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A Data-Centric Review of AI-Based Rice Disease Detection Challenges in Generalization, Dataset Diversity, and Varietal Representation

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***Abstract*—This paper presents an analysis of AI-based rice disease recognition from the perspective of data-related problems, such as issues associated with generalization and variety representation. Although deep learning architectures, especially CNNs, have demonstrated excellent classification results in controlled experiments, their ability to perform adequately in field settings is still questionable. A systematic narrative review covering peer-reviewed literature published from 2015 to 2025 was conducted. As a result, we observe that all existing models heavily depend on datasets containing samples collected under highly consistent environmental conditions and relatively few varietals. As a result, there is a risk of overfitting, and the models' generalization becomes problematic. At the same time, one important limitation identified during our research is the lack of diversity among rice varieties used in existing models, namely, black rice. The study interprets the data issue as a representational bias.**

***Index Terms*—Artificial intelligence, CNN, dataset diversity, plant disease detection, rice disease classification, varietal representation.**

I. INTRODUCTION

Rice is an important factor that influences global food security, especially in countries such as India, where it provides employment and sustenance for many families. Diseases that affect rice include blast, bacterial leaf blight, and brown spot. These diseases affect the rice yield and reduce its quality. Manual disease detection involves inspecting the leaves and applying one's expertise to identify signs of diseases, which is both tedious and unreliable.

However, artificial intelligence (AI), specifically deep learning, offers a promising approach to automated disease detection in plants. CNNs have shown great promise in accurately classifying various plant diseases using leaf images. Notwithstanding these developments, a vital challenge still persists.

Current models undergo training on controlled data that lacks variability regarding the environment in which the data is captured. As such, deploying these models in practical scenarios proves difficult. Furthermore, underrepresented rice varieties, such as black rice, are not represented in current datasets.

This paper seeks to (i) investigate the current methods used in rice diseases detection based on AI, (ii) analyze the weaknesses associated with the use of varied datasets, and (iii) identify any deficiencies in terms of varietal representation. This research takes a data-oriented approach, underscoring the need for improved datasets.

II. LITERATURE REVIEW

In the field of rice disease detection, there has been a shift in research from conventional machine learning techniques that use manually engineered features towards deep learning architectures that allow for automatic feature extraction. Deep CNN architectures, including ResNet, VGG, and EfficientNet, have emerged as preferred options because of their classification precision.

For instance, Mohanty et al. [1] and Ferentinos [2] showed the superiority of deep learning by achieving accuracies exceeding 95%, employing the PlantVillage database. Later on, researchers incorporated transfer learning and ensemble learning to enhance model performance, which was mostly an improvement on a marginal scale and depended on controlled datasets.

One of the main challenges highlighted in the literature is the use of curated datasets with consistent backgrounds and optimal lighting conditions, which can achieve higher accuracies but lack realistic representation. Studies employing field images have reported comparatively lower accuracies, indicating limitations in model generalizability under real-world conditions [5], [13], [15].
Another important challenge is dataset homogeneity. The majority of the studies considered only a few types of rice and diseases, thus implicitly assuming homogeneity among crops. This is questionable since there is morphological variation among different rice varieties.
Moreover, varieties like black rice, which fall under underrepresented classes, are not included in current data sets. This creates a representational bias problem because the model cannot generalize to other crops outside the training data set. Several studies suggest that dataset diversity has a greater influence on model robustness and generalization capability than architectural complexity alone [13], [15].
From all the above, it can be concluded that deep learning algorithms perform excellently in terms of accuracy, but their application faces challenges due to dataset inadequacy.

III. METHODOLOGY

A. Study Design
For the analysis of AI-based disease detection studies, a systematic narrative review strategy will be used. Different from meta-analysis which focuses on statistical aggregation of studies, this strategy offers the possibility to engage in critical interpretative synthesis especially when seeking for structures like datasets' biases, non-generalization of research findings, underrepresentation of different varieties.
The research methodology follows PRISMA criteria for reporting of systematic reviews and meta-analyses but remains flexible enough for incorporating qualitative approaches applicable in multidisciplinary areas like AI applications in agricultural studies.

B. Data Sources and Search Strategy
The literature survey was conducted using databases including Scopus, Web of Science, IEEE Xplore, SpringerLink, and Google Scholar.
Publications dated from 2015 till 2025 have been sought to account for transition from machine learning models to the deep learning ones.
The following Boolean search expressions were used during the literature search process: “rice disease detection,” “deep learning” AND “CNN,” “plant disease classification,” “dataset diversity” OR “generalization,” and “crop variety” AND “AI.”
To specifically investigate varietal representation issues, additional search queries such as “black rice disease detection,” “pigmented rice dataset,” and “underrepresented crop varieties AI” were also utilized.

C. Inclusion and Exclusion Criteria
The inclusion criteria consisted of studies that explored rice disease detection using ML/DL techniques, provided empirical findings or methodological insights, and were peer-reviewed articles written in the English language.
Studies were excluded if they focused on unrelated crops without transferable insights, lacked clear methodological information, or were non-peer-reviewed sources such as blogs, editorials, and abstracts.

D. Selection of Studies
The study selection process followed three major stages: title and abstract screening, full-text eligibility assessment, and final study selection.
The initial identification was estimated between 80-100 studies, out of which 40 studies were selected for analysis.

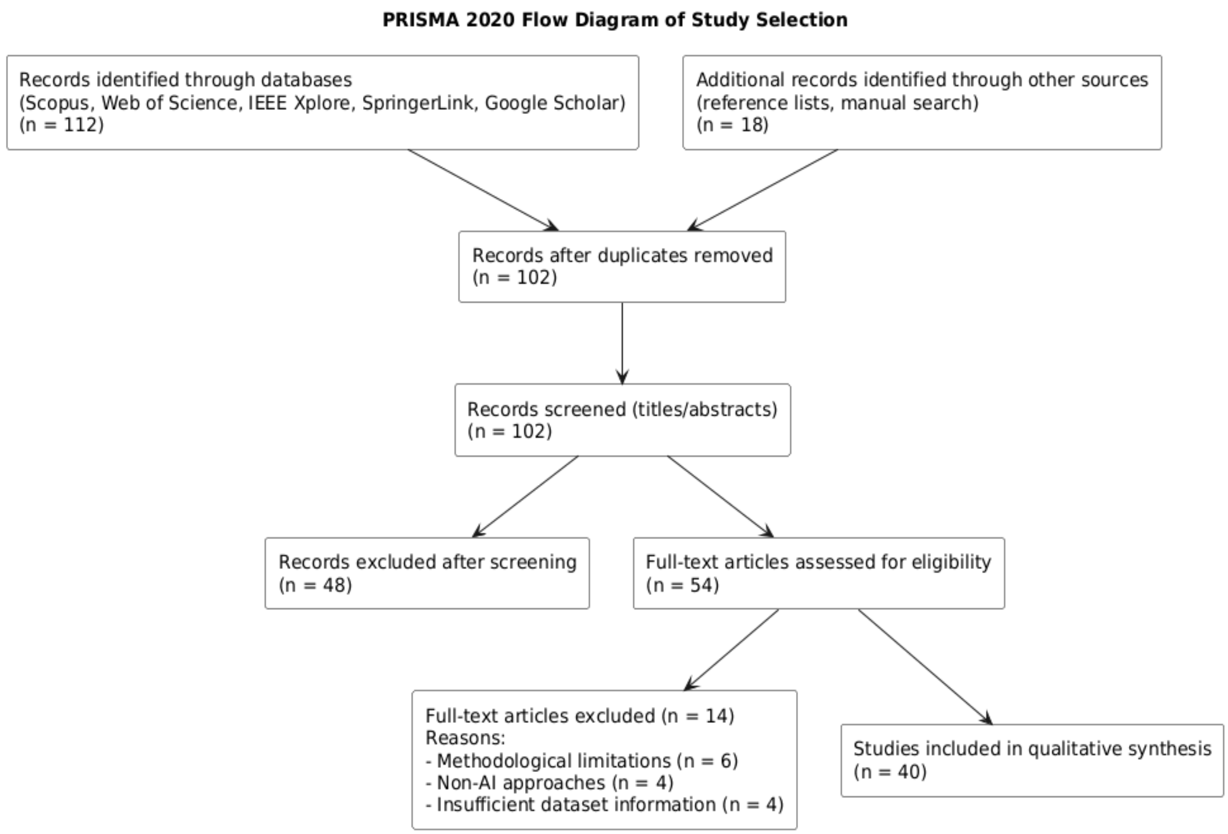

Fig. 1. PRISMA Flow Diagram of Study Selection Process

The PRISMA flow diagram shows how studies were systematically filtered, ensuring the transparency and reproducibility of the review process.

E. Data Extraction

For each selected study, information regarding model architecture (CNN, ResNet, etc.), dataset type (controlled or field-based), number of classes or varieties, performance metrics (accuracy, precision, and recall), and identified limitations was extracted and analyzed.

Particular attention was paid to dataset diversity, environmental variability, and representation of different rice varieties.

F. Analytical Strategy

The studies were grouped into thematic categories such as CNN-based models, transfer learning models, ensemble learning models, and dataset-specific studies.

The analysis additionally evaluated dataset representativeness, generalizability, and practical applicability.

IV. RESULTS

Patterns of artificial intelligence (AI)-based rice disease detection have been identified through a systematic review. Table I is a summary of these studies, which included methodology, performance, and limitations.

Table I clearly indicates that studies based on controlled datasets have achieved greater accuracy than studies utilizing real-world datasets.

A. Prevalence of Deep Learning Models

Deep CNNs are the most prevalent models, which demonstrate accuracies above 90–99%. Further improvement can be made by using transfer learning with pre-trained models like ResNet and MobileNet, reducing training time.

Nevertheless, these high accuracies are mostly achieved under controlled datasets, suggesting their sensitivity to idealistic conditions.

B. Relationship Between Dataset Properties and Model Performance

One of the most important discoveries of the study is the significant relationship between dataset properties and model performance:

Controlled datasets such as PlantVillage demonstrated very high accuracies ranging from 95% to 99% with minimal variance. In contrast, field datasets achieved comparatively moderate accuracies of approximately 85%–93% and exhibited larger variability in performance.

These findings suggest that the level of realism of a dataset influences model robustness.

C. Lack of Diverse Datasets

The majority of available datasets represented only a small number of rice species, included limited disease classes, and lacked geographical diversity. Consequently, many AI models became highly tailored to specific datasets and demonstrated poor generalization capability.

D. Lack of Varieties

One of the important findings is the lack of black rice and other similar pigmented varieties in existing data sets.

This indicates the presence of bias in dataset design and highlights the failure to include diverse rice varieties in existing research.

E. Generalization Problem

Very few studies examined cross-dataset analysis or evaluated models under different environmental conditions. These findings suggest that current research primarily prioritizes accuracy over model generalization.

Table I Summary of Ai-Based Rice Disease Detection Studies (2015–2025)

No.	Author (Year)	Method / Model	Dataset	Classes	Accuracy	Key Contribution	Limitation
1	Mohanty et al. (2016)	CNN (AlexNet, GoogLeNet)	PlantVillage	38	99.35%	Pioneered deep learning for plant disease	Controlled dataset; no field conditions
2	Ferentinos (2018)	Deep CNN	Multi-crop dataset	58	99.53%	Multi-disease classification	Limited real-world variability
3	Too et al. (2019)	Transfer Learning (VGG, ResNet)	PlantVillage	11	~97%	Compared pretrained models	Overfitting on small datasets
4	Sladojevic et al. (2016)	CNN	Leaf dataset	13	96.3%	Early automation of disease detection	Small dataset size
5	Picon et al. (2019)	CNN + Field Images	Real-field images	9	93%	Focus on real-world applicability	Lower accuracy than lab datasets
6	Lu et al. (2017)	CNN	Rice leaf dataset	6	95.48%	Rice-specific disease detection	Limited disease classes
7	Zhou et al. (2019)	Deep CNN	Rice dataset	10	96%	Improved feature extraction	Dataset imbalance
8	Chen et al. (2020)	CNN + Data Augmentation	Rice dataset	10	97.2%	Improved performance via augmentation	Still controlled conditions
9	Li et al. (2024)	Deep CNN	Rice leaf dataset	12	96%	Multi-class rice disease detection	Poor generalization

10	Latif et al. (2022)	Optimized CNN	Rice dataset	9	95%	Model optimization	Limited dataset diversity
11	Karthik et al. (2020)	CNN	Indian rice dataset	8	94%	Region-specific study	Small dataset
12	Rahman et al. (2020)	CNN + MobileNet	Field images	7	95%	Mobile deployment	Reduced field accuracy
13	Arsenovic et al. (2019)	Deep Learning	Large dataset	26	93%	Large-scale dataset analysis	Imbalanced classes
14	Brahimi et al. (2017)	CNN	PlantVillage	14	98%	Demonstrated CNN superiority	Dataset bias
15	Kamilaris & Prenafeta (2018)	Review	Multiple	—	—	Survey of deep learning in agriculture	No experimental validation
16	Seelwal et al. (2024)	Review	Multiple	—	—	Identified dataset gaps	No varietal focus

V. DISCUSSION

A. Model Effectiveness Versus Practicality

The results indicate a critical dilemma:

Highly effective models cannot sustain accuracy in practical settings.

This observation aligns with findings reported in previous studies regarding dataset bias and limited generalization capability in agricultural AI systems [13], [15].

This is not a flaw in the algorithms; it is an issue in the data.

B. Data Diversity as a Crucial Factor

The research confirms that:

Data diversity carries more weight than model intricacy.

Non-diverse datasets contribute to overfitting, generalization errors, and reduced practical effectiveness of AI models.

C. Representation Bias and Varietal Discrimination

One of the critical contributions of this research is that it redefines the problem with data sets as one of representation bias.

The omission of varieties such as black rice results in insufficient feature extraction, dataset bias, and limited practical utility of the developed models.

This points to an even wider problem: AI reflects the biases inherent in its data.

D. Research Directions in the Future

Future research should focus on collecting real-world datasets, incorporating diverse crop species, adapting AI models to limited-data environments through domain adaptation, and utilizing multispectral imaging techniques.

VI. LIMITATIONS

Limitations of the study include its reliance on secondary sources and available databases. There is no mention of testing of any of the AI models in question. It is worth noting that some new publications might not be included in the database search due to their recent publication dates. This notwithstanding, the paper offers a comprehensive data-focused assessment of issues in AI-based detection of rice diseases.

VII. CONCLUSION

This work shows that even though there have been many advancements in AI-based rice disease detection, the usefulness of such algorithms is hindered by the limitations of the data used in training them due to a lack of variety, including underrepresented types like black rice.

It becomes clear that future endeavors should focus on changing the perspective from a model-oriented one to a data-oriented one, taking into account issues of dataset diversity and ethical considerations.
Addressing these challenges can significantly improve the reliability and practical applicability of AI-based rice disease detection systems.
Further research must center on creating rice disease datasets on a larger scale that incorporate geographical diversity and a variety of different rice strains so that the AI-based agricultural system can become more effective.

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