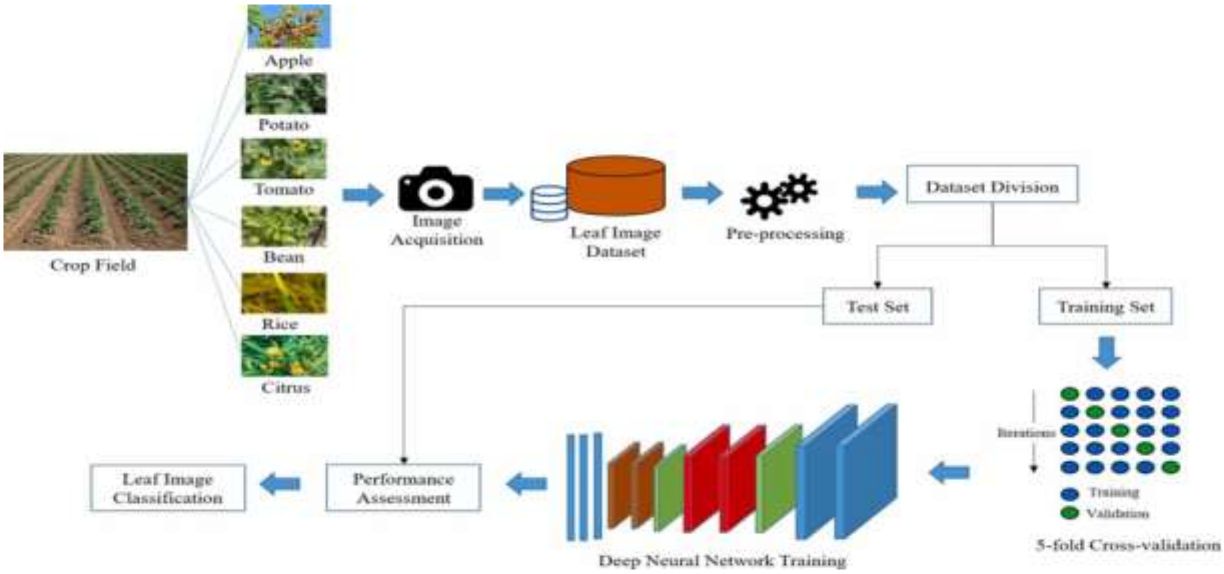


Fig.2.2: Architecture Design

1.Convolutional neural network (CNN): A convolutional neural network (CNN or Conv Net) is a network architecture for deep learning that learns directly from data. CNNs are particularly useful for finding patterns in images to recognize objects, classes, and categories. They can also be quite effective for classifying audio, time-series, and signal data. Primarily used for image-based tasks in agriculture, such as plant disease detection, crop classification, and weed identification. CNN architectures like **Alex Net**, **Google Net**, are discussed for their effectiveness in extracting features from agricultural images. Purpose: CNNs are primarily used for image processing tasks, such as identifying plant diseases, classifying crops, and distinguishing weeds from crops. Architecture Highlights: CNNs consist of convolutional layers that extract features from images, pooling layers that reduce dimensionality, and fully connected layers that perform classification Different CNN layers (convolution, pooling, fully connected) extract hierarchical features from agricultural images, capturing both low-level and high-level features to identify patterns related to plant health or species type. The below fig 2.3 describing the workflow of the model using CNN algorithm.

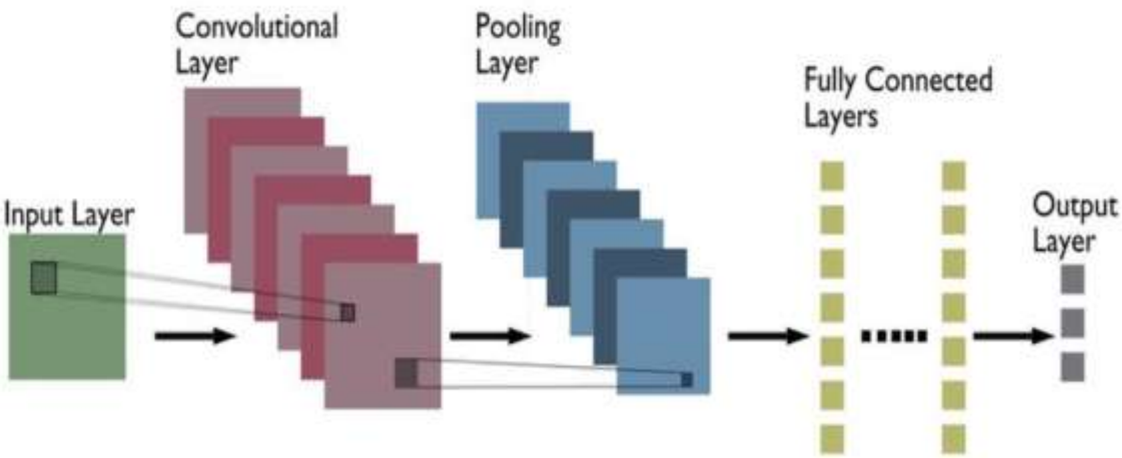


Fig.2.3: Convolutional neural network

2.Recurrent Neural Networks (RNNs):

A recurrent neural network (RNN) is a deep learning model that processes sequential data inputs to produce sequential data outputs. RNNs are used to solve problems that involve time series or sequences, such as language translation, natural language processing (NLP), and sentiment analysis. For time-series data, such as monitoring vegetation quality over time, methods like Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) are used. These models are effective in tasks that require understanding sequential patterns, such as seasonal changes in crop health. Purpose: RNNs are used for sequential data analysis, which is essential in agriculture for tasks involving time-series data, such as monitoring crop growth stages, predicting seasonal yield, and assessing soil moisture over time. Architecture Highlights: RNNs have connections that form directed cycles, enabling them to remember previous inputs, making them ideal for time-dependent tasks. The below fig 2.4 describing the workflow of the model using RNN algorithm and fig 2.5 describing Application of RNN.

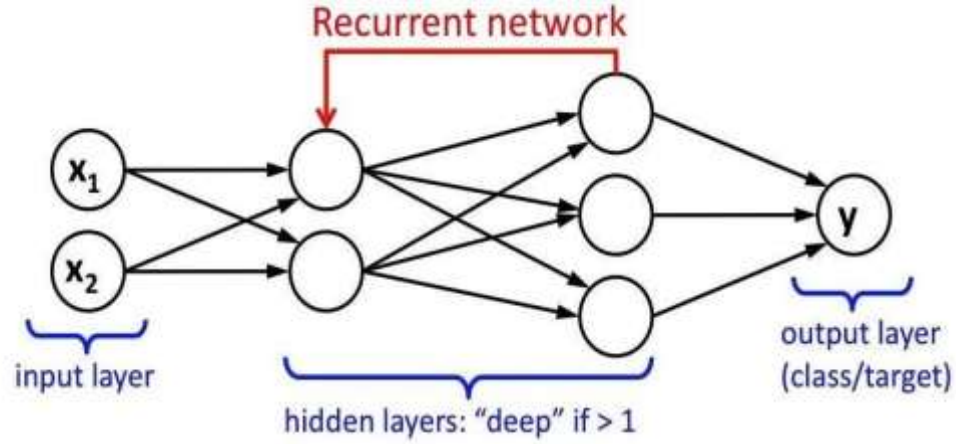
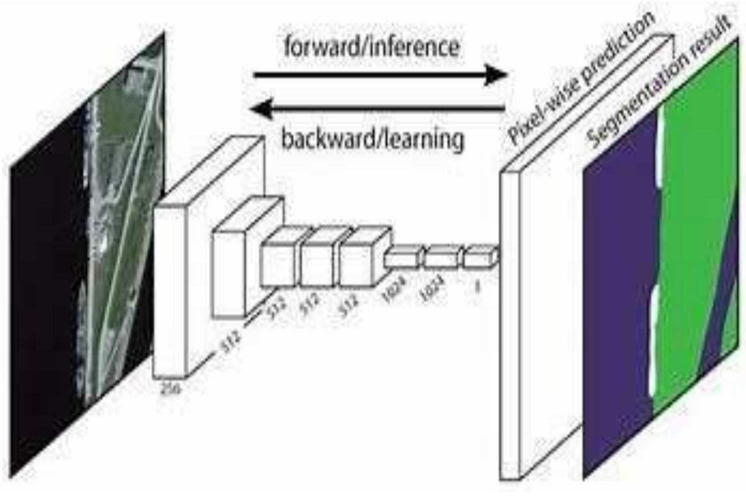


Fig.2.4: Recurrent Neural Networks

3.Fully Convolutional Networks (FCNs):

Fully Convolutional Networks, or FCNs, are an architecture used mainly for semantic segmentation. They employ solely locally connected layers, such as convolution, pooling and up sampling. Purpose: FCNs are used for pixel-level image classification tasks, which can help in creating detailed spatial maps of agricultural fields, such as identifying zones of high or low vegetation density. Architecture Highlights: FCNs consist only of convolutional layers, without fully connected layers, allowing them to produce pixel-wise segmentation. This feature is useful for detecting diseases or crop density in specific field regions A Fully Convolutional Network (FCN) is a type of neural network architecture designed for tasks like image segmentation, where the goal is to classify every pixel in an image. Unlike traditional Convolutional Neural Networks (CNNs), FCNs replace fully connected layers with convolutional layers, enabling the network to process images of arbitrary sizes and output spatially coherent predictions. The below fig 2.6 describing the workflow of the model using Fully Convolutional Network algorithm.



. **Fig.2.6: Fully Convolutional Networks**

Paper3:

Haug and Ostermann primarily focus on presenting the Crop/Weed Field Image Dataset (CWFID) and outlining its use for evaluating computer vision tasks in precision agriculture. The paper does not introduce a specific algorithm or method but rather sets up the dataset as a benchmark for testing various existing methods.

Dataset Creation:

Image Acquisition: High-resolution images were captured in real-world field conditions using RGB cameras mounted on a tractor. The dataset reflects varying illumination, weather, and plant growth stages to simulate real-world challenges. Annotation: Each image in the dataset was manually annotated to classify pixels as either crop, weed, or background. This annotation is crucial for training and evaluating segmentation and classification models. the Crop/Weed Field Image Dataset (CWFID) and outlining its use for evaluating computer vision tasks in precision agriculture. The paper does not introduce a specific algorithm or method but rather sets up the dataset as a benchmark for testing various existing methods.

Performance Metrics:

The methodology emphasizes using pixel-wise accuracy and intersection-over-union to assess model performance. Algorithms were evaluated on their ability to generalize across images with diverse conditions, including shadows, overlapping plants, and soil variability. evaluated based on the quality, diversity, and realism of the generated outputs. Unlike supervised learning models, GANs require unique evaluation techniques due to their unsupervised nature. Here's how GAN performance is assessed, optimized. Precision and Recall for Distributions: Evaluates coverage of real and generated distributions. implementing segmentation (e.g., using Python and OpenCV or deep learning), or do you want to discuss a specific application, like precision agriculture. The below fig 4.1 representing performance metrics of this model.

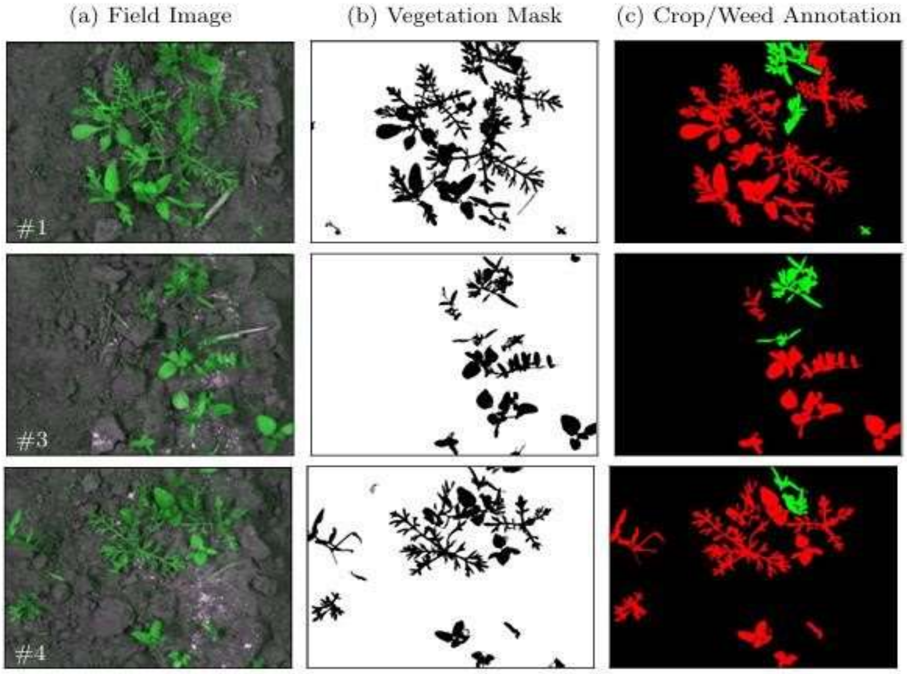


Fig.4.1: Performance Metrics

This image showcases a dataset used in precision agriculture for crop and weed classification. The dataset is divided into three components: raw field images, vegetation masks, and annotated crop/weed maps. The raw field images represent natural scenes of crops and weeds in soil, capturing real-world variability in lighting, shadows, and plant density. The vegetation masks segment the plants from the soil, using binary representation where vegetation appears white and the background black. This dataset is vital for training machine learning models, such as Convolutional Neural Networks (CNNs), to automate tasks like weed detection, selective herbicide application, and crop monitoring. By leveraging these labelled datasets, precision agriculture aims to improve efficiency, reduce chemical usage, and enhance sustainability in farming.

Segmentation Algorithms:

U-Net:

A popular architecture for medical and agricultural image segmentation tasks. • convolutional neural network (CNN) architecture specifically designed for biomedical image segmentation tasks. Its design enables precise localization and boundary detection, making it ideal for tasks requiring detailed and accurate segmentation. U-Net is a convolutional neural network architecture specifically designed for image segmentation tasks, making it widely used in fields like medical imaging, precision agriculture, and autonomous systems. Its architecture consists of two main parts: a contracting path and an expanding path. The contracting path, similar to a traditional CNN, extracts feature through successive convolutional and pooling layers, reducing the spatial dimensions while capturing high-level information. The expanding path performs up sampling and combines it with features from corresponding layers in the contracting path through skip connections. The below fig 4.2 describing the workflow of the model using U-Net algorithm.

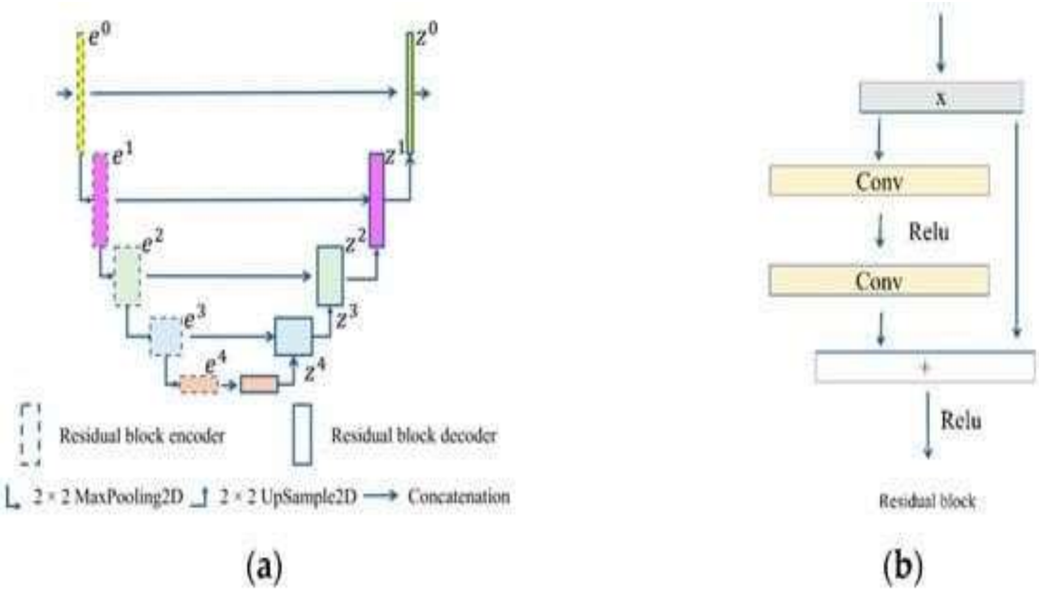


Fig.4.2: U-NET

Feature-Based Approaches:

Support Vector Machines (SVMs):

Used with handcrafted features for classification. Supervised machine learning algorithm widely used for classification and regression tasks. It is particularly effective for binary classification problems and excels in scenarios with high dimensional data or when the classes are not linearly separable. SVM aims to find the optimal hyperplane that separates the data points of different classes with the maximum margin. The margin is the distance between the hyperplane and the nearest data points (called support vectors). Support Vector Machine (SVM) is a supervised machine learning algorithm primarily used for classification and regression tasks. It works by finding the hyperplane that best separates the classes of data in a high-dimensional space. Support Vector Machine (SVM) is a supervised machine learning algorithm primarily used for classification and regression tasks. It works by finding the hyperplane that best separates the classes.

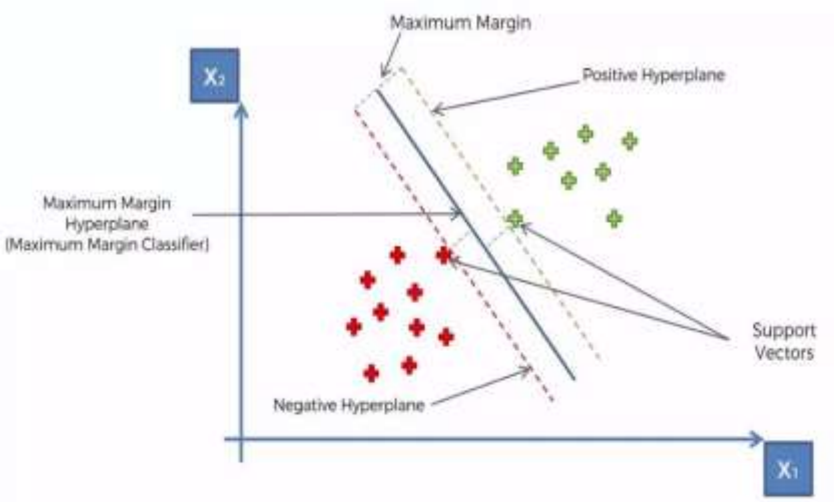


Fig.4.3: Support Vector Machines

Random Forests:

Random Forest Another machine learning approach for segmentation. Supervised machine learning algorithm used for both classification and regression tasks. It builds multiple decision trees during training and combines their outputs (through majority voting for classification or averaging for regression) to improve predictive accuracy and control overfitting. Random Forest is an ensemble method that aggregates the predictions of multiple decision trees, making it more robust and less prone to overfitting compared to a single decision tree. It operates by constructing an ensemble of decision trees during training and outputting the mode of the classes (classification) or the mean prediction (regression) from individual trees. Random Forests perform well with large datasets and high-dimensional spaces and can handle missing values and outliers robustly. Random Forest is a popular ensemble learning method in machine learning that operates by constructing multiple decision trees during training and outputting the mode of the classes (classification) or mean prediction (regression) of the individual tree. The below fig 4.4 describing the workflow of the model using Random Forests algorithm.

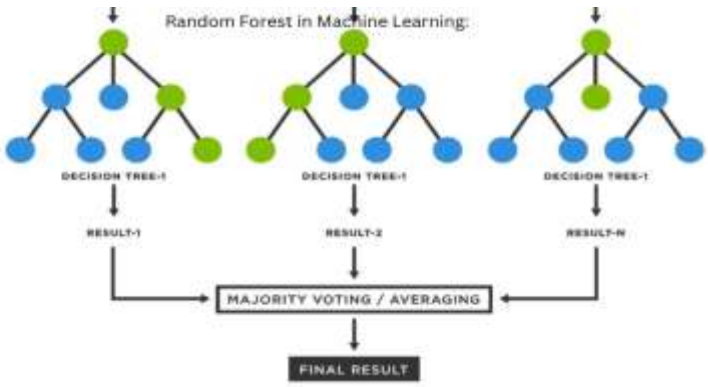


Fig.4.4: Random Forests

Histogram of Oriented Gradients (HOG):

detecting crop rows or patterns. is a feature extraction technique widely used in computer vision and image processing, particularly for object detection tasks like pedestrian recognition. It captures the structure or shape of an object by analysing the gradient direction of pixel intensity changes The image is divided into small cells (e.g., 8×8 pixels), and for each cell, a histogram is created that counts the gradients' directions. The orientation is typically divided into bins (e.g., 9 bins for 0°– 180°). Less effective for complex textures or objects with minimal gradient variation. Requires tuning of parameters (e.g., cell size, block size) for optimal performance. Histogram of Oriented Gradients (HOG) is a feature descriptor widely used in computer vision for object detection and image analysis. It works by dividing an image into small regions (cells), calculating the gradient magnitude and direction for each pixel, and creating histograms of gradient orientations for each cell. The below fig 4.5 describing the workflow of the model using HOG algorithm.

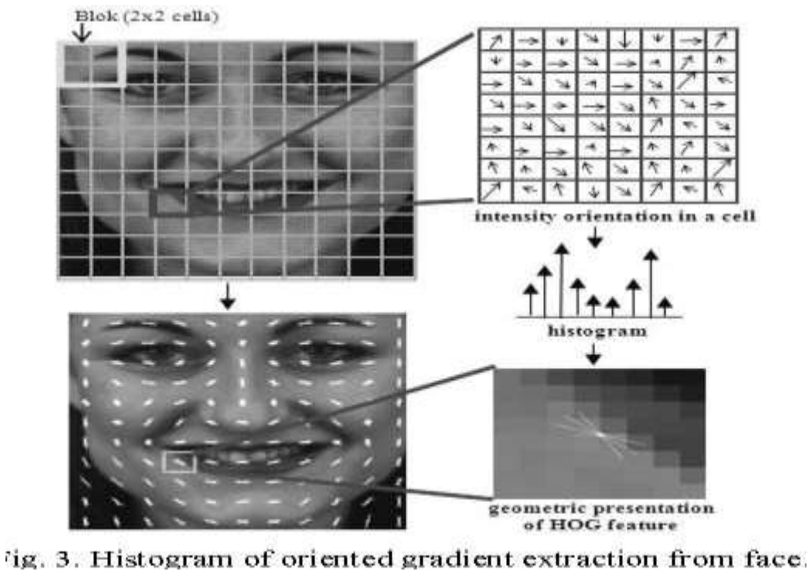
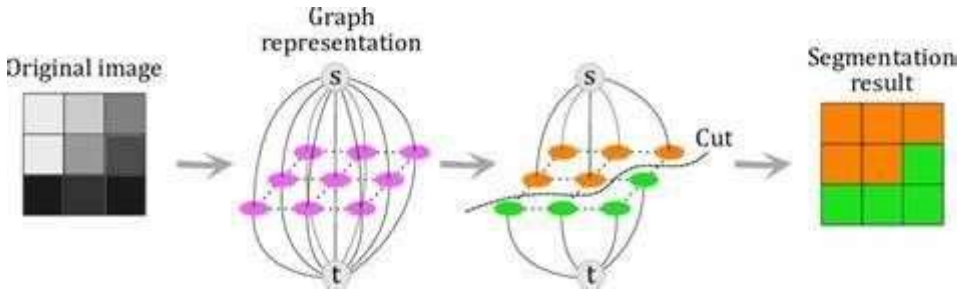


Fig.4.5: Histogram of Oriented Gradients

Graph-based Cut (Graph Cut):

Graph cut For segmenting overlapping or connected plant regions. Graph-based Cut (Graph Cut) is an optimization technique widely used in computer vision and image processing for segmentation tasks. It models an image as a graph, where pixels (or regions) are represented as nodes, and the relationships between them are represented as edges. The goal is to partition the graph into segments (subgraphs) that correspond to meaningful regions in the image. The task is to find the minimum cut, balancing the trade-off between segment size and boundary smoothness. This ensures meaningful segments in the image. The method employs algorithms such as the max-flow/min-cut algorithm to find an optimal cut, which determines the segmented regions. Graph Cut is especially effective in applications requiring high-quality segmentation, such as object detection, medical imaging, and video processing. Its strengths include robustness to noise and the ability to integrate prior information through energy function modelling, but it can be computationally expensive for large-scale problems. The below fig 4.3 describing the workflow of the model using Graph Cut algorithm.

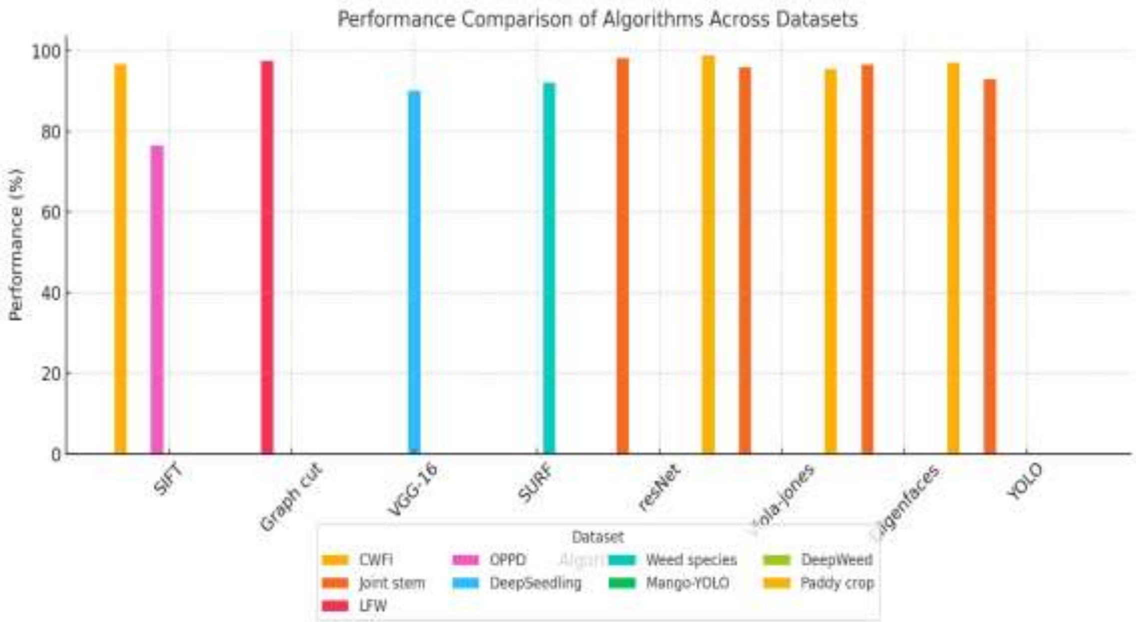


. **Fig.4.6: Graph-based Cut (Graph Cut)**

4. Results and Comparison

Metric	**SIFT**	**GRAPH CUT**	**SURF**	**HOG**
Weed Control	**97.4**	**96**	**91**	**90**
Fruit Detection	**95**	**94**	**97**	**95**
Deep Seeding	**92**	**97.45**	**94**	**93**
Precision	**98**	**92**	**93**	**98**
Disease Detection	**89**	**96**	**91**	**92**

The lack of publicly available image datasets continues to be a significant obstacle in the advancement of computer vision and AI-driven systems for precision agriculture. Although there has been progress in recent years, there remains a strong demand for more diverse datasets, particularly in specialized agricultural applications. This section discusses key aspects of addressing this challenge, including image collection, data augmentation, labelling, and open data sharing. To evaluate existing datasets, four widely used algorithms—SIFT, Graph Cut, SURF, and HOG—are applied to 30 datasets, covering 15 for weed management, 10 for fruit detection, and 9 for other agricultural applications. The characteristics of these datasets, such as acquisition techniques, structure, annotation quality, and possible limitations, are analysed in detail. The importance of developing high-quality datasets is also emphasized, as they provide researchers with better data selection options and facilitate the creation of new datasets to support precision farming. With advancements in computer vision, including RGB, NIR multispectral, and hyperspectral imaging, along with the integration of robotics in agriculture, modern farming increasingly depends on technology for crop monitoring, weed control, harvesting automation, and yield estimation.



5. Discussion:

The lack of comprehensive public image datasets remains a significant barrier to the development of next-generation computer vision and intelligent systems, particularly in specialized fields like precision agriculture. While there has been notable progress over recent years, considerable efforts are still required to create new public image datasets, especially for niche application areas where dedicated datasets are currently absent. This section highlights key considerations in overcoming these challenges, including image collection, augmentation, curation, and data sharing practices. Additionally, it offers recommendations to assist researchers in the future creation of public image datasets to support the continued advancement of these technologies.

6. Conclusion

This study explores how deep learning can assist farmers by automating tasks such as crop health monitoring, yield prediction, and optimal fertilizer usage. These advancements enable farmers to increase crop production, reduce costs, and minimize environmental impact. The research focuses on 34 publicly available image datasets relevant to agriculture, which can streamline the development of tools for tasks like crop monitoring and weed management. The datasets are categorized into three areas: 15 for weed control, 10 for fruit detection, and 9 for other agricultural applications. The study provides an overview of each dataset, including details about image capture methods, formats, and potential challenges. It also suggests ways to improve these datasets through better image collection, accurate labelling, and open sharing, which will help researchers select the most suitable data and develop new datasets for emerging agricultural needs Additionally, the study highlights various types of images used in agriculture, such as standard color images, near-infrared images, and 3D imaging. Computer vision plays a critical role in tasks such as crop inspection, weed control, and harvesting. The paper also discusses the role of farming robots, powered by computer vision and AI, which are capable of performing tasks traditionally carried out by humans or conventional machinery, like weeding and harvesting. Despite the progress, the lack of sufficient public image datasets remains a challenge, hindering the development of more effective tools for these tasks. The study emphasizes the need for increased efforts in creating specialized datasets to address these gaps and foster the continued advancement of precision agriculture technologies.

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