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 SURVEY

Deep Learning Based Models for Paddy Disease Identification and Classification: A Systematic Survey

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ABSTRACT Automated early detection and classification of paddy diseases help in applying treatment efficiently according to the detected diseases. Early detection also minimises the usage of chemical substances and pesticides and hinders the spread of the disease to healthy crops. On a broader scale, it aids in halting the global spread of diseases. Thus, it ultimately promotes healthier rice crops and increased yield. In this survey paper, we present a thorough exploration of deep learning (DL) models for the classification of paddy diseases. Our paper delves into the motivation behind this research study, reveals different paddy diseases and their associated symptoms, and unravels various deep-learning models employed for disease detection. We have also discussed strategies used by researchers for improving the performance of DL models, along with adaptations tailored for application-specific contexts. Additionally, we illustrate relevant research findings, explore datasets utilised in this domain, and analyse approaches for data augmentation. Through an exhaustive investigation, we emphasise existing research gaps, challenges, and open issues, concluding in a discussion on avenues for future exploration.

INDEX TERMS Smart farming, precision agriculture, paddy disease detection, paddy disease classification, paddy disease segmentation, deep learning.

I. INTRODUCTION

Rice is a pivotal global crop, particularly in nations such as India, Bangladesh, and China and has historically been essential for global agriculture, providing sustenance and fostering economic development [1], [2], [3], [4]. With the global population expected to reach 9.7 billion by 2050, rice plays a crucial role in securing food resources for nations, serving as a primary grain for over half of the world's population [5], [6], [7]. The rising demand for rice production is further intensified by complex challenges from climate change, affecting soil, air, and food quality, especially in vulnerable paddy cultivation areas, leading to

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significant production losses due to disease threats [3]. It is estimated that paddy diseases cause a 20%—40% annual yield reduction [8].

The integration of advanced technologies, including computer vision and machine learning, is revolutionising precision agriculture, especially in paddy disease detection—allowing for early and precise identification of diseased crops. This innovation not only mitigates yield losses and ensures healthier agricultural output but also optimises resource utilisation, prevents financial waste, and minimises environmental degradation—establishing it as a sustainable agricultural solution [4], [9], [10]. Additionally, it provides accessible agronomic advice through user-friendly applications, benefiting farmers without advanced infrastructure or access to experts [9].

By this research, we have made the following contributions which will aid the new researchers in this domain.

- Identified motivating factors to inspire research in the identification and classification of paddy and plant diseases.
- An extensive review of prevalent paddy diseases has been conducted, during which their scientific names, causative agents, visual symptoms, and potentially affected areas were systematically identified.
- Recent research methodologies in computer vision-based paddy and plant disease detection and classification have been systematically categorised and reviewed.
- Recent applications within this domain, along with the models used and their limitations, have been systematically identified, enabling future researchers to address these challenges in their work.
- We have reviewed and summarised accessible open-access datasets. This dataset analysis will guide researchers in planning future data collection with enhancements and new attributes.
- Data augmentation strategies to address data scarcity in this domain have been reviewed, including their limitations.
- Performance evaluation metrics have been identified and their usage in recent paddy and plant disease diagnosis research has been tabularised.
- Research gaps within this domain have been identified, facilitating and providing a roadmap for other researchers to address these gaps.
- Research challenges and open issues in this domain have been identified to make the researchers aware of the possible issues they might encounter.

Integrating computer vision technologies into agriculture, especially in the context of paddy disease detection, offers a promising solution [4], [9]. By harnessing the synergy between precision agriculture and advanced image processing and machine learning techniques [11], [12], research in this field will facilitate early detection and efficient treatment of paddy diseases—benefiting farmers worldwide. Moreover, it will aid in ensuring food security for our ever-growing global population. As part of our future work, we aimed to introduce a novel and effective mobile-friendly paddy disease detection model. We also plan to introduce a novel paddy disease segmentation dataset and provide a comparative analysis of the existing segmentation models.

II. MOTIVATION FOR RESEARCH IN PADDY DISEASE IDENTIFICATION

Despite recent research efforts, the applications for plant disease detection face multiple challenges. To overcome the challenges posed by manual disease detection including inaccuracies and individual biases, time constraints, limited expert availability, and limitations in existing research, this study explores innovative solutions integrating image processing techniques to address these challenges [1], [8], [13]. This work also emphasises the global impact of plant



FIGURE 1. Motivational factors: We illustrate research motivating factors in terms of five aspects including the limitations of manual detection among others.

diseases and the urgent need for efficient and automated systems [14]. The motivating factors behind this study are highlighted in Fig. 1 and details are provided below.

- **Limitations of manual detection:** Manual disease detection methods are error-prone, time-consuming, and often rely on subjective visual observations [1]. The current manual disease detection method requires significant labour and lacks accuracy—particularly in large fields where farmers face challenges in accessing experts to identify diseases timely and precisely [8], [13], [14]. Moreover, due to the complex nature and similar symptoms of paddy diseases, farmers often struggle to accurately diagnose and treat plant diseases. Lastly, symptomatic approaches and laboratory identifications are often impractical and demand more accessible and rapid solutions [1], [9].
- **Need for efficient disease diagnosis:** Automated disease detection systems can bridge the gap between limited expert availability and the extensive agricultural landscape [13]. By integrating image processing techniques and visual feature-based classifications, these systems reduce human intervention and processing time, ensuring quicker and more accurate disease diagnosis [6], [8].
- **Limited access to specialists:** Due to the lack of access to plant disease specialists in remote areas, farmers face difficulties in reaching experts for consultations—making disease management a costly and time-consuming affair [5]. It often leads to potential crop losses and reduced agricultural productivity [2], [3].
- **Global spread of diseases:** Recent studies have revealed that plant diseases can occur at various stages and rates. They also have the potential to spread worldwide and create new diseases. It emphasises the urgent need for rapid, precise, and localised image-based diagnosis of paddy diseases to effectively treat and control them [14].
- **Advances in image processing techniques:** Emerging technologies use image processing for prompt disease detection, reducing labour, enhancing accuracy, and

providing cost-effective solutions. These techniques facilitate broad-scale crop monitoring and early symptom detection leading to increased crop yields [9].

Increased efforts to automate efficient plant disease detection are vital for addressing the challenges faced by farmers ensuring timely interventions and improving agricultural productivity [13]. Leveraging innovative technologies in disease identification can pave the way for sustainable and efficient farming practices which will benefit both farmers and consumers [9]. The efficient usage of pesticides helps to have sustainable crop yields resulting in a healthier crop ecosystem and ultimately aiding both farmers and crop-producing nations.

III. PADDY DISEASES AND THEIR SYMPTOMS

Paddy cultivation faces severe threats from diseases caused by unfavourable conditions such as imbalances in temperature and soil quality and by microorganisms such as fungi, viroids, bacteria, nematodes, and viruses, leading to varied symptoms [1], [3]. It eventually affects both the quality and quantity of rice production and challenges agricultural stability [1]. Due to environmental factors, these diseases manifest unique or sometimes overlapping symptoms in different parts of the rice plant—including the leaves, stems, and grains demanding accurate identification [2], [14]. By the causative factors, paddy diseases have been classified into four categories: those caused by bacteria, fungi, viruses, and pests. A concise overview of the most prevalent diseases is provided below, alongside a tabular presentation in Table 1. It will aid novice researchers in initiating their exploration of this subject matter. Fig. 2 and 3 illustrate the common paddy diseases and their sub-classes.

A. FUNGI-CAUSED DISEASES

Fungal diseases in paddy are caused by various fungi that attack various plant parts—including leaves, sheaths, and grains. These infections typically lead to the development of identifiable lesions, discolouration, and rotting—significantly impacting the overall health and yield of rice crops [1], [5], [7], [9], [15], [17].

1) BLAST DISEASE (BD)

Induced by the fungus *Magnaporthe oryzae* or *Magnaporthe grisea* (anamorph: *Pyricularia oryzae*) [1], [15], Blast primarily occurs under specific environmental conditions characterised by rain showers, cool temperatures, and limited soil moisture [7], [15]. It impacts paddy throughout their entire life cycle, spanning from germination to harvest, and affects various plant components—including leaves, collars, nodes, necks, panicles, and seeds [1], [5]. It primarily affects nodes and neck tissues, reducing grain quality and quantity and forming dark brownish-black spots on grains [17]. Additionally, it is visible on leaves as diamond-shaped lesions in shades of green-grey surrounded by dark green borders, which later expand, forming grey centres and dark brownish

borders—ultimately resulting in the complete demise of the leaf [5], [7], [16].

2) BROWN SPOT DISEASE (BSD)

Caused by *Cochliobolus miyabeanus* (anamorph: *Bipolaris orzye*) [1], [8], Brown spot disease initially manifests as small brown spots and later develops into cylindrical, oval, and circular forms. It affects various parts of the paddy, including leaves, coleoptiles, panicle branches, leaf sheaths, spikelets, and glumes [1], [2], [15], [18]. Occasionally, it leads to extensive leaf damage, eventually causing the complete demise of affected leaves [9]. This disease thrives in temperatures ranging from 16 to 35°C, commonly occurring in soils lacking nutrients and adequate water, accompanied by elevated humidity levels [7], [8], [18]. Seeds contaminated by this fungus yield unfilled or discoloured grains, serving as the primary source of infection and impacting future crop yields [9]. Hence, it emphasises the importance of preventive measures [9], [15], [19].

- **Thin brown spot disease:** Resulting from the fungus *Sphaerulina oryzina*, this disease predominantly impacts rice leaves. It intensifies in potassium-deficient soils at temperatures between 25 to 28 degrees Celsius, mainly in the late stages of the rice plant. The disease appears as dark brown lesions along leaf veins [20].

3) SHEATH BLIGHT

Caused by *Rhizoctonia solani Kuhn* fungi, Sheath blight primarily affects the plant stems, especially in the rainy season, rendering crops highly susceptible [1], [7], [17]. Initially appearing as greenish-grey spots on leaf sheaths near water levels, the disease progresses with irregular purple-brown and blackish-brown borders, earning it the names ‘mosaic foot stalk’, ‘snake-skin disease’, and ‘rotten food stalk’ [7]. Sclerotia falling off the straw during or before rice harvesting exacerbates the disease’s impact, affecting grain quality and panicles [17].

4) FALSE SMUT

Caused by the plant pathogen *Ustilaginoidea virens*, False smut is prevalent in soils with drastic nitrogen levels and regions characterised by elevated humidity [17]. Due to fungal growth, it causes the individual grains to form clusters of velvety spore masses or yellow fruiting bodies. In the early stages, these clusters exhibit yellow or orange hues, but upon maturation, the spores transform into a greenish-black colour—indicative of mature black fungal mycelium [5], [9]. Additionally, it often causes the development of grain chalkiness, diminishing both their quality and overall yield [5].

5) LEAF SMUT

Induced by the *Entyloma oryzae* fungus, Leaf smut causes small black lesions on paddy leaf blades with brown or golden circles [5], [21]. In severe cases, the leaves turn yellow, and the tips appear grey due to dying [18].

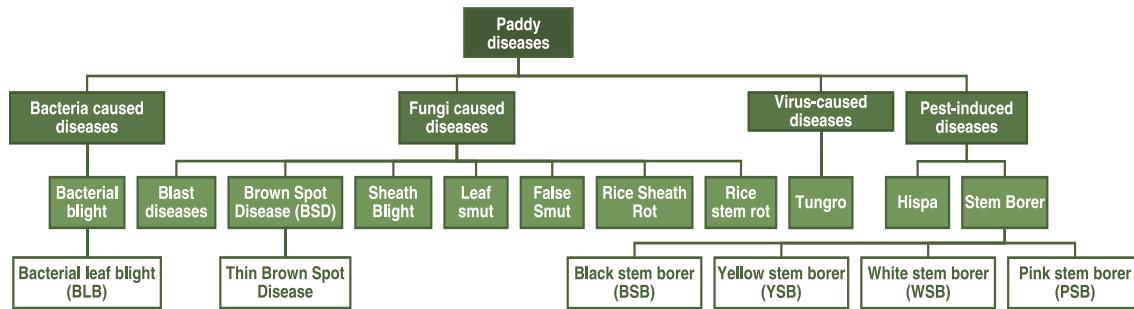


FIGURE 2. Paddy diseases and their categories. These diseases can be mainly classified into four categories namely: bacteria-caused diseases, fungi-caused diseases, virus-caused diseases, and pest-induced diseases. Each one is further classified into sub-categories.

TABLE 1. Overview of paddy disease traits.

Disease name	Disease's scientific name	Causative agent	Disease symptoms	Affected areas	References
Rice blast	<i>Magnaporthe oryzae</i>	Fungus	Dark brownish-black spots on grains; diamond-shaped lesions on leaves	Leaves, collars, necks, panicles, seeds, and grains	[1], [5], [7], [15]–[17]
Brown spot	<i>Cochliobolus miyabeanus</i>	Fungus	Circular dark brown lesions	Leaves, leaf sheath, panicle branches, and glumes	[1], [2], [7]–[9], [15], [18], [19]
Thin brown spots	<i>Sphaerulina oryzina</i>	Fungus	Dark brown lesions along leaf veins	Leaves	[20]
Sheath blight	<i>Rhizoctonia solani Kuhn</i>	Fungus	Greenish-grey spots with irregular purple-brown and blackish-brown borders	Leaf sheaths	[2], [7], [16], [17]
False smut	<i>Ustilaginoidea virens</i>	Fungus	Clusters of yellow fruiting bodies, orange to greenish-black spores	Rice grains	[2], [5], [7], [9], [17]
Leaf Smut	<i>Entyloma oryzae</i>	Fungus	Black linear lesions with dark gold or light brown halos	Leaves	[5], [18], [21]
Rice sheath rot	<i>Sarocladium oryzae</i>	Fungus	Irregular spots with dark reddish-brown margins, grey centre, and later-phase darker dots	Leaf-sheaths	[1], [5], [9]
Rice stem rot	<i>Sclerotium oryzae</i>	Fungus	Black lesions on leaf sheaths, expanding to the culm, with white and black sclerotia and mycelium inside infected stems, unfilled panicles and chalky grains	Leaf sheaths and culms	[5], [22], [23]
Bakanae or Footrot	<i>Fusarium moniliforme</i>	Fungus	Pale, slender, yellow-shaded leaves, less tillering, white powdery growth on the lower portion of the plants, and lesions on roots	Seeds, seedbed, lower portion of the plants (roots, and crowns)	[17], [24]–[26]
Bacterial blight	<i>Xanthomonas oryzae</i> pv. <i>oryzae</i>	Bacterium	Wilting seedlings, yellowing, drying leaves, small grey to olive spots	Leaves, spikes, and seedlings	[3], [9], [15]
Bacterial leaf blight	<i>Xanthomonas oryzae</i> pv. <i>oryzae</i>	Bacterium	Grey-white lesions on leaf veins, yellow lesions on leaves	Leaves	[1], [7], [9], [18], [21]
Tungro	Rice Tungro Spherical Virus and Rice Tungro Bacilliform Virus	Viruses	Yellowing, mottled or striped appearance, rust-coloured spots, and interveinal necrosis	Leaves	[15], [27]
Hispa	<i>Dicladispa Armigera</i>	Insect (pest)	White membranous leaves leading to wilting	Leaves	[2], [8], [19]
Yellow stem borer	<i>Scirpophaga incertulas</i>	Insect (pest)	'Dead heart' and 'white ear' like shapes on leaves, dried, yellow shoots and chaffy ear heads	Shoots and leaves	[28], [29]
Pink stem borer	<i>Sesamia inferens</i>	Insect (pest)	Insect waste and eggs on leaf sheath and stems	Leaf sheath and stems	[28], [30]

6) RICE SHEATH ROT

Caused by *Sarocladium oryzae*, Rice sheath rot is a prevalent disease exacerbated by damp conditions, primarily transmitted through seeds and crop residues [1], [9]. The infection initiates as elongated or inconsistent dark markings on the top leaf sheath surrounding the young panicles. It exhibits reddish-brown or brownish-tan patches with a grey or brownish-grey centre, and with disease advancement, the darker dots within the patches increase [5], [9]. It reduces grain yield by hindering panicle emergence, resulting in

the formation of sterile panicles and unfilled discoloured seeds [5], [9]. Thus, it can significantly lower the yield and can spread to uninfected crops [1].

7) RICE STEM ROT

Caused by *Sclerotium oryzae*, stem rot manifests as small black lesions on the outer leaf sheath, extending to the inner sheath, particularly at the water line in water-sown rice [5], [22]. As it progresses, sheaths die and detach, with severe cases penetrating the culm—leading to visible white

and black sclerotia and mycelium within, causing lodging, and affecting grain with unfilled panicles and chalky grains. The disease thrives on wounded plants and is influenced by panicle moisture and nitrogen fertiliser [23].

8) BAKANAE

This seed-borne fungal disease is caused by *Fusarium moniliforme* (sexual stage: *Gibberella fujikuroi*) [25], [26]. This disease spreads mainly through contaminated seeds. But can also arise from infected plant material or soil, moving between plants via wind or water and during agricultural activities like harvesting and seed soaking. The pathogen targets rice plants via their roots or crowns which triggers a widespread growth that results in unusually tall plants, with leaves that are pale, slender, yellow-shaded and dry, diminished tillering, and grains that are either partially filled or empty [17], [25], [26]. The symptoms also include white powdery growth on the lower portion of the plants [25]. The infected seedlings may become dry and exhibit root lesions, potentially compromising their survival through the transplantation process [17], [24].

B. BACTERIA-CAUSED DISEASES

Bacterial diseases in paddy, caused by various types of bacteria, lead to wilting, yellowing, and lesions in different parts of the plant. These infections spread swiftly in conducive conditions, inflicting significant damage on rice crops [7], [16], [18], [21].

1) BACTERIAL BLIGHT

Caused by *Xanthomonas oryzae* pv. *oryzae*, bacterial blight is a deadly disease leading to significant crop losses, especially in warm and humid conditions. It manifests as expanding wet streaks on leaves, drying into yellow droplets. Subsequently, leaves develop grey-white lesions, indicating the infection's end. The infected seedlings typically perish within 2 to 3 weeks after the initial infection [9]. Additionally, small grey to olive spots surrounded by elongated brown edges appears on leaves, leading to leaf dryness and grain atrophy [3]. In extreme cases, it can result in up to 75% crop loss [15].

- **Bacterial leaf blight (BLB):** A subset of bacterial blight, bacterial leaf blight affects paddy in tropical and temperate regions [9]. The disease is identifiable by elongated yellow lesions on the leaves [21]. Additionally, it especially demonstrates grey-to-white lesions along the leaf veins, intensifying during plant growth [7], [21]. This disease is transmitted through plant debris and insect feeding [1]. Bacterial leaf blight flourishes in temperatures ranging from 25°C to 34°C, especially in consistent winds and continuous rainfall, causing a notable decline in rice yield [18].

C. VIRUS-CAUSED DISEASES

Viral diseases in paddy are caused by various strains of viruses and transmitted by insects, resulting in yellowing,

stunted growth, and reduced yields in infected plants, significantly impacting crop yield and quality [15].

1) TUNGRO

Tungro infection can occur at any stage of paddy growth, with the vegetative phase being the most common. Rice tungro spherical virus (RTSV) and Rice tungro bacilliform virus (RTBV) are the causes of tungro disease in paddy. It is mainly disseminated by the leafhoppers feeding on infected plants, but the sources also include infected seedlings and stubble from previous crops. The infected plants develop yellow leaves, starting at the tip and spreading downward [15]. Additionally, mottled or striped patterns, rust-coloured spots, and necrosis between veins can also appear on infected leaves [27].

D. PEST-INDUCED DISEASES

Pest-caused paddy diseases occur due to insect infestations, resulting in leaf damage, lesions, and overall plant weakness. These diseases can lead to reduced tillering, deformed grains, and substantial crop loss [8], [19].

1) HISPA

Hispa is caused by the black insect *Dicladispa armigera*, which scrapes the surface of rice leaves, leaving distinct white lines where female insects lay their eggs [8]. The resulting grubs accelerate the scraping process, leading to the eventual death of the leaf [8], [19]. Without prompt intervention using pesticides, Hispa has the potential to impact rice fields within three weeks [19].

2) STEM BORERS

Stem borers are of six species, such as yellow, white, striped, gold-fringed, dark-headed striped, and pink stem borers. These pests significantly impact rice by attacking stems and grains, with damage exacerbated by high nitrogen levels and late planting [2]. These pests bore into stems, leading to “dead hearts” in the vegetative phase and “white heads” during the reproductive stage, with symptoms including unfilled panicles and stem holes. Distinguishing these symptoms from similar damages caused by other pests and diseases is crucial for effective management [28].

- **Yellow stem borer (YSB):** It is caused by *Scirphophaga incertulas* which impacts rice by laying eggs near leaf tips, leading to ‘dead heart’ like shapes in the vegetative stage and ‘white ear’ like shapes in mature plants, with symptoms including dry, yellow shoots and chaffy ear heads that detach easily. This pest is prevalent in flooded rice fields, where larvae create tubes from leaf wrappings for mobility and stem entry [28], [29].

- **Pink stem borer (PSB):** Caused by *Sesamia inferens*, it primarily targets sugarcane and occasionally affects upland rice cultivated near sugarcane fields or similar grasses [30]. It uniquely lays eggs directly between the rice leaf sheath and stems. Alternate hosts aid this



FIGURE 3. Illustrating samples of common paddy diseases covering four categories: (1) fungi-caused (Brown spot, Narrow brown spot, False smut, Leaf smut, Sheath blight, Sheath rot), (2) Bacteria-caused (Bacterial leaf blight), (3) virus-caused (Tungro), and (4) pest-caused (Hispa, Black stem borer, White stem borer and Yellow stem borer).

pest's survival and proliferation in winter or dry seasons, marking its distinction from other stem borers [28], [30].

IV. RECENT RESEARCH ON PADDY DISEASE CLASSIFICATION

With the recent advancements in image processing and machine learning [31], researchers have proposed diverse techniques for automatic paddy disease diagnosis—optimising accuracy and minimising the need for manual efforts and resources. Recent research and developments related to paddy disease detection in computer vision have been classified into four main categories. The categories depend on the architecture of the proposed models, techniques adapted for enhancing the model performance, adaptations made for specific applications, and the practical implementations and applications of these models. Fig. 4 illustrates these categories, and the details are provided below.

A. DEEP LEARNING ARCHITECTURES FOR PADDY DISEASE DETECTION

In recent paddy disease detection and classification research, several DL architectures have been observed such as classical convolutional neural networks [15], [32], [33], [34], [35], [36], [37], [38], vision transformers (ViT) [3], [21], [39], [40], [41], [42], [43], [44], and memory-efficient models [2], [45], [46], [47], [48], [49], [50], [51], [52], [53]. Among

these, even though ViT requires high computational power and cost, it has surpassed the traditional CNN models in many cases—while small-scale and memory-efficient models have been developed for deployment in IoT and mobile devices. The recent research from each category and its possible limitations have been described below.

1) CNN-BASED MODELS

In recent years, CNNs have been pivotal in various fields—from detecting diseases in major crops like maize and wheat to medical applications such as pulmonary nodule detection. Their versatility and high generalisation performance have made them essential in diverse image analysis studies [15], [33].

Singh et al. [15] proposed a custom CNN architecture for paddy disease detection, achieving 97.61% accuracy using a dataset limited to five disease classes, which does not cover the range of existing diseases. Similarly, Hari et al. [38] introduced Plant disease detection neural network (PDDNN) which surpassed MobileNet [45] in performance achieving an accuracy of 97.5%. They utilised a simplified Plant Village [54], [55] dataset limited to one disease and one healthy class per plant type (maize, grape, apple, and tomato), which does not meet the goals of plant disease identification.

Furthermore, an attention-based depthwise separable neural network with Bayesian optimisation (ADSNN-BO)

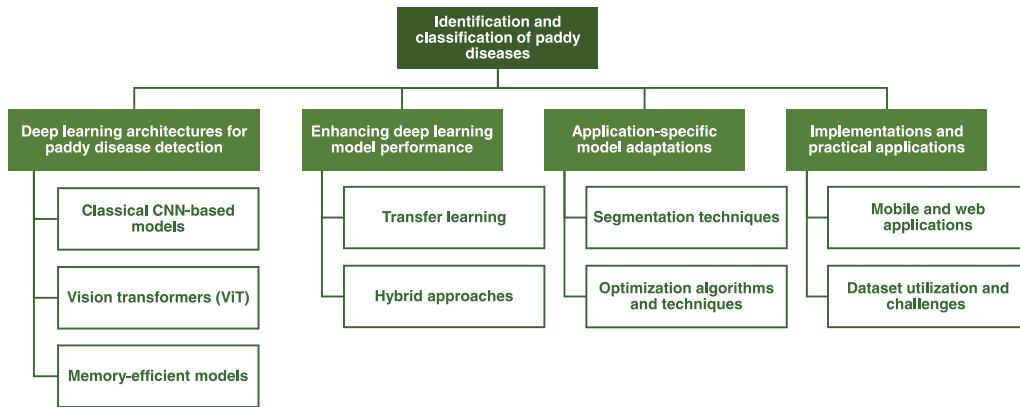


FIGURE 4. Research related to paddy disease classification has been categorised into four categories: deep learning architectures for paddy disease detection, enhancing deep learning model performance, application-specific model adaptations and implementations and practical applications. Each category has been further classified into sub-categories.

incorporating a MobileNet [45] structure, and an enhanced attention mechanism have been presented by Wang et al. [35]. Their attention mechanism focuses on extracting informative features by employing an optimisation-based approach to emphasise critical features. Their model is tailored for portable devices and its interpretability has been evaluated via comprehensive feature analysis, incorporating methods such as activation maps and filter visualisation techniques. The dataset used for comparison comprises only three distinct paddy disease classes, covering a limited variety of diseases.

Specifically for the identification of paddy diseases, the ‘Paddy Doctor’ [34] dataset has been introduced. To benchmark and evaluate this dataset, Petchiammal et al. [34] devised a custom deep CNN (DCNN) model. However, their model failed to surpass the performance metrics of existing models like ResNet34 [56], Xception [57], VGG16 [58], and MobileNet [45]. Additionally, using the same dataset, Petchiammal et al. [33] introduced PaddyNet which demonstrated superior performance over other DL models, including DCNN, VGG16 [58], MobileNet [45], Xception [57], and Resnet34 [56]. Although the dataset utilised in studies by Petchiammal et al. [33], [34] encompass 12 rice plant diseases, they were sourced from a singular geographical location. This limited scope raises questions about the representations of symptom variations in diverse geographical areas, thereby impacting the model evaluation and indicating a necessity for more extensive research.

Sujatha et al. [32] used the existing AlexNet [59], DenseNet [60] and ResNet [56] to classify seven paddy diseases. They used 235 samples and an Arduino-equipped unmanned ground vehicle (UGV) was utilised to collect additional environmental data.

In general, CNNs and their variants require rigorous parameter training and substantial computational resources, needing abundant labelled samples [13]. They might struggle to capture complex leaf diseases due to limitations in modelling long-range dependencies and contextual

information [3]. Despite these difficulties, prior studies have showcased the potential of CNN [15], [33], [34], [35].

2) VISION TRANSFORMERS (ViT)

ViTs introduced by Dosovitsky et al. [61] have produced outstanding classification performance with substantially lower memory consumption [39]. The ViT model structure has been illustrated in Fig. 5. ViT has been applied to classify diverse plant diseases across multiple crops [3], [21], [39], [40], [41], [42], [43], [44].

Salamai et al. [3] proposed a ViT-based lesion-aware paddy disease detection system to identify discriminatory lesion features. They incorporated a multiscale contextual feature extraction network, capturing local and global disease features across scales and channels. Besides this, a weakly supervised paddy lesion localisation (PLL) method was introduced for prioritising the lesion areas and a feature-tuning unit was used to enhance the spatial exchanges between visual semantics and improve disease discrimination.

On the other hand, a simplified ViT-based real-time plant disease classifier was implemented by Borhani et al. [21]. They combined attention blocks with CNN blocks to mitigate the lengthy prediction time, outperforming other models on small, medium, and large-scale datasets. Despite fewer parameters, their ViT model was slower due to attention blocks. So, they integrated attention blocks and convolutional blocks, which led to faster predictions than ViT models and exhibited higher accuracy than CNN-based models.

PlantXViT, a lightweight ViT model [39] comprising only 800 thousand parameters, enables the precise identification of various plant diseases in IoT-based smart agriculture. This model has been rigorously tested on five distinct datasets covering several crop varieties. They validated their model predictions as interpretable using gradient-weighted class activation maps (Grad-CAM) and local interpretable model agnostic explanation (LIME) methods. It can be observed that Salamai et al. [3] conducted tests exclusively on paddy data,

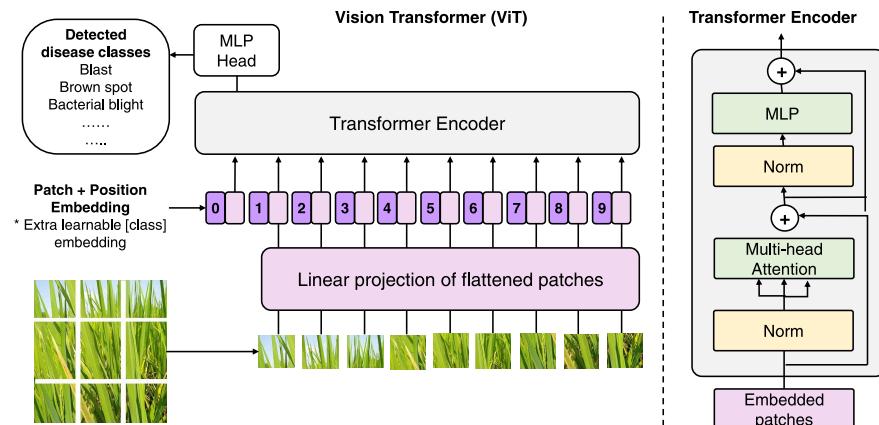


FIGURE 5. Illustrating the ViT model architecture. For image classification, ViT divides the images into several fixed-size patches. These patches are flattened into a sequence and processed by a transformer encoder to learn inter-patch relationships, generating a feature vector representing the image. Lastly, a multi-layer perceptron (MLP) head is used for the final classification. This figure is inspired by Dosovitsky et al. [61].

whereas Borhani et al. [21] and Thakur et al. [39] evaluated their models across multiple crops—primarily utilising the Plant Village [54], [55] dataset. It is noteworthy that their used datasets had samples from controlled environments and may show inflated performance.

Thai et al. [40] developed ViT-based FormerLeaf for detecting leaf diseases. Their work focused on optimising the self-attention mechanism within the ViT structure by proposing two techniques to enhance the model's performance. These methods not only decrease the model size and speed up both inference and training but also maintain classification accuracy. They utilised the least important attention pruning (LeIAP) algorithm to identify and remove less crucial attention heads in each transformer layer, resulting in higher F_1 scores compared to the original FormerLeaf in most cases. In addition to that, they used sparse matrix-matrix multiplication (SPMM) to optimise the model's training phase, reducing computational and memory costs. This method sped up training by calculating correlations between image patches, cutting down computation complexity and resource usage. Evaluated on the Cassava Leaf Disease Dataset, these enhancements yielded significant results. Their dataset included only four disease classes, revealing limitations in selection. A lower number of disease classes generally produce better results, whereas, in reality, more than 13 variations of paddy diseases exist, as detailed in section 1.

Despite resolving certain transfer learning issues, ViT still struggles to converge effectively on small datasets compared to CNN models because of its emphasis on distant feature dependencies. However, combining CNN's local feature extraction with ViT's self-attention modules might capture both local and global features effectively [39].

3) MEMORY-EFFICIENT MODELS

Although large-scale CNN architectures show superior performance, they face challenges due to their large

number of parameters. To address this issue, research focused on memory-efficient high-performance models suitable for mobile and IoT-based devices has been made. MobileNet [45], EfficientNet [46], MobileNetV2 [47], NasNetMobile [48], ShuffleNet [49], and SqueezeNet [50] are leading examples of memory-efficient models.

Yang et al. [53] proposed DGLNet which incorporates a global attention module (GAM) and a dynamic representation module (DRM) with a pre-trained MobileNetv3 [62]. The GAM effectively captures critical spatial information and channel mappings in complex field environments which enhances the model's generalisation capabilities. On the other hand, the DRM improves feature representation through the dynamic generation of adaptive convolutional kernel parameters, reducing the need for supplementary network layers and channels. For performance evaluation, the authors utilised a controlled environment dataset, Plant Village [54], [55], to assess the model's generalisation capability across various plant diseases. Additionally, a simplified and nearly balanced Paddy Doctor [34] dataset, containing only 10 diseases, was employed to evaluate the model's efficiency in complex real-life field environments, achieving classification accuracies of 99.82% and 99.71% respectively. The original Paddy Doctor [34] dataset contains 12 disease categories with a pronounced imbalance—ranging from 450 to 2405 images per class. Therefore, the model's performance was not assessed in addressing skewed datasets and classifying a higher number of disease categories.

Additionally, Rahman et al. [2] provided a model called “Simple CNN” featuring a unique two-stage training approach. They also provided a new dataset comprising nine classes in total: five diseases, three pests, and one healthy plant class. Apart from this, Nobi et al. [51] proposed a transfer learning-based model, GLD-Det for the instantaneous detection of guava leaf disease. Utilising an adapted MobileNet [45] version with additional features, their model achieves lightweight yet robust performance by

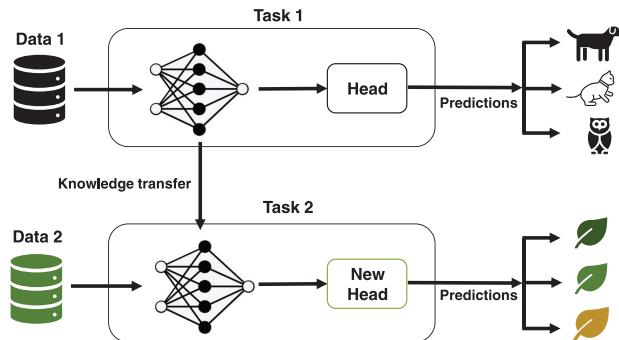


FIGURE 6. Illustrating the mechanism of transfer learning, where knowledge acquired from an animal classification task is transferred to a plant disease classification task, and for making the final prediction a new head (output layer) is added.

overcoming challenges like illumination variation and leaf obstruction.

B. ENHANCING DEEP LEARNING MODEL PERFORMANCE

To elevate the performance of DL models in precision agriculture several advanced techniques have been utilised, such as leveraging the pre-existing knowledge via transfer learning [5], [8], [13], [44], [51], addressing the limitations of an individual model and improving the accuracy of disease classification via the creation of hybrid models [1], [4], [6], [9], [20], [41], [42], [43], [44], [63], [64], [65], [66].

1) TRANSFER LEARNING-BASED MODELS

Transfer learning resolves challenges faced by classical DL techniques and has been utilised in several works [5], [8], [13], [44], [51]. In this process, a pre-trained neural network with weights from extensive prior training is selected as the base. The model is then adapted to the specific task by modifying layers and further fine-tuned to meet new requirements without needing to infer all parameters from scratch [13]. Fig. 6 demonstrates the mechanism of transfer learning.

Latif et al. [8] proposed a modified VGG19 [58] model which employs two stages of fine-tuning. In the first stage, feature extraction layers are frozen, and fully connected layers are unfrozen for classification. In the second stage, specific layers, including the initial 10 layers of VGG16, are frozen—while the rest are retrained for fine-tuning. According to them, it is anticipated to deliver superior outcomes. Their proposed model demonstrated proficient classification across six classes, encompassing one healthy class, achieving an accuracy rate of around 96%. Additionally, Nobi et al. [51] introduced the GLD-Det model utilising transfer learning for immediate guava leaf disease detection.

Chen et al. [13] proposed a hybrid model combining pre-trained VGGNet [58] and Inception [67], leveraging the strengths of both to achieve 92% validation accuracy for rice data and nearly 80% for maize data which had been collected by their researchers. Additionally, it achieves a notable

validation accuracy of around 92% on a publicly accessible maize dataset and sustains an impressive average accuracy of approximately 92% even in intricate and challenging background environments. All of their used datasets cover a limited number of disease classes (not more than 5), suggesting their model may not effectively classify over 13 classes in practice. Similarly, to classify 12 paddy diseases, Chen et al. [5] presented a model named Mobile-Atten which uses pre-trained MobileNet-V2 [47] with an attention mechanism. Their model structure has been illustrated in Fig. 7. Similar to Latif et al. [8] and Rahman et al. [2], a two-stage fine-tuning approach is employed for training this model.

Lastly, despite attempts at transfer learning to improve CNN-based leaf disease detection, their limited transferability hampers their generalizability. The assumption of similarity between the source and target domains might transfer potential biases from the source domain to the target domain, compromising accuracy and fairness in paddy leaf disease detection systems [3].

2) HYBRID MODELS

The amalgamation of multiple models has yielded superior classification accuracy compared to singular approaches, and this approach has been observed in previous studies [1], [4], [6], [9], [20], [41], [42], [43], [44], [63], [64], [65], [66].

Sobiyaa et al. [1], Radhakrishnan [6], Lamba et al. [63], and Haridasan et al. [9] have employed identical hybrid structures in the construction of their respective models using CNN and support vector machine (SVM) for plant disease diagnosis. Diverse CNN models were systematically applied for intricate feature extraction. Then, these extracted features were effectively incorporated into a classification system utilising SVM [1], [6], [9], [63]. Furthermore, a novel hybrid model, GCL integrates long short-term memory (LSTM), CNN, and generative adversarial networks (GAN) [68] for identifying and classifying paddy diseases. GAN augments the dataset, CNN extracts features, and LSTM performs disease classification. This approach is particularly effective with limited data, addressing the scarcity of real data by efficiently generating new images and expanding the dataset size with minimal overhead [4].

Additionally, a deep ensemble model called Plant-Det, incorporating InceptionResNetV2 [69], EfficientNetV2L [70], and Xception [57], has been introduced by Shovon et al. [64]. However, their study suffers from a limitation: their model has yet to be tested on datasets featuring a broader range of disease classes—highlighting the complexity associated with increasing target label classes. Their utilised dataset comprises only five distinct paddy disease classes, and they only distinguish between healthy and unhealthy states without identifying any disease classes for betel leaves [64].

Zeng et al. [44] presented the squeeze-and-excitation vision transformer (SEViT) which enhances the relevant

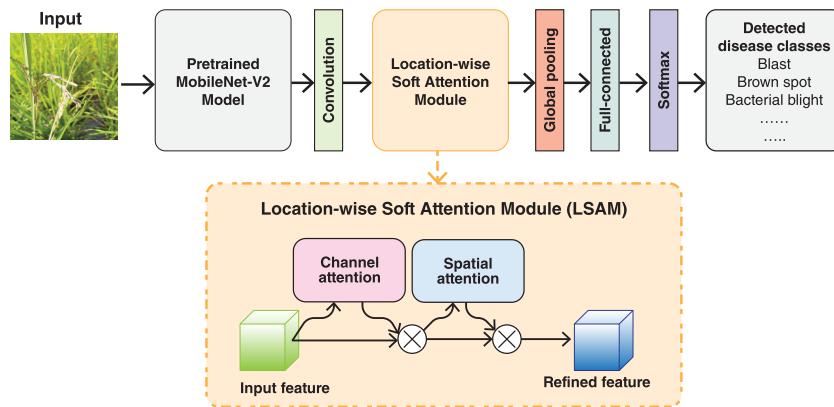


FIGURE 7. Illustrating the architecture of transfer learning and attention mechanism based Mobile-Atten model. This model uses a modified MobileNet-V2 model leveraging pre-trained weights from ImageNet to extract initial features. Then, it is followed by a location-wise soft attention module capable of identifying spatial attention and channel-wise attention to capture the spatial points and inter-channel relationships to have enhanced performance. Lastly, additional refinement is obtained through a supplementary convolution layer and global pooling layer and final disease predictions is achieved through a fully connected layer and softmax function. This figure is inspired by Chen et al. [5].

channel features by embedding the squeeze-and-excitation (SE) module in a modified ResNet101 [56] network. Then, uses a pre-trained ViT as a feature extractor and final disease classifier. This model's proficiency in classifying diseases within and across diverse crops was validated through experiments on grain, fruits, cash crops, and vegetables. Although the model has 88.34% test accuracy, it suffers from significant depth and model parameters, and heavy dependence on pre-trained weights for superior results.

Thakur et al. [43] presented a lightweight hybrid model plant vision transformer (PlantViT) incorporating CNN and ViT. Their model has only 400 thousand parameters and employs its initial convolutional layers for low-level features and multi-head attention-based transformer layers for high-level feature extraction. Pretrained on ImageNet, this model has been fine-tuned on plant disease datasets (PlantVillage, Embrapa) and achieves 98.61% accuracy on PlantVillage (with controlled plain backgrounds) and 87.87% on Embrapa (cropped disease portion) datasets, demonstrating its robust performance in diverse background conditions. Since their model was not tested with field image data, its performance on real-life samples is uncertain.

A lightweight model with 850 thousand trainable parameters, leveraging a hybrid combination of CNN and ViT similar to the approach used in PlantViT [43] has been proposed by Thakur et al. [41]. The model utilises pre-trained VGG16 [58] and Inception-v7 [71] convolutional blocks for local feature extraction and four transformer encoder modules for global feature extraction. This model's generalisability was tested on diverse datasets from various geographic origins and crops. They also employed confusion matrices, t-distributed stochastic neighbour embedding (t-SNE) plots, Grad-CAMs, and LIME for comprehensive performance evaluation and explainability analysis. However, the model's higher floating point operations per second (FLOPS) count resulted in

comparatively longer than the average test times indicating a notable drawback.

Lamba et al. [63] introduced a hybrid model for assessing different levels of blast disease severity in rice plants. This four-tier paddy blast disease severity prediction system employs CNN for feature extraction and SVM for classification. Similar to this, Pal et al. [72] presented AgriDet, a segmentation-based model for three-tier disease severity detection across seven plants, including apple, bell pepper, corn, tomato, potato, and squash. The model employs the Multivariate Grabcut Algorithm (MGA) [73] for segmenting diseased leaf regions.

C. APPLICATION-SPECIFIC MODEL ADAPTATIONS

This section incorporates several techniques for effective and precise identification and diagnosis of paddy disease such as segmentation of the original data [20], [42], [65], [66], [74], [75], [76] and choosing the best hyper-parameters through the usage of various optimisation algorithms and techniques [77], [78], [79], [80], [81].

1) SEGMENTATION TECHNIQUES

Image segmentation plays a crucial role in plant disease analysis by isolating the diseased regions from healthy parts of a leaf [75]. Various studies have leveraged segmenting diseased areas of plants as an initial step for classifying diseases [20], [42], [65], [66], [74], [75], [76], [82]. This segmentation can be executed utilising masks [42], [65], various image processing techniques [20], [66], [74], [75], [76], [82] and neural networks [74]. However, segmenting diseased leaf parts from complex backgrounds is challenging due to variations in illumination, distance, and clutter, even in controlled environments. The accuracy of the classification outcome can be heavily influenced by the

segmentation inconsistencies [75]. Fig. 8 illustrates the process of segmentation-based disease classification.

Raj et al. [74] developed a crop disease detection technique that starts with image denoising via Gaussian filtering, followed by image quality enhancement through signal-to-noise Ratio (SNR). Subsequently, they employed a deep active contour CNN (DACCNN) for segmentation tailored with custom loss functions to improve disease detection and a 2DCNN for disease classification on tomato and brinjal which achieved a test accuracy of 98%.

Raja et al. [66] and Nigam et al. [20] provide MATLAB-based frameworks for disease detection. Raja et al. [66] developed a model named PLDC-RBFNN-SSA for paddy disease diagnosis using a salp-swarm algorithm (SSA) [83] optimised radial basis function neural network (RBFNN) [84]. The process begins with segmenting the pre-processed images using black widow's k-means method [85] to identify regions of interest (ROI). Then, the grey-level symbiotic matrix windowed adaptation algorithm (GLCMWAA) [86] is utilised to extract the key radiomic features such as haralick texture and grayscale statistics. These features are used for disease classification with the PLDC-RBFNN-SSA. Meanwhile, Nigam et al. [20] employed 3Dbox and Gaussian filters for noise reduction in the pre-processing phase, followed by the conversion of RGB images to HSV for disease segmentation via k-mean clustering. The feature extraction is conducted using PCA and bacterial foraging optimisation algorithm (BFOA) [87] is used to enhance the feature selection. Their disease classifier utilising a deep neural network (DNN) achieved an accuracy of 93.50%, whereas a hybrid system combining DNN with BFOA attained a higher accuracy of 98%.

Daniya et al. [65] developed a rider water wave-based neural network (RWW-NN) for paddy disease detection, combining the rider optimisation algorithm (ROA) [88] with water wave optimisation (WWO) [89] to fine-tune the neural network. They used histogram equalisation for pre-processing, followed by a segmentation network (SegNet) [90] for segmentation to eliminate the background distortions, and employed a CNN for optimal feature extraction. Then, these extracted features were processed with a neural network where rider water wave (RWW) was used to optimise the weights and achieved an accuracy of 90.8% for three disease classes.

On the other hand, Kappali et al. [75] employed Otsu, K-means clustering, and colour thresholding in both RGB and LAB colour spaces for segmenting and classifying three paddy diseases. Using the same segmentation process, Ramesh et al. [76] developed a method called DNN_JOA for paddy disease diagnosis. Initially, RGB images were converted to HSV format and the hue component was utilised for background removal. Following this, clustering was applied to segment the diseased areas. Finally, the DNN_JOA method was employed where the best weights were selected by Jaya algorithm (JOA) [91] to classify four disease types and achieved a test accuracy of 97%.

Mahadevan et al. [82] have proposed a system called deep spectral generative adversarial neural network (DSGAN²) that employs an improved threshold neural network (ITNN) for noise reduction and resizing. The segment multiscale neural slicing (SMNS) is subsequently used for ROI and colour segmentation. Then, these segmented parts are utilised by the spectral scaled absolute feature selection (S²AFS) for feature selection depending on the spider optimization to extract the most relevant features for the final disease classification by DSGAN². Their utilised dataset consisted of only three disease classes and one healthy class, captured in a controlled environment against a simple background. However, most practical test samples are usually taken in complex field environments, which indicates a limitation of their research. The use of a single dataset in their study further questions the generalisability of their model.

Arshad et al. [42] introduced PLDPNet to classify potato leaf diseases leveraging mask-based segmentation techniques. They utilised U-Net [92] for segmenting ROI on potato leaves and subsequently extracted deep features using VGG19 [58] and Inception-V3 [93] models. Then, those extracted features were combined into a latent feature vector to work as input for a ViT-based classifier. Their architecture has been illustrated in Fig. 9. An ablation study demonstrated the effectiveness of their model on tomato and apple leaf datasets without the segmentation stage. However, their research lacked consideration for complex field backgrounds, highlighting a limitation in real-world precision agriculture scenarios.

Image processing facilitates segmentation without the necessity for masks [20], [66], [74], [75], [76], whereas the advanced CNN-based methods require the use of masks [42] or coordinates to identify diseased regions [65]. The lack of publicly available plant-based masks poses a significant barrier to new researchers in this field.

2) OPTIMIZATION ALGORITHMS AND TECHNIQUES

Researchers employ a systematic methodology, integrating trial-and-error techniques with grid search tuner [77], random search tuner [78], Bayesian optimisation tuner [79], and hyperband tuner [80] to identify optimal parameter combinations for CNN architectures. Despite their efficacy, these methods require significant processing time and computational resources. David et al. [81] introduced the innovative MUTPSO-CNN method, utilising mutant particle swarm optimisation (MUT-PSO) algorithms for paddy leaf disease classification. This approach systematically generates an optimised CNN structure tailored to the input dataset, outperforming traditional handcrafted CNN architectures with superior performance.

D. IMPLEMENTATIONS AND PRACTICAL APPLICATIONS

This section encompasses the usage of mobile and web applications in paddy disease identification [19], [94], [95],

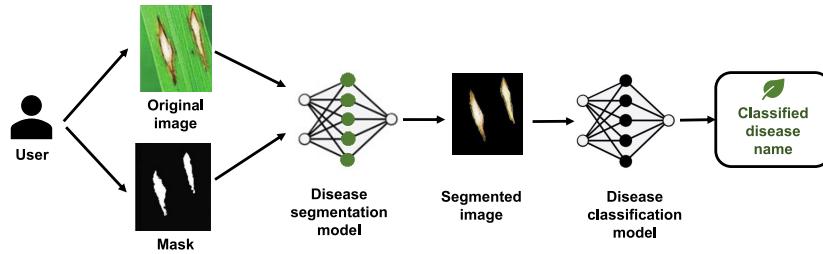


FIGURE 8. Illustration of a segmentation-based plant disease classification process, where the segmentation step extracts the ROI, which is then utilised by the classifier for disease identification.

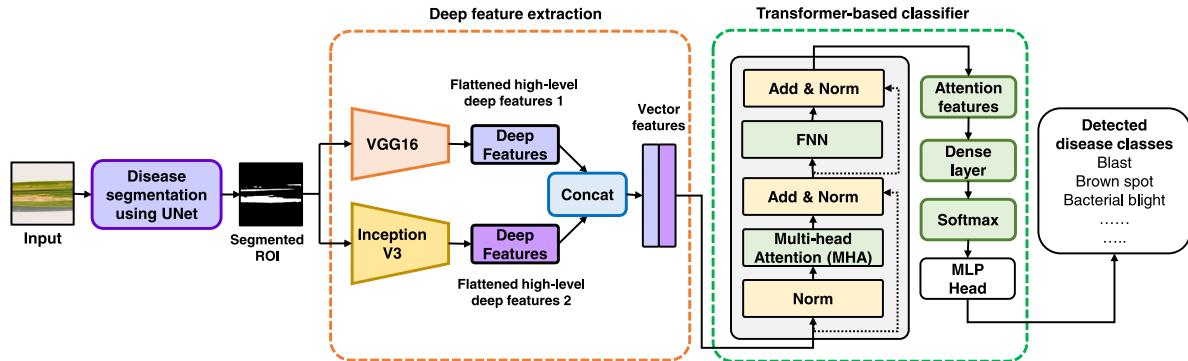


FIGURE 9. Illustrating the architecture of PLDPNet. Using UNet, the diseased part of the leaves are segmented which works as an input for the VGG19 and Inception-V3 models. The features extracted by these models are concatenated into a latent feature vector, which a ViT-based classifier uses to make the final disease prediction. This figure is inspired by Arshad et al. [42].

[96], [97], [98] and an overview of dataset utilisation and their associated limitations.

1) DATASET UTILISATION AND CHALLENGES

To develop an efficient paddy disease detection system to improve early disease detection and preserve agricultural yields diverse and accurately labelled datasets are required [3]. Conducting a comprehensive review of existing paddy datasets is imperative before initiating new data collection. It allows the researchers to assess the strengths and limitations of current datasets and strategise improvements for future collections. To assist researchers, an overview of open-access datasets related to paddy disease is provided in Table 2. The process of comprehensive and accurately labelled data collection for paddy disease detection faces several challenges such as the variability caused by manual image-capturing methods and environmental factors [99], [100], difficulty in acquiring images of rare diseases, ensuring consistent and uniform backgrounds [99], [101], managing complex environmental backgrounds [101], occlusion and visibility difficulties [7], [102], and the need for expert plant pathologists to accurately label and distinguish similar disease symptoms [20]. Lastly, a significant amount of funding and time is needed to execute the data collection process.

2) MOBILE AND WEB APPLICATIONS

This section emphasises the usage of DL in precision agriculture for immediate crop health monitoring and disease

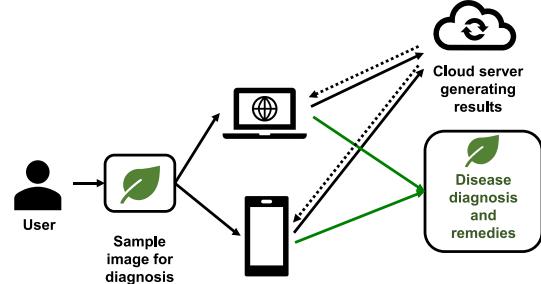


FIGURE 10. Illustrating disease diagnosis through web and mobile platforms, where users upload a test image to the application, which is then processed by a cloud-based server that returns a diagnosis report with remedies.

diagnosis by deploying mobile and web applications. Fig. 10 demonstrates the paddy disease diagnosis process via web and mobile platforms.

Zeng et al. [94] presented a compact CNN model named “lightweight dense-scale network” (LDSNet) for corn leaf disease diagnosis in complex environments. This model incorporated an innovative dual-dilation convolution (IDDC) block for advanced feature extraction and employs coordinated attention scale fusion (CASF) for precise feature localisation. They also developed a new loss function, named adaptive symmetric cross-entropy (ASCE) to enhance the parameter optimisation, accelerate model training, and minimise the effects of noise and outliers in the dataset. Pre-training data enhancement was achieved through contrast-limited adaptive histogram equalization (CLAHE)

[103]. Their model achieved a 95.4% accuracy on test data and was optimised for real-time use on mobile devices which had been further confirmed by the deployment viability on mobile platforms. The model's training utilised a dataset comprising six classes of maize diseases which was sourced from various sources.

Islam et al. [95] implemented a Flask-based web application leveraging a refined Xception [57] model via transfer learning to identify diseases in cotton leaves, attaining an accuracy of 98.70%. They also employed Particle Swarm Optimisation (PSO) for optimal feature selection. Their used dataset consisted of only two categories: fresh and diseased leaf. They also developed another web application that detects plant diseases with a 98.98% success rate, employing a transfer learning-based ResNet50 [56] model. Their evaluation was conducted on the PlantVillage [55] dataset with a simple background, which included various diseases of pepper plants (3 classes), potato plants (2 classes), and tomato plants (10 classes) lacking the variety of classes and complex environment [96].

Debnath et al. [97] employed a CNN for real-time brown spot disease detection in Paddy, using a specialised image processing tool for both preprocessing and feature selection. This tool marked the affected areas into specific classes for model training. They also developed a smart farming application allowing farmers to monitor crop health on mobile devices, enhancing decision-making for crop management. Babatunde et al. [98] enhanced a VGG16 model (MVGG16) achieving 98.79% accuracy in distinguishing between healthy and habanero-infected leaves. This model was utilised in a smartphone application that permits users to upload pictures for diagnosis and review diagnostic history.

Paddy disease detection system that incorporates a cloud-based machine learning application utilising VGG16 [58] and a smartphone application has been developed by Andrianto et al. [19]. The smartphone captures rice plant leaf images, transmits them to the cloud server, and then the cloud server sends the disease classification results to users. Their system demonstrated flawless training accuracy (100%), but experienced reduced accuracy (60%) during testing, indicating the presence of overfitting issues.

The models used in these applications [19], [94], [95], [97], [98] were not tested with samples with complex environments. Hence, with real-life samples with complex field environments, their performance may decline.

V. ANALYZING LITERATURE CATEGORIES

The models, algorithms, and applications detailed in Section IV have been systematically tabulated in Table 3, Table 4, Table 5, and Table 6 to facilitate comparative analysis and condensed overview. Table 3 and Table 4 comprises models utilising exclusively paddy datasets, while Table 5, and Table 6 includes models incorporating both paddy and other crop datasets.

VI. DISCUSSION ON RELEVANT RESEARCH AND DATASETS

The literature review reveals varied focuses in paddy disease detection research within the broader context of plant disease detection. Few of the studies focused on developing memory-efficient models for mobile or IoT devices, emphasising portability [2], [51]; while others prioritised accuracy, requiring significant computational power and limiting portability [3], [4], [13], [21], [39], [40], [41], [42], [43], [44], [64], [81]. Additionally, research goals varied from specific paddy disease detection [1], [2], [3], [4], [5], [6], [8], [9], [15], [19], [33], [34], [35], [63], [81] to general plant disease detection [13], [21], [39], [40], [41], [42], [43], [44], [51], [64]. Dataset considerations ranged from covering a few disease classes (less than 6) [1], [4], [6], [8], [9], [15], [19], [35], [40], [63] to a higher number of classes (more than 5) [3], [5], [13], [21], [33], [34], [39], [41], [42], [43], [44], [51], [64]—with the latter posing increased classification challenges due to overlapping symptoms. Furthermore, variations in image environments, spanning controlled settings [104], [105], intricate field conditions [34], [106], [107], and a combination of both [2], [108], [109], [110], were observed. Controlled environments yielded superior results, attributed to the mitigation of background challenges and noise in the field images. Lamba et al. [4] and Chen et al. [5] applied GAN-based data augmentation, while others relied on original data or traditional image augmentation techniques.

VII. DATA AUGMENTATION STRATEGIES

Data augmentation is essential in DL for generating large, diverse datasets that train robust models with enhanced generalisation, prevent overfitting and mitigate the need for costly and time-consuming new data collection [8], [9], [10], [33], [42], [51], [64]. Data augmentation can be executed pre-training or dynamically during training, where the latter approach eliminates the need for additional storage space and enhances efficiency [38]. The class imbalance can also be addressed by augmenting underrepresented categories, ensuring balanced training and improved model accuracy [5]. Data augmentation strategies are classified into two main categories: traditional and generative-model-based. A detailed chart outlining these strategies is provided in Fig. 11, with subsequent elaboration presented below. The research papers, particularly those concerning plant disease classification studies, that employ each augmentation strategy, have been identified and listed in Table 7.

A. TRADITIONAL DATA AUGMENTATION

Tools such as Python's ImageDataGenerator, Augmentor library, and PyTorch's built-in functionalities facilitate these augmentations [10], [38], [101]. Fig. 12 demonstrates the traditional augmentation strategies.

B. GENERATIVE MODEL-BASED AUGMENTATION

Generative model-based augmentation uses sophisticated algorithms to generate synthetic data and this category

encompasses three sub-categories: autoencoders (AE), variational autoencoders (VAE), and GAN.

- **GANs:** Traditional data augmentation methods can create new images but may compromise the linear relationship within raw images, which limits the diversity and variability of the generated images [5]. Various GAN variants serve distinct purposes and can be employed for data augmentation [111], [112], [113], [114], [115]. Lamba et al. [4] utilised GAN-based augmentation for paddy disease detection, while Chen et al. [5] employed traditional data augmentation paired with an enhanced DCGAN algorithm for generating low-resolution images. Wang et al. [116] proposed the generative adversarial classified network (GACN), combining a generator, discriminator, and classifier to enhance plant disease recognition. It enhances CNN accuracy by generating synthetic images for dataset balance and directly classifying plant diseases.
- **Autoencoder (AE) and Variational autoencoder (VAE):** Although AEs are not traditionally employed for new data generation, they are highly effective in data pre-processing, particularly in applications requiring denoising [123]. Meanwhile, VAEs overcome the issues of non-convergence and complex evaluation seen in GANs. Their capacity to control latent representations not only aids in representation learning but also enables the generation of meaningful samples in an unsupervised manner, making them highly efficient for data augmentation [124], [125]. However, original VAEs still face certain challenges, such as producing blurry images, having non-interpretable latent representations, being constrained by the unimodal nature of Gaussian priors, and suffering from the curse of dimensionality due to reliance on the L2-norm. To address the limitations, various adaptations have been developed tailored to specific application needs [124]. Among these, CVAE integrates VAEs with class-specific data generation enhancing targeted data generation for improved representation and classification, making it efficient for data augmentation [124], [126].

VIII. PERFORMANCE EVALUATION METRICS

Performance metrics assess a model's efficacy, providing insights into how well it aligns with the data. This enables us to fine-tune the model parameter to enhance efficiency [18], [64]. Table 9 and Table 10 summarise performance metrics for classification and segmentation tasks, detailing each metric's equation, description, and associated studies. Table 8 charts the total number of performance metrics used (excluding the confusion matrix) and references the studies corresponding to these metrics.

IX. RESEARCH GAPS

Identified research gaps in paddy disease diagnosis have been illustrated in Fig. 13 and details are provided below to provide

invaluable insights for future researchers to address these gaps.

- **Lack of large datasets:** To improve the accuracy of automatic disease detection systems, DL methods require extensive datasets for training entailing additional computational expenses [3], [100], [102]. At present, for comprehensive paddy disease benchmarks only the imbalanced 'Paddy Doctor' [34] dataset is available. Although data augmentation can artificially expand the dataset, it may sometimes result in decreased model accuracy [100]. Thus, there is a critical need for a balanced, diverse dataset of paddy diseases suitable for both field and laboratory research.
- **Detecting multiple diseases within a single crop:** Existing research on plant disease identification primarily focuses on detecting a limited range of diseases, typically considering only one disease per image and overlooking the possibility of concurrent diseases in plants [99], [100]. Object detection offers a promising solution by enabling the simultaneous identification of multiple diseases and instances within images and videos [99], [102].
- **Standard and accurate disease severity detection:** Disease severity measures the impact of diseases on plant growth and yield and for this varied estimation criteria across studies have been observed. The most common method calculates the ratio of lesion area to total leaf area [63], [99], [102]. So, establishing a standardised criterion for severity estimation is necessary. Additionally, the coexistence of multiple diseases within a plant complicates the severity estimation process [99]. Accurate severity assessment is crucial for predicting crop yield and guiding disease management [4]. Traditional visual estimates by plant pathologists are inefficient due to high costs and potential bias [99]. Thus, developing a standardised method for precise disease severity estimation is essential.
- **Lack of dataset containing several factors:** Several diseases may exhibit similar symptoms, complicating accurate diagnosis [41], [100]. Therefore, comprehensive diagnosis requires supplemental data, including pest details, geographic location, environmental conditions like weather patterns, soil characteristics, and information from various crop development stages. Such data can enhance the effectiveness of disease management and diagnostic systems [35], [65], [100].
- **Lack of segmentation data:** Semantic segmentation using DL is efficient for identifying plant diseases, as it involves detailed segmentation of objects in images, classifying each pixel based on training labels. This approach necessitates exact ground truth annotations for supervised training and delivers more accurate object localisation compared to bounding boxes. The absence of publicly accessible paddy disease segmentation datasets with masks presents a substantial challenge for new researchers in the field [99].

TABLE 2. Overview of open-access paddy disease datasets, detailing their limitations, the diseases covered, and the studies utilising these datasets.

Reference	Dataset	Location	Image resolution	Sample background	Image type	No. of images	No. of diseases	Name of paddy diseases	Limitations	Studies utilised
[34]	Paddy Doctor	Tirunelveli district of Tamil Nadu, India	1080 x 1440	Field	RGB	16225	12	Bacterial leaf blight (BLB), Bacterial leaf streak (BLS), Bacterial panicle blight (BPB), Black stem borer, Blast, Brown spot, Downy mildew, Hispa, Leaf roller, Tungro, White stem borer and Yellow stem borer	Heavily imbalanced: 450 (lowest class) - 2405 (highest class) images	[10], [33], [34], [53]
[106]	Mendeley Data: Rice Leaf Disease	Western tract of Odisha, India	300 x 300	Field	RGB	5932	4	Bacterial blight, Blast, Brown spot, and Tungro	Limited disease coverage, some classes augmented	[15], [66]
[104]	Kaggle, UCI Machine Learning Repository: Rice Leaf Diseases Dataset	Gujrat, India	Varies with samples	Plain white or black	RGB	120	3	Leaf smut, Brown spot, and Bacterial leaf blight	Limited disease coverage, low sample count, lacks complex environment coverage	[21], [37], [75]
[108]	Dhan-Shomadhan: Bangladeshi Local Rice	Bangladesh	1952 x 4160	Field and plain white	RGB	1106	5	Brown spot, Leaf scaled, Rice blast, Tungro, and Sheath blight	Limited disease coverage, low sample count, poor illumination in simple background data	None
[2]	No name was given to this dataset	Bangladesh Rice Research Institute (BRRI), Bangladesh	224 x 224	A mixture of field and plain	RGB	1426	8	False smut, Brown plant hopper (BPH), Bacterial leaf blight (BLB), Neck blast, Stem borer, Hispa, Sheath blight rot, and Brown spot	Low sample count, combination of different sample environments	[2]
[107]	Microsoft Rice Disease Classification Challenge	Egypt	500x400	Field	RGNI, RGB	Total: 7632 (RGNI: 3817, and RGB:3815)	2	Rice blast, and Brown spot	Limited disease coverage, heavily imbalanced: 2 (lowest class) - 518 (highest class) images	None
[109]	Kaggle: Rice leaf diseases in Taiwan	Taiwan	Varies with samples	Field, and 5 images with plain background	RGB	929	3	Rice blast, Brown spot, and Herbicide damage	Limited disease coverage, low sample count, combination of original and augmented data, non-uniform background, a combination of different sample environments	None
[110]	Kaggle: Philippines Rice Diseases	Philippines	224 x 224	A mixture of field and plain	RGB	1555	13	Bacterial leaf blight, Bacterial leaf streak, Bakanae, Brown spot, Grassy stunt virus, Narrow brown spot, Ragged stunt virus, Rice blast, False smut, Sheath blight, Sheath rot, Stem rot, and Tungro	Low sample count, poor illumination, combination of different sample environments	None
[117]	Kaggle: Rice Diseases Image Dataset	Unknown	Varies with samples	Plain white	RGB	3355	3	Brown spot, Hispa, and Leaf blast	Limited disease coverage, lacks complex environment coverage	None
[105]	Kaggle: Leaf Rice Disease	Southeast Sulawesi, Indonesia	Height 1920 (fixed), width varies with samples	Plain white	RGB	240	3	Bacterial leaf blight, Blast, and Turngo	Limited disease coverage, lacks complex environment coverage	[4]

TABLE 3. Overview of publications related to only paddy disease classification (Part 01).

Reference	Year	Dataset name and capturing location	Number of samples	Number of diseases	Diseases classified	Category of model	Methods	Highest accuracy (%)
[15]	2023	(1) Mendeley Data: Rice Leaf Disease [106]; Western Orissa, India (2) Imphal East District, Manipur, India	5932	5	Brown spots, Tungro, Blast, and Blight	Deep learning architectures: Classical CNN	Customised CNN	99.66
[35]	2021	Location unknown	2370	3	Brown spot, Hispa, and Leaf blast	Deep learning architectures: Classical CNN	Attention-based CNN	94.65
[34]	2022	Paddy Doctor [34]: Tirunelveli district of Tamil Nadu, India	16225	12	Bacterial leaf blight (BLB), Bacterial leaf streak (BLS), Bacterial panicle blight (BPB), Black stem borer (BSB), Blast, Brown spot, Downy mildew, Hispa, Leaf roller, Tungro, White stem borer, and Yellow stem borer	Deep learning architectures: Classical CNN	DCNN	88.84
[33]	2023	Paddy Doctor [34]: Tirunelveli district of Tamil Nadu, India	16225	12	Bacterial leaf blight (BLB), Bacterial leaf streak (BLS), Bacterial panicle blight (BPB), Black stem borer (BSB), Blast, Brown spot, Downy mildew, Hispa, Leaf roller, Tungro, White stem borer, and Yellow stem borer	Deep learning architectures: Classical CNN	Customised CNN	98.99
[37]	2021	Kaggle: Rice Leaf Diseases Dataset [104]: Gujarat, India	120	3	Bacterial blight, Brown spot, leaf blast	Deep learning architectures: Classical CNN	CNN	85.878
[118]	2022	Kaggle: location unknown	2000	4	Brown spot, Hispa, Bacteria leaf blight, and Leaf blast	Deep learning architectures: Classical CNN	Inception-v3, ResNet50, VGG16	91.86
[32]	2024	Not given	235	7	False Smut (FS), Sheath Blight (SB), Rice Blast (RB), Leaf Scald (LS), Brown Spot (BS), Bacterial Leaf Blight (BLB) and Bakane (BE)	Deep learning architectures: Classical CNN	AlexNet, DenseNet and ResNet	91.16
[2]	2020	No name was given to this dataset [2]: Bangladesh Rice Research Institute (BRRI), Bangladesh	1426	8	False smut, Brown plant hopper (BPH), Bacterial leaf blight (BLB), Neck blast, Stem borer, Hispa, Sheath blight, Sheath rot, and Brown spot	Deep learning architectures: Memory-efficient	CNN	93.3
[97]	2022	Not given	Not given	1	Brown spot	Implementations and practical applications: Mobile and web applications	CNN	97.01
[81]	2022	(1) Kaggle: Paddy leaf disease: location unknown (2) Kaggle: Paddy leaf images: location unknown	Not given	Not given	Not given	Application-specific model adaptations: Optimization algorithms and techniques	MUT-PSO, MUTPSO-CNN, CNN	(1) 92.39 (2) 97.36
[19]	2020	Kaggle: location unknown	1600	3	Brown spot, Leaf blast, and Hispa	Implementations and practical applications: Mobile and web applications	VGG16	60
[10]	2023	Paddy Doctor [34]: Tirunelveli district of Tamil Nadu, India	16225	12	Bacterial leaf blight (BLB), Bacterial leaf streak (BLS), Bacterial panicle blight (BPB), Black stem borer (BSB), Blast, Brown spot, Downy mildew, Hispa, Leaf roller, Tungro, White stem borer and Yellow stem borer	Deep learning architectures: ViT	Lesion-aware visual transformer, PLL	98.74

- Lack of high sensory image data:** RGB images are widely utilised for disease analysis due to their

cost-effectiveness and easy access. Nearly all open-access paddy datasets employ RGB imaging [34],

TABLE 4. Overview of publications related to only paddy disease classification (Part 02).

Reference	Year	Dataset name and capturing location	Number of samples	Number of diseases	Diseases	Category of model	Methods	Highest accuracy (%)
[4]	2023	(1) Mendeley Data: Rice Leaf Disease [106]: Western Odisha, India (2) UCI (Rice Leaf Diseases) [104]: Gujarat, India (3) Kaggle: location unknown (4) Github: location unknown	(1) 3024 (2) 80 (3) 80 (4) 351; in total 3535	3	Bacterial blight, Leaf smut, and Rice blast	Enhancing model performance: Hybrid	LSTM, CNN, GAN	97
[1]	2022	Online: BRRI, Plantix, IRRI, BRKB, Tamil Nadu horticultural college, India	Not given	4	Rice blast, Brown spot, Bacterial leaf blight, and Sheath blight	Enhancing model performance: Hybrid	CNN, SVM	93
[6]	2020	Plant Village [54], [55]: location unknown	60000	1	Rice blast	Enhancing model performance: Hybrid	CNN, SVM	96.8
[63]	2023	(1) Primary data: Patiala, Punjab State, India (2) Secondary: Mendeley Data: Rice Leaf Disease [106]: western Odisha, India (3) Secondary: Github: location unknown	(1) 152 (2) 1440 (3) 159; in total 1751	1	Rice blast	Enhancing model performance: Hybrid	CNN, SVM	Not given
[9]	2022	Kerala, India	2000	5	Bacterial leaf blight, False smut, Brown leaf spot, Rice blast, and Sheath rot	Enhancing model performance: Hybrid	CNN, SVM	88.93
[5]	2021	Not given	1100	12	Stackburn, Leaf smut, Leaf scald, False smut, Rice blast, Stem rot, White tip, Sheath rot, Stripe blight, Sheath blight, Bacterial leaf sheath blight, and Brown spot	Enhancing model performance: Transfer learning	DCGAN, MobileNet-V2	99.67
[8]	2022	Not given	Not given	5	Bacterial leaf blight, Leaf scald, Brown spot, Narrow brown spot, and Leaf blast	Enhancing model performance: Transfer learning	DCNN, modified VGG19	96.08
[66]	2023	Mendeley Data: Rice Leaf Disease [106]: Western Orissa, India	5932	4	Bacterial blight, Blast, Brown spot, and Tungro	Application-specific model adaptations: Segmentation techniques	SSA, RBFNN, GLCMWAA, black widow's k-means	Not given
[20]	2020	Not given	Not given	Not given	Not given	Application-specific model adaptations: Segmentation techniques	KMC, PCA, CNN	98
[75]	2023	Kaggle: Rice Leaf Diseases Dataset [104]: Gujarat, India	120	3	Leaf smut, Brown spot, and Bacterial leaf blight	Application-specific model adaptations: Segmentation techniques	Otsu, KMC, and colour thresholding	Not given
[65]	2023	Not given	276	3	Bacterial leaf blight, Blast, and Brown spot	Application-specific model adaptations: Segmentation techniques	RWW-NN, RWW, ROA, WWO, SegNet, CNN	90.8
[76]	2020	Ayikudi and Panpoli, Tirunelveli District, Tamilnadu, India	650	4	Bacterial blight, Blast, Sheath rot, and Brown spot	Application-specific model adaptations: Segmentation techniques	DNN_JOA	97
[82]	2024	Kaggle: Rice Diseases Image Dataset [117]: location unknown	Original: 3355, with augmentation: 10080	3	Brown spot, Hispa, and Leaf blast	Application-specific model adaptations: Segmentation techniques	DSGAN ² , ITNN, SMNS, S ² AFS, S ² O-FCW	99

[99], [104], [105], [106], [108], [109], [110], [117], with only one exception [107]. However, the demand for sophisticated disease diagnostic systems using

multi-spectral, hyperspectral, fluorescence, and thermal images is increasing. The utilisation of these images for disease diagnosis is described as follows:

TABLE 5. Overview of publications related to paddy and additional plant disease classification (Part 01).

Reference	Year	Dataset capturing location	Number of samples	Classes to classify	Diseases of different crops	Category of model	Methods	Highest accuracy (%)
[39]	2022	(1) USA (2) Unknown (3) Unknown (4) Unknown (5) Unknown	(1) 1821 (2) 46376 (3) 481 (4) 54305 (5) 560	(1) 4 (2) 93 (3) 4 (4) 38 (5) 5	(1) Apple: Not given (2) Embrapa: Not given (3) Maize: Not given (4) Plant village [54], [55]: location unknown (5) Rice: Not given	Deep learning architectures: ViT	ViT, CNN, PlantXViT	(1) 93.55 (2) 89.24 (3) 92.59 (4) 98.86 (5) 98.33
[21]	2022	(1) Kaggle: Rice Leaf Diseases Dataset [104]: Gujrat, India (2) Kaggle: Wheat Rust Classification Dataset: Location unknown (3) Plant Village [54], [55]: Location unknown	(1) 120 (2) 3679 (3) 54306	(1) 3 (2) 2 (3) 26	(1) Rice: Bacterial leaf, Brown spot, and Leaf smut (2) Wheat: Yellow rust, and Brown rust (3) Plant village [54], [55]: Location unknown	Deep learning architectures: ViT	ViT	Not given
[40]	2022	Uganda, Africa	21397	5	Cassava bacterial blight (CBB), Cassava brown streak disease (CBSD), Cassava green mottle (CGM), and Cassava mosaic disease (CMD)	Deep learning architectures: ViT	ViT, SPMM, LeIAP	Not given
[43]	2023	(1) Plant Village [54], [55]: Not given, (2) Embrapa: Not given	(1) 54305 (2) 46376	(1) 38 (2) 93	(1) Plant Village [54], [55]: Not given (2) Embrapa: Not given	Enhancing model performance: Hybrid	CNN, ViT	(1) 98.61 (2) 87.87
[41]	2023	(1) Apple: not given (2) Embrapa: Not given (3) Maize: Not given (4) Plant Village [54], [55]: Not given (5) Rice: Not given	(1) 1821 (2) 46376 (3) 481 (4) 54305 (5) 560	(1) 4 (2) 93 (3) 4 (4) 38 (5) 5	(1) Apple: Rust, Scab, and rest not given (2) Embrapa: Several crops and several diseases (details not given) (3) Maize: Eyespot, Goss's bacterial wilt, Gray leaf spot, and Phaeosphaeria spot (4) Plant Village [54], [55]: Several crops and several diseases (details not given) (5) Rice: Bacterial leaf streak, leaf scald, leaf smut, stack burn, and white tip	Enhancing model performance: Hybrid	VGG16, Inception-v7, ViT	(1) 93.55 (2) 89.24 (3) 92.59 (4) 98.86 (5) 98.33
[44]	2023	(1) Cereal: Not given (2) Fruits: Not given (3) Cash Crop: Not given (4) Vegetables: Not given	(1) 2631 (2) 2951 (3) 484 (4) 2930	(1) 24 (2) 35 (3) 9 (4) 38	(1) Cereal: Not given (2) Fruits: Not given (3) Cash Crop: Not given (4) Vegetables: Not given	Enhancing model performance: Hybrid	ResNet101, ViT, SE	88.34
[42]	2023	(1) Potato: Not given (2) Apple: Not given (3) Tomato: Not given	(1) 2152 (2) 3171 (3) 18160	(1) 4 (2) 4 (3) 10	(1) Potato: Early blight, Late blight (2) Apple: Scab, Black rot, Cedar rust (3) Tomato: Bacterial spot, Early blight, Late blight, Leaf mold, Septoria leaf spot, Two-spotted spider mite, Target spot, Mosaic virus, and Yellow leaf curl virus	Application-specific model adaptations Segmentation techniques	U-Net, VGG19, Inception-v3, ViT	(1) 97.63 (2) 96.42 (3) 94.25
[64]	2023	(1) Kaggle: location unknown (2) Kaggle: location unknown	(1) 2710 (2) 1000	(1) 6 (2) 2	(1) Rice: Bacterial leaf blight, Brown spot, Leaf blast, Leaf scald, and Narrow brown spot (2) Betel leaf: Healthy, Unhealthy (no specific disease mentioned)	Enhancing model performance: Hybrid	PlantDet (ensemble of Inception, ResNetV2, EfficientNetV2L, Xception)	(1) 98 (2) 97.5
[13]	2020	(1) Fujian Institute of Subtropical Botany, Xiamen, China (2) Fujian Institute of Subtropical Botany, Xiamen, China (3) Plant Village [54], [55]: location unknown	(1) 500 (2) 466 (3) 3852	(1) 6 (2) 5 (3) 4	(1) Rice: Stackburn, Leaf scald, Leaf smut, White tip, and Bacterial leaf streak (2) Maize: Phaeosphaeria spot, Maize eyespot, Grey leaf spot, and Goss's bacterial wilt (3) Maize: Gray leaf spot, Common rust, and Northern leaf blight	Enhancing model performance: Transfer learning	VGGNet, Inception	(1) 92 (2) 80.38 (3) 91.83

- **Multi-spectral images:** By capturing changes in reflectance, multispectral sensors effectively

identify high stress in plants across specific bands, including red, green, near-infrared, and red-edge.

TABLE 6. Overview of publications related to paddy and additional plant disease classification (Part 02).

Reference	Year	Dataset capturing location	Number of samples	Classes to classify	Diseases classified	Category of model	Methods	Highest accuracy (%)
[74]	2022	Not given	1000	2	Tomato and brinjal: not given	Application-specific model adaptations: Segmentation techniques	DCACNN, 2DCNN	98
[51]	2023	(1) Tropical areas of Pakistan (2) Bangladesh	(1) 1842 (2) 527	(1) 6 (2) 6	(1) Guava leaf diseases: Canker, dot, mummification, and rust (2) Guava leaf diseases: Phytophthora, Red rust, Scab, and Styler end rot	Deep learning architectures: Memory-efficient models	GLD-Det (modified MobileNet)	(1) 98 (2) 97
[95]	2023	Not given	2310	2	Not given	Implementations and practical applications: Mobile and web applications	CNN, PSO, Xception	98.7
[96]	2023	Not given	(1) 2475 (2) 2152 (3) 16012	(1) 3 (2) 2 (3) 10	(1) Potato: Early blight, Late blight (2) Pepper: Bacterial spot (3) Tomato: Bacterial spot, Early blight, Late blight, Leaf mold, Septoria leaf spot, Two-spotted spider mite, Target spot, Mosaic virus, and Yellow leaf curl virus	Implementations and practical applications: Mobile and web applications	CNN, ResNet50	98.7
[94]	2022	(1) Corn grey leaf spot: Plant Village [54], [55]: Not given (2) Corn northern leaf blight: Cornel University's Musgrave research farm in Aurora (3) Downy mildew, rust, gnawing beet armyworm, and healthy: Anqing City, Anhui province, China	3363	6	Corn: downy mildew, northern leaf blight, rust, gnawing beet armyworm, grey leaf spot disease	Implementations and practical applications: Mobile and web applications	CNN, IDDC, CASF, ASCE, CLAHE	95.4
[38]	2019	Not given	(1) 2575 (2) 3121 (3) 2903 (4) 3604 (5) 3007	(1) 2 (2) 2 (3) 2 (4) 2 (5) 2	Plant Village [54], [55]: (1) Apple: Scab (2) Maize: Rust (3) Grape: Measles (4) Tomato: Blight (5) Potato: Blight	Deep learning architectures: Classical CNN	CNN	97.5
[98]	2024	Not given	2475	2	Habanero	Implementations and practical applications: Mobile and web applications	Modified-VGG16	98.79
[53]	2023	(1) Paddy Doctor [34]: Tirunelveli district of Tamil Nadu, India (2) Plant Village [54], [55]: Not given	(1) 10407 (2) 54305	(1) 9 (2) 26 (including healthy)	Simplified Paddy Doctor [34]: Bacterial leaf blight (BLB), Bacterial leaf streak (BLS), Bacterial panicle blight (BPB), Blast, Brown spot, Downy mildew, Hispa, Tungro, Black stem borer Plant Village [54], [55]: Apple (5 classes), maize (3 classes), grape (4 classes), tomato (9 classes), potato (2 classes), pepper (2 classes), blueberry (1 class), cherry (2 classes), orange (1 class), peach (2 classes), raspberry (1 class), soybean (1 class), squash (1 class), & strawberry (2 classes).	Deep learning architectures: Memory-efficient	MobileNetV3, GAM, DRM	(1) 99.71 (2) 99.82

Furthermore, these images facilitate the diagnosis of plant diseases, weed presence, water stress, and nutrient deficiencies [99].

– **Hyperspectral images:** Hyperspectral imaging excels in detecting multiple disease signatures through its ability to capture extensive bands,

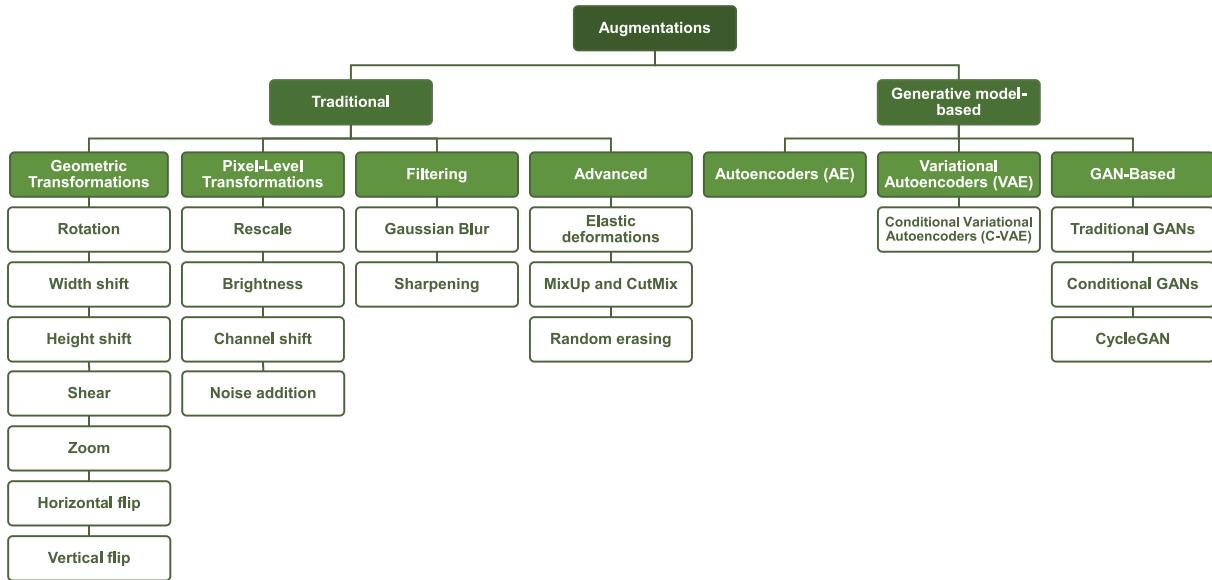


FIGURE 11. Illustration of augmentation strategies divided into traditional methods (geometric, pixel transformations, filtering, advanced techniques) and generative models (AE, VAE, GAN-based).



FIGURE 12. Samples of traditional data augmentation showing width shift, shear, zoom, elastic deformation, rotation, height shift, brightness shift, horizontal and vertical flip techniques.

TABLE 7. Classification of augmentation types and their associated studies.

Augmentation type	Associated study/referenced research
No augmentation	[3], [6], [7], [16], [18]–[21], [32], [34], [35], [39]–[41], [63], [65], [72], [75], [76], [81], [118], [119]
Traditional	[5], [8]–[10], [13]–[15], [33], [37], [38], [42]–[44], [51]–[53], [64], [66], [74], [94], [101], [120]–[122]
Generative model-based - AE & VAE	None
Generative model-based - GAN	[4], [5], [116]

providing in-depth spectral analysis for early disease identification. By merging conventional imaging and spectroscopy, it aims to evaluate each pixel's spectrum. However, the usage of

TABLE 8. Summary of performance measures and reference studies.

Total number of performance measures used (excluding confusion matrix)	Reference studies
1	[1], [2], [4], [10], [14], [32], [37], [38], [97], [120], [127]
2	[20], [75], [119]
3	[6], [9], [13], [40], [72]
4	[7], [18], [19], [21], [33]–[35], [44], [63], [65], [74], [95], [96], [98], [101], [121]
5	[3], [8], [16], [42], [51], [64], [82], [94], [122]
6	[5], [66]
7	[39], [41], [53]
10	[76]

hyperspectral images for disease detection faces limitations due to elevated acquisition costs and considerable memory requirements [99].

TABLE 9. Overview of performance evaluation metrics used in recent plant disease identification studies (Part 01).

Performance metric	Equation	Description of performance metric	Studies utilising performance metric
Accuracy (Acc) [‡]	$Acc = \frac{TP+TN}{TP+TN+FP+FN}$	Proportion of correct model predictions out of total predictions.	[1]–[10], [13]–[16], [18]–[20], [32]–[35], [37]–[39], [41]–[44], [51]–[53], [63]–[66], [72], [74], [76], [82], [94]–[98], [101], [119]–[122], [127]
Precision (Pr)/ Positive predicate value (PPV) [‡]	$Pr = \frac{TP}{TP+FP}$	The ratio of correct positive predictions to total positive predictions.	[5]–[9], [15], [18], [19], [21], [33]–[35], [39]–[44], [51]–[53], [63], [64], [66], [74], [76], [82], [94]–[96], [98], [101], [121], [122]
Recall (Rec) / Sensitivity (Sen) / True positive rate (TPR) [‡]	$Rec = \frac{TP}{TP+FN}$	Proportion of positive instances correctly identified.	[3], [5], [7]–[9], [13], [15], [16], [18], [19], [21], [33]–[35], [39]–[44], [51]–[53], [63]–[65], [72], [74], [76], [82], [94]–[96], [98], [101], [121], [122]
F_1 -score (F_1) [‡]	$F_1 = 2 \times \frac{Pr \times Rec}{Pr + Rec}$	Harmonic mean of precision and recall which creates a balance of precision and recall. When used in segmentation, it is called the dice similarity coefficient (DSC).	[3], [5], [7]–[9], [15], [16], [18], [19], [21], [33]–[35], [39]–[44], [51]–[53], [63]–[66], [74], [76], [94]–[96], [98], [101], [121], [122]
Confusion matrix (CM) [‡]	$CM = \begin{array}{c cc c} & PP & PN \\ \hline AP & TP & FN \\ \hline AN & FP & TN \end{array}$ <p>In this formula, AP: Actual Positive, AN: Actual Negative, PP: Predicted Positive, PN: Predicted Negative</p>	Evaluates classification model performance by comparing predicted to actual outputs.	[2], [6], [13], [15], [18], [19], [33], [37]–[39], [41], [42], [51]–[53], [63], [64], [74], [76], [94], [95], [98], [101]
Error rate (ER) [‡]	$ER(\text{segmentation}) = \frac{FP+FN}{TP+TN+FP+FN}$	The ratio of incorrectly classified instances against the total instances.	[75], [119]
Overlap rate (OR) [‡]	$OR = \frac{TP}{TP+FP+FN}$	Quantifies agreement between segmented and original mask images (only used for segmentation).	[75]
Mean intersection over union (mIoU) / Jaccard Index (JAC or JI) / Jaccard Similarity Coefficient (JSC)	$mIoU = \frac{1}{n} \sum \frac{\text{Area of overlap}}{\text{Area of union}}$	Measures similarity between ground truth and predicted masks at the pixel level (only used for segmentation).	[42]
Specificity (Sp) / True negative rate (TNR)	$Sp = \frac{TN}{TN+FP}$	The proportion of negative instances correctly identified.	[3], [5], [6], [8], [13], [16], [52], [53], [64]–[66], [72], [76], [82], [121], [122]

Note: For this table, TP represents True Positives, TN represents True Negatives, FP represents False Positives, and FN represents False Negatives.

‡ When Acc, Pr, Rec, F_1 , and ER are used for segmentation tasks and for OR:

TP: Pixels correctly classified in both segmented and original mask images; TN: Pixels correctly identified as not part of the segmented image in both images; FP: Pixels incorrectly marked in the segmented image, not in the original mask; FN: Pixels missed in the segmented image but present in the original mask.

- **Fluorescence and thermal images:** Fluorescence and thermal imaging techniques offer insights into plant health by revealing photosynthetic capacities and heat signatures, aiding in early disease detection. While fluorescence imaging detects variations in photosynthesis, its efficiency depends on controlled conditions. Thermal images enable the assessment of plant temperatures and hydration states, though their accuracy can be affected by external environmental factors [99].
- **Lack of UAV image data:** Despite the availability of open-access UAV datasets for plants, none focus on disease detection. There is a crucial need for UAV data targeting paddy diseases to facilitate the analysis of disease spread [99], [100]. UAVs operate at low altitudes for detailed imaging but face reduced operational time

due to battery constraints and additional sensor weights compromising the flight duration. Since high-altitude flights decrease spatial resolution, employing close-up methods like handheld or boom-mounted sensors is advantageous for capturing detailed disease lesions. Therefore, single images can be used for detailed disease analysis, while mosaics are effective in evaluating and observing disease coverage in the field [99].

- **Optimising disease segmentation:** For improved disease classification, segmentation is commonly performed as an initial or preprocessing step to isolate diseased regions, facilitating concentrated analysis. However, field images often include irrelevant elements such as grass and soil, complicating accurate disease segmentation and potentially degrading the disease identification performance [100]. Moreover, extensively

TABLE 10. Overview of performance evaluation metrics used in recent plant disease identification studies (Part 02).

Performance metric	Equation	Description of performance metric	Studies utilising performance metric
False positive rate (FPR)	$FPR = \frac{FP}{FP+TN}$	The ratio of incorrectly identified negative cases to total actual negatives.	[76]
False negative rate (FNR)	$FNR = \frac{FN}{TP+FN}$	The ratio of incorrectly identified positive cases to total actual positives.	[76]
False discovery rate (FDR)	$FDR = \frac{FP}{TP+FP}$	The ratio of incorrectly identified positive cases to total predicted positives.	[76]
Negative predictive Value (NPV)	$NPV = \frac{TN}{TN+FN}$	The ratio of correctly identified negative cases to total predicted negatives.	[76]
The area under the curve (AUC)	No equation is needed.	Area under the ROC curve.	[3], [16], [39], [41], [51], [66]
Frames per second (FPS)	No equation is needed.	Measures processing speed in real-time operations.	[53]
Floating point operations (FLOPs) / Giga floating-point operations per second (GFlops)	No equation is needed.	Assesses computational complexity and performance via floating-point calculations.	[21], [53]
Number of operations measured by multiply-adds (MAdds)	No equation is needed.	Counts multiplication and addition operations to measure computational complexity.	[94]
Loss function / Categorical cross-entropy loss (CCEL)	$CCEL = -\frac{1}{n} \sum_{i=1}^n y_i \log(\hat{y}_i)$ In this formula, n is the total number of samples in the batch, i is the observed sample, y_i is the actual class & \hat{y}_i is the predicted class.	Measures classification accuracy by calculating the negative log of predicted probability for the true class.	[20], [39], [41], [43], [51], [76]
Matthews correlation coefficient (MCC)	$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)(TN+FN)}}$	Evaluate binary classification quality.	[52]
Cohen's kappa score (CKS)	$\kappa = \frac{p_o - p_e}{1 - p_e}$ In this formula, p_o denotes the probability of agreement between observers & p_e denotes the hypothetical probability of agreement by chance among the observers.	Assesses agreement between observers in classification.	[39], [41]

Note: For this table, TP represents True Positives, TN represents True Negatives, FP represents False Positives, and FN represents False Negatives.

processed training data may lose resemblance to actual field images, leading to models that perform well on simplified data but poorly on complex real-world images [98]. This discrepancy can result in inaccurate disease detection in practical applications. Therefore, there is a need for a disease diagnosis system capable of effectively using segmentation to eliminate irrelevant background elements and identify disease regions.

- Lack of interpretability of DL results:** The interpretability of DL-based plant disease identification results can be enhanced by integrating Explainable AI (XAI), which offers visual heat maps to interpret the AI model's results [99]. These heat maps identify the critical regions of the image that the model analyses for accurate predictions [42], [51], [52], [120]. This approach not only aids in understanding but also fosters trust among users by making the model's workings transparent [64]. For instance, Shovon et al. [64] utilised Grad-CAM++ and Score-CAM for model prediction interpretability, while Thakur et al. [39] employed Grad-CAM and LIME. Apart from these two studies [39], [64], there is a lack of use of Explainable AI

(XAI) in existing research, highlighting a significant opportunity for further research in this area.

- Global paddy disease diagnosis:** The effectiveness of detecting diseases in paddy leaves is influenced by diverse environmental factors, creating challenges in building a universal plant disease diagnosis model [3]. Global datasets from different seasons and countries are vital for developing universally functional systems. Additionally, diseases with overlapping symptoms require supplementary environmental data, including external agents like insects, animals, weather, and soil conditions, for precise diagnosis. Further research is needed to create automated detection systems integrating location, weather, soil data, and plant images [2].

- Paddy disease severity analysis:** Accurate detection of paddy disease severity plays a pivotal role in yield estimation and formulating effective treatment strategies for affected plants [3]. An existing hybrid model designed for detecting paddy blast disease severity has been introduced by Lamba et al. [63]. However, this study is limited to a single disease, highlighting the need for further research. Moreover, despite the model

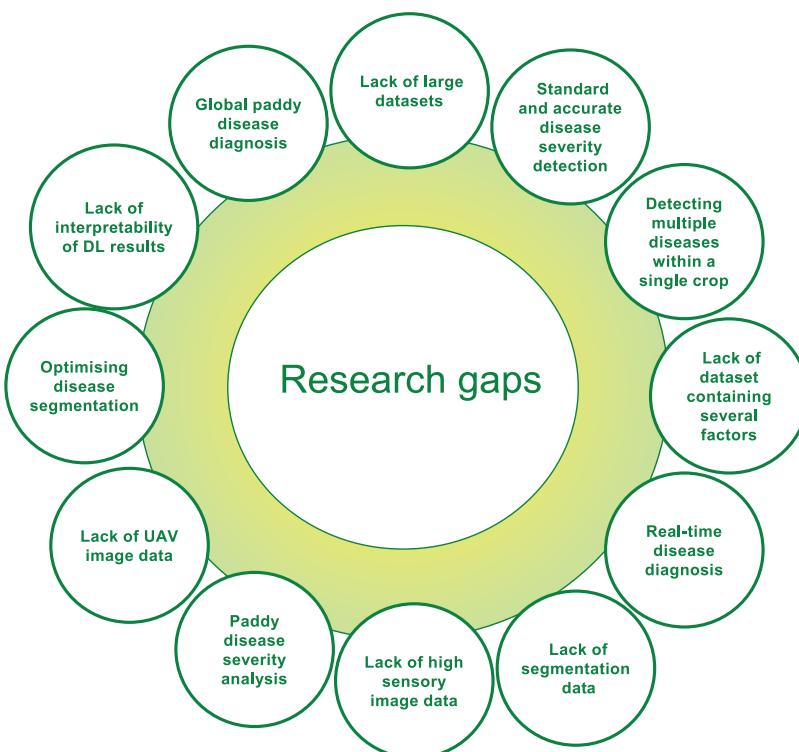


FIGURE 13. Illustrating twelve identified research gaps in this domain requiring immediate attention from the research community, including the lack of large datasets, segmentation data, and interpretability of deep learning results, among others.

proposed by Pal et al. [72] encompassing seven plant diseases, it lacks a standardized approach for extracting the diseased regions, which are crucial for subsequent severity analysis. Comprehensive efforts are required to classify diverse paddy diseases based on their severity levels. To achieve this, extensive data labelling covering a wider range of disease types is essential.

- **Real-time disease diagnosis:** Integrating drone and IoT technologies for real-time disease diagnosis [8] and developing smart robotics for efficient data collection [3] are shaping the future of precision agriculture. These innovations accelerate the disease detection processes, reduce training burdens, and pave the way for more sustainable farming practices [8]. Continued research in these fields is crucial to realising the full potential of these advancements.

The identified research gaps in computer vision-based paddy disease diagnosis emphasise the urgent need for focused research efforts. Bridging these gaps is vital for transformative progress in this field, enhancing accuracy and effectiveness.

X. CHALLENGES AND OPEN ISSUES

DL-based paddy disease detection encounters significant challenges, from the economic constraints faced by small-scale farmers to the complexities of data acquisition and model generalisation. These challenges highlight the

need for optimised models, accessible technologies, and accurate data collection methods to advance the field effectively. The challenges and open issues identified in this research domain are depicted in Fig. 14 and further details are provided below.

- **Economic feasibility and reach:** DL-based paddy disease detection face barriers in accessibility and affordability for small-scale farmers, particularly in developing countries due to high-end equipment requirements [3]. To address this, models need to be optimised for mobiles and IoT devices to ensure low memory usage and cost-effectiveness with or without utilising cloud servers [51]. Andrianto et al. [19] exemplify a cloud-based application allowing farmers to upload photos for disease identification without the burden of high-end computations. Ensuring technology access for all farmers worldwide necessitates diverse datasets and collaborations between researchers, farmers, and governments—enhancing the feasibility and practicality of the solution [3].
- **Data acquisition hurdles:** Collecting comprehensive, accurately labelled data for training DL models in paddy disease detection is a formidable task [3]. Challenges arise from the need for diverse data encompassing various diseases and pests, necessitating the expertise of field workers and plant pathologists. Incorrectly labelled data or low-quality images can hamper model accuracy.

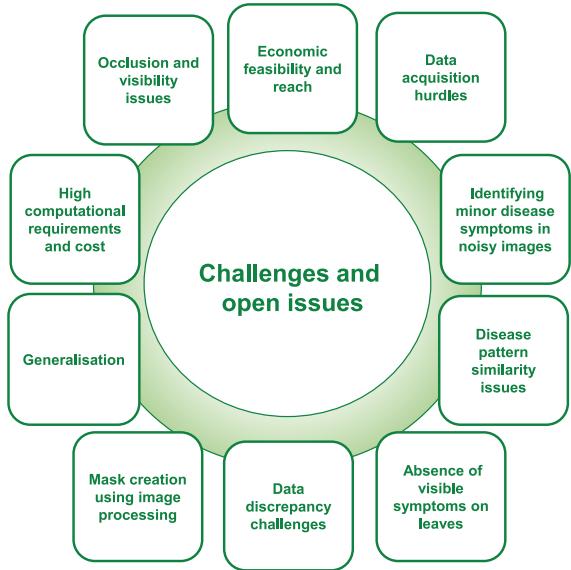


FIGURE 14. Illustrating the identified ten challenges and open issues within this domain including disease pattern similarity issues, generalisation, and high computational requirements and cost, among others.

Variability in images captured with handheld devices, caused by uncontrolled sensor height and angle, further complicates data collection. However, this issue can be alleviated by mounting cameras and sensors on booms or autonomous systems. It standardises height and angle and ensures more consistent data collection [99]. Moreover, images taken over time are subject to changes due to factors such as moisture, environmental conditions, and light intensity [100]. These issues with the image collection process, emphasise the importance of high-quality images, which are challenging to secure, particularly for rare diseases. The data acquisition process is time-consuming, expensive, and reliant on significant funding.

- **Data discrepancy challenges:** DL models in smart agriculture face challenges in generalising to new data, particularly when the data characteristics differ. Images captured by drones or IoT devices often feature plants against complex field backgrounds. However, some data samples have plain white or black backgrounds, leading to poor performance when tested on complex backgrounds. For example, datasets with distinct backgrounds impact model performance significantly—as seen in [19] and [35] (white background) and [33], [34] (complex field backgrounds). Fig. 15 presents a selection of environment samples. Models trained on the former and tested on the latter exhibit subpar results, whereas the reverse scenario artificially inflates performance metrics which potentially leads to inaccurate assessments of model capabilities. To enhance generalisation, maintaining consistent backgrounds and scenarios in both the training and testing part of the

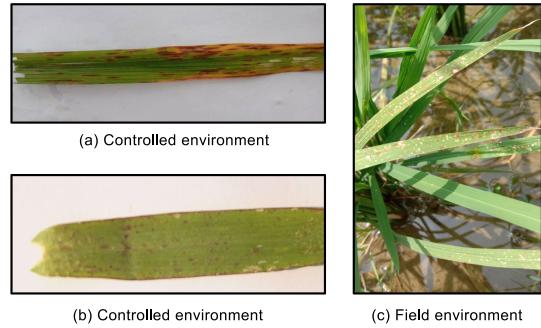


FIGURE 15. Sample images from controlled and field environments.

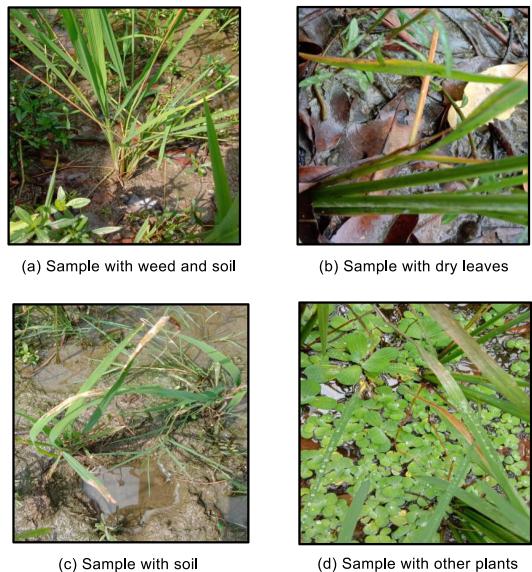


FIGURE 16. Sample of weed, soil, dry leaves and other plants introducing challenges in the field environment.

dataset is crucial. Additionally, the presence of weeds and soil in field images introduces colour interference, posing challenges for accurate disease detection on leaves [101]. Fig. 16 illustrates how weeds and soil in field images cause colour interference, complicating the detection of diseases on leaves. Models trained on images with unclear symptoms struggle to detect them accurately during testing, even when visible symptoms are present. Fig. 17 displays samples of blurry and top-view images, leading to inadequate model learning.

- **Identifying minor disease symptoms in noisy images:** Misrecognition can occur in images with complex, noisy backgrounds, particularly in low-resolution field images, where minor disease symptoms are frequently discarded as noise during the noise reduction processes. Implementing attention mechanisms can help the models to focus on relevant information and disregard the irrelevant, addressing these issues effectively [102].
- **Disease pattern similarity issues:** Several paddy diseases exhibit overlapping symptoms, complicating accurate diagnosis. For instance, Brown spot and Leaf smut

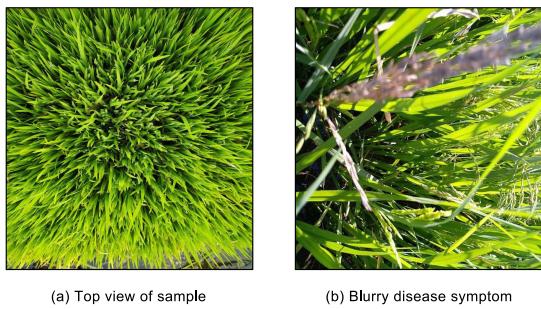


FIGURE 17. Sample of images with unclear disease symptoms including samples taken from a top view, and with blurriness around disease areas.

both exhibit circular dark brown lesions on leaves [1], [2], [15], [18], while Bakanae and Bacterial blight are characterised by yellowing leaves [9], [17], [25], [26]. The difficulty in differentiating these diseases poses significant challenges. Accurate disease identification is crucial for the effectiveness of the complete paddy disease management system [41], [99], [100].

- **Absence of visible symptoms on leaves:** Some plant diseases may not manifest visible symptoms on the leaves but rather on other parts of the plant, such as the roots or lower stems. For example, diseases such as Bakanae or Footrot exhibit no visible symptoms on the leaves; instead, symptoms appear on the roots [17], [25], [26]. Since most diagnostic systems primarily focus on leaf disease identification, they often neglect other critical factors. This can lead to diseases remaining undiagnosed until they reach advanced stages.
- **Mask creation using image processing:** The creation of segmentation masks via image processing is susceptible to errors and might require potential manual adjustments. The variability in lesion shapes (e.g., spot, round, oval, taper, spindle) and colours (e.g., yellow, white, brown, black, reddish black, grey) complicates the process. Assumptions about symptom shape or colour may not hold across different samples, and shadows with colours similar to diseases could be incorrectly identified [20], [119].
- **Generalisation:** Generalisation means a model's ability to accurately classify previously unseen images. Generalisation is divided into two types: same-dataset and cross-dataset generalisation. Same-dataset generalisation occurs when a model is tested on unseen images from its training dataset, typically resulting in high accuracy due to identical data acquisition conditions. On the other hand, cross-dataset generalisation involves testing the model with images from varied datasets and conditions, which often leads to reduced accuracy due to increased complexity [99]. High cross-dataset generalisation accuracy is essential for models to identify disease features across various agricultural settings, mirroring the diagnostic skills of expert plant pathologists [20]. However, current models underperform in cross-dataset

performance, emphasising the need for robust models adaptable to diverse data [3], [99].

- **High computational requirements and cost:** DL models usually demand substantial computational resources for training and operation, with some recent models featuring increased complexity due to larger sizes and more layers [3], [98]. For instance, ViT-based models necessitate advanced computing capabilities, posing challenges in resource-constrained environments like rural areas where such technology might not be accessible to farmers [3], [21], [39], [40], [41], [42], [43], [44]. To address this gap, the development of lightweight mobile models, such as MobileNets [45], [47], NasNet Mobile [48], and SqueezeNet [50], is essential. These models can be integrated into applications for farmers, offering a practical solution for plant disease detection in settings with limited resources.

- **Occlusion and visibility issues:** Occlusion and illumination challenges significantly impact image analysis due to varying light conditions and complex backgrounds, complicating object recognition [7], [102]. Despite these difficulties, advancements in DL have progressively improved plant disease identification in such conditions, laying a solid foundation for practical applications [66], [102]. However, further research is necessary to enhance the handling of images from real-life environments.

Addressing these above-mentioned challenges is crucial for advancing paddy disease management. Overcoming such hurdles requires concerted efforts in research, model optimization, and collaborative data collection to enhance agricultural outcomes globally.

XI. RESEARCH METHODOLOGY

For the literature collection, we have focused on image-based techniques for plant (mainly paddy) disease identification and classification and selected publications from 2020 to June 2024 to ensure current and relevant content. Then, we have provided a categorised and tabularised analysis of the collected literature. Additionally, we have analysed the existing open-access paddy disease datasets highlighting their strengths and limitations for giving insights for making new data collection plans. Moreover, we have identified the research gaps, challenges, and open issues within this domain. Fig. 18, provides a comprehensive visual representation of the entire process.

XII. FUTURE WORK

Our future goals encompass implementing a small-scale model for the effective paddy diseases diagnosis utilising publicly available datasets [2], [34], [104], [105], [106], [107], [108], [109], [110]. Additionally, due to the lack of an open-access paddy disease segmentation dataset, we aim to develop one to address this research gap. A comparative analysis assessing the suitability of leading segmentation



FIGURE 18. Illustrating the ten-step research methodology employed in this seven-month intensive survey study, including our significant contributions: literature categorisation and analysis, an overview of open-access paddy disease datasets, and identification of research gaps, open issues, and challenges.

models for paddy disease segmentation will be conducted to explore their adaptability to this domain.

XIII. CONCLUSION

Considering the constraints associated with population expansion, climate change, and limitations of manual paddy disease diagnosis, a computer vision-based paddy disease detection and classification has become vital for effective disease management with the potential to assist in ensuring global food security [1], [3], [5], [6]. In this research, we have presented a summary of the most prevalent paddy diseases, their visible manifestations, and their causing factors. To help researchers plan future data collection with improvements and new features, an overview of the open-access paddy disease datasets has been presented identifying their strengths and limitations. We have assembled and categorised the latest research and highlighted the research gaps that still need to be addressed. Furthermore, we have identified open issues and challenges in this research field. For further advancement of precision agriculture, this analysis will assist the upcoming researchers in addressing these identified research gaps and managing the challenges and open issues effectively.

CONFLICTS OF INTEREST

The authors confirm that they do not have any conflicts of interest to disclose.

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