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Article

A SYSTEMATIC REVIEW OF EDGE COMPUTING FOR SUGARCANE DISEASE DIAGNOSIS

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Abstract: Timely disease identification and control are crucial for sugarcane agricultural output, which is a vital crop for economic growth in developing nations like India. Traditional disease detection techniques, however, have drawbacks including slow reaction times, large processing requirements, and reliance on centralized cloud systems—which might be sluggish and constrained by connectivity problems in remote locations.With an emphasis on real-time data collection, processing, and analysis using IoT, Artificial Intelligence (AI), and edge-fog-cloud architectures, this study examines developments in early disease detection throughout the phenological phases of sugarcane utilizing edge computing. Our research shows that algorithmic methods, especially CNN-based deep learning models incorporated into edge computing frameworks, greatly lower latency and processing cost while achieving over 90% illness detection accuracy.The study also shows how edge computing might revolutionize preventative therapies by identifying possibilities in real-time IoT connections and lightweight model modifications for early illness identification. The resilience and sustainability of sugarcane farming in resource-constrained locations are improved by this strategy, which closes important gaps in scalability, cost-efficiency, and accessibility.

1. INTRODUCTION

In many nations, especially developing ones like India, where a sizable section of the population is employed in the agricultural sector, agriculture is essential to economic progress. One of the most important crops is sugarcane, which is widely grown for its ability to produce sugar, bioethanol, and other useful byproducts including molasses and bioelectricity. Sugarcane crops' production and health are crucial to the sector, but they are constantly threatened by a range of pests and illnesses that can result in significant financial losses.Therefore, to ensure good yields, preserve soil health, and maximize resource usage, early disease diagnosis and management—particularly throughout sugarcane's phenological stages—are essential.

1.1 Phenological stages of Sugarcane Crop:

The several stages of a crop's development cycle, from planting to maturity to harvest, are referred to as the phenological stages of sugarcane. In order to monitor crop health, optimize inputs like water and fertilizer, and identify possible disease risks, each stage requires distinct physiological and developmental changes that are impacted by external conditions.

The normal phenological phases of sugarcane are broken down as follows:

Germination Stage: This is the first stage following planting, during which the sugarcane stalk breaks through the ground and roots start to grow. Here, soil health, moisture content, and temperature are crucial.

Tillering Stage: At this point, many stems, or tillers, sprout from the parent plant's base. The best tiller growth is supported by enough sunshine, nutrients, and water.

Growth or Vegetative Stage: Sugarcane grows quickly in thickness and height at this time. Plants build up biomass as their leaves enlarge. Since infections at this stage can have a major influence on productivity, monitoring for pests and diseases is crucial.

Maturation Stage: As the cane reaches its ultimate size, the plant's growth slows and the concentration of sugar rises. Harvesting at the ideal time may be determined by keeping an eye on moisture and sugar content.

Harvesting Stage (Ripening Stage): The cane is prepared for processing and cutting in the last stage. Here, quality is guaranteed and post-harvest losses are reduced through effective disease control and storage procedures.

Historically, agricultural disease identification has been accomplished by human inspections, which are labor-intensive, time-consuming, and prone to errors. When illnesses are not detected in their early stages by manual techniques, pesticides and fertilizers are applied less effectively, which results in crop losses and environmental harm from excessive chemical usage. Precision agriculture, where real-time monitoring and early disease diagnosis through automation and advanced computing technologies are becoming more and more feasible, is a result of recent technological breakthroughs to address these issues.

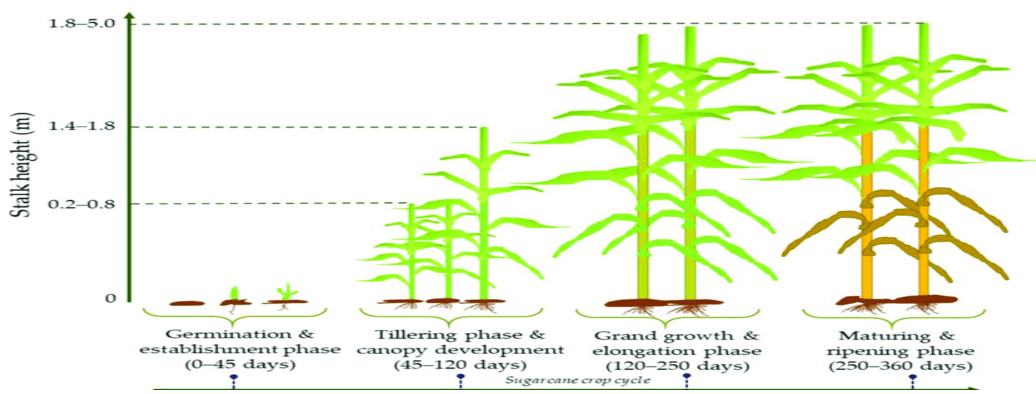

Figure 1: Phenological stages of Sugarcane Crop. Source: [30]

1.2 Role of Machine Learning in Sugarcane crop disease prediction

With its accurate, scalable, and data-driven solutions, Machine Learning (ML) is transforming the diagnosis and treatment of illnesses in sugarcane crops. As a high-value crop, sugarcane is vulnerable to rust, smut, and red rot, which can have a major effect on quality and productivity. In order to anticipate the risk of disease outbreaks, ML models—such as Random Forests, Support Vector Machines (SVMs), and Deep Learning (DL) techniques—analyze massive datasets that contain environmental characteristics, past disease occurrences, and crop phenotypic attributes. By processing intricate and non-linear correlations in data, these models are able to produce precise forecasts that enable farmers to take preventative measures.

The use of computer vision and image processing in sugarcane disease prediction is a noteworthy use of ML. In order to identify early indicators of diseases, such as discolouration, lesions, or texture changes, sophisticated simulations such as Convolutional Neural Networks (CNNs) examine leaf pictures. ML algorithms can anticipate diseases particular to a certain place when paired with satellite imaging and Internet of Things (IoT)-based sensors for real-time observing of environmental factors like soil moisture, temperature, and humidity. Furthermore, ML supports breeding initiatives targeted at improving crop resilience by assisting in the identification of disease-resistant sugarcane cultivars through genetic data analysis. ML guarantees increased yields, lower financial losses, and sustainable farming methods for sugarcane production by facilitating prompt interventions and maximizing resource utilization.

1.3 Emergence of Edge Computing in Agriculture

Edge computing is revolutionizing the agriculture sector by bringing processing power closer to the records source, enabling real-time decision-making and boosting operational effectiveness.

Important Elements of Agriculture's Edge Computing:

IoT Devices:

Sensors: Keep an eye on a number of variables, including nutrient levels, light intensity, temperature, humidity, and soil moisture.

Cameras: Take pictures and videos to track plant health, identify pests, and estimate productivity.

Drones: Gather aircraft data for precise spraying, crop health evaluation, and field mapping.

Edge Devices:

Gateways: Before transferring data from IoT devices to the cloud or for local analysis, aggregate, filter, and preprocess the data.

Edge Servers: Make decisions, handle data, and analyze it in real time.

Cloud Connectivity:

Securely sends important data to the cloud for remote monitoring, enhanced analytics, and long-term storage

A promising tool for improving real-time agricultural surveillance is edge computing. By bringing computing capacity closer to the data source, it speeds up data processing and lowers latency, both of which are essential for

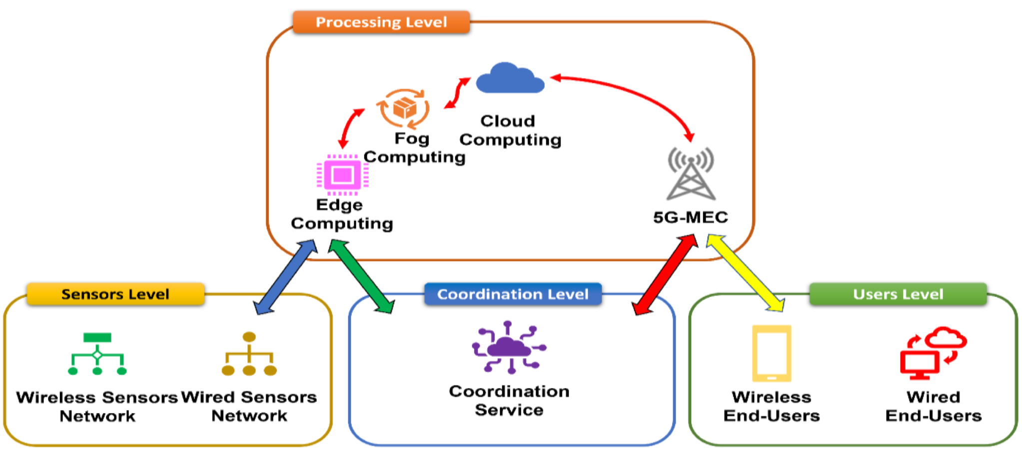

Figure 2: Edge Computing Architecture. Source : [1]

prompt crop management actions. Edge computing makes it possible to handle data from IoT devices like environmental sensors, drones, and Unmanned Aerial Vehicles (UAVs) on-site in the context of sugarcane farming.To find early indicators of illness, these gadgets take high-resolution photos and record crop conditions. ML procedures are then used to investigate the records. Farmers may make proactive decisions by gaining real-time insights on crop health through the integration of edge computing with AI and IoT frameworks.During the phenological periods of the crop, when early diagnosis can minimize productivity losses and avoid extensive damage, edge computing is especially crucial for sugarcane disease detection. The important stages of a plant's life cycle, including germination, development, blooming, and maturity, are referred to as phenological stages. If not identified early, diseases that impact sugarcane during crucial phenological periods can significantly lower yields. A strong answer to this issue is provided by technologies that integrate edge computing with satellite data, environmental sensors, and AI-based illness detection algorithms.With an emphasis on edge computing and remote sensing technologies, several research have investigated different approaches to sugarcane disease detection. For example, in order to monitor sugarcane phenology, Herdiyeni et al. (2023) [2]carried out an early warning research utilizing remote sensing technology such as the Landsat 8 satellite. In order to assess crop health using the Normalized Difference Vegetation Index (NDVI), their study showed the importance of monitoring significant phenological periods between January and June. Utilizing cloud-based systems like Google Earth Engine (GEE) for data processing, this study demonstrated how remote sensing may be utilized to track agricultural conditions across long distances. The advantages of edge computing for real-time illness diagnosis were not thoroughly examined in the study, though.

In order to monitor plant health, Chavan et al. (2023) [3]suggested a system that combines fog-edge-cloud architecture, IoT, and environmental sensors.Their method made use of Recurrent Neural Networks (RNNs) to predict changes in the environment and provide farmers early warnings. The latency that comes with cloud-only designs is successfully decreased by this approach by moving the processing capacity closer to the data source. But rather than delving deeper into the phenological phases of sugarcane or disease detection, the study concentrated mostly onenvironmental factors.In a separate study, Yeasin et al. (2022) [4]used a combination of Sentinel-1 and Sentinel-2 data to assess phenology using a range of machine learning models, such as logistic regression, decision trees, and SVMs. With model accuracies ranging from 76% to 88%, the study demonstrated that combining Sentinel-1 and Sentinel-2 data improved the precision of sugarcane phenology forecasts. Although the phenology monitoring information obtained by remote sensing was effectively employed in this study, edge computing was not used for real-time analysis or early illness diagnosis.In addition to these investigations, a number of researchers have looked at the application of DL models for sugarcane leaf disease detection. In order to diagnose sugarcane leaf diseases with high accuracy, Militante et al. (2020)[5]incorporated many CNN architectures, such as VGGNet, AlexNet, and LeNet. The VGGNet model achieved up to 95% precision. This study, like others, concentrated mostly on post-infection detection rather than early-stage identification during important phenological periods, notwithstanding major achievements in the categorization of leaf diseases.Using IoT, DL, and Edge computing approaches, we explore sugarcane disease prediction in this review study. We've consulted a number of research studies and journal publications that concentrate on detecting plant diseases, usually in sugarcane, by utilizing the newest technology. We have made every effort to use recent years as a point of comparison.

Following distribution and graphs show the analysis of this review papers article wise

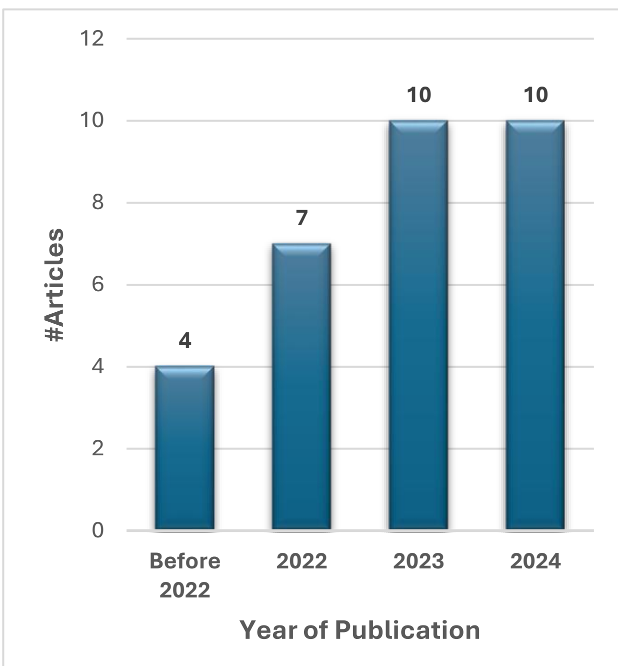

Figure 4:Year wise distribution of Articles

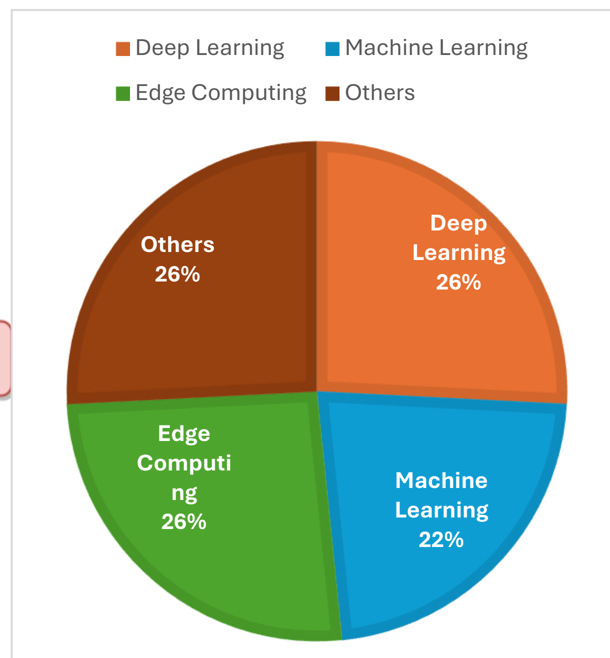

Figure 5:Topic wise Distribution

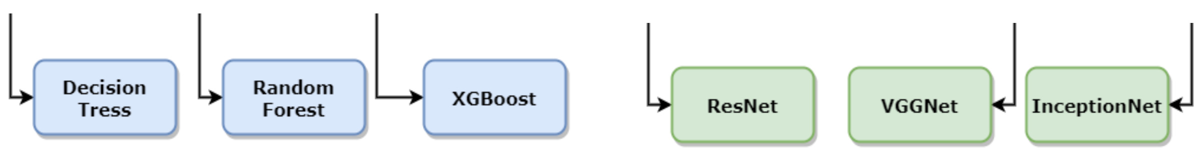

Figure 3: Machine Learning and Deep Learning Algorithm Tree Structure

The distribution of publications referred to in this review study by year is depicted in Figure 4, while the percentage distribution of articles referred to by topic, such as deep learning, machine learning, edge computing, etc., is shown in Figure 5.

2. LITERATURE REVIEW:

All four facets of society are impacted by agriculture, which is the sector that has the most impact on the nation's economic development. Sugarcane is the most extensively grown and promising crop in India. It may be developed as a primary crop or as a cash crop. Small to mediocre in size peasants gather sugarcane to make brown sugar, which is used to feed animals. To boost output and maintain the sector, sugarcane health must be tracked throughout its phenological phases. In the sugarcane industry, sugarcane complexes are utilized to produce white sugar, bio-ethanol, bio-electricity, and several other organic goods.A rise in sugarcane yields is necessary to meet the growing global population. Sugarcane production is significantly impacted by diseases and pests. As a result, the nation and farmers suffer large financial losses. Therefore, early detection of various sugarcane illnesses and pest control methods are required to boost productivity.Inaccurate pesticide regulator measurements result from the incapacity to visually detect sugarcane leaf diseases. To improve productivity and quality, sugarcane illnesses must be automatically identified and diagnosed early. Images are processed using algorithms that quickly extract information from sugarcane leaves and detect the sorts of diseases early on.

2.1 Traditional and Early Technological Approaches

The first attempts used distant sensing methods to overcome the limits of manual checks. To solve this problem, a number of scholars created both conventional and early technology methods. To establish an early warning system for sugarcane growth, for example, Yeni Herdiyeni et al. employed remote detecting with the Landsat 8 satellite during a crucial phenological phase. Using linear and harmonic regression representations, seasonal trends were examined to estimate regional sugarcane growth patterns for the early warning. The NDVI spectral index's statistical value determines the growth patterns and the crucial phenological phase. Lastly, using NDVI, NDBaI, NDWI, and NDDI to confirm sugarcane growth. Cloud-based Google Earth Engine (GEE) was used for all operations. The findings showed how important it is to track and evaluate sugarcane phenology between January and June. The four criteria demonstrated how important it is to monitor conditions for the health of sugarcane. Due to drought and surplus water, respectively, two sites had periods of poor vegetation, with values below 0.489 and vice versa [2].

Although DL models improved the ability to detect diseases, they needed a lot of processing power and dependable connection, both of which are frequently lacking in remote locations. Sensor data may now be processed on-site for real-time analysis thanks to the revolutionary shift towards edge computing. Edge-fog-cloud architecture is used by systems such as those put forth by R.S. Chavan et al. to gather data from sugarcane fields and send out alerts to farmers through an intuitive user interface. The solution avoids latency and connection issues by processing data locally through edge devices, enabling farmers to respond quickly to variations in the environment. The Recurrent Neural System model, which is used to predict future data, is trained using the gathered data.Users like farmers will be able to respond appropriately to impending environmental changes because to this. The Flask framework serves as the foundation for a straightforward and smooth user experience that shows the user the collected and predicted data in addition to alert alerts [3].

By using data to forecast disease incidence, the incorporation of machine learning (ML) algorithms into crop monitoring opened up new possibilities for disease detection. For instance, Md Yeasin et al. employed Sentinel-1 and Sentinel-2 satellite records together with ML representations including Logistic Regression (LR), Decision Trees (DT), and Random Forests (RF) to classify the stages of sugarcane growth. By merging Sentinel records sources, this integration made it possible to identify crucial spectral indices like NDVI, which greatly increased the accuracy of illness prediction. The predictive performance of seven ML models—fuzzy rule-based systems, LR, DT, RF, ANN, SVMs, and naïve Bayes—was evaluated after they were put into practice.Exactness, accuracy, specificity, sensitivity, recall, kappa value, F score, and area under the receiver functioning distinctive curve were among the performance metrics. The research was carried out in the Indo-Gangetic alluvial plains in the Indian districts of Hisar and Jind. Sentinel-1 backscatters and metrics VV, alpha, and anisotropy, together with the regularized variance vegetation index and weighted variance vegetation index among Sentinel-2 indices, were shown to be the most important features for predicting sugarcane phenology. The accuracy ranges for the models were 40–60% for Sentinel-1, 56–84% for Sentinel-2, and 76–88% for the combined records. Both the kappa values and the region under the ROC curve further confirmed the advantages of combining Sentinel-1 and Sentinel-2 records combined. This study shows that Sentinel-

1 and Sentinel-2 records together are more successful than Sentinel-1 and Sentinel-2 data alone in forecasting sugarcane phenology [4].

A study of several deep learning and image processing methods for sugarcane diagnostic extraction and quick evaluation is presented by G. Tomar et al. Along with potential future opportunities, the difficulties supporting computational methods for evaluating sugarcane infections are also emphasized [6].

New architectures and model improvements were investigated in later research. Automated robots were used by T. Natarajan et al. to identify sugarcane leaf disease in the field with 98.6% accuracy. These DL systems demonstrated the scalability of automated illness detection by offering quick and accurate diagnosis. Lastly, the remaining injury area and leaf area are calculated to classify the vulnerabilities. The analysis's accuracy is thought to be 98.60%. This method for determining the degree of leaf disease is quick and accurate, according to research [7].

Despite ML's success, DL, specifically CNNs, was used for improved accuracy due to its limitations in processing large-scale picture data.Using a dataset of sugarcane images comprising 20,000 disease-infected and non-infected sugarcane leaves, S.V. Militante et al. plan to combine and train several CNN architecture models. StridedNet, AlexNet, LeNet, VGGNet, and GoogleNet are the 5 proficient representations that were working in the education. Among the trained models, GoogleNet has the lowest accuracy rate (65%) while the VGGNet model has the highest (95%). The trained CNN models can identify and categorize photos of sugarcane leaves into two groups based on their outlines: those with and those without illness. Deep learning algorithms for the early diagnosis of sugarcane illnesses may assist farmers maintain their output and revenue [8].

In their survey article, N.K. Hemalata et al. examine the several approaches and strategies that may be applied to identify illnesses in sugarcane crops. First, they give an overview of the various input data types related to photography, including RGB, multispectral, and hyperspectral. The various methods used for illness recognition—ML, DL, transfer learning, and spectral information divergence—were then emphasized. A summary of the outcomes obtained by applying the various strategies is also provided by the author [9].

Using non-invasive multispectral pictures taken with a UAV in the field, ML algorithms were utilized to detect Cercospora leaf spot (Cercosporabeticolasacc.), an illness that causes significant financial losses in sugar beet creation, in its early stages. K.M. Turgul et al. finished their investigation using photographs taken in farmer fields in two regions where the disease was well documented. As training and test data, index rate records from digital surface model maps produced by treating the captured photos remained utilized. Five distinct approaches to supervised machine learning were used to assess numerical data.Based on the index ranges obtained from the photos and the physiological changes that occur before the illness agents appear on sugar beet leaves, almost 70% of the models that were analyzed were successful in predicting the appearance of sickness. Among the models analyzed in the study, the K-Nearest Neighbor Classifier (KNN) classical outperformed the others across both diseases with 83% precision and 76% and 86% f1-score values. The SVM model's accuracy, 75%, and 86% f1-score standards matched those of the KNN model. The study's findings indicate that plant illnesses may be detected before symptoms appear, and that early disease detection may be achieved by processing photos acquired using UAV-based MS imaging [10].

To investigate how well existing state-of-the-art cataloging algorithms work in abandoned environments, like those seen on-site, H.S. Malik et al. acquired a set of data of 5 sugarcane plant illnesses that were gathered from fields throughout different areas of Karnataka, India. Camera equipment were used to record the data in a variety of lighting and resolution conditions. Models trained on the proposed sugarcane dataset achieved top precision of 93.40% (on test set) and 76.40% (on pictures collected from many trustworthy online sources), demonstrating the method's robustness in identifying complex patterns and variations found in real-world scenarios. To further pinpoint the affected regions, the author used two different object-detection systems: Yolo and Faster R-CNN. Both networks achieved a top mean average precision mark of 58.13% following testing on the dataset. Overall, using CNNs to a very diverse dataset may pave the way for automated disease detection systems [11].

The health of sugarcane has a direct influence on agricultural production and the sugar industry, making it an essential crop. In order to overcome the difficulties in detecting diseases in sugarcane, Kumar K. suggested a method that makes use of DL systems. CNNs and image analysis are used in the study to precisely identify and categorize a range of sugarcane illnesses. The deep learning program demonstrated exceptional illness detection accuracy by examining high-resolution photos of sugarcane leaves and stems, providing a viable means of early diagnosis. This study helps maintain sugarcane cultivation's economic viability and promotes sustainable agriculture [12].

The first approach for the preliminary detection of sugarcane WLD was provided by Gonzalez, F. et al. using multispectral high-resolution sensors mounted on small UAVs and supervised machine learning classifiers. The validation location for the recognition pipeline discussed in this article was a sugarcane field at Gal-Oya Plantation in Hingurana, Sri Lanka. The pixel-by-pixel segmented records were classified as early symptoms, severe symptoms, shadow, ground, and healthy plants. Four ML procedures—XGBoost (XGB), RF, DT, and KNN—as well as five spectral bands and a number of Python libraries were utilized to detect WLD in the sugarcane field. In the field, WLD could be detected with 94% precision by the XGB, RF, and KNN. In XGB, RF, and DT, the three most important Vegetation Indices (VIs) for distinguishing between healthy and ill sugarcane crops are Excess Green (ExG), Normalized Difference Vegetation Index (NDVI), and Modified Soil-Adjusted Vegetation Index (MSAVI). Red in XGB and RF and green in DT are the greatest spectral bands. The findings showed that this approach offers a reliable, more straightforward, economical, and rapid way to identify WLD [13].

By combining DL with edge computing, a potent framework for accurate and proactive disease management has been produced. For example, models created by Upadhye et al. include CNN algorithms into edge devices and identify sugarcane illness with 98.69% accuracy. Similarly, in real-world scenarios where complicated lighting and resolutions are difficult, implementations of object identification procedures like YOLO and Faster R-CNN in edge computing frameworks have demonstrated encouraging results.Farmers are able to properly focus interventions thanks to these devices, which not only identify illnesses early but also visualize their spread. In addition, a web-based tool for detecting sugarcane crop diseases was created and put into use to get and track disease data in order to assist farmers. Future research areas are also suggested in the paper, including: (i) allowing the user to provide feedback that can be adjusted by the model to accurately predict sugarcane crop diseases and update the database dynamically; and (ii) combining the impact of disease detection with price forecasting and agricultural productivity enhancement using AI tools and techniques to help farmers make better decisions [14].

A study by Daphal, S.D. et al. proposed an attention-based multilevel deep learning architecture for accurately diagnosing plant diseases, with a focus on sugarcane leaf diseases. The proposed architecture combines characteristics from lower to higher levels and includes spatial and channel attention for saliency detection. With an accuracy of 86.53% on a self-made database, the model beat state-of-the-art representations such as VGG19, ResNet50, XceptionNet and EfficientNet_B7.The results demonstrate the importance of all-level features for picture classification and how they may boost productivity even with small databases. The proposed design may facilitate early plant disease diagnosis and detection, allowing for quick mitigation of crop harm. Additionally, there is a chance for the broad use of mobile phones in the categorization of sugarcane illnesses due to the implementation of the suggested AMRCNN model in the Android phone-based application [15].

Using a set of data of 20,000 photos of sugarcane plants, a DL model based on multi-layer perceptrons (MP) was created to identify and classify SRR illness. This model was trained using two hundred thousand photographs of sugarcane leaves. The dataset was categorized into five levels of sickness severity. The proposed model's accuracy rate was 97.97% for binary classification and for total multi-classification, 98.03%. An evaluation of the several stages of SRR disease was also carried out, and the results demonstrated that the proposed model is a helpful tool for accurately categorizing sugarcane pictures based on the severity of SRR disease. This work contributes to the development of an accurate and effective model for the primary recognition and diagnosis of SRR disease in sugarcane crops, which is necessary to increase agricultural output and prevent financial losses [16].

Using 13,842 sugarcane picture datasets of diseased and healthy leaves, Militante, Sammy V. et al. developed and evaluated a deep learning model, attaining a 95% accuracy rate. By identifying and categorizing photos of sugarcane leaves into two groups—healthy and diseased—the trained model accomplished its goal. In order to help farmers choose and categorizing sugarcane infections, this research offers a deep learning algorithm [17].

Shivanshi Singh et al. reviewed the classification presentation for seven different types of sugarcane leaf illnesses. For each illness class, the preceding table provides key performance indicators, including accuracy, recall, F1-score, support, and total precision. This comprehensive analysis demonstrates a consistent model performance and a high level of precision in accurately identifying positive cases within each sickness category, with precision rates ranging from 94.34% to 94.86%. The F1-score consistently maintains a value of 94.57% while successfully balancing accuracy and recall, demonstrating the model's durability in identifying sugarcane leaf diseases. Support metrics, which vary from 795 to 875, provide important information by displaying the frequency of recurrence of each class in the sample. The model can accurately predict all classes, as evidenced by its 94.57% total accuracy. With applications that might enhance crop management and boost agricultural output, this work significantly advances the area of agricultural disease detection [18].

A set of data of five sugarcane plant illnesses was gathered from fields across different locations of Karnataka, India, and acquired by H.S. Malik et al. To investigate how present state-of-the-art cataloguing representations would function under abandoned settings, as might be faced on site, the dataset was captured by camera devices under various lighting conditions and resolutions. The models developed on the sugarcane set of data showed the method's resilience in identifying complex patterns and changes that occur in real-world scenarios, achieving a high precision of 93.40% (on the test set) and 76.40% on images collected from multiple trustworthy online sources. Furthermore, the author used two different object-recognition procedures—faster R-CNN and Yolo—to accurately identify the affected regions. The top mean regular accuracy mark for both systems was 58.13% after testing on the dataset. All things considered, using CNNs to a very diverse dataset may pave the way for automated systems that identify illnesses [11].

The feasibility study and efficacy of the DL-based CNN algorithm in crop disease identification were described by R. Walia et al., with particular reference to four specific illnesses of the Indian sugarcane crop. The suggested system analyzes high-resolution photos taken by unmanned aerial vehicles (UAVs) or ground-based sensors by integrating cutting-edge DL approaches, utilizing CNNs and recurring models. By offering a thorough overview of the sugarcane plantation, these photos make it possible to see early-stage illnesses and subtle indications that the human eye could miss.A strong image preprocessing pipeline to increase the superiority of input records, a specialized deep neural network architecture trained on a variety of sugarcane image datasets, and a real-time observing structure for prompt intervention are the main elements of the created system. A sizable dataset gathered from sugarcane farms in various geographical locations is used to measure the performance of the model. The outcomes display that the system outperforms conventional techniques in identifying and categorizing the Top Borer illness with high accuracy [19].

In order to attain the maximum accuracy rate in identifying and diagnosing sugarcane illnesses, Militante, Sammy V., and Gerardo, Bobby D. used multiple CNN architectures ofDL representations.

In this work, three CNN architectures—StridedNet, LeNet, and VGGNet—were utilized to train the models, which achieved a maximum accuracy rate of 9540% utilizing 14,725 pictures of both healthy and diseased sugarcane leaves.During training, the VGGNet classical outperforms two more representations with a 9540% precision ratio, LeNet obtains 9365%, and StridedNet achieves 9010%. By using the leaf attributes to distinguish between photos of healthy and sick, infected sugarcane leaves, the three trained models accomplish their goal. Additionally, this study hopes to produce positive outcomes for researchers working on sugarcane disease identification systems [8].

To address the problem of sickness diagnosis, D.K. Sharma et al. employ the CNN model, whose constraints are modified using the grey wolf optimization NN. The accuracy of the IGWO-based model was competitive with that of the three other optimization methods, namely GA, PSO, and GWO. However, PSO and GWO algorithms are more accurate [20].

A hybrid template matching and support vector machine approach was presented by Zhou, Rong, et al. for reliable and early sugar beet Cercospora leaf spot detection. A three-stage structure was used to accomplish the study's goal: In order to automatically choose the first sub templates, a plant segmentation index of G-R first separates the leaf parts from the backdrop that is included in soil. Second, the author employed orientation code matching (OCM), a strong template matching technique that is reliable for nonrigid plant item searching in scene lighting, foliar translation, and sm and that can constantly and site-specifically watch disease progression. According to the results of the indoor trial, the early sickness detection system can withstand complex environmental changes [21].

A diagnosis and early warning system for sugarcane disease anomalies based on unsupervised learning features was proposed by Li, Dongrui, et al. in response to the challenge of limited annotation data and a variety of disease kinds in sugarcane disease detection. To create a complete feature vector, features were first extracted using two unsupervised learning techniques: clustering and self-encoder. These features were then combined.Next, anomalous sugarcane disease conditions were identified using the local anomaly factor (LOF) method. According to the experimental results, the suggested approach significantly improves accuracy and recall rate when compared to the conventional supervised learning method. This successfully addresses the issue of inadequate annotation data in the identification of sugarcane diseases. This approach may strongly help the prevention and management of sugarcane illnesses and has excellent accuracy and stability in the abnormal detection and early warning of sugarcane diseases [22].

A thorough synopsis of the evaluated literature is given in the following table, which also highlights noteworthy contributions to the use of sugarcane crop-specific datasets for sugarcane disease diagnosis. In order to guarantee that all approaches and conclusions stated are based on research using sugarcane-specific datasets, the references in this table were chosen for their direct relevance to sugarcane agricultural production.

Table 1: Literature Review in Tabular Format

Ref. /Year	**Insight**	**Method used**	**Results**	**Limitation**
[2] 2023	The study focuses on remote sensing and monitoring using Google Earth Engine, rather than early disease diagnosis of sugarcane phenological phases utilizing edge computing.	Regression models that are both linear and harmonic Using remote sensing to analyze seasonal patterns	The phenology of sugarcane from January to June is essential for observation and evaluation. Unhealthy vegetation was present in two areas during particular times.	NA
[3] 2023	The suggested method improves monitoring using edge-fog-cloud architecture to maximize plant health and production by using environmental sensing and artificial intelligence (AI) for early disease identification in sugarcane.	Monitoring using environmental sensing and the Internet of Things. Future data forecasting using a recurrent neural network.	LSTM networks and edge-fog-cloud computing are used in the suggested system for plant health forecasting and monitoring. Created a user interface for alert notifications and data visualization.	NA
[4] 2022	The study focuses on phenology evaluation utilizing Sentinel-1 and Sentinel-2 records with ML models, rather than early disease detection of sugarcane phenological phases using edge computing.	Systems based on fuzzy rules, naïve Bayes, support vector machines, ANNs, logistic regression, DTs, RFs, and SVMs were used. The mean decline in the Gini index was used to determine the variable's relevance.	Sugarcane phenology may be predicted more accurately when Sentinel-1 and Sentinel-2 records are used in tandem. Sentinel-1 data showed an accuracy of 40–60%, Sentinel-2 data showed an accuracy of 56–84%, and combined data showed an accuracy of 76–88%.	NA

Ref. /Year	Insight	Method used	Results	Limitation
[6] 2022	Edge computing may improve real-time monitoring and assessment during phenological stages, according to the study, which highlights the necessity of automatic detection and early diagnosis of sugarcane illnesses.	Techniques for image processing Deep learning techniques	The study offers an overview of deep learning methods and image processing strategies for the diagnosis of sugarcane diseases. The difficulties and potential use of computational methods for evaluating infections in sugarcane are emphasized.	Incapacity to visually detect sugarcane leaf diseases Problems with computational methods for evaluating infections in sugarcane
[7] 2020	The study does not particularly target early disease identification during phenological phases with edge computing; instead, it concentrates on disease detection in sugarcane leaves utilizing IoT and image processing.	Techniques for segmenting leaf area and disease region using image processing (triangle thresholding and edge thresholding). An automated robot is used to identify diseases in sugarcane leaves.	The accuracy of the suggested technique in identifying sugarcane leaf diseases was 98.60%. To identify diseases, the system included automated robots and image processing algorithms.	Overuse of pesticides raises expenses and pollutes the environment. The illness severity analysis has a 98.60% accuracy rate.
[8] 2020	The study does not directly address early disease diagnosis using edge computing during phenological phases; rather, it focuses on deep learning models for sugarcane disease detection.	VGGNet, GoogleNet, StridedNet, AlexNet, and LeNet are CNN architectures.	The maximum accuracy rate of 95% is attained by VGGNet. GoogleNet's accuracy rate is the lowest at 65%.	Out of all the trained models, GoogleNet has the lowest accuracy rate, at 65%. The material provided makes no mention of any further restrictions.
[9] 2023	Early disease diagnosis utilizing edge computing in sugarcane phenological phases is not directly covered in the study. It focuses on several machine learning methods for identifying illnesses.	Hyperspectral, RGB, and multispectral images Divergence of spectral information, machine learning, deep learning, and transfer learning	The outcomes of various methods are emphasized. The abstract does not provide specific outcomes.	There are no particular outcomes in the abstract. The abstract makes no mention of any particular restrictions.

Ref. /Year	Insight	Method used	Results	Limitation
[10] 2024	Instead of concentrating on sugarcane or edge computing applications, the article employs machine learning and UAV-based multispectral pictures to identify sugar beet illness early.	Methods of supervised machine learning were evaluated. Support vector machines and the K-nearest neighbor classifier were employed.	Over 70% of cases of Cercospora leaf spot disease were successfully detected early. At 83%, the KNN model had the best accuracy.	NA
[11] 2021	Early disease diagnosis utilizing edge computing for sugarcane phenological phases is not directly covered in the study. It focuses on deep learning methods for illness identification.	Architectures for CNNs Algorithms for object detection (YOLO and Faster R-CNN)	93.40% top accuracy on the sugarcane dataset 58.13% is the mean average accuracy score for object detection.	Model performance is impacted by uncontrolled circumstances. Algorithms for object detection obtained a mean average accuracy score of 58.13%.
[12] 2023	The study does not really target early illness diagnosis utilizing edge computing; instead, it concentrates on deep learning methods for sugarcane disease detection.	CNNs Using image analysis to classify and identify diseases	Diseases of sugarcane are accurately detected via deep learning. Promising method for agricultural early diagnosis.	NA
[13] 2022	The article focuses on UAV multispectral pictures and ML approaches for white leaf illness identification, however it does not cover early disease detection of sugarcane phenological phases employing edge computing.	Multispectral sensors with high resolution installed on tiny unmanned aerial vehicles (UAVs) Machine learning classifiers under supervision (K-nearest neighbors, random forest, decision tree, and XGBoost)	94% accuracy in identifying WLD was attained. MSAVI, NDVI, and ExG are the best vegetation indices for differentiating between healthier and diseased crops.	

Ref. /Year	Insight	Method used	Results	Limitation
[14] 2023	Although early disease identification utilizing edge computing in phenological phases is not directly addressed, the article concentrates on deep learning for disease detection in sugarcane.	CNN illness detection technique based on deep learning (DL) Web-based tool for tracking and detecting diseases in sugarcane crops	The study used CNN to detect sugarcane illness with a 98.69% accuracy rate. A web-based tool was created to identify diseases in sugarcane crops.	Farmers lack the diagnostic and identification abilities to diagnose diseases. Accurate illness prediction requires dynamic database updates and user feedback.
[15] 2024	Instead of concentrating on early detection during sugarcane phenological phases or edge computing applications, the article employs deep learning to classify diseases.	Architecture for multilayer deep learning based on attention For the detection of saliency, spatial and channel attention	Exceeded the accuracy of VGG19, ResNet50, XceptionNet, and EfficientNet_B7 by 86.53%. Highlights the significance of all-level features for the effectiveness of picture classification.	
[16] 2023	Not precisely early disease identification utilizing edge computing in sugarcane phenological phases, but rather deep learning for SRR disease detection is the main emphasis of the article.	Model for DL based on multi-layer perceptrons (MP) Using 20,000 leaf pictures, sugarcane disease classification	97.97% is the binary classification accuracy rate. 98.03% is the total multi-classification accuracy rate.	
[5] 2019	The work is not especially about early detection utilizing edge computing during phenological phases, but rather on deep learning for sugarcane disease recognition.	Sugarcane picture collection was used to build a deep learning network. Methods of computer vision for identifying diseases	The trained deep learning model's accuracy was 95%. Sugarcane disease detection and classification is done by the model.	Farmers' lack of expertise in identifying diseases. Rapidly expanding disease classifications make identification difficult.

Ref. /Year	Insight	Method used	Results	Limitation
[23] 2013	This research does not discuss the use of Edge computing for early disease detection in sugarcane phenological phases. For the detection of sugarcane smut disease, it focuses on PCR and nested PCR methods.	Ustilagoscitamina detection using PCR tests. PCR tests with nesting for improved detection precision.	80% for PCR, 35% for nested PCR, and 70% for all three. For the detection of sugarcane smut, nested PCR is more appropriate.	Very early seedlings are not a good candidate for PCR or nested PCR. Prior to the three-leaf stage, early detection is useless.
[18] 2024	The study concentrates on CNN and SVM-based prediction analysis of leaf illnesses rather than early disease detection of sugarcane phenological phases utilizing Edge computing.	SVM and CNN are used in predictive analysis. Performance evaluation of classification for seven sugarcane leaf diseases	The range of precision rates is 94.34% to 94.86%. The model's overall accuracy is 94.57%.	
[24] 2022	Although the study highlights the difficulties and developments in existing detection techniques, it does not particularly target edge computing. Instead, it stresses the necessity of quick on-site diagnostic tools for early identification of sugarcane diseases.	Assays based on enzyme-linked immunosorbents, loop-mediated isothermal amplification, microarrays, and real-time polymerase chain reactions. How to identify microbes that cause illness in sugarcane.	The necessity of quick on-site diagnostic instruments for identifying sugarcane diseases is covered in the study. The most recent approaches to solving diagnostic problems are critically examined in this work.	The current techniques for identifying sugarcane diseases are labor-intensive and need sophisticated equipment. The diagnostic tools that are now available are quite specific and selective, but they are not appropriate for on-site use.

Ref. /Year	Insight	Method used	Results	Limitation
[9] 2023	Early disease diagnosis utilizing edge computing in sugarcane phenological phases is not directly covered in the study. Various machine learning methods for illness diagnosis are its main emphasis.	Hyperspectral, multispectral, and RGB images Divergence of spectral information, machine learning, deep learning, and transfer learning	The outcomes of various methods are emphasized. The abstract does not provide specific results.	Yield loss results from early illness identification. The abstract makes no mention of any particular restrictions.
[11] 2021	Early disease diagnosis of sugarcane phenological phases utilizing edge computing is not directly covered in the study. It focuses on using deep learning techniques to the identification of diseases.	Architectures for CNN Algorithms for object detection (YOLO and Faster R-CNN)	Model performance is impacted by uncontrolled circumstances. Algorithms for object detection obtained a mean average accuracy score of 58.13%.	93.40% is the highest accuracy on the sugarcane dataset. 58.13% is the mean average accuracy score for object detection.
[25] 2019	The study does not particularly target early disease diagnosis utilizing edge computing; instead, it concentrates on mobile apps for image processing-based sugarcane disease detection.	NNs and K-means clustering are used to classify and categorize illnesses. Methods for detecting plant diseases using image processing.	The study suggests a method for identifying sugarcane leaf diseases that makes use of texture and color characteristics. The technology is able to identify sugarcane leaf diseases and offer treatments.	Plant disease monitoring by hand takes a lot of time and effort. Accurate monitoring requires knowledge of plant diseases.
[19] 2023	CNN-based deep learning for disease categorization is the main emphasis of the article, rather than early disease detection of sugarcane phenological phases utilizing Edge computing.	CNN illness detection technique based on deep learning (DL). Personalized deep neural network architecture, real-time monitoring, and an image preparation pipeline.	High precision when utilizing the CNN model to detect Top Borer sickness. Outperformed conventional approaches in the categorization of diseases.	Training requires large and varied datasets. Impact of unbalanced data and model interpretability are addressed.

Ref. /Year	Insight	Method used	Results	Limitation
[26] 2016	Although the study highlights the need of prompt responses and examines many methods for early sugarcane disease diagnosis, it makes no mention of edge computing applications.	The many diseases that affect sugarcane plants are covered in the study. The study assesses current methods for identifying plant diseases in sugarcane.	Various sugarcane plant diseases are covered in the study. The study assesses the methods currently used to identify illnesses in sugarcane plants.	NA
[27] 1967	This research does not discuss the use of Edge computing for early disease detection in sugarcane phenological phases. It focuses on the detection of Ratoon Stunting Disease in relation to polyphenol oxidase levels.	Elevated levels of polyphenol oxidase following infection. There is currently no useful application for early diagnosis.	Infected sugarcane showed elevated levels of polyphenol oxidase. RSD early diagnosis is not currently feasible.	Early diagnosis is not yet feasible in practice. Technique based on elevated levels of polyphenol oxidase.
[8] 2019	Instead of employing edge computing for early disease identification during phenological phases, the article concentrates on DL representations for sugarcane illness recognition.	CNN architectures: VGGNet, LeNet, and StridedNet Identifying sugarcane illnesses using DL representations	The VGGNet model's accuracy rating is 95.40%. The LeNet model's accuracy percentage is 93.65%.	NA
[28] 2024	Without addressing phenological phases or Edge computing for sugarcane, the article employs transfer learning and the Plant Village dataset to identify plant diseases in potatoes and tomatoes, not sugarcane.	Transfer learning using a VGG16 architectural foundation. Use of the dataset known as "Plant Village".	Edge AI technique for plant disease detection. Uses the Plant Village dataset with VGG16 for transfer learning.	NA
[20] 2024	Utilizing CNN and optimization methods, the article focuses on disease diagnosis rather than early illness detection of sugarcane phenological phases utilizing edge computing.	Better Algorithm for Grey Wolf Optimization Neural Network Convolution	The accuracy values for IGWO and GA were competitive. The accuracy of the PSO and GWO algorithms was higher.	There aren't enough specialists to identify diseases. The PSO and GWO algorithms had higher precision.

Ref. /Year	Insight	Method used	Results	Limitation
[21] 2013	The study employs template matching and SVM to identify Cercospora leaf spot in sugar beets, not sugarcane, early. Edge computing applications are not covered.	OCM, or orientation code matching, is used to match templates. SVM (support vector machine) for classifying diseases.	Strong early Cercospora leaf spot detection was accomplished. For illness quantification, efficient templates are automatically chosen.	NA
[22] 2023	This research does not discuss the use of Edge computing for early disease detection in sugarcane phenological phases. Unsupervised learning for early warning systems and illness detection is its main emphasis.	Feature extraction using self-encoder and clustering. To discover abnormalities, use the local anomaly factor (LOF).	Significant increase in recall rate and accuracy. High stability and accuracy in identifying diseases.	Insufficient annotation data to detect sugarcane diseases. Accurate detection is complicated by a variety of illness kinds.
[29] 2022	The study does not particularly target early disease identification in sugarcane phenological phases using edge computing; instead, it concentrates on applying machine learning to identify plant illnesses.	Methods for classifying data using machine learning An algorithm for detecting canny edges	The study included an analysis of many plant diseases. The dataset of plants was subjected to machine learning classification techniques.	NA

3. RESEARCH GAP AND DISCUSSION

According to the literature review, there has been a lot of progress in identifying sugarcane diseases; nevertheless, some critical gaps still need to be addressed for long-term, workable remedies. The majority of current research focuses on the detection and categorization of post-infection diseases, which restricts the opportunity for prompt intervention during crucial phenological periods. Since current solutions sometimes rely on cloud-based designs that introduce delay and are inappropriate for areas with poor connection, the potential of edge computing for real-time, on-site illness diagnosis is still largely unrealized. Although sensors and drones are common IoT devices for gathering data, there is little integration of these devices with edge computing and AI frameworks for early illness prediction. Small-scale farmers cannot afford many high-accuracy models due to their high computing requirements, underscoring the need for scalable, reasonably priced technology that may be used in a variety of farming environments. Additionally, there aren't many all-inclusive solutions that integrate predictive analytics and real-time monitoring for the phenological phases of sugarcane, which is essential for proactive disease control.

The shift in sugarcane disease identification from conventional techniques to cutting-edge technologies highlights both opportunities for improvement and notable advancements. Although they offered insightful information, traditional methods like NDVI-based remote sensing were inadequate for precise, early-stage identification. Although machine learning methods increased the accuracy of illness predictions, they frequently depended on centralized cloud infrastructures, which caused latency and connection issues.CNNs and other deep learning models showed excellent illness detection accuracy, but their processing requirements made them impractical in environments with restricted resources. Edge computing offers a revolutionary solution by facilitating local data processing, cutting down on latency, and giving farmers quick, useful insights—all of which are particularly helpful in remote locations with spotty internet service. A strong foundation for real-time monitoring and early disease diagnosis is provided by combining edge computing with IoT and AI. This enhances decision-making and efficiently reduces crop losses.

Future studies should concentrate on creating affordable, scalable solutions for small and medium-sized farms. Throughout the sugarcane growth cycle, proactive disease control will be made possible by improving real-time monitoring using IoT and predictive modeling. Computational difficulties can be solved by using effective and lightweight deep learning models that are tailored for deployment on edge devices. To guarantee dependability and efficacy, systems must also be strong and flexible enough to adjust to a variety of field situations. Making the integration of edge computing and AI for early-stage disease detection a top priority will guarantee prompt treatments, making the management of sugarcane diseases a more accessible, effective, and sustainable practice.

4. CONCLUSION:

Edge computing has the potential to significantly increase crop health management and monitoring effectiveness in agriculture, especially in the identification of sugarcane diseases. Real-time illness detection is made possible by a number of technologies and approaches that have been examined in this study, including deep learning models, artificial intelligence, and IoT-based sensing. Research has demonstrated that machine learning methods, such as CNNs, and edge-fog-cloud architectures are capable of very precise identification of sugarcane illnesses.

These developments enable farmers to take preventative measures, increasing output and lowering losses, by giving them early insights into the health of the crop during its phenological stages. In order to improve scalability and accessibility for small to medium-sized farmers, future research should concentrate on improving these technologies to function flawlessly in a variety of field settings. AI and edge computing together have the potential to build an effective and sustainable agricultural ecosystem that not only increases output but also protects the environment.

DataAvailability

This manuscript is a review based on the published articles that are referred and listed in the reference lists of the manuscript.

ConflictsofInterest

Theauthorsdeclarethattheyhavenoconflictsofinterest.

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