A Survey on AI-Powered Smart Farming Assistant: Transforming Agriculture with Machine Learning and Deep Learning

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Abstract:* This research presents an IoT-based Smart Farming System designed to monitor, analyze, and optimize various agricultural processes. The system employs IoT-enabled sensors to collect real-time data on environmental parameters such as soil moisture, temperature, humidity, and light intensity, which are critical for effective crop management. This research focuses on predicting agricultural yields using a combination of regression models and deep learning approaches, which analyze complex, high-dimensional datasets derived from environmental, meteorological, and historical agricultural records. The methodology includes the application of machine learning regression techniques, such as linear regression, support vector regression, and decision tree regression, for preliminary yield predictions. The study aims to assist farmers and policymakers in making informed decisions to maximize productivity and sustainability. This research focuses on the development of a leaf-based plant disease detection system using machine learning techniques. Artificial intelligence is now being used extensively in the agricultural industry. The Agriculture sector faces various threats and challenges and to mention a few, Information on pest control techniques, Yield Maximization, inappropriate Soil treatment, Pest control system, Disease control information, Information on farm technology and innovation etc . This research explores the transformative role of AI in addressing key challenges in agriculture, such as crop management, pest control, soil monitoring, and resource optimization.

Keywords:* Internet of things, Agricultural Technology, Smart farming, Machine learning, Artificial intelligence, Smart sensors, Deep learning, Support vector machine, Decision tree, Fog computing.

INTRODUCTION

Traditional agricultural practices face many inefficiencies and challenges that reduce productivity. These include inadequate monitoring of soil conditions, leading to poor resource use and lower crop yields. Additionally, the lack of real-time information on weather conditions affects decision-making, impacting overall farm productivity and sustainability. Agriculture is essential for providing food, jobs, and economic growth. People started organized farming about 11,000 years ago during the Neolithic era (New Stone Age). In India, agriculture supports the economy and meets most of the country’s food needs. However, due to population growth and climate changes, it is becoming harder to maintain the balance between food supply and demand.

To address these challenges, modern technology and are being used to improve scientific methods crop production and ensure food security.

Plant disease recognition is done by analyzing changes in the plant’s appearance. AI and deep learning models help detect diseases using images of infected leaves. Smartphone-based AI apps allow farmers to identify and diagnose diseases early, preventing major outbreaks. Techniques like image segmentation, clustering, and feature extraction are used to analyze leaf characteristics. Methods such as Support Vector Regression (SVR) and Principal Component Analysis (PCA) further improve Accuracy in disease detection.

Smart farming uses AI, IoT, and machine learning to improve farming by monitoring crops, soil, and weather. It helps farmers detect diseases, automate irrigation, and make better decisions to increase crop yield and reduce waste. With the growing population, traditional farming methods are not enough to meet food demands. AI-based technologies can improve food production and quality while addressing challenges like data accuracy and security. This research reviews 190 studies on AI in agriculture, highlighting its benefits and identifying gaps to improve farming practices. Agriculture is essential for providing food, raw materials, and supporting industries. In India, it employs about 50% of the workforce and contributes 17% to the GDP. However, challenges like climate change, population growth, and resource shortages are making it difficult

for farmers to meet the growing demand for food.
To address these challenges, precision farming uses modern technologies like AI, IoT, and machine learning to improve crop production and decision-making. A Smart Agricultural Assistant is being developed to help Indian farmers by recommending the best crops, fertilizers, and pest management techniques, ensuring higher yields and better quality.

LITERATURE SURVEY

According to a study presented by Tseng et al. the rice seedling dataset Yang et al. was utilized for detecting rice seedlings in paddy fields, by employing two machine learning models, namely, EfficientDet-D0 and Faster RCNN. Additionally, for comparing the outcomes to the legacy approach, support vector machine (SVM) classification based on histograms-oriented gradients (HOG) was used. In both training and testing, a 99% FI was scored by the HOG-SVM classifier after training. The performance of EfficientDet, HOG-SVM, and Faster R-CNN models was evaluated according to mean average precision (mAP), achieving 70.0%, 95.5% as well as approximately 100%, respectively, for training, and 70.2%, 83.2% and 88.8% for testing. Moreover, mean Intersection-over-Union (mIoU) was used for assessing the models, achieving 46.5%, 67.6% and 99.6% training scores, and 46.6%, 57.5% and 63.7% testing scores. For object detection aiming at complete rice seedlings counting and positioning in the rice seedlings datasets Yang et al., the YOLO model was applied by Li et al. As an enhancement of the model's performance, an adjustment of the YOLOv4 architecture was conducted to reduce the training time and process, thus achieving the lightweight model objective. This improved model was called YOLO4-L. This means that the study constructed an automatic positioning system for detecting objects and calculating rice seedlings. The suggested model training was made in 3.88 hours, achieving 90%, 98%, 94%, 74.4%, and 97.68% for precision, recall, F-score, IoU, and mAP, respectively. Sa et al. [14] employed SegNet, the encoder-decoder cascaded convolutional neural network, for inferring semantic classes that are dense while permitting whichever number of input image channels and class balancing with the WeedNet dataset. In such a study, a field of experiment of various herbicide levels comprising either crop or weed only was constructed for obtaining training datasets. This allowed the normalized difference vegetation index to be a distinguishing factor of automatic ground truth generation. Six models of numerous input channels and conditions were trained (finetuned) to reach ∼0.8 F1-score and 78% Area Under the Curve (AUC) classification metrics.

This review of previous studies reveals gaps that have to be bridged. Firstly, these studies often focus on specific crop types or small datasets, thus limiting scalability. Secondly, many existing systems are based on batch processing; hence, they do not support real-time data analysis. These research gaps are addressed using advanced machine learning models like MobileNet which are known for their efficiency in handling large-scale datasets. This enables the application of the proposed system to different crops and larger agricultural areas, enhancing scalability.

METHODOLOGY

The current study approach encompasses five pivotal stages to ensure accurate and meaningful results. The initial stage involves meticulous data acquisition, wherein two essential datasets, the 'rice seedling' and 'weednet', are leveraged. The choice of using the 'rice seedling' and 'weednet' datasets in the initial stage depends on the agricultural context:
Crop Monitoring: Rice seedling is a significant agricultural crop, and monitoring its growth is crucial for farmers. Using a dataset focused on rice seedlings allows the development of models that can assist in crop monitoring and management.
Weed Detection: The 'weednet' dataset likely contains images of various types of weeds. Weed detection is a critical task in agriculture, as weeds can negatively impact crop yield. Developing models to distinguish between crops and weeds can aid in designing precision farming solutions.
Moving forward, the second stage employs the powerful MobileNet architecture for feature extraction, allowing to capture the intricate details critical for subsequent analysis. The third stage of classification distinguishes between bareland and riceshoot in the 'rice seedling' dataset, and between crop and weed in the 'weednet' dataset using a robust SVM classifier. SVM is used for three main reasons. Firstly, it performs well in high-dimensional spaces, rendering it proper for tasks like image classification or text categorization, where the feature space is large.Secondly, it can use various kernel functions (Polynomial, linear, radial basis function, etc.), allowing its handling of linearly and non-linearly

separable data. Thirdly, SVM is less inclined to overfitting, particularly in high-dimensional spaces because the training points' subset (support vectors) rather than all data points determines the decision boundary. The main reasons for selecting the proposed models, especially MobileNet and SVM, are clarified as follows:

MobileNet is designed to be lightweight and efficient, making it ideal for use in devices with limited computational resources, such as smartphones and embedded systems commonly employed in agricultural IoT setups.
Due to its simplified architecture that uses depthwise separable convolutions, MobileNet is faster than many other convolutional neural networks (CNNs). This makes it suitable for real-time applications, including real-time monitoring and analysis in agriculture.
MobileNet reduces the number of parameters and computational complexity significantly. This means less power consumption and lower requirements for processing power, which is crucial for on-device computations in remote farming locations.
After the training phase, SVMs do not need to retain all the training data, but only a subset of the support vectors, which makes the model memory relatively efficient for deployment.
MobileNet can be easily pre-trained on a large dataset like ImageNet and fine-tuned for specific tasks, such as crop or weed detection, leveraging transfer learning to adapt to the agricultural context effectively.
Despite its reduced complexity, MobileNet still delivers robust performance, achieving high accuracy in many vision-based tasks, which is essential for precision in identifying crop health, pest infestations, or nutrient deficiencies.
SVM is particularly effective in high-dimensional spaces, which is common in image data and other complex feature sets derived in agriculture for classification tasks.
SVMs can be equipped with different kernel functions (linear, polynomial, radial basis function, etc.) to handle linear and non-linear data. This flexibility allows for tailored approaches to various agricultural data types and classification problems.

A. DATA ACQUISITION

1) RICE SEEDLING DATASET The rice seedling smart map components are the orthomosaic image, the demo dataset, and the training-validation dataset Yang et al. [12]. The orthomosaic image means an image patched from a set of nadir-like view UAV images. For consecutive growth stages, 13 images were provided by the dataset, collected in 2018, 2019, and 2020. While TWD97 / TM2 zone 121 (EPSG: 3826) projected coordinate system was utilized for georeferencing all such images. Figure (1 (a)) depicts the data collection area above the satellite image, while Figure (1 (b)) presents the flight routes (white dots) and orthomosaic images overlapping on the satellite image. With an 80% designated route overlap and 75% left-side overlap, 349, 299, and 443 images, respectively, were reached in total. In other words, the increase in the number of images was due to overlapping or taking different positions and orientations to facilitate the increase of inputs to the system. For a rapid extraction of rice seedlings, a semi-auto annotation method via the excess-green-minus-excess-red index (ExGR) is proposed in this paper as a preprocessing step for enhancing image greenness Meyer and Neto.

semiauto annotation through the ExGR index involves automating the calculation of ExGR values from remote sensing data to identify regions indicative of healthy vegetation. Automated algorithms leverage ExGR information for initial annotations. Then, human annotators refine and correct these annotations. This, in turn, fosters a collaborative approach. The iterative feedback loop enhances algorithmic accuracy by incorporating human expertise, making the process effective for such tasks as precision agriculture, where the combined strengths of automated computation and human review are crucial for precise vegetation analysis in remote sensing cameras. An application of the thresholding method proposed by Yen is made for a binary map to be obtained [19]. Then, extracting the contour from the OpenCV library is employed to calculate every object's centric point Yen et al. [19]. Ultimately, rice seedling objects are subset and saved as single images successively, and annotations for the object detection training set are generated. Figure (2) below exhibits the preprocessing workflow. At the end of the preprocessing, the final rice seedling images are obtained. After the images are obtained, the model is trained on them to determine if the plant image is rice seedling or not. In addition, detection is performed before classification to be useful for many purposes, such as plant diagnosis and the amount of water and fertilizer needed for this plant.

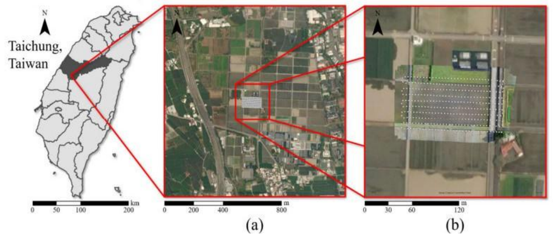

Fig- 4.2 (a) Data collection area above a satellite image; (b) Flight routes (white dots) and orthomosaic image Yang et al

2) WeedNet DATASET

WeedNet dataset Sa et al. [14], the smart map dataset, contains 465 multispectral images combined utilizing the UAV platform supplied with a Sequoia camera of four channels flying 2 meters above a sugar beet crop. For data collection, a 40 m × 40 m weed test field is used. Various herbicide levels (min, mid, and max) are applied to the field. Hence, crop-only, crop/weed, and weed-only are contained in the images. Then, a Sequoia multispectral sensor is employed for image acquisition, featuring four narrow-band global shutter imagers (1.2 MP) as well as one rolling shutter RGB camera (16 MP). This leads to the production of near-infrared (NIR, 790 nm) and red (660 nm) channels Sa et al.

B. PRE-PROCESSING

There are two important steps of data preprocessing. In Image Alignment, essential image processing of NIR and Red images is performed for the calculation of indices via image undistortion, geometric transformation estimation employing image correlation, and cropping.

It is to be noted that since there is a requirement for computing these transformations only once for cameras with rigid attachments to each other, the processing time of such procedures is insignificant. However, no alignment of other image channels, e.g., Green and Red Edges, could be similarly performed due to the lack of similarities. Additionally, the images cannot be easily and correctly matched without the depth of each pixel being precisely estimated. Consequently, the method adopted in this study assumes that the camera baseline is smaller than the distance between the ground and the camera (~two magnitude orders) Sa et al.

C. FEATURE EXTRACTION

Feature extraction is a pivotal process in data analysis and pattern recognition, serving as a crucial bridge between raw data and meaningful information. It involves the transformation of input data into an informative representation, highlighting pertinent characteristics or features. These features encapsulate distinctive aspects of the data, capturing patterns, textures, edges, and other relevant attributes that are essential for subsequent analysis and decision-making. In the computer vision realm, techniques like convolutional neural networks (CNNs) have revolutionized feature extraction, enabling automatic and hierarchical extraction of features from images. This process leads to a reduction in computational complexity, as well as enhancement of subsequent algorithms' discriminatory power, facilitating such tasks as object recognition, classification, and segmentation.

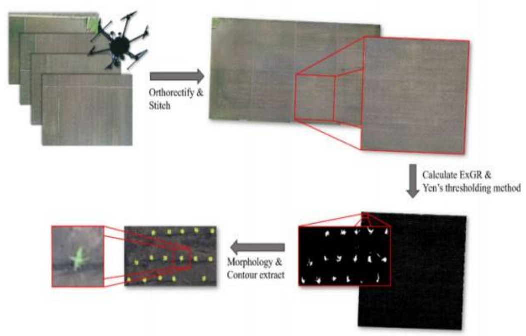

Fig- 4.3 Workflow of semi-auto annotation Yang et al.

MobileNet represents a groundbreaking convolutional neural network architecture customized for lightweight and efficient computations on mobile and edge devices. MobileNet is distinguished for its emphasis on streamlined operations and parameter efficiency, making it particularly well-suited for resource-constrained environments. Through the utilization of depthwise separable convolutions, MobileNet significantly reduces computational burden while retaining the ability to extract meaningful features from input data. Leveraging transfer learning from the ImageNet dataset, MobileNet can be pre-trained on a vast array of diverse images, allowing it to learn a broad spectrum of features that are transferrable to a wide range of tasks. This pre-trained model serves as a powerful starting point for various computer vision applications, providing a foundation for feature extraction. Through the network fine-tuning on a specific dataset related to the required task, MobileNet can adapt and specialize in its feature extraction capabilities, achieving high performance even with limited computational resources. In the baseline MobileNet, a total of 28 layers are included, in case of considering the pointwise and the depthwise convolution layers individually. Figure (4) illustrates the MobileNet baseline architecture as presented in a schematic diagram with all of its layers.

There are four main features extracted by MobileNet:
• Low-level information: MobileNet initial layers represent low-level features like edges, corners, and satellite images simple texture.
• Mid-level information: Moving deeper into the network, the features become more complex and abstract, capturing intermediate-level representations of objects and patterns of satellite images.
• High-level information: Towards the end of the network, the features become highly abstract representing high-level semantic information about the input image. These features are often crucial for image classification or object detection.
• Spatial information: MobileNet architectures preserve spatial information well, making them suitable for tasks that require precise object localization, such as object detection.

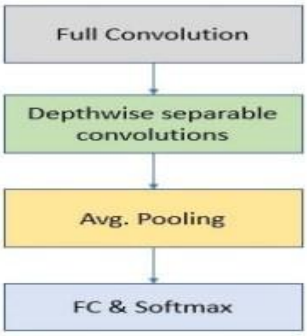

Fig- 4.4 MobileNet layers Sinha and El-Sharkawy

D. CLASSIFICATION
Classification is a fundamental task in machine learning and pattern recognition, playing a pivotal role in organizing and categorizing data into distinct classes or categories. It aims at model training for accurately predicting a given input class label based on its features or attributes. This process involves learning the underlying relationships and patterns within the data, allowing the model to reach informed decisions concerning new, unseen instances. Various algorithms are employed for classification, ranging from traditional methods like decision trees and Support Vector Machines (SVMs) to more complex techniques like neural networks. Choosing the algorithm depends on the nature of the data and the present task complexity. Successful classification involves widespread applications, from medical diagnosis and sentiment analysis to image recognition and fraud detection. Its ability to automatically and accurately label data makes it an indispensable tool across diverse domains, facilitating informed decision-making and streamlining data-driven processes. Linear Support Vector Machines (SVMs) signify powerful algorithms employed to perform binary classification tasks. They operate by finding the ideal hyperplane with the best separation of two classes in a feature space. The positioning of the hyperplane is made in a way that allows maximization of the margin, i.e., the distance amid the closest data points of every class. Linear SVMs are particularly effective when the relationship between classes is roughly linear, meaning that the decision boundary can be represented as a straight line. In using a linear kernel function, these models transform input data into a higher-dimensional space in which it is possible to achieve a clear linear separation between classes. The stated simplicity and efficiency make linear SVMs computationally less demanding compared to their non-linear counterparts.

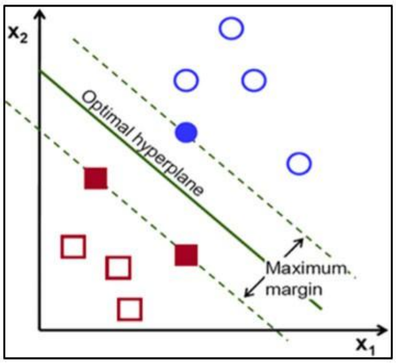

Fig-4.5 The SVM approach.

E. DETECTION
Detection is a fundamental task in data analysis and pattern recognition, involving the identification and localization of specific objects, events, or anomalies within a given dataset. Its role is paramount for the extraction of meaningful information from raw data, enabling machines to discern and respond to pertinent features or occurrences. In various fields, from computer vision to signal processing, detection serves as the cornerstone for tasks like object recognition, event monitoring, and anomaly detection. The process typically involves applying a model or algorithm to the input data, which scans to find predefined patterns or characteristics that signify the presence of the target entity. This can range from identifying faces in images to detecting specific patterns in time-series data. The efficiency and accuracy of detection methods profoundly impact the downstream tasks' performance, making it an integral component in many real-world applications.

K-means clustering indicates a versatile unsupervised learning technique for detection tasks that involve identifying distinct groups or clusters within a dataset.

F. EVALUATION

This study adopts several evaluation metrics to evaluate the suggested system Sokolova et al. Ration of correct classification to the total classifications in the determined class is called precision. False positives in huge numbers are indicated by low precision. The precision is represented as follows:

Precision = TP/(TP + FP)

where TP is the depiction of the positive class correctly classified by the model, and FP represents the model's misclassification of samples as the positive class.

The ratio of correct classifications to the total samples' number is called recall. A small number of misclassified samples is indicated by a high recall. A representation of recall is given below:

Recall = TP/(TP + FN)

where the misclassification of samples as the negative class is represented by FN.

Accuracy means the model's correctness fraction with calculation in the form of summing up correct classifications and dividing them by all classifications:

Accuracy = (TP + TN)/(TP + FP + FN + TN)

where the classification of samples as negative class is signified by TN

RESULTS & DISCUSSION

Experiments were conducted using Python-based software packages on an Intel i5 computer with 12 GB RAM. For the rice seedling dataset, the data consisted of 862 images, divided into 430 rice images and 432 land images. After that, it was classified into a training set with 145 images, and a testing set with 717 images. Then, the training set included 73 rice images and 72 land images, whereas the testing set had 357 rice images and 360 land images. For the WeedNet dataset, the data was acquired from the farm. It consisted of 95 multispectral images for the farm, acquired from the Unmanned Aerial Vehicle (UAV). The data was classified into 43 crop images and 52 weed images. These images were available on the Near-Infrared (NIR) and Red channels. Then, these channels were employed for extracting the Normalized Difference Vegetation Index (NDVI). After that, the NDVI images were divided into testing and training sets, including 17 NDVI images for the training set and 78 NDVI images for the testing set. The training set had 7 crop images and 10 weed images, whereas the testing set had 36 crop images and 42 weed images

TABLE 2. Datasets split.

Dataset	Training set		Testing set	
WeedNet	Crop	7	Crop	36
	Weed	10	Weed	42
Rice Seedling	Rice	73	Rice	357
	Land	72	Land	360

In both datasets, it is important to highlight that the testing set is larger than the training set, which may seem unconventional. This is attributed to the utilization of ImageNet weights for transfer learning with the MobileNet model. The pre-trained model has already been exposed to data similar to the current input, reducing the need for extensive training on the dataset of this study. As a result, a larger portion can be allocated to testing, allowing for a more robust evaluation of model performance. The confusion matrix marks a pivotal tool in machine learning, especially for classification tasks. It comprehensively summarizes the performance of model by detailing true positive, true negative, false positive, and false negative predictions. These metrics allow for a granular assessment of the model's F1 score, precision, accuracy, and recall. By optimizing precision and recall, a model can be fine-tuned to achieve better overall performance.

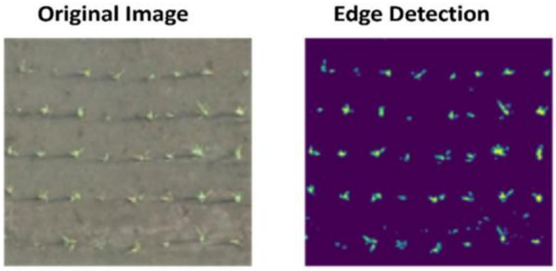

Fig-5.1 Rice seedling detection results.

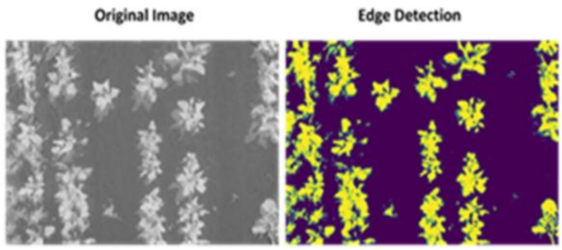

Fig- 5.2 WeedNet detection results.

The model's ability to achieve an accuracy exceeding 99% is a testament to its robustness and effectiveness in accurately classifying data points. This exceptional level of accuracy indicates that the model has successfully generalized from the limited training data to perform exceptionally well on unseen samples. Such results underscore the power of the model architecture and its ability to learn complex patterns and relationships within the data. It also suggests that the features extracted during training have proven highly informative for accurate classification. This achievement indicates the quality of the model and shows well its potential applications in realworld scenarios. Figures (7 and 8) show the detection results using k-means for both rice seedling and WeedNet datasets, respectively. The study proceeds to this step if the classification results are rice for the rice seedling dataset and crops for the WeedNet dataset. The significance of this detection process extends to a multitude of practical applications. For instance, detection enables automation in tasks like targeted watering, where identifying the precise location of seedlings or crops is essential for efficient irrigation management.

CONCLUSION

Smart farming is a concept that involves handling and controlling farms using new technologies such as the IoT, robotics, drones, and AI to increase the quantity and quality of products while reducing the human labor required for production. These benefits will have positive effects on the profitability and the growth of the economy as population sizes are dramatically increasing worldwide. Therefore, researchers and scientists are moving toward the utilization of recently introduced IoT technologies in smart farming to help farmers use AI technology in the development of improved seeds, crop protection, and fertilizers. AI in agriculture is emerging in the three major areas of soil and crop monitoring, predictive analytics, and agricultural robotics. In this regard, farmers are rapidly

In this survey, we have studied many AI applications in the agricultural sector to investigate the various developments and solutions to improve the productivity of farms and solve some environmental problems encountered during the production of different types of products in agriculture. The AI models for farms help countries to maintain sustainability in this sector. We began with background on AI, which included a discussion of all AI methods utilized in the agricultural sector, such as machine learning, the IoT, expert systems, image processing, and computer vision. Second, a comprehensive literature review was presented, focusing on how researchers have utilized AI applications effectively in data collection by using sensors, utilizing smart robots, monitoring crops, and monitoring irrigation leakage. It was shown that quality, productivity, and sustainability are maintained while utilizing AI applications. Third, the benefits and challenges of AI applications were explored along with a comparison and discussion of several AI methodologies applied in smart farming.

In this survey, we have also discussed the most recent applications of AI methods in smart farming while focusing on which AI methods or algorithms are used and the accuracy rates that were obtained. Tables were provided to demonstrate the most recent AI techniques and the associated applications as well as the obtained accuracies and, researchers have obtained very promising results while utilizing AI methodologies effectively.

The motivation behind this research stems from the profound impact that smart agriculture, driven by innovative technologies, is poised to have on the food production sector and global food safety. By harnessing the potential of IoT, Artificial Intelligence (AI), and agricultural data analytics, farmers have the opportunity to optimize resource usage, reducing inputs like fertilizers, labor, seeds, and water, while simultaneously increasing crop yields. Furthermore, the earth observation technology evolution, particularly satellite remote sensing, has offered an unprecedented wealth of data for agricultural research and applications.
This paper presents a comprehensive system for advancing smart map agriculture, encompassing five pivotal stages designed to yield accurate and meaningful results. Furthermore, K-means clustering is used to detect rice or crops, respectively. Notably, the achieved precision, accuracy, recall, and

F1_score metrics demonstrate the robustness of this approach, attaining exceptional performance for both datasets. With accuracy rates exceeding 99% and recall, precision, and F1_score metrics surpassing the 97% mark, the proposed system showcases its potential to significantly impact smart agriculture. By providing invaluable insights for enhanced farming management and productivity, it is expected that this system will play a pivotal role in reshaping modern agricultural practices for the best.

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