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TOPICAL REVIEW

Deep Learning and Edge Computing in Agriculture: A Comprehensive Review of Recent Trends and Innovations

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ABSTRACT Rice is a vital staple for over half of the global population, yet its production is significantly threatened by leaf diseases caused by fungal and bacterial pathogens. Early and accurate detection of such diseases is critical to minimizing crop loss, particularly under conditions of labor shortages and climate variability. Traditional inspection methods are labor-intensive and error-prone, highlighting the need for automated, intelligent solutions. This systematic literature review explores recent advancements in deep learning and edge computing for rice leaf disease detection, focusing on challenges such as small and overlapping lesion detection and real-time model deployment. These lesions are difficult to detect due to their limited size, irregular shapes, and visual similarity to healthy areas, especially in field conditions. A comprehensive search across five databases (2020–2024) using the keywords ''rice leaf disease detection,'' ''object detection,'' and ''edge computing'' identified 2,072 articles. After applying inclusion criteria, 76 peer-reviewed journal articles were selected. Among the models reviewed, You Only Look Once version 7 (YOLOv7) achieved the highest accuracy (99% mAP), outperforming Faster Region-Based Convolutional Neural Network (Faster R-CNN) and YOLOv8. Edge devices like NVIDIA Jetson Nano demonstrated real-time capabilities, achieving 0.0549 seconds latency per image using YOLOv7-tiny at 640 × 640 resolution. Vision Transformers (ViTs) also performed well (up to 98% mAP) but faced challenges related to computational and data efficiency. Future directions include leveraging lightweight models, solar-powered edge devices, and hybrid ViT–CNN architectures. This review underscores the transformative role of AI technologies in precision agriculture, offering scalable tools to improve crop monitoring and global food security.

INDEX TERMS Rice leaf disease detection, deep learning, edge computing, vision transformers, precision agriculture.

I. INTRODUCTION

Rice (Oryza sativa) functions as the foundation of worldwide food safety and represents the key dietary substance for greater than fifty percent of global society. More than millions of people across Southeast Asia earn their living through rice production that supports substantial economic development in the region [1]. Practicing agriculture of this essential crop remains challenging because it must continuously fight fungal and bacterial infections caused by

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Magnaporthe oryzae (rice blast), Xanthomonas oryzae (bacterial blight) and Helminthosporium oryzae (leaf spot). The infections cause severe crop damage, leading to a 40% yield loss and an annual financial loss of 5 billion dollars in the region [2]. The wide occurrence of these diseases demonstrates that better diagnostic and management systems need immediate creation to safeguard rice crops [3].

Traditional disease detection methods mainly relied on farmer visual inspections, yet this approach shows significant labor ranges and contains a high risk of human mistakes. The detection of earliest disease markers caused by Helminthosporium oryzae requires special know-how which many operators lack [4]. Physical inspections require substantial labor while delayed interventions due to such checks make crop damage more severe. Environmental factors that vary between morning and afternoon hinder accurate field-based diagnosis due to their constant fluctuations [2]. Advanced technical solutions need to be developed since current disease identification methods have major limitations.

The recent progress in artificial intelligence (AI) and computer vision technology has developed new strategies to solve plant disease identification problems. A designation of deep learning models with Convolutional Neural Networks (CNNs) and You Only Look Once (YOLO) demonstrates remarkable ability for plant disease identification and classification tasks [5]. Recent years have seen a growing interest in integrating Artificial Intelligence (AI) and Internet of Things (IoT) technologies into agricultural practices. These technologies are increasingly applied to automate irrigation systems, monitor plant health, and identify crop diseases through real-time surveillance systems [6]. In particular, the development of lightweight AI models tailored for edge computing has gained attention due to their potential for deployment in resource-constrained environments such as farms. Multiple improvements such as Slicing Aided Hyper Inference (SAHI) and YOLOv8 among its versions were developed to address specified detection challenges including small and overlapping objects in rice leaves [7]. The improvements serve as fundamental tools to boost medical identification accuracy in agricultural settings.

Despite the progress in object detection models, accurately detecting small and overlapping lesions remains a key challenge in rice disease identification. Lesions in rice leaves can be extremely small, irregular in shape, and partially occluded by neighboring leaves. Their low contrast against the leaf background and clustered appearance under natural lighting conditions make them difficult to differentiate from healthy tissue. These factors often lead to missed detections or false positives, especially in real-time field applications, and highlight the need for models optimized for fine-grained feature recognition [3], [8].

The practicality of these solutions improves through the use of NVIDIA Jetson Nano and Raspberry Pi edge computing devices that process data in real-time at the source. The device combination reduces latency so that interventions take place in real-time even in remote agricultural settings [7], [8]. Edge computing demonstrates its superiority over cloud-based systems by reducing latency which makes it fitting for heterogeneous field environments according to research findings [8]. Reliable detection processes become more efficient when combined with these technologies which leads farmers to take quick informed decisions improving their crop management practices.

The research field of rice leaf disease detection using deep learning and edge computing has made significant advancements; however, several important knowledge gaps remain. The primary obstacle relates to identifying small items. SAHI and YOLOv8 continue to experience accurate failures when identifying objects that are smaller than 5 pixels in size, particularly when these objects appear as overlapping structures on rice leaves. According to Simhadri et al. the recognition rates fall below 70% in such situations [3].

The implementation of deep learning models on edge devices leads to unavoidable conflicts between performance speed and reliability when executing the models. The modeling accuracy decreases between 10% to 15% when environmental factors such as lighting noise conditions vary, according to Ji et al. [8]. Research lacks adequate studies which evaluate the performance differences between Vision Transformers (ViT) and CNNs when employed for rice disease identification purposes. The lack of sufficient research comparing Vision Transformers and CNNs creates uncertainty about their performance characteristics, hindering the selection of an optimal architecture for this use case [1].

Although CNNs have dominated the field of plant disease classification due to their ability to efficiently extract local features, they are inherently limited in modeling long-range dependencies across an image. This becomes a critical drawback in scenarios involving small or overlapping lesions on rice leaves, where local context alone may not be sufficient. ViTs, with their self-attention mechanism, can capture such global spatial relationships, making them a promising but underutilized architecture in agricultural applications. This review emphasizes the need to benchmark ViT and CNN models in this specific context to understand their comparative strengths and deployment suitability.

Artificial Intelligence-based leaf disease detection for rice follows computer vision which contains three essential components. Among all essential components the acquisition of data establishes its fundamental base. Drone or UAV researchers are increasingly focusing on the integration of AI and IoT in agriculture to enable automated irrigation systems, crop disease identification programs, and plant surveillance systems. Imaging systems on these drones collect the necessary raw data through their high-resolution image-capturing capabilities [11]. The following processing stage uses advanced algorithms to segregate small and overlapping items including disease spots on rice leaves. During the disease classification phase, models perform specific disease category assignment for objects which have been

recognized in the previous stages. The structured framework does not only details technical procedures, yet it also demonstrates the relevance of each step as it determines exact and trusted disease detection outcomes.

The systematic research explores both challenges and developments related to utilizing edge computing and deep learning techniques for detecting rice leaf diseases.

Section I (Introduction) outlines the urgency of early disease detection in rice cultivation and introduces AI-based solutions as a response to agricultural sustainability concerns. Section II (Background Study) discusses core concepts, including CNNs, YOLO variants, and Vision Transformers, along with their limitations in detecting small, overlapping lesions and handling computational constraints. Section III (Research Methods) details the systematic literature review process guided by PRISMA, including search strategies, inclusion and exclusion criteria, and data extraction protocols. Section IV (Results) presents a quantitative synthesis of recent studies, evaluating model performance through metrics such as mean Average Precision (mAP), frames per second (FPS), and deployment feasibility. Section V (Conclusion) synthesizes key findings and highlights future research directions, particularly the integration of lightweight models and knowledge graphs for precision agriculture, as well as the need for dataset expansion and interpretable AI techniques.

These sections outline a systematic approach for improving rice disease detection through AI, combining theoretical underpinnings with practical deployment considerations. Building upon this introductory overview, the next section elaborates on the fundamental deep learning and edge computing technologies that reinforce rice disease detection systems, along with the historical evolution, technical challenges, and limitations faced in real-world agricultural settings.

II. BACKGROUND STUDY

The section presents key information about deep learning along with edge computing specifically used for agricultural disease detection while exploring their historical development together with their current challenges. Rice maintains its position as the staple food for more than 50% of global citizens while facing with severe threats from bacterial and natural stress-related leaf diseases [3]. Traditional detection methods including manual inspection remain faulty when it comes to differentiating overlapping symptoms and small lesions. The advancements made in object detection models during recent times [12], [13] and present-day real-time applications can become more powerful through and edge computing frameworks [14], [15], automated disease identification.

Different agricultural ecosystems restrict the implementation of machine learning approaches because of their so far unmanageable computational power and scarcity of annotated datasets and weak model flexibility. The following portion evaluates the basic principles alongside crucial technologies as well as the unsolved difficulties of this domain.

A. RICE LEAF DISEASE DETECTION

The identification of lesions and discolorations and pest infestations in rice leaves serves as the foundation to avoid yield reduction through detection methods. The detection of objects and Vision Transformers through AI solutions have replaced manual systems to detect rice leaf diseases in controlled environments. The detection of planthoppers through Faster R-CNN model by Khairunniza-Bejo et al. [16] faced challenges when densities exceeded acceptable levels. Researchers Hong et al. [17] developed a YOLOv4 model designed for lightweight detection of wheat Fusarium head blight. The complexities of edge deployment exist because it requires limited resources as Lema et al. [18] verified through their research ''Quantitative comparison and performance evaluation of deep learning-based object detection models on edge computing devices''.

B. RICE LEAF DISEASE

Different types of rice leaf diseases that affect rice crop health and yield appear in Figure 1. The diseases exhibit specific symptoms that allow for their identification and classification. The following is an overview of each rice leaf disease depicted in the images.

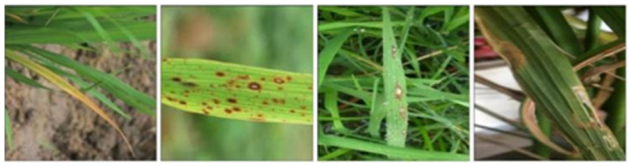


FIGURE 1. Rice leaf diseases.

The viral condition called Tungro exists from the combination of the Rice Tungro Bacilliform Virus (RTBV) and Rice Tungro Spherical Virus (RTSV) transmitted through leafhoppers (Figure a). This virus causes leaf and growth abnormalities, leading to yellow or orange leaf discoloration, stunted growth, and reduced tillering. Infected plants exhibit shorter growth due to poorly developed panicles, resulting in a substantial reduction in yield.

Brown Spot (Figure b) emerges as a fungal disease that originates from Bipolaris oryzae. The fungal disease appears through brown circular spots with a surrounding yellow section that grows into bigger necrotic areas on rice foliage [2]. The disease frequently occurs when rice plants are nitrogen-deficient and exposed to dry environmental conditions. As one of the most destructive fungal diseases in rice cultivation, blast is caused by Magnaporthe oryzae (Figure c). These spindle-shaped lesions display grayish centers and brown outer boundaries that spread to connect with each other thus causing leaves wilting and drying. The disease has multiple target growth stages from leaves to nodes to panicles which can produce severe yield reductions unless appropriate control measures are utilized.

Bacterial Blight results from the infection of Xanthomonas oryzae pv. oryzae which attacks rice crops as a major bacterial

disease (Figure d). Bacterial Blight produces first symptoms like water-soaked lesions which develop into yellow streaks until they turn brown before causing leaves to dry. The disease transmission occurs through rain splashes as well as irrigation water and the vectors of insects who spread it quickly in warm and humid environments.

Rice production faces important threats from these diseases so farmers need to detect them early and execute proper management to sustain their rice farming. Deep learning-based disease detection models and other improved approaches are becoming increasingly common for precise identification and classification of rice diseases which streamlines response strategies [3].

C. EVOLUTION OF DEEP LEARNING MODELS

The discovery of plant diseases has witnessed major developments because of deep learning model improvements, traditional methodologies based on image processing along with feature extraction techniques constituted the earlier detection methods. The development of deep learning methods brought total transformation to this discipline by creating automatic systems that execute precise disease diagnoses effectively. Different network architectures were sequentially developed to expand the performance capabilities of preceding models regarding accuracy and robustness and efficiency. A historical overview in Fig. 2 shows the development of deep learning models dedicated to plant disease detection through key phases starting with AlexNet in 2012 up to modern ViT and SAHI developments [6].

According to Dananjayan et al. [19] plant disease detection through deep learning models started with AlexNet during 2012 as a major milestone for deep learning image classification methodologies. Three new models emerged in 2013 ZFNet, NiN, and OverFeat introducing enhanced capabilities for image feature extraction. In 2014, several advanced network architectures, including VGG, GoogLeNet, R-CNN, and Generative Adversarial Networks (GANs), further improved feature extraction, particularly for medical diagnosis applications.

In 2016, YOLO was introduced alongside SSD, Faster R-CNN, and R-FCN, transforming object detection capabilities to support real-time identification of disease regions in plants. In 2017, new models such as DCRN, 2RU-Net, Mask R-CNN, and Transformer networks were developed to enhance localization and segmentation performance. The year 2018 marked a significant advancement with the introduction of sophisticated network architectures, including FractalNet, PyramidNet, PolyNet, Wide ResNet, and ResNeXt FPN, which improved both precision and mechanical stability [20].

In 2019, further progress was made through the development of AlexNet–VGG16 hybrid models, transfer learning approaches, and Dense CNN-based VGGNet variants, making deep learning models more suitable for a wide range of plant pathology applications. Through this period, the YOLO v3+SP algorithm along with DasNet-V2 and CNN-based VGG-16, enabled real-time disease detection at its highest level.

ViT bring new power to CNN-based architecture through self-attention mechanisms which detect global dependencies among images effectively for plant disease detection. SAHI was designed to boost object detection capabilities while working on high-resolution images which lead to superior disease spot detection in plant leaves.

The timeline illustrates deep learning development in plant disease detection which shows gradual evolution from standard CNN frameworks to contemporary Transformer and hybrid models that enhance accuracy and operational efficiency and scalability.

Building upon this trajectory, recent studies have begun to explore hybrid architectures that integrate ViT with CNN. These models aim to combine the local feature extraction strengths of CNNs with the global attention capabilities of transformers, offering a potential balance between computational efficiency and detection precision. Although still emerging in agricultural contexts, ViT-CNN hybrids represent a promising direction for future research in rice disease detection, especially for small lesion identification under resource constraints.

D. RELATED WORK

The current research on deep learning detection of crop diseases does not focus on rice despite its worldwide impact on agriculture. The research from Simhadri and coauthors [3] presents extensive information about detecting rice leaf diseases by extending their examination from leaves into every plant section including roots, stems, and grains. Specialized detection models should be developed since this holistic approach shows the necessity to address rice disease detection challenges in specific ways.

Setyanto et al. [15] provide a systematic overview of model compression techniques that involve replacing regional proposal networks, compacting backbone networks, and adapting detector heads to enhance edge device deployment of object detection models for drones and autonomous vehicles. Their research discusses performance trade-offs between detectors that work in one stage (such as YOLO variants) and detectors that work in two stages (such as Faster R-CNN), because of their specific relevance to restricted agricultural equipment systems. Research shows the necessity of creating customized deep learning models specifically for agricultural purposes which especially benefit rice farming. Plant disease detection combined with optimal irrigation optimization and pesticide use management as well as crop yield enhancement becomes achievable through Machine Learning (ML) and Deep Learning (DL) methods according to Ayoub Shaikh et al. [20].

Existing studies confirmed that precision farming enhances agricultural production through technologies including remote sensing, GPS, and data analytics as it minimizes environmental damage. High accuracy in plant disease detection

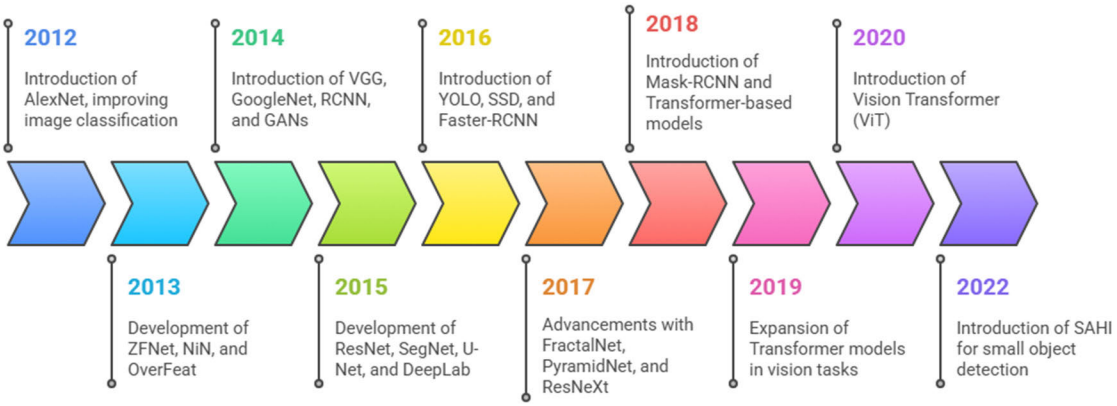


FIGURE 2. Evolution of deep learning model.

relies on image recognition together with artificial neural networks and pre-trained models which analyze large-scale datasets including PlantVillage and ImageNet. The models' precision depends greatly on the extent of image collection along with its corresponding environment. Plants collected through controlled systems in databases such as PlantVillage perform better than materials obtained from complex real-world settings. This reinforces the need for robust models that generalize well under diverse agricultural conditions [21].

Detecting small targets remains a critical ongoing problem within computer vision systems, particularly when used in agricultural applications [22]. Numerous model enhancements have been introduced to address this issue:

- Enhanced-YOLOv8 integrates a Small Target Detection Level (STDL) within its feature layer, which improves semantic understanding and enhances both object localization and bounding box precision [23]. It is especially effective in detecting small disease lesions in plant leaves under natural lighting conditions.
- Fusion Convolutional Block Attention Module (FCBAM) enhances standard CBAM by integrating a Position Attention Module (PAM), allowing the model to focus more effectively on both spatial and channel features. This results in better identification of critical visual cues, particularly in dense or cluttered leaf patterns.
- Semantic Fusion Network (SFN) improves detection precision by integrating high-level semantic features from residual networks into lower-level spatial features. This fusion reduces semantic degradation across layers, allowing more accurate detection of small or overlapping objects [7].
- Generalized Efficient Layer Aggregation Network (GELAN) employs bi-level routing attention and multi-scale modules with optimized loss functions to retain critical features while reducing model complexity. It supports effective multi-scale feature extraction and real-time performance, particularly suitable for embedded systems [7]. Overall, such model modifications including GELAN's bi-level routing attention and multi-scale modules achieve essential feature retention while reducing computational complexity. These architectural refinements enable efficient real-time detection and confirm the promise of Transformer-based YOLOv8 designs for complex rice leaf disease scenarios, particularly for deployment on embedded smart agriculture devices [24].
- SAHI enhances detection of small targets by partitioning high-resolution images into smaller segments. This allows models to focus on localized details that are often lost in global analysis. SAHI significantly improves the granularity of detection, which is crucial in applications where lesions appear in dense or cluttered patterns [25].

Given the increasing complexity and diversity of these detection models, it becomes essential to systematically evaluate existing research to determine which architecture and techniques best support accurate, real-time detection under agricultural constraints. The following section outlines the SLR approach employed to achieve this.

III. RESEARCH METHODS

A systematic literature review (SLR) represents a meticulous research procedure which seeks to find and evaluate previous works related to research questions and subject areas. This method evaluates a comprehensive set of deep learning approaches together with edge computing solutions and detection techniques that researchers have developed in recent years for leaf disease detection in rice [26]. A literature review methodology enables the assessment of strengths and weaknesses between CNN, YOLO, Transformers, and SAHI algorithms and their ability to detect small objects within rice leaves despite overlapping objects. The review includes a discussion about the best practices for model optimization that enables real-time agricultural deployment on edge devices. Traditional literature reviews differ from SLRs because they use defined procedures to compile available information accurately in a transparent way, making it possible for others to reproduce the synthesis of knowledge while driving progress in smart rice farming. The research

utilizes various procedures extending from the development phase through empirical data collection stages to fulfil its research objectives. The schema of action steps is presented in Figure 3, where each step is clarified in the subsequent sections.

To improve transparency and efficiency during the review, we used the following tools throughout the SLR process:

- Zotero was used to manage, organize, and de-duplicate references gathered from Scopus, Web of Science, IEEE Xplore, and ScienceDirect. It also assisted in citation integration within the manuscript.
- Rayyan facilitated the collaborative title and abstract screening process by enabling blind inclusion/exclusion decisions and reducing screening time.
- XMind was used to organize mind maps and build the research framework, allowing us to clearly visualize conceptual relationships.
- Napkin helped generate clear diagrams and illustrations that visually support the textual content.
- Google Colab was utilized for running Python scripts that enabled bibliometric data visualization (e.g., keyword co-occurrence networks and publication trends), as well as model performance tabulation.
- Draw.io was employed for designing the systematic workflow diagram (Figure X), which visually maps each PRISMA stage (Identification, Screening, Eligibility, Inclusion) to its corresponding research tool.

These tools were not part of the core methodology itself but served to support the literature review process by enhancing organization, accuracy, and visual clarity.

The SLR process is illustrated in Figure 3, which presents a flowchart containing all the planned steps for conducting the study. The review initiation leads to a planning segment where researchers define both the review limits and its associated objectives. The researcher must formulate a research question that remains specific and focused throughout the entire review.. The established research question becomes the foundation for a database search that includes IEEE Xplore alongside Scopus and Web of Science and ScienceDirect and ACM Digital Library. The next stage requires analysis of the selected publications for their suitability.

The researchers define specific selection standards through inclusion and exclusion criteria to evaluate study relevance toward the research inquiry. The established criteria during this stage determine which studies can progress to the following stage. The evaluation produces an important juncture because studies that match the pre-established inclusion standards continue, while all others are eliminated. The evaluation process known as quality check examines studies which meet the pre-established inclusion requirements through an analysis of their methodology plus sample size alongside reliability assessments and their field-based contributions.

The process continues by analyzing if the paper exceeds established quality standards to qualify for the review stage or get rejected. The selected papers advance to data collection procedures during which researchers extract essential

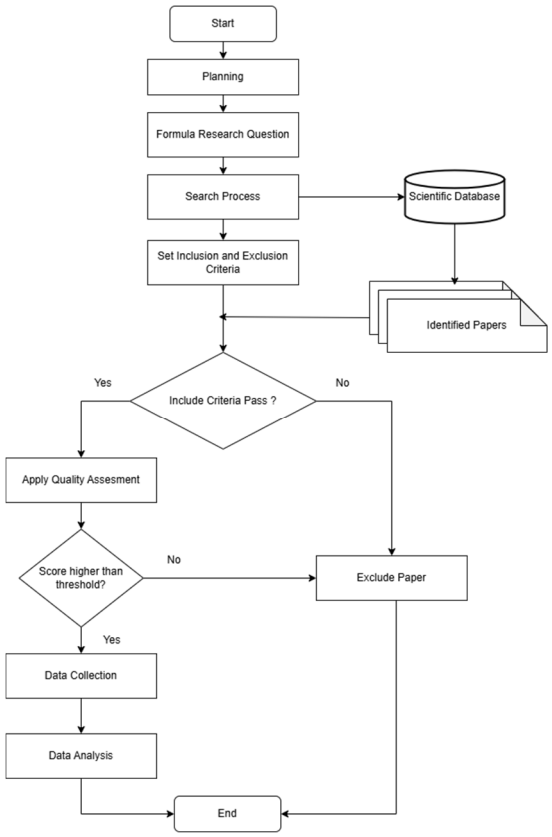


FIGURE 3. Flow diagram of the data search strategy.

elements like research methods, outcomes and contribution and limitations sections. The data analysis phase begins with researchers who interpret and summarise the obtained data to discover research gaps along with future research directions through identifying patterns. The research design determines whether a meta-analysis or qualitative synthesis needs to be performed.

A comprehensive review paper or report summarizes findings during the last stage of the process. The structured format enables researchers to perform a rigorous transparent reproducible SLR which helps identify analyze relevant literature in a systematic manner to maintain credibility and quality of the final review.

A. PLANNING

This shows that the research steps in this phase are well structured and organized. These steps include several procedures, such as establishing the parameters for the review of existing literature, defining the databases required for the search and establishing the criteria for the selection of studies. This phase is crucial to ensure that the studies included in the review are diverse and independent of each other.

B. FORMULATING RESEARCH QUESTION

Research questions receive their definition at this phase for the purpose of specific objective fulfillment. All important

TABLE 1. Research question and motivation.

No.	Research Questions	Motivations
RQ1	Which deep learning model is most effective for detecting rice leaf diseases, and how do their performances compare in handling small objects and overlapping objects?	To identify the best-performing model for detecting early symptoms of diseases, which often appear as small spots or overlapping patterns on rice leaves.
RQ2	What is the role of edge computing in implementing rice leaf disease detection systems, and what are the challenges and opportunities in heterogeneous field environments?	To evaluate the feasibility of detection models on edge devices for real-time applications, considering trade-offs such as latency, accuracy, and resource efficiency.
RQ3	How can Vision Transformers (ViT) be effectively applied to rice leaf disease detection, and what are the challenges associated with their implementation based on top-performing models in terms of mAP?	To evaluate the effectiveness of Vision Transformers (ViT) in detecting rice leaf diseases by analyzing their performance in terms of mean Average Precision (mAP), while identifying key challenges in deploying these models for agricultural applications.

aspects of the review examination are included in the questions which deal specifically with study identification and selection criteria definitions and information acquisition procedures. The research questions need to be direct while remaining centered on the analysis goals. The field of rice leaf disease detection has challenges that the research questions specifically address. The SLR should deliver complete information on recent developments in deep learning along with edge computing and ViT.

The Table 1 present the research questions alongside their fundamental reasoning. The reasons demonstrate why each question matters for practical leaf disease detection in rice since they concern small object recognition and real-time edge devices alongside the comparison between ViT and traditional CNN approaches. The strategic approach ensures the SLR active focus on major problem-solving tasks and aiding the achievement of smart agricultural and precision farming goals.

C. SEARCHING PROCESS

The systematic literature review built its search method on a defined system to locate research about rice leaf disease detection that utilized deep learning and edge computing techniques. The study accessed five top databases, Web of Science, Scopus, ScienceDirect, ACM Digital Library, and IEEE Xplore because of their recognized publications in artificial intelligence, agriculture and computer science fields. The study examined titles together with keywords and abstracts through its research procedure. Table 2 details the keyword string and search information.

Standardized search terms were applied to five major research databases Web of Science, Scopus, ScienceDirect, IEEE Xplore, and ACM Digital to identify relevant articles. The search focused on detection methods and technologies, including object detection, rice leaf disease detection, overlapping and small object detection, detection models, transformers, vision transformers, edge computing, and smart farming.

Filtering by article type and publication years (2020–2024) yielded 124 articles from Web of Science, 192 from Scopus, 879 from ScienceDirect, 299 from IEEE Xplore, and 578 from ACM Digital. From an initial 2,072 publications, those failing title, abstract, and keyword evaluation were excluded. A rigorous selection process ensured only relevant studies were included.

D. SET INCLUSION AND EXCLUSION CRITERIA

The SLR included articles based on strict inclusion and exclusion criteria. Selected studies met four requirements: (1) research on deep learning or edge computing for rice leaf disease detection, (2) peer-reviewed journals (2020–2024), (3) English language content, and (4) technical details on detection models, datasets, or implementation methods. The research only included articles published in peer-reviewed journals because it focused exclusively on articles from this category. The research excluded manuscripts which did not clearly describe object detection issues affecting small objects combined with pattern overlap or were not applied to agricultural scenarios. The research objectives and IT literature review integrity were reinforced through a structured filtering approach which picked only studies of high relevance and credibility. Table 3 shows the complete requirements for study admission into the analysis.

E. QUALITY ASSESSMENT

This study performed a strict quality assessment after their inclusion-exclusion criteria analysis to verify the reliability and relevancy of selected articles for their future data collection work. The goal of this evaluation was to determine if authors from chosen studies properly addressed essential research questions identified in the SLR about deep learning models combined with edge computing implementation and deep learning with ViT in rice leaf disease detection.

TABLE 2. Keywords utilized in various databases.

Database	Search String	Result
Web of Science	All Field= ("object detection" OR "rice leaf diseases detection" OR "overlapping objects detection" OR "small object detection") AND ("object detection model" OR "detection models" OR "transformer" OR "vision transformer") AND ("edge computing" OR "smart farming")	124
Scopus	TITLE-ABS-KEY ("object detection" OR "rice leaf diseases detection" OR "overlapping objects detection" OR "small object detection") AND ("object detection model" OR "detection models" OR "transformer" OR "vision transformer") AND ("edge computing" OR "smart farming")	192
ScienceDirect	("object detection" OR "rice leaf diseases detection" OR "overlapping objects detection" OR "small object detection") AND ("object detection model" OR "detection models" OR "transformer") AND ("edge computing" OR "smart farming")	879
IEEE Explorer	("object detection" OR "rice leaf diseases detection" OR "overlapping objects detection" OR "small object detection") AND ("object detection model" OR "detection models" OR "transformer" OR "vision transformer") AND ("edge computing" OR "smart farming")	299
ACM Digital	"query": ("object detection" OR "rice leaf diseases detection" OR "overlapping objects detection" OR "small object detection") AND ("object detection" OR "detection models" OR "transformer" OR "vision transformer") AND ("edge computing" OR "smart farming")} "filter": Article Type: Research Article, Survey, E-Publication Date: (01/01/2020 TO 12/31/2024), ACM Content: DL}	578
Total		2072

TABLE 3. Selection and screening criteria.

Inclusion Criteria		Exclusion Criteria	
a.	Each article must focus on rice leaf disease detection using deep learning or edge computing technologies.	a.	Studies that are unrelated to rice leaf disease detection or agricultural applications are excluded.
b.	Articles must be published in peer-reviewed journals between 2020 and 2024.	b.	Articles published outside the specified period (before 2020 or after 2024) are excluded.
c.	Articles must be written in English and provide clear, understandable technical details.	c.	Articles written in languages other than English or those with unclear content are excluded.
d.	Articles must address specific challenges such as small object detection or overlapping objects in rice leaf disease detection.	d.	Studies that do not explicitly address small object detection or overlapping objects are excluded.
e.	Articles must provide sufficient information about the detection models, datasets, or implementation methods.	e.	Articles lacking technical details about detection models, datasets, or implementation methods are excluded.
f.	Only original peer-reviewed journal research articles or critical review articles are included.	f.	Conference papers, proceedings, preprints, book chapters, and non-peer-reviewed publications are excluded.

This process enabled researchers to eliminate studies which lacked sufficient details or contribution to the research but included studies with high quality relevance to the analysis. The selected quality assessment criteria for evaluating published articles receive a detailed description in Table 4.

A systematic assessment was conducted during the review to determine the quality of chosen articles using pre-established evaluation standards. Each article received a numerical score through Table 5 based upon its ability to address the research questions about rice leaf blight detection, deep learning models, edge computing implementation and ViT.

A review contained only articles reaching minimum score level 3. The researchers implemented this methodology to select studies which contained both sufficient technical details and clarity. The scoring matrix used for assessment evaluation comprises Table 5 with three explanation quality categories tracking High (H = 1), Medium (M = 0.5) and Low (L = 0).

Each selected study was evaluated across the five QA criteria (QA1 to QA5), as defined in Table 4. For each criterion, a score of 1, 0.5, or 0 was assigned based on the definitions in Table 5. The Total Quality Score for each study was calculated as:

$$Total\ Score = QA1 + QA2 + QA3 + AQ4 + QA5 \quad (1)$$

The maximum possible score is 5, while the minimum is 0. A cut-off score of 3.0 out of 5.0 was used to filter out low-quality studies. This threshold ensures the inclusion of studies that demonstrate methodological clarity, relevance to the research questions, and sufficient technical detail necessary for further analysis in this systematic literature review.

These quality scores not only guided inclusion decisions but also determined which studies were prioritized for

TABLE 4. Quality assessment criteria.

	Quality assessment question	Relevant to the research question
QA1	How do the author(s) define and present the research problem related to rice leaf disease detection?	RQ1
QA2	How effectively do the author(s) describe the implementation of deep learning models for detecting small objects and overlapping patterns?	RQ1
QA3	How do the author(s) evaluate the role of edge computing in real-time rice leaf disease detection systems?	RQ2
QA4	How comprehensively do the author(s) compare Vision Transformers (ViT) with traditional CNN models in terms of accuracy and computational efficiency?	RQ3
QA5	How well do the author(s) provide sufficient technical details about the datasets, models, and implementation methods used in their studies?	All RQ

TABLE 5. Quality assessment scoring criteria.

Quality Assessment Score Level	Description	Score
High (H)	The study thoroughly, clearly, and precisely addresses the quality assessment question.	1
Medium (M)	The study addresses the QA question but lacks detail, clarity, or depth.	0.5
Low (L)	The study provides minimal or no information relevant to the QA question.	0

deeper comparative analysis in subsequent sections, including Tables 6, 7, and 9. High-scoring studies provided the foundation for evaluating model performance, edge deployment feasibility, and Vision Transformer relevance across the three research questions.

F. DATA COLLECTION

Following original descriptions by Moher et al. [27], Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines the systematic review process in this through three consecutive steps named Identification, screening, eligibility and include assessment according to Figure 4. The initial identification process discovered 2072 documents between Web of Science (124), Scopus (192), study proceeded. The data collection process operated.

Figure 4. The initial identification process discovered 2072 documents between Web of Science (124), Scopus (192), ScienceDirect (879), ACM Digital Library (578) and IEEE Xplore (299). The initial dataset containing 2072 documents went through a reduction process using parameters for English language and journal articles and the publication years 2020-2024. Web of Science returned 82 articles alongside 93 articles from Scopus while ScienceDirect provided 622 articles and ACM presented 40 articles and IEEE Xplore gave 55 articles. The authors executed snowballing techniques which revealed four additional studies by examining reference lists of chosen articles to achieve complete search methodology.

PRISMA brought substantial advantages which improved the research process during this investigation. PRISMA provides experts with a practical methodological structure to perform literature review assessments that guides their work through research question development to search strategy creation and findings compilation. The chosen methodology protected the results from bias because it established clear study selection criteria to prevent researchers from adding subjective or random sources. The PRISMA approach made the review procedure more transparent and dependable thus enabling the study to produce reliable conclusions together with practical solutions. The methodological application of PRISMA principles produced higher-quality literature synthesis and reinforced the reliability of the research findings regarding the detection of rice leaf diseases using deep learning and edge computing together with vision transformers.

G. DATA ANALYSIS

The final step of the SLR methodology takes place in the data analysis segment. The researchers use information collected from studies to address the three principal research questions developed during this investigation.

Based on the data extracted through the PRISMA-guided process, the following section summarizes the results of the systematic review. It highlights how each selected study contributes to the three core research questions, and presents performance metrics, model types, and deployment feasibility.

IV. RESULTS

The systematic literature research using Web of Science (124), Scopus (192), ScienceDirect (879) and ACM together with IEEE (299) produced a total of 2,072 articles. The application of PRISMA methodology together with year publication criteria (2020 - 2024) and a series of refinement steps such as journal article selection and non-English article exclusion and duplicate removal and quality assessment led to a final set of 75 relevant articles.

The analysis conducted based on 75 articles identified from a larger pool formed the groundwork for building a

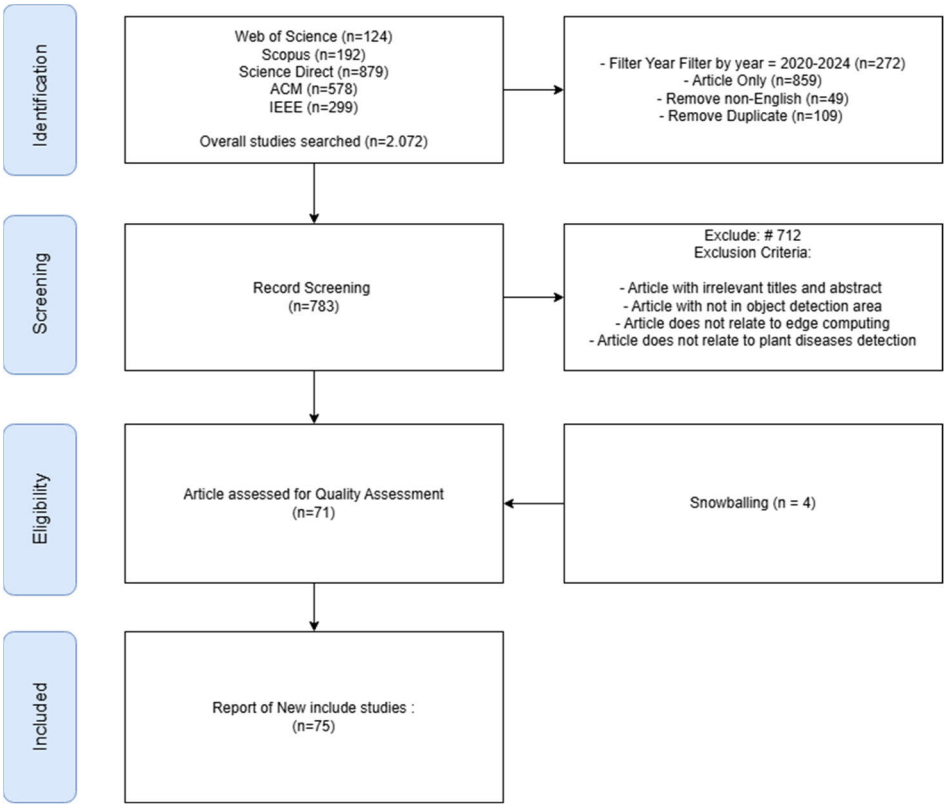


FIGURE 4. Overview of systematic literature.

keyword coincidence network using VOSviewer. The visualization technique functioned to reveal vital research topics and patterns alongside relationships among typical keywords from the analyzed literature. An illustration of co-occurrence network keyword visualization appears as Figure 5.

VOSviewer enables the creation of the Keyword Co-Occurrence Network to demonstrate complex relationships between data set keywords through visual displays. The network includes nodes represented by circles which represent keywords and show frequency level through node size. The network links depict coincidence relationships because they present the frequency dimensions at which node keywords appear together in research papers. The network visualizes keywords from different clusters through their colored groupings as research topics while the clusters display thematic similarities with coincidence patterns. The defined structure enables researchers to observe the essential research fields together with their relationship pathways.

Various essential research areas have materialized in the visualization which forms different cluster groups. Object recognition techniques through deep learning and transfer learning form the largest central research group based on their related conceptual terms CNNs, YOLOv8, and machine vision and deep learning. As part of this cluster, researchers demonstrate the crucial significance of deep learning methods for object recognition specifically when detecting diseases in agricultural plants.

The cluster that focuses on edge computing integrates multiple concepts which include both federated learning together with DNN processing acceleration and sensors integration. The topic demonstrates several research approaches in deploying AI models onto edge systems that support real-time functionality and minimal latency needs. Automatic irrigation control together with agricultural automation features as primary concepts under the Smart Agriculture and Precision Farming cluster which integrates AI and IoT technologies and automation methods for agricultural sustainability improvement.

The artificial intelligence and feature extraction clusters work together through image detection and recognition tasks that demonstrate image processing technique advancement. Research aimed at optimizing AI models for mobile and embedded systems is the focus of the Lightweight Models and Mobile AI cluster, with discussions centered on lightweight architecture and Android implementations.

Finally, the Disease Detection and Precision Agriculture cluster combines leaf disease detection, attention mechanisms, remote sensing and UAV-based agriculture and refers to the application of deep learning and remote sensing in the early detection of plant diseases.

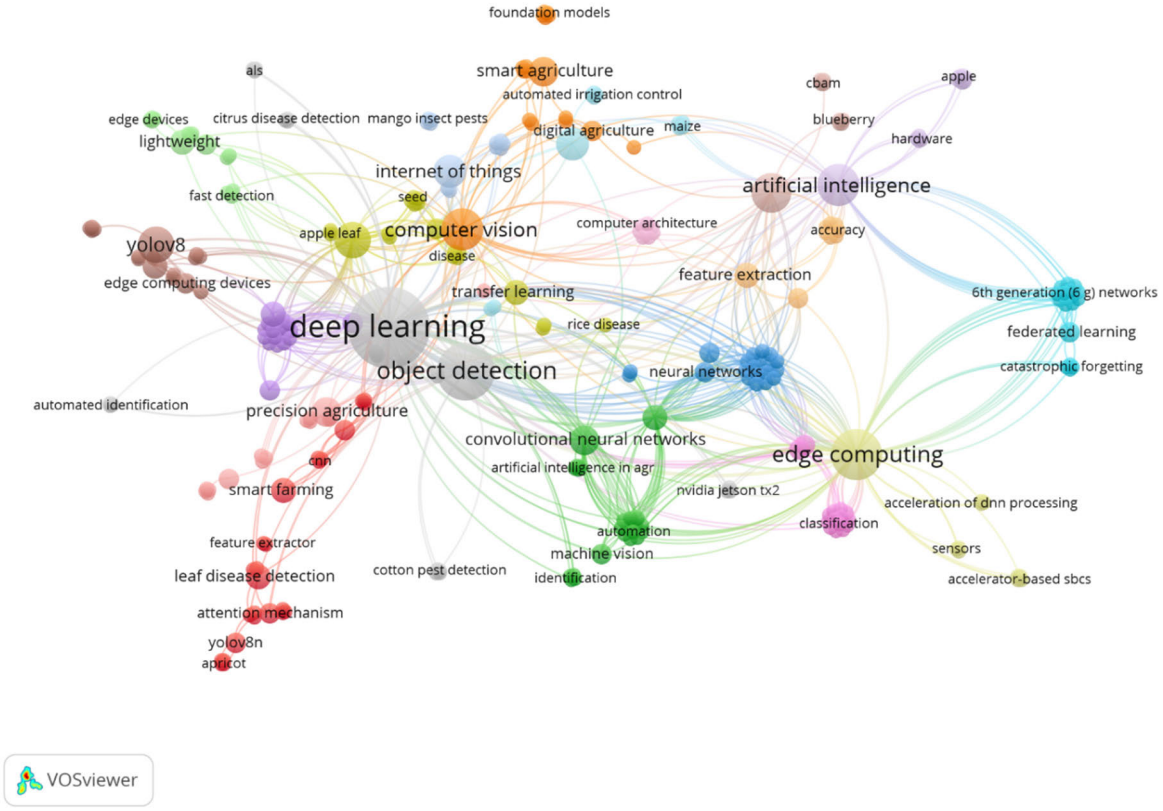


FIGURE 5. The keyword co-occurrence network visualization.

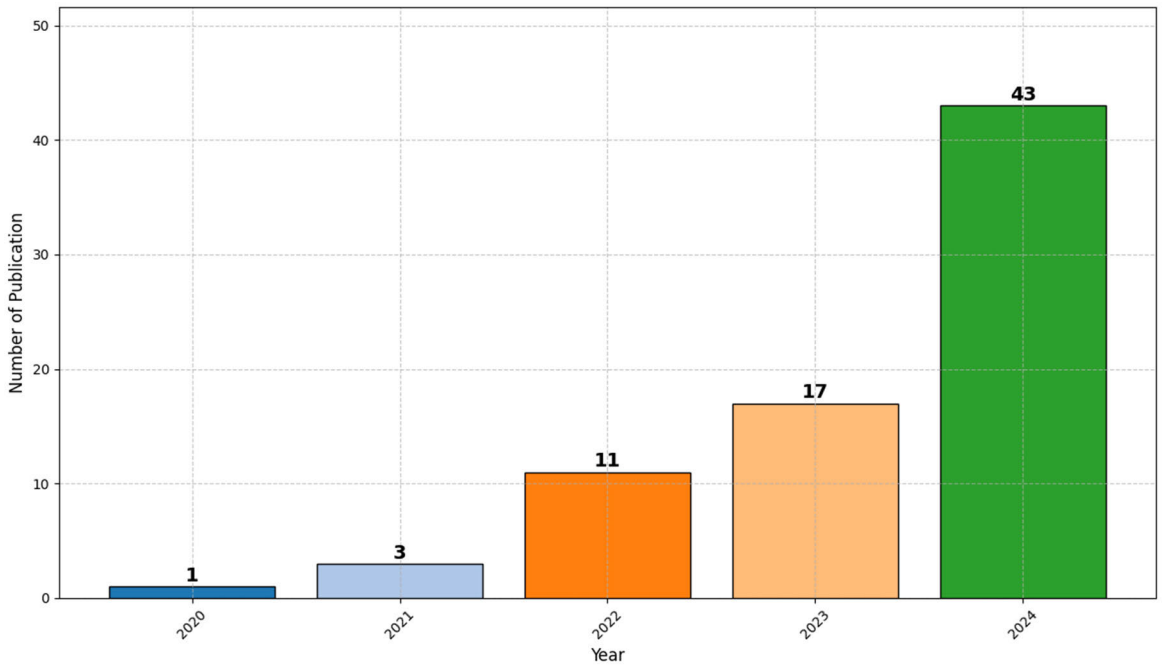


FIGURE 6. Number of publication.

This visualisation articulates vital understanding about ongoing research evolution. Research in deep learning together with object recognition controls the market while being widely applied in agricultural settings for crop dis-

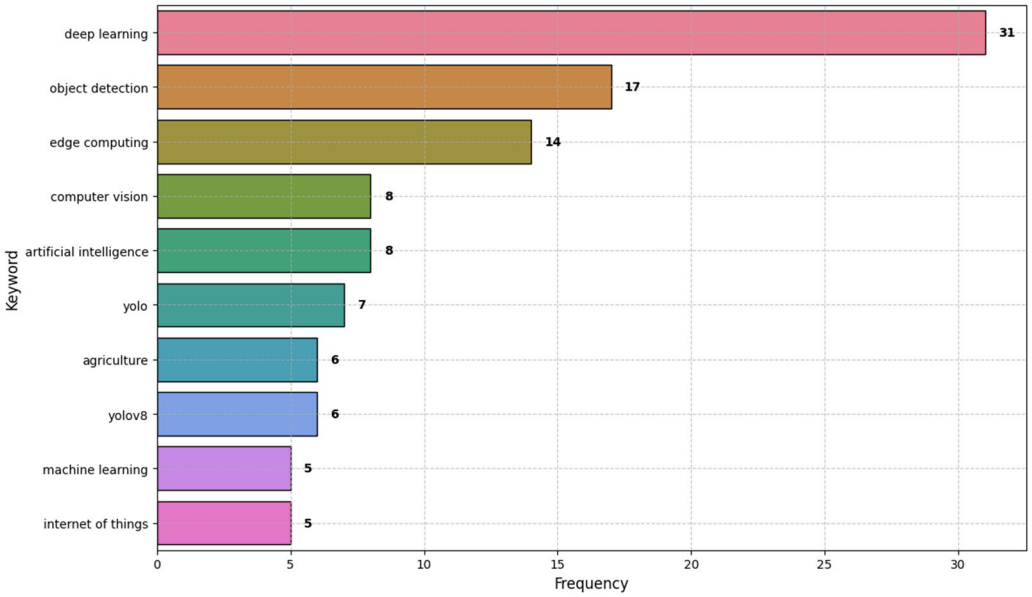


FIGURE 7. Top 10 Keyword trends.

ease analysis and automation systems. The development of precision agriculture and enhanced crop monitoring systems basically depends on these methods. Research on edge computing establishes itself as a vital field which studies how AI models operate on restrained devices to accomplish time-sensitive processing. The requirement for fast AI inference in agriculture has increased because of the rising market need.

The emerging trend involves developing lightweight AI applications specifically designed for mobile and embedded devices, as indicated by terms such as ''lightweight AI'' and ''Android.''. The number of people interested in running AI solutions from portable devices increases which suggests growing practical mobile applications. Finally, the emphasis on disease detection and precision agriculture highlights the potential of deep learning and remote sensing technologies to revolutionise early disease detection and crop management.

Figure 6 illustrates the number of research publications from 2020 to 2024 and shows a clear upward trend over the years. The number of publications remained low until 2020 with only one more paper. However, a steady increase began in 2021 with three publications, followed by an even more significant increase in 2022 with 11 publications. This upward trend continued in 2023 with 17 publications and peaked in 2024 with 43 publications, the highest number in this period. The rapid growth in research output in recent years reflects the increasing academic interest in this area and indicates the growing importance of further developing methods and researching innovative solutions.

As can be seen in Figure 7, the frequency of different keywords used in these publications provides further insight into the dominant themes driving this trend. ''Deep learning'' emerges as the key driving force in research directions since it appears 31 times throughout the text. The terms ''object recognition'' appear 17 times while ''edge computing'' occurs 14 times in the data which demonstrates the increasing necessity of efficient real-time solutions for handling complex problems especially in agricultural and IoT applications. The research field continues to expand while multiple essential technological areas merge to define innovation pathways according to these trends.

Research publications on deep learning and object recognition with edge computing have become increasingly important trends in agricultural development, as indicated by keyword frequency data from 2020 to 2024. These modern technologies promote innovation and at the same time reshape the content direction within multiple academic publications. This graphical representation shows how research works are distributed across multiple publishers and across specific platforms where this innovative research reaches readers.

The ''Computers and Electronics in Agriculture'' journal stands out as the most influential publication platform given its 18 released publications according to Figure 8. The research publication data supports these essential agricultural applications of deep learning and object recognition for managing pests through identification and monitoring crops and detecting diseases. A total of three publications were found in each of the journals ''Frontiers in Plant Science'', ''IEEE Access'', ''Artificial Intelligence in Agriculture'', ''Smart Agricultural Technology.'' Those numbers demonstrate how contemporary agricultural research brings together plant science, artificial intelligence and engineering as interrelated fields.

The research field benefits from 2 publications distributed among 5 journals including ''Agriculture (Switzerland)'', ''Applied Sciences (Switzerland)'', ''Journal of King Saud

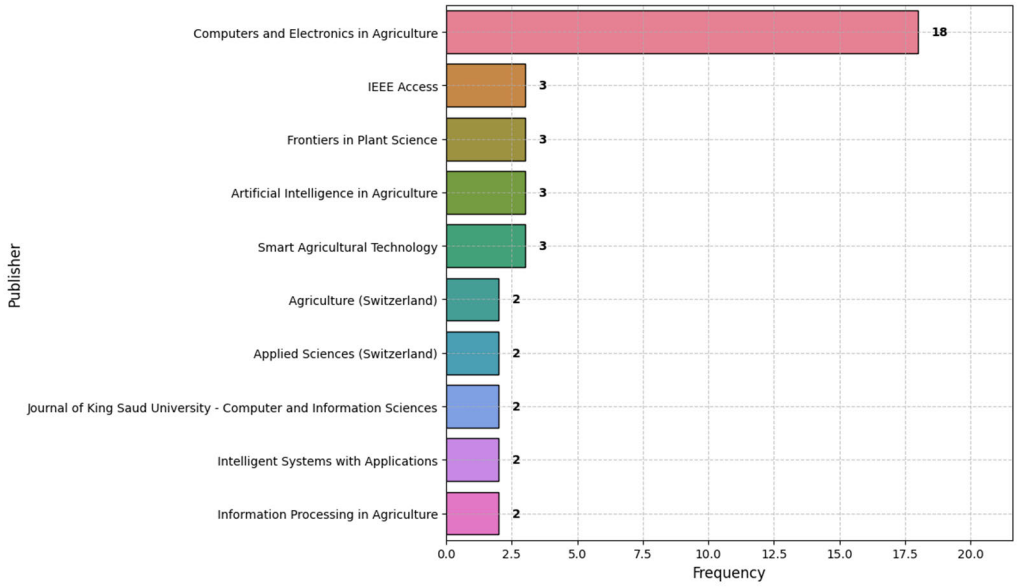


FIGURE 8. Top 10 number of publications by journal.

University - Computer and Information Sciences'', ''Intelligent Systems with Applications'' and ''Information Processing in Agriculture''. The large number of research publications about agricultural computer usage and artificial intelligence appear in ''Computers and Electronics in Agriculture'' which serve as the top research outlet. A group of journals focusing on artificial intelligence together with plant sciences and applied sciences demonstrates the combined disciplinary approach to resolving modern agricultural issues.

Research data indicates that journals increasingly publish publications about advanced technologies consisting of edge computing together with deep learning and object recognition. The modern technologies lead to innovation as well as determine how scientists approach their work especially when studying agriculture and automated systems. Research publications demonstrate their keyword distribution patterns through the graphical representation in Figure 9. The representation consists of boxes where keyword frequency determines box size. The keyword ''deep learning'' appears most frequently with 31 publications (29.0%), which indicates its dominant role in research. Object detection stands as the second most used keyword in the field with 17 publications comprising 15.9% of the total research. The term ''Edge computing'' occurs 14 times (13.1%) to indicate the increasing interest in distributed data processing for effective intelligent systems.

Results show a strong connection between Artificial Intelligence and computer vision through keywords ''computer vision'' (''8 publications 7.5%'') and ''artificial intelligence'' (''8 publications 7.5%'') and ''agriculture'' (''6 publications 5.6%'') appears frequently in the literature. The research shows that YOLO and YOLOv8 have been used seven times (6.5%) and six times (5.6%) respectively, highlighting their significance in object recognition methods. The research contains 5 publications utilizing ''machine learning'' and ''Internet of Things'' terms with proportions of 4.7% each while standing as key elements within the analyzed research.

Modern research exhibits an interdisciplinary approach because keywords are distributed proportionally across various fields of study including the combination of deep learning and object recognition which addresses real-field problems in agriculture and automation systems. Research finds its direction from this technological environment which presents itself as a complete overview.

The analysis of the Treemap visualization shows that research publications refer to the-growing importance of the advanced technologies like deep learning, object recognition, and edge computing from their frequency of keywords. Although neutral and characterized by their innovative nature, these technologies play a crucial role in shaping scientific contributions in agriculture, automation, and other fields. Figure 10 further emphasizes this point by presenting a word cloud that illustrates keyword frequencies in research publications. The font size in the word cloud represents the occurrence of the word: frequent words are displayed in bigger font while less common words are displayed in smaller font.

A word cloud reveals its most prominent words in the word cloud as ''recognition'', ''deep'', ''learning'', ''computing'', ''edge'', ''network'' and ''object''; which indicates that these are major topics under study. ''disease'','' ''agriculture'','' ''machine'','' ''vision'' and ''artificial'' frequently show up, which implies an unmistakable connection with artificial intelligence, computer vision and agricultural applications. Notable other terms in these fields include ''YOLO'',

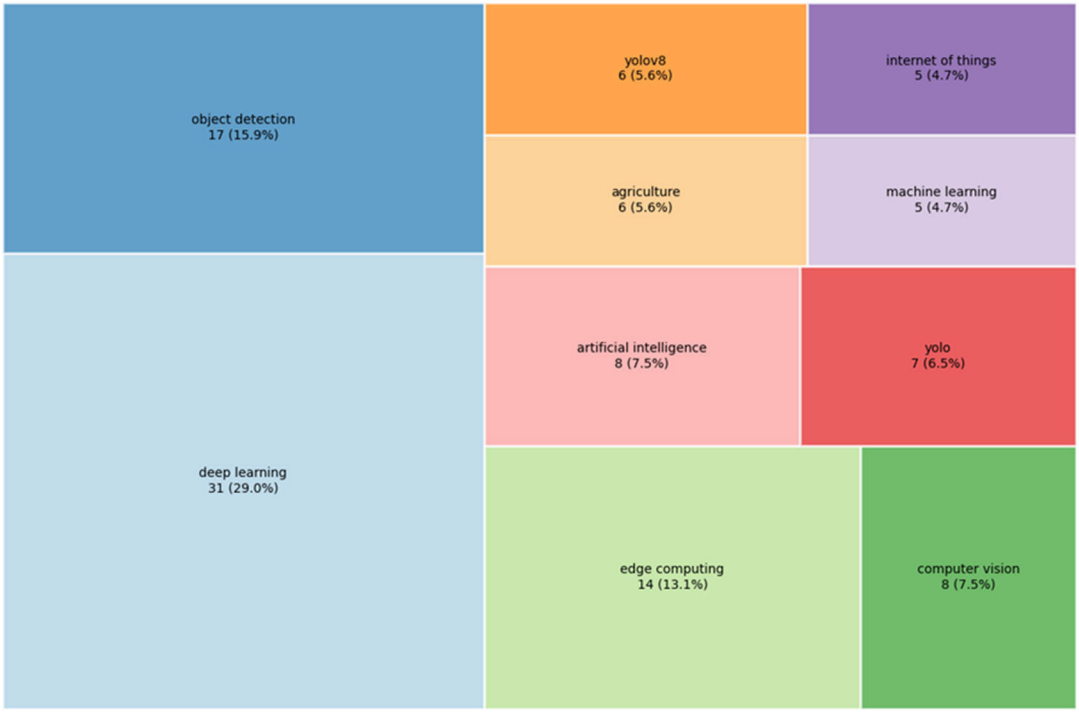


FIGURE 9. Top 10 TreeMap keyword.

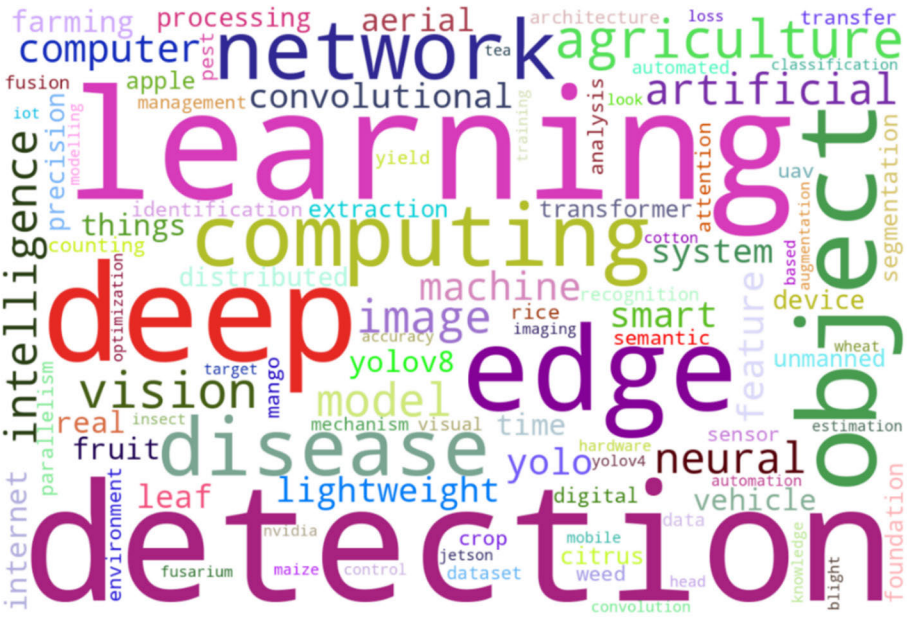


FIGURE 10. World cloud of rice leaf diseases detection.

''convolutional'', ''precision'', ''sensor'', ''farming'', ''internet'' and ''neural'' which signal different methods and technologies used. This is because there is presence of terms like ''model'', ''recognition'', ''segmentation'', ''classification'' and ''identification'' which imply that research is being done for an automation and efficiency in agriculture through AI based solutions as well as for smart computing applications.

The use of cutting-edge technologies such as deep learning and object recognition in practical and essential fields like agriculture and automation highlights the interdisciplinary nature of the research, as reflected in the word cloud. All

together, these insights offer a look into the technological domain that is responsible for generating recently conducted research.

A. RESEARCH QUESTION AND SELECTED PAPER

The section explores detection barriers for leaf diseases within rice using deep learning integrated with edge computing technology. The study relies on three research questions which target distinct problem elements. Table 6 provides information on the number of research papers supporting the different research questions (RQs).

Table 6 presents all 75 studies selected through the PRISMA process that are directly aligned with the three research questions (RQ1, RQ2, and RQ3) formulated in this systematic literature review. Each study was assessed for its relevance to deep learning model performance, edge computing integration, or the application of Vision Transformers in rice leaf disease detection. The table summarizes key information, including the model types, datasets utilized, and evaluation metrics, thereby ensuring transparency in how these studies contribute to the analytical objectives of the review.

Only studies that achieved a minimum quality score of 3.0 were included in the final analysis. High-scoring studies were given analytical emphasis in Tables 6, 7, and 9 to support robust comparisons of model accuracy, computational performance, and suitability for real-time agricultural deployment.

Each row in the table indicates whether a research paper supports one or more of these RQs. By analyzing the combinations of different RQs, we can understand the relationships between them in the collected research papers.

Figure 11. illustrates the distribution of research papers based on the Research Questions (RQs) they support. The interpretation is as follows: A total of 36 papers supports only RQ1, making it the most common category. In contrast, only one paper exclusively supports RQ2, indicating that very few studies focus solely on this aspect. Interestingly, no papers support only RQ3, suggesting that this research question does not stand alone in any study. Additionally, 22 papers address both RQ1 and RQ2, showing a strong connection between these two aspects. Meanwhile, three papers support the combination of RQ2 and RQ3, indicating that few studies link these two questions without involving RQ1. Furthermore, eight papers support both RQ1 and RQ3, highlighting some research that explores the relationship between these two aspects without including RQ2. Lastly, six papers address all three RQs (RQ1, RQ2, and RQ3), demonstrating that a subset of research comprehensively covers all three aspects. Overall, these results suggest that RQ1 has the broadest coverage and is the most frequently addressed in research, whereas RQ2 and RQ3 have more limited scopes and tend to appear in combination with RQ1 rather than independently.

Figure 12. illustrates the distribution of the models that support the individual research questions (RQ). The analysis shows that RQ1 is supported by most models (62), indicating that most studies focus on aspects related to this research

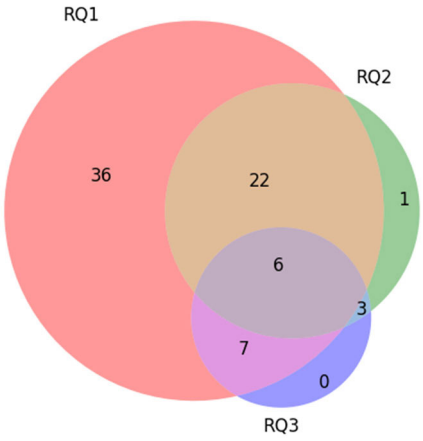


FIGURE 11. Distribution research paper based on RQ.

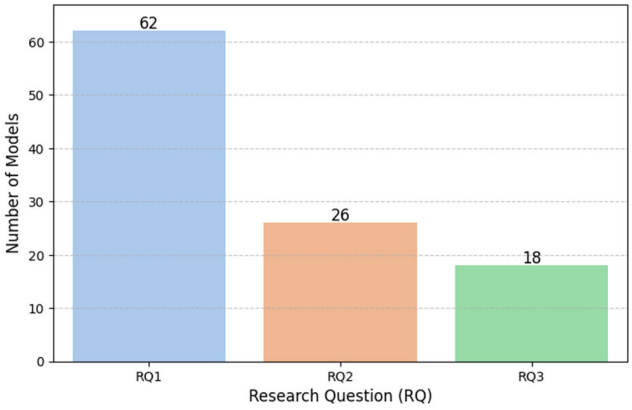


FIGURE 12. Distribution of model based on RQ.

question. RQ2 is supported by 26 models, indicating moderate research engagement. In contrast, RQ3 is supported by the lowest number of models (18), indicating that fewer studies have addressed this particular aspect.

This chart is consistent with the results of the previous Venn diagram, which showed that RQ1 was the most prevalent in the research papers. The dominance of RQ1 in all studies suggests that it plays a central role in the research landscape, often appearing independently or in combination with RQ2 and RQ3. Conversely, the relatively low support for RQ2 and RQ3 confirms that these research questions are treated less frequently in isolation and tend to appear alongside RQ1.

B. RICE LEAF DISEASE DETECTION TAXONOMY

Through the analysis of various research references on rice leaf disease detection, it has been found that deep learning-based methods are increasingly being used to enhance accuracy and efficiency in detecting and classifying different types of rice leaf diseases. The primary challenges in detection include variations in shape, size, and lighting conditions, as well as the presence of multiple diseases in a single leaf. The detection of rice leaf diseases requires multiple methodologies that involve convolutional neural network

TABLE 6. Selected paper selected primary studies on object detection.

No.	Author	RQ1	RQ2	RQ3	Model	Dataset	Metric	Quality Score
1.	[12]	√	×	√	YOLOv1-YOLOv8	Various dataset	mAP, FPS	4.0
2.	[28]	√	×	×	CNN, VGG, ResNet, Xception, Inception, DenseNet, MobileNet, EfficientNet, U-Net, YOLOv5, and hybrid models.	Various maize disease	Accuracy, Precision, Recall, F1, AUC, mAP, IoU	3.5
3.	[16]	√	×	×	Faster R-CNN, VGG16, ResNet50, ResNet101, ResNet152	Costum Dataset	mAP, Accuracy	3.0
4.	[13]	√	×	×	YOLOv8	Costum Dataset	Accuracy, mAP, FPS	4.5
5.	[4]	√	×	×	YOLO (v3, v3-tiny, v4, v4-tiny)	Costum Dataset	mAP	4.0
6.	[11]	√	√	×	YOLO v3, v3-tiny, v4, v4-tiny	Costum Dataset	FPS	3.5
7.	[17]	√	×	×	YOLOv4, MobileNet	Costum Dataset	Accuracy, AP	3.0
8.	[24]	√	×	√	Transformer, YOLOv8	Costum Dataset	Accuracy, mAP, FPS	4.0
9.	[29]	√	×	×	S-YOLO	Costum Dataset	Accuracy, mAP, FPS	4.0
10.	[30]	√	×	×	YOLOv8-ASFF	Costum Dataset	mAP, F1 scores	3.5
11.	[31]	√	√	√	Symmetric Former, Symmetric Block and Symmetric FFn	ImageNet-1K, COCO, Pascal VOC, ADE20K, Cityscapes	AP, mIoU	3.0
12.	[14]	√	√	×	TC-GAN	Costum Dataset	AP	3.0
13.	[8]	√	√	×	YOLOv4-tiny, U-Net, CNN, CS-YOLOv4-tiny model	Costum Dataset	mAP, FPS	4.5
14.	[32]	√	×	√	Transformer, Neural Architecture Search (NAS), Knowledge Graphs, ResNet18, Dynamic Head	Agricultural Databases	Precision, Recall, mAP, FPS	4.5
15.	[33]	√	×	×	LSA-Net, YOLO (AE-YOLO)	Apple leaf images	CRC, mAP	3.0
16.	[15]	√	√	×	R-CNN, YOLO, SSD, MobileNet, SqueezeNet, EfficientDet	PASCAL VOC, Microsoft COCO, ImageNet	Accuracy, mAP, FPS	4.0
17.	[34]	√	×	×	Deep Learning	Costum Dataset	Accuracy, mAP, FPS	3.0
18.	[35]	√	×	×	MLP, CNN, AE, RNN, LSTM, DRL, DCGAN	NSL-KDD and UNSW-NB15, CICIDS , CIFAR-10	Precision, Recall, mAP50	3.5
19.	[36]	√	×	×	DNE-YOLO	Costum Dataset	Accuracy, mAP50	3.5
20.	[37]	√	√	×	Richardson-Lucy algorithm, Wiener filter, Markov random field method, Variational Bayesian method, Edge prediction method, Kernel estimation methods (motion vector kernel and frequency domain kernel), Direct image-to-image regression methods, Generative	Various datasets	PSNR, MSE, RMSE	
21.	[38]	√	√	×	Various models	-	-	4.0
22.	[39]	√	×	×	Optimised YOLO-V4, EfficientNet	Costum Dataset	Accuracy, F1 Score	3.0
23.	[19]	√	×	×	CenterNet, YOLOv4, Faster R-CNN, DetectoRS, Cascade R-CNN, Foveabox, Deformable DETR, CenterNet2	CCL'20	AP, AR	
24.	[40]	√	√	×	Various models	-	-	
25.	[41]	√	×	×	YOLO-WDNet, a lightweight YOLO v5 based network	Costum Dataset	mAP	3.0
26.	[42]	√	√	×	Deep Learning	MS-COCO 2017, Pascal VOC 2012, and Cityscapes	Accuracy, F1 Score	3.0
27.	[43]	√	×	×	Data Envelopment Analysis	Google Dataset	mAP	3.0
28.	[44]	√	√	×	Deep learning, Tiny YOLOv3	Costum Dataset	F1 Score	3.0
29.	[45]	√	×	×	YOLOv8l (large). YOLOv9-c (compact)	MS-COCO dataset	mAP, RMSE	3.0
30.	[46]	√	√	√	Various models	-	-	4.5
31.	[47]	√	×	×	CNN, RNN, SVM, RF, Deep Learning, ResNet, Inception, Ensemble Learning, Bayesian Network	Kaggle, UCI Machine Learning	Accuracy	3.0
32.	[48]	×	×	√	Support Vector Machines (SVM), Random Forests (RF), XGBoost, DenseNet, MobileNet, Convolutional Neural Networks (CNN), Vision Transformer	Public Dataset	mAP, Accuracy, Precision, recall, F1-Score	3.0
33.	[1]	√	×	×	Convolutional Neural Networks	Public Dataset	accuracy, precision, recall, F1-score	3.0

TABLE 6. *(Continued.)* **Selected paper selected primary studies on object detection.**

34.	[49]	√	×	×	Improved YOLOv8 model	Public Dataset	FPS	3.0
35.	[50]	√	√	×	Review article	-	-	4.0
36.	[51]	√	×	×	YOLO-SDW	Public Dataset	mAP	3.0
37.	[52]	√	√	×	Tiny YOLOv4	Costum Dataset	mAP, FPS	4.0
38.	[53]	√	×	×	YOLOv5-Nano	Costum Dataset	ACP, MOTA	3.0
39.	[54]	√	×	×	MFAF-YOLO	Costum Dataset	mAP, AP	3.0
40.	[55]	√	×	×	YOLOv8n	Costum Dataset	Precision, mAP	3.0
41.	[26]	√	×	×	GANs	Village dataset, CottonWeed dataset, Global Wheat-Head Dataset (GWHD)	Precision, mAP	3.0
42.	[56]	√	×	×	YOLOX	Costum Dataset	mAP, FPS	4.0
43.	[2]	√	×	√	FHTW-Net	Cross-Modal Rice Leaf Disease Retrieval Dataset	mAP, FPS	
44.	[57]	√	×	×	YOLOv5s, DeepSORT, StrongSORT, ByteTrack, MultiMap	Video data from two strawberry farms.	-	3.0
45.	[58]	√	×	×	Convolutional Neural Networks (CNN), VGG-16, VGG-19, ResNet-50, Transfer Learning	Dataset of 10,000 plant images from Kaggle's Plant Village.	Confusion matrix, accuracy	3.0
46.	[59]	√	×	×	YOLO, Faster R-CNN, Mask R-CNN, SSD, RetinaNet, Multi-scale multilayer perceptons, Convolutional Neural Networks (CNN), Support Vector Machines (SVM)	Various datasets	-	3.0
47.	[10]	√	√	×	Lightweight deep learning models	-	-	3.0
48.	[21]	√	√	×	Deep Learning, CNN, YOLO	Weedmap, Rice Seedling Dataset, PlantVillage Dataset	Accuracy	3.0
49.	[60]	√	√	×	RTSD-Net, YOLOV3, YOLOv4, YOLOv3-tiny, YOLOv4-tiny	Costum Dataset	mAP, F1 scores, FPS	3.0
50.	[61]	√	√	×	Improved YOLOv8n (merged with FasterNeXt, GIoU, and DSConv)	Costum Dataset	mAP	
51.	[62]	√	√	×	RTFD (Real-Time Fruit Detection)	Costum Dataset	mAP, FPS	4.0
52.	[63]	√	√	×	Deep Convolutional Neural Networks (DCNN): CropClassiNet, CanopySegNet, PlantCountNet, InsectNet	Costum Dataset	mAP	
53.	[23]	√	×	×	YOLOv8	PASCAL-VOC-2007, PASCAL-VOC-2012, MSCOCO, ILSVRC2012, Open Images V6	Precision, Recall, F1-score, mAP	3.5
54.	[64]	√	√	×	YOLOv8n-CDDA	Costum Dataset	mAP, mAP50	3.5
55.	[65]	√	√	×	YOLOv5, Random Forest Regression, XGBoos, recursive feature elimination	Costum Dataset	MAE, mAP	3.0
56.	[66]	√	√	√	Transformer	CIFAR100, FC100, COR50, MiniImageNet, TiniImageNet	-	3.0
57.	[18]	√	√	×	YOLOv3, YOLOv5, YOLOX, SSD-Mobilenet v2, EfficientDet-Lite 1, YOLOv8	MS COCO	AP, AP50	3.0
58.	[67]	√	×	×	Faster-RCNN, YOLOv4	Costum Dataset	mAP	3.0
59.	[3]	√	√	√	CNN, Transfer Learning, Ensemble Learning, Hybrid	Public Dataset	-	
60.	[68]	×	√	×	Various models	-	-	3.0
61.	[69]	√	×	×	ANN, CNN, RNN, AlexNet, ResNet, Supervised, Semi-supervised, Self-supervised, Unsupervised, and Reinforcement Learning	-	-	3.0
62.	[70]	×	√	√	LeNet-5, MobileNetV2	Landing or not landing datset	Accuracy, Recall, Precision, F-Score	3.0
63.	[20]	×	√	√	SVM, Decission Tree, K-NN, Random Forest, Naïve Bayes, K-Mean, Fuzzy C-Mean, Artificial Neural Network, PCA, ANMM, Deep Learning	PlantVillage	Accuracy, precision, recall, RMSE, MAE	3.5
64.	[71]	√	×	√	CropDetDiff, Faster RCNN, Cascade RCNN, DETR, YOLOv8, DiffusionDet	Strawberry dataset and Plant diseases Detection dataset	mAP, FPS	4.0
65.	[5]	×	√	√	Deep Learning	-	-	3.0

TABLE 6. *(Continued.)* **Selected paper selected primary studies on object detection.**

66.	[22]	√	×	×	YOLOv8	Costum Dataset	mAP, FLOP	3.0
67.	[72]	√	√	√	Linear Regression, Logistic Regression, Decision Trees, K-Nearest Neighbours, Support Vector Machines, Naive Bayes, Deep Learning (DL), Generative Adversarial Networks (GANs), Vision Transformer (ViT)	-	-	3.0
68.	[73]	√	×	×	Faster-YOLO-AP, YOLOv8	Apple Dataset	mAP	3.0
69.	[74]	√	√	×	YOLO-Spot (based on YOLOv7-tiny architecture)	Weed species	mAP	3.0
70.	[9]	√	√	√	Transfer Learning, BeanWatchNet, EfficientNet v2 B0, ResNet-50 v2, MobileNet v3, YOLOv8, YOLO-NAS, YOLOv9, DETR	Bean Images	Precision, Recall, F1 Score, mAP	3.0
71.	[75]	√	√	×	YOLOv7	Apple Dataset	Precision, recall, mAP, Inference Time	3.0
72.	[7]	√	×	√	YOLOv8, SAHI, Faster-RCNN, SSD, YOOLOv5, YOLOv7	Costum Dataset	Precision, recall, mAP	3.0
73.	[6]	√	×	√	YOLOv8m object detection model with Slicing Aided Hyper Inference (SAHI)	Costum Dataset	MAPE, Recall, F1-score	3.0
74.	[25]	√	×	√	RT-DETR-X, SAHI	VisDrone-DET	AP, FPS	3.0
75.	[76]	√	×	×	Deep Learning, R-CNN, YOLO, RetinaNet	-	-	3.0

(CNN) architectures and object detection algorithms with attention mechanism-based models.

Figure 13 displays the complete examination of research elements which contribute to rice leaf disease detection by explaining the dataset requirements with preprocessing steps alongside needed tools and detection methods as well as platform requirements algorithms with identified obstacles and used evaluation metrics.

Public and custom datasets produce the research data as indicated in the figure. The public domain consists of source data from PlantVillage, ImageNet V10, and YouTube-BoundingBoxes, the collection of custom datasets employs a range of camera equipment like RGB cameras and DSLRs, high-definition cameras and iPhone, Xiaomi, and Huawei mobile devices. The image resolution availability spans between 512 × 512 pixels up to 1920 × 1080 pixels for different analytical requirements.

During preprocessing data scientists utilize labelling and annotation together with data augmentation for preparing datasets into training and validation and testing subsets. Annotation tools such as YOLO Mark, VGG Image Annotator, LabelImg, and MATLAB Image Labeler are used to ensure that the dataset is well-prepared for deep learning model training.

The tools section incorporates diverse hardware components to handle the computational requirements of training models using RTX 8000 GPUs and NVIDIA Tesla hardware and NVIDIA K40 and GTX 1080Ti GPUs and Google Colab cloud computing services. Data analysis functions together with model implementation run through deep learning frameworks which include TensorFlow and PyTorch and OpenCV as main software applications.

Few-shot learning (FSL) and detection alongside classification methods from deep learning constitute the detection techniques.

The platform section explains that users can run their detection system through various devices spanning Android or iOS smartphones up to IoT edge servers and embedded boards using Arduino or FPGA technology along with embedded processors such as Raspberry Pi and Nvidia Jetson.

Multiple detection methods guide the enhancements in rice leaf disease identification through Faster R-CNN, Deep RNN, Mobile ViT, FOCS, FSAF and Mask R-CNN. The detection methods of YOLO as well as SSD along with RetinaNet are utilized as competitive one-stage and two-stage object detection algorithms. Transformers and SAHI Multi-Scale Fusion attention-based models execute two functions by enhancing the identification of small objects and adjusting for image variations.

The detection of rice leaf diseases faces various obstacles which include image blurriness, obstructed views, murky details and irregular angular movements and multiple diseases shown in each picture. Furthermore, detecting small and overlapping objects remains a significant challenge in deep learning-based models.

Finally, model performance is evaluated using various metrics, including precision, recall, intersection over union (IoU), mAP, and FPS to assess the accuracy and efficiency of disease detection and classification.

By understanding the structure of rice leaf disease detection as outlined in the figure, research in this field can continue to evolve toward more reliable and practical applications in the agricultural sector.

C. RESEARCH QUESTION 1

What deep learning model is most effective for detecting rice leaf diseases, and how do their performances compare in handling small objects and overlapping objects?

The author categorizes several studies that utilize models specifically designed to handle small object detection and

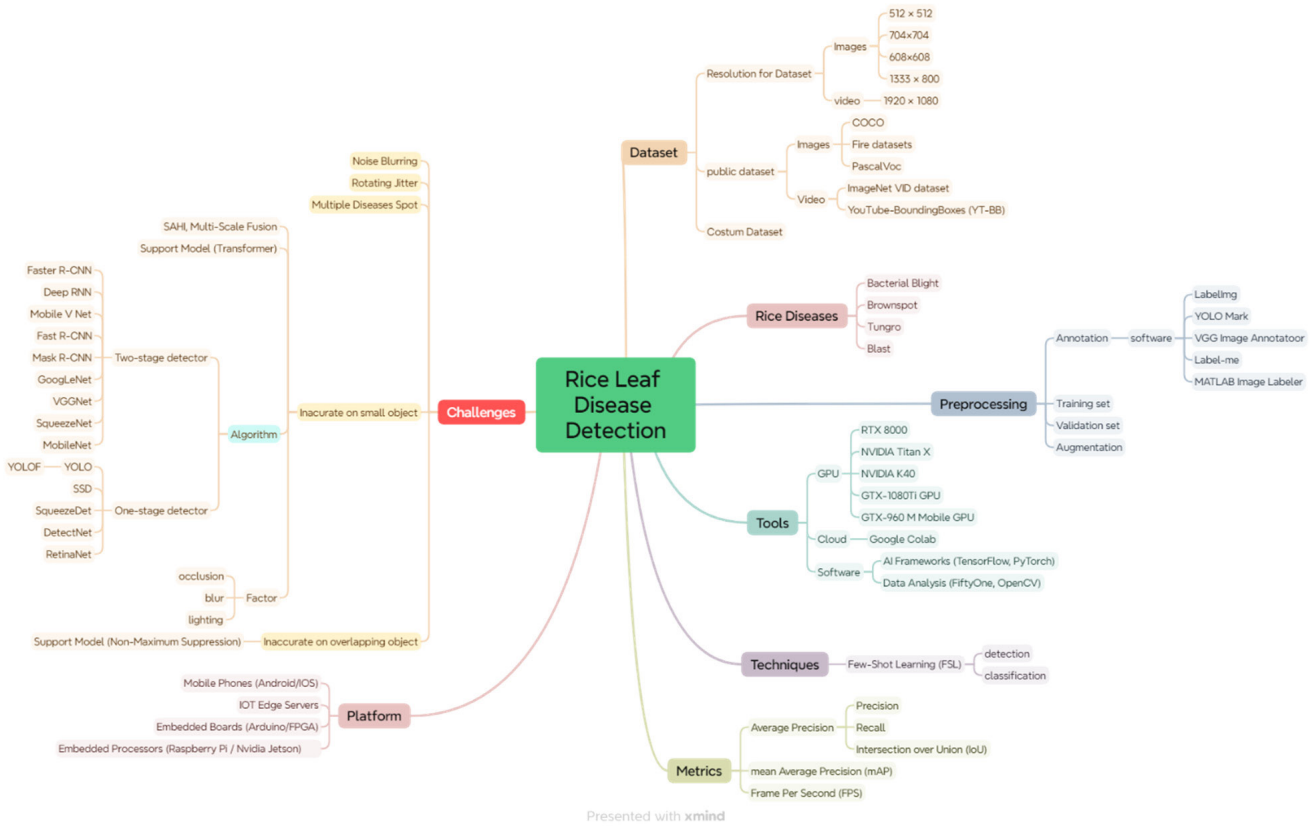


FIGURE 13. Rice leaf diseases detection taxonomy.

overlapping objects. Through this categorization, the results reveal which model performs best under these two conditions.

TABLE 7. The top five papers for RQ1.

Author	Model Name	mAP
[75]	YOLOv7	0.99
[67]	Faster R-CNN, YOLOv4	0.98
[7]	Improved YOLOv8 with SAHI	0.98
[59]	YOLO, Faster R-CNN, Mask R-CNN, RetinaNet	0.98
[49]	Improved YOLOv8	0.98

Table 7 highlights the top five studies with the highest mAP values for small and overlapping object detection analysis. The highest-performing model, YOLOv7, achieved a mAP of 99%, followed closely by Faster R-CNN and YOLOv4 with 98% mAP. Other notable models include the improved YOLOv8 with SAHI, YOLO and Faster R-CNN variants, and an enhanced YOLOv8 architecture, all demonstrating robust performance with mAP scores of 98%.

D. RESEARCH QUESTION 2

What is the role of edge computing in implementing rice leaf disease detection systems, and what are the challenges and opportunities in heterogeneous field environments?

To address RQ2, the author grouped the reference data with the aim of obtaining information on edge computing, including aspects such as latency, power consumption, and the performance of the models utilized in various agricultural applications. This approach helps to evaluate the role of edge computing in implementing rice leaf disease detection systems and to identify the challenges and opportunities in heterogeneous field environments.

Table 8 presents five models with the best performance based on mAP (mean Average Precision), which is relevant to answering RQ2 regarding the role of edge computing in implementing rice leaf disease detection systems and the associated challenges and opportunities in heterogeneous field environments. These models demonstrate exceptional capabilities in addressing the complexity of object detection in agricultural settings, such as high population density, varying lighting conditions, and complex backgrounds. For instance, YOLOv7, running on the NVIDIA Jetson Nano, achieves extremely low latency (0.0549 seconds) and the highest mAP (0.99), making it ideal for real-time applications. The reported latency of 0.0549 seconds was measured during inference using the YOLOv7 model on the Jetson Nano (4GB) device. The test used a single image input with a resolution of 640 × 640 pixels and batch size of 1, executed under FP16 (half precision) mode. This latency reflects the average time required for a forward pass and

TABLE 8. The top five papers for RQ2.

Author	Model Name	mAP	FPS	Egde Device	Latency	Power Consumption
[75]	YOLOv7	99.13	135.0	NVIDIA Jetson Nano	0.0549	None
[23]	Transformer, YOLOv8, RetinaNet	95.00	49.7	Apple's iOS	None	None
[62]	RTFD	91.10	None	Qualcomm Snapdragon 865 (Redmi K30 Pro)	None	None
[11]	YOLOv3 and YOLOv3-tiny	99.70	1.7	NVIDIA Jetson Nano, NVIDIA Jetson Xavier NX	None	2.18
[65]	YOLOv5-based object detection with Random Forest	911.80	158	Sony Xperia 1 III (smartphone)	None	None

was benchmarked under controlled conditions simulating real-world field use. While this performance supports real-time application, it is important to note that sustained outdoor deployment still depends on thermal stability and energy optimization.

Additionally, the model LeNet-5, MobileNetV2, and Custom MobileNetV2, implemented on a Raspberry Pi with Movidius NCS, demonstrates good power efficiency (0.246 watts) despite higher latency (44.9 seconds). Meanwhile, the RTFD model, running on Qualcomm Snapdragon 865, shows great potential for mobile applications, although data on power consumption is unavailable.

However, some models, such as YOLOv3 and YOLOv3-tiny, which use NVIDIA Jetson devices, have relatively high-power consumption (15.2 watts), which could be a limitation in field environments with limited energy resources. Overall, these results indicate that edge computing plays a strategic role in supporting real-time detection, reducing latency, and improving resource efficiency in agricultural environments.

Nevertheless, challenges such as complex integration of models with edge devices, power consumption, and environmental variability must still be addressed for further development.

E. RESEARCH QUESTION 3

How can Vision Transformers (ViT) be effectively applied to rice leaf disease detection, and what are the challenges associated with their implementation based on top-performing models in terms of mAP?

To address the research question, the author seeks papers that support the application of ViT in agricultural research, particularly focusing on their advantages and limitations in tasks such as rice leaf disease detection.

Table 9 presents the top five studies selected to answer RQ3, which investigates the application of ViT in rice leaf disease detection and the challenges involved. Although not all models listed are explicitly labeled as ViT, they incorporate ViT principles such as self-attention mechanisms, transformer-based architectures, or patch-based input encoding. These include hybrid models (e.g., ViT-CNN), enhanced YOLO variants with SAHI, and architecture utilizing long-range dependency modeling. Therefore, all selected studies are considered conceptually relevant to RQ3 and offer insights into the adoption of ViT-like techniques in the agricultural domain.

Table 9 presents the top five papers relevant to Research Question 3 (RQ3), which explores the effective application of ViT in rice leaf disease detection and the associated challenges. The table highlights key findings from each study, comparing their models based on mAP, advantages, and limitations.

The highest-performing models, achieving an mAP of 0.98, include a ViT-CNN hybrid model [43] and an improved YOLOv8 with SAHI [7]. The ViT-CNN hybrid effectively identifies and localizes plant diseases using self-attention mechanisms, making it adaptable for real-time applications despite dataset constraints. However, the study notes challenges such as limited access to well-labeled datasets, the need for further research in real-time applications, and the complexity of ViT affecting processing speed and efficiency. Meanwhile, YOLOv8 with SAHI leverages self-attention for long-range dependency capture and contextual modeling, ensuring robust small-target detection. Nevertheless, its computational demands and potential processing overhead pose challenges for deployment of resource-constrained devices.

Another deep learning-based model [24] achieves an mAP of 0.95, demonstrating high accuracy in plant disease detection. It effectively captures global contextual information and performs well in varying environmental conditions. However, its implementation requires large training datasets, faces computational complexity issues, and risks overfitting due to its deep architecture.

A Transformer-CNN-ResNet18 model [32] with an mAP of 0.94 benefits from self-attention for detecting morphological disease features and Neural Architecture Search (NAS) for optimization. Additionally, the dynamic head module enhances small-feature detection. However, the study identifies high computational complexity and redundancy in multi-head attention as limitations.

Lastly, a YOLOv5s-based model [57] achieves a mAP of 0.92 and demonstrates efficient image processing through token-based sequence analysis. However, it has high memory consumption (4.97G) compared to Swin Transformer (4.75G) and experiences performance declines when increasing attention heads beyond a certain threshold.

TABLE 9. The top five papers for RQ3.

Author	Model Name	mAP	Advantage	Disadvantage
[48]	CNN, DenseNet, MobileNet, Vision Transformer	0.98	• Identification & Localization – ViT effectively detects and pinpoints plant leaf diseases using self-attention. • High Performance – ViT-CNN Hybrid achieves high accuracy. • Field Adaptability – Can be applied in real-time despite dataset access challenges.	• Limited Dataset – Access to diverse and well-labeled datasets remains a challenge. • Further Analysis Needed – More research is required for real-time applications & transfer learning methods. • Model Complexity – ViT's complex structure may impact processing speed and efficiency.
[7]	Improved YOLOv8 with SAHI	0.98	• Capturing Long-Range Dependencies – Self-attention enables global information aggregation for detecting small targets. • Contextual Information Modeling – Preserves essential contextual information often lost in CNNs when detecting small targets. • Flexible Resource Allocation – BiFormer allows more efficient distribution of computational resources and perceptual features.	• High Computational Demand – Self-attention requires complex calculations, increasing memory and computational needs. • Potential Processing Overhead – Additional complexity in BiFormer may slow down inference if not well-optimized. • Flexible Resource Allocation – BiFormer allows more efficient distribution of computational resources and perceptual features.
[24]	Deep Learning	0.95	• Captures Long-Range Dependencies – Self-attention enhances global context understanding in images. • Global Information Processing – Analyzes global relationships, crucial for detecting plant diseases and pests. • High Accuracy – Achieves excellent detection performance with accuracy up to 0.94 and mAP 0.95. • Good Adaptability – Performs well under varying environmental conditions, including different lighting.	• High Data Requirement – Requires larger training datasets than traditional CNNs for optimal performance. • Computational Complexity – Demands high computational resources, limiting use on low-power devices. • Challenges in Domain Knowledge Integration – Effective incorporation of expert knowledge remains difficult. • Overfitting Risk – Deep and complex architecture increases the risk of overfitting with limited data diversity.
[32]	Transformer, CNN, ResNet18	0.94	• Captures Long-Range Dependencies – Self-attention effectively detects morphological disease features anywhere in an image. • Optimized via Neural Architecture Search (NAS) – NAS helps find the best model structure for disease detection, enhancing performance. • Dynamic Head Module – Replaces traditional multi-head attention, improving accuracy in detecting small features.	• High Computational Complexity – Transformer-based design increases processing demands, limiting speed on low-resource devices. • Redundancy in Multi-Head Attention – While capturing diverse features, it may introduce inefficiencies in certain contexts.
[57]	YOLOv5s	0.92	• Improved Detection Accuracy – ViT with 16 attention heads achieves a superior mAP50 score of 0.929. • Efficient Image Processing – Treats images as token sequences, enabling parallel computation and improved recognition efficiency.	• High Memory Consumption – Requires 4.97G memory, higher than the more efficient Swin Transformer (4.75G). • Limitations in Attention Heads Scaling – Increasing attention heads to 32 in Swin Transformer led to performance decline.

Across all three research questions, YOLO-based models consistently demonstrate high accuracy and real-time applicability in detecting rice leaf diseases. However, their performance is influenced by the computational constraints of edge devices, as highlighted in RQ2. Furthermore, ViT-based architecture shows strong promise in accuracy (RQ3), although limited by model complexity and data demands. These insights reveal a trade-off between accuracy and computational feasibility that should guide future innovations.

The findings collectively highlight key advancements, trade-offs, and unresolved challenges that shape the current research landscape. The following conclusion synthesizes these insights and reflects on their practical implications and directions for future work.

V. CONCLUSION

This SLR examines advances in the detection of leaf diseases in rice using deep learning and edge computing technologies. A rigorous search across five major academic databases Web of Science, Scopus, ScienceDirect, IEEE Xplore, and ACM Digital Library was conducted to identify high-quality, peer-reviewed articles published between 2020 and 2024. Standardized keywords such as ''object detection,'' ''rice leaf disease detection,'' ''small object detection,'' ''vision transformer,'' and ''edge computing'' yielded an initial pool of 2,072 articles. After screening titles, abstracts, and keywords, studies were filtered using predefined inclusion and exclusion criteria to ensure relevance and quality. Only articles addressing disease detection on rice leaves, providing technical details on detection models or datasets, and tackling challenges like overlapping or small objects were retained. This process resulted in a refined selection of 75 studies aligned with the research objectives.

The findings reveal significant progress in deep learning models, particularly one-stage detectors (e.g., YOLO variants) and two-stage detectors (e.g., Faster R-CNN), for accurate disease detection. For RQ1, YOLOv7 emerged as the top-performing model (99% mAP), excelling in detecting small and overlapping objects due to its advanced architecture. Close contenders like Faster R-CNN and enhanced YOLOv8 variants (e.g., SAHI-integrated YOLOv8) demonstrated robust performance (98% mAP), highlighting the effectiveness of hybrid approaches integrating self-attention mechanisms. Addressing RQ2, edge devices like the NVIDIA Jetson Nano enabled low-latency (0.0549s) deployments, proving critical for real-time detection in resource-constrained environments. However, challenges such as high-power consumption (e.g., 15.2W for YOLOv3) underscored the need for optimized hardware-software integration. For RQ3, ViTs showed promise in capturing long-range dependencies (up to 98% mAP) but faced barriers like computational complexity and reliance on large datasets.

Unexpected findings in this review include the limited real-world deployment of models on actual edge devices despite claims of efficiency, as well as inconsistencies in reporting benchmarking parameters such as latency, FPS, and hardware specifications across studies. There is also a noticeable bias in research favoring staple crops like rice and maize, with insufficient attention given to other high-value crops. Furthermore, although ViT variants have demonstrated strong performance in general vision tasks, their adoption in agricultural applications remains limited. Few studies explored multimodal data fusion, such as combining RGB with thermal or spectral data, which could further enhance detection robustness.

Practical implications suggest prioritizing lightweight models (e.g., YOLOv7, MobileNetV2) paired with edge devices for scalable, real-time solutions. While ViTs offer accuracy gains, innovations in model compression and dataset augmentation are critical to mitigate computational costs. Limitations and future directions include expanding dataset diversity via collaborative open-source repositories, standardizing performance metrics for better comparability, improving energy efficiency in edge deployment, and investigating hybrid models (e.g., ViT-CNN or Transformer-YOLO architectures) for optimized balance between accuracy and complexity.

This study underlines the transformative potential of deep learning and edge computing in advancing precision agriculture. By bridging technical and infrastructural gaps, these technologies can revolutionize crop health monitoring, contributing to global food security efforts.

VI. FUTURE DIRECTIONS AND RECOMMENDATIONS

Practical implications suggest prioritizing lightweight models (e.g., YOLOv7, MobileNetV2) paired with edge devices for scalable, real-time solutions. While ViTs offer accuracy gains, innovations in model compression and dataset augmentation are critical to mitigate computational costs. Limitations and future directions include expanding dataset diversity via collaborative open-source repositories, standardizing performance metrics for better comparability, improving energy efficiency in edge deployment, and investigating hybrid models (e.g., ViT-CNN or Transformer-YOLO architectures) for optimized balance between accuracy and complexity.

To support future advancements, we recommend that interdisciplinary collaborations between agronomists, AI researchers, and embedded systems engineers be actively pursued. Such partnerships can foster the co-design of efficient models and edge hardware tailored to agricultural realities. Furthermore, the creation of benchmark datasets with standardized protocols for latency, FPS, and mAP reporting will enhance cross-study comparability and reproducibility. Ultimately, a strategic roadmap combining research innovation, field validation, and policy support will be essential to fully realize the benefits of deep learning and edge computing in agricultural disease management.

Furthermore, this study recommends establishing a cross-organizational collaboration platform to openly share and annotate rice leaf disease datasets. Such initiatives would promote data transparency, enable fair algorithm

benchmarking, and support reproducible research. By adopting standardized annotation protocols and encouraging institutional cooperation, future work can generate diverse and high-quality datasets that reflect real-world agricultural complexities ultimately advancing model generalizability and accelerating innovation in AI-driven precision farming.

Furthermore, future deployment strategies should consider solar-powered edge devices to support continuous operation in off-grid agricultural environments. Lightweight models deployed on low-power hardware platforms such as Raspberry Pi, integrated with photovoltaic energy systems, offer a sustainable solution for real-time disease monitoring in rural or remote farms. These energy-autonomous systems enhance the scalability and resilience of AI-based precision agriculture technologies.

To further optimize system efficiency in real-world deployments, future work should investigate edge–cloud collaborative architectures. In such hierarchical inference systems, edge devices can perform real-time, low-latency disease detection tasks directly in the field, while complex processing such as historical pattern analysis, model retraining, or multimodal data integration can be offloaded to the cloud. This distributed processing framework can balance latency and energy constraints at the edge with the scalability and analytical power of the cloud, enabling intelligent decision-making under diverse agricultural conditions.

In addition, future work should prioritize the development of lightweight, pruned, or quantized YOLOv7 variants to enhance deployment feasibility on edge devices while maintaining high accuracy. Drawing inspiration from recent industrial applications, such as the use of attention-enhanced YOLO architectures and optimized loss functions [77], researchers can achieve improved detection performance with minimal computational overhead. Similarly, studies applying semantic segmentation and intelligent control systems to optimize real-time recognition pipelines [78] offer valuable insights for designing multi-stage learning frameworks in agriculture. These methods demonstrate the potential for balancing inference speed, detection precision, and model complexity critical for practical use in remote and resource-constrained environments. By integrating such techniques with agricultural-specific datasets and requirements, future innovations can deliver scalable, energy-efficient, and highly interpretable AI models suitable for smart farming applications.

Moreover, to support hardware-aware optimization, future research should establish a standardized evaluation toolkit for quantifying the trade-offs between latency, energy consumption, and detection accuracy across diverse edge devices such as NVIDIA Jetson Nano and Xavier NX. Such a framework would enable fair comparisons of model performance under varying hardware constraints, guiding the selection of appropriate models for deployment in real-world agricultural environments. This type of analysis is essential for balancing detection precision with operational efficiency, especially in resource-limited or remote farming scenarios where energy availability and response time are critical.

To enhance model generalization, especially for detecting small or overlapping lesions in complex field environments, future research should explore the use of dynamic data augmentation techniques. In particular, the application of GANs can be leveraged to generate synthetic training samples that simulate rare or underrepresented disease patterns. GAN-based augmentation has shown promising results in addressing data imbalance and enriching feature diversity, which are critical for improving detection accuracy in real-world agricultural scenarios. Incorporating synthetic data into model training pipelines may also reduce overfitting and enhance robustness across varying lighting, occlusion, and background conditions commonly encountered in rice fields.

Additionally, future work should explore cross-crop migratory learning to reduce annotation costs and improve scalability. Models trained on rice leaf disease datasets could be adapted to other crops such as wheat, maize, or soybean using transfer learning or domain adaptation techniques. This approach can assess the reusability of learned feature representations across plant species and supports the development of general-purpose agricultural AI systems under limited data availability.

To further enrich hybrid model development in the context of agricultural disease detection, future research can take inspiration from recent progress in combining physical-informed modeling with data-driven approaches. For example, hybrid methods using stochastic state-space models integrated with machine learning corrections have demonstrated enhanced accuracy in remaining useful life prediction under nonlinear degradation patterns [79]. In addition, multi-stage neural architectures incorporating CNN, BiLSTM, and attention modules have been shown to effectively handle signal complexity and improve interpretability in fault diagnosis under extreme load variations [80]. These advances suggest that applying similar hybrid or interpretable learning strategies to plant disease detection tasks may improve robustness, explainability, and field-deployment reliability, especially in small or noisy datasets typical of real agricultural scenarios. Furthermore, physically-constrained deep learning frameworks have been proposed to embed domain knowledge into the model training process, thereby enhancing interpretability while maintaining high performance [81].

Furthermore, dual-input architectures such as the Digital Twin for Multi-margin Physical Information via Double-input Vision Reasoning (DTMPI-DIVR) have demonstrated potential in enhancing detection performance through multi-source visual reasoning and physical correlation [82]. These twin-model networks can effectively integrate spatial and physical signals to improve anomaly detection, particularly in cases involving overlapping or

subtle lesions common challenges in real-world agricultural datasets. Integrating such twin-based architectures into crop disease detection pipelines may improve the robustness, generalization, and decision-making reliability of lightweight models deployed on edge devices.

Moreover, recent advances in physical constraint-guided deep learning (PCG) have demonstrated notable improvements in interpretability and robustness. By embedding physical laws directly into the loss function, these hybrid models guide neural networks to align with real-world mechanical behaviors, such as acceleration and velocity dynamics in rolling components [83]. For instance, a PCG framework combining Quadratic Neural Networks with Bidirectional LSTM has achieved near-perfect accuracy in damage detection, even under zero-fault scenarios. Integrating similar physical constraints into agricultural disease detection models could improve credibility and generalizability, particularly when annotated data is limited or when models are deployed in uncertain, real-world field environments.

In addition, to enhance real-world impact and encourage practical adoption by end-users, future work should explore the development of mobile-based interactive applications tailored for farmers. These apps can integrate real-time disease detection results with localized pest management recommendations, ensuring actionable insights are accessible on-site. Co-designed with agricultural stakeholders, such interfaces should account for linguistic, cultural, and technological constraints to support usability in diverse rural contexts and promote effective human-AI collaboration in precision farming.

Lastly, to ensure long-term system reliability, future research should incorporate environmental performance monitoring of edge devices deployed in agricultural settings. Given the harsh conditions of high temperature, humidity, and dust in many rural areas, predictive maintenance frameworks that utilize sensor data (e.g., thermal, humidity, voltage) can be employed to track hardware health and anticipate failures. Establishing such systems will help reduce downtime, extend equipment lifespan, and support the stable operation of AI-driven disease detection technologies in real-world farming environments.

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