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Lenet Based Deep Learning Convolutional Neural Networks of Low to Moderate Spatial Resolution for Recognition of Sheath Blight Disease of Rice (Sheath blight disease detection)

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Abstract- This study evaluated a comparative performance of LeNet models, specifically configured for low to moderate ($LeNet_{4x4}$-$LeNet_{32x32}$) spatial resolutions to detect sheath blight disease in rice (*Oryza sativa* L.). Models were developed using Kaggle data-set comprising 7075 disease and 2970 healthy images partitioned into 80:20:: training: validation. LeNet exhibited strong classification performance, particularly at highest spatial resolution ($LeNet_{32x32}$), which achieved F1-score of 0.99 for both disease and non-disease classes with an overall accuracy of 99.67%. $LeNet_{4x4}$ produced compact feature maps with fewer parameters, which although showed effective performance, but was limited in specificity. However, at higher resolutions ($LeNet_{16x16}$/$LeNet_{32x32}$), model yielded improved feature representations, thereby, producing increased sensitivity and specificity. Models showed strong Pearson's correlation coefficient between training and validation accuracy (PPCr=0.8250*-8973**), highlighting reliable alignment and stability. These findings underscore the scalability and adaptability of LeNet models for disease detection, with high-resolution models proving particularly effective for precision tasks in rice disease management.

Keywords: Automatic disease detection; DL models; CNNs; sheath blight of rice; spatial resolution

I. Introduction

Sheath blight caused by *Rhizoctonia solani* Kühn has been amongst the most destructive diseases of rice, next just to rice blast [1]. Yield losses due to sheath blight vary from ~20–50%, reliant upon severity [2]. It grows slowly at initial growing stages, but increases quickly at tillering and advanced stages [3]. Its typical symptoms are greenish-gray colored water-soaked lesions appear on the leaf sheath and spread to upper plant parts causing leaf desiccation and affect grain filling [4-5].

Rice (*Oryza sativa*), a staple crop cultivated on ~11% of global arable land which experience a significant threats from sheath blight. The traditional disease detection methods trust profoundly on farmers' experience and visual inspection, and are often subjective and prone to errors [6]. A limited access to expert support and analytical tools further challenges effective disease management [7]. Advancements in deep learning (DL) particularly convolutional neural networks (CNNs) are emerged as robust tools for computerized disease detection through image analysis [8]. Several machine learning and DL models (e.g., decision trees, random forests, support vector machines, SVM) and CNN architectures (e.g., AlexNet, VGG, Inception and Xception) showed high accuracy in crop disease classification [9-11]. However, limited evidence is available on the application of LeNet-based CNNs for sheath blight detection [12].

Therefore, the present study focuses on developing and evaluating LeNet models across low (4×4 pixels) to moderate (32×32 pixels) spatial resolutions using a large *Kaggle* dataset (80:20 training: validation split). The study aims to assess the efficiency of lightweight DL models for accurate and scalable sheath blight detection. Such approaches can enable timely diagnosis, improve disease management, reduce yield losses, and support sustainable rice production systems.

II. Methodology

Data collection and pre-processing

A LeNet-based deep learning CNN model was established to categorize sheath blight disease in rice using an online dataset sourced from *Kaggle* (https://www.kaggle.com/). The dataset comprised 10,045 images, including 7,075 diseased and 2,970 healthy samples. These images were partitioned as 80% for training and 20% as validation data-set. To improve computational efficiency and reduce storage requirements, all images were pre-processed prior to model training. The images were resized to multiple spatial resolutions (4×4, 8×8, 16×16, and 32×32 pixels) to evaluate model performance under varying levels of image detail. This approach enabled a systematic comparison of classification accuracy across different resolutions. Following pre-processing, the images were subjected to segmentation and subsequently used for classification through the LeNet model.

LeNet model architecture

LeNet, a pioneering CNN architecture introduced by LeCun [13], has demonstrated strong adaptability in image classification tasks, including agricultural disease detection [10]. Although originally designed for handwritten digit recognition, its capability to capture fine spatial features makes it suitable for identifying disease symptoms in crop images. The design comprised of sequential convolutional and pooling layers, followed by fully connected layers for classification. Convolutional layers extract essential visual features such as texture, color variation, and lesion patterns associated with sheath blight. Pooling layers reduce spatial dimensions while preserving critical information, thereby improving computational efficiency. The mined structures were then conceded through fully connected layers, where the model performs classification. A softmax function at the output layer assigns probabilities to each class, enabling differentiation between diseased and healthy samples. This structured pipeline ensures effective feature learning and accurate classification.

Segmentation and feature extraction

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Image segmentation was achieved using the k-means clustering technique to isolate diseased areas from healthy leaf areas. Based on visual assessment, three distinct clusters were identified, and the algorithm was implemented with k = 3 to achieve optimal segmentation. Contour tracing was applied to accurately delineate leaf boundaries, ensuring precise isolation of infected regions. Following segmentation, key features related to color and texture were extracted using the co-occurrence matrix method, as described by Yakkundimath et al. [6]. This integrated approach of segmentation and feature extraction enhanced the model's ability to detect subtle disease patterns, thereby improving classification performance.

III. Results

Max-pooling output shape and trainable parameters

The LeNet models exhibited a clear increase in structural complexity with rising spatial resolution (Table 1). At lower resolutions (4×4 and 8×8), the first convolutional layer generated compact feature maps with identical trainable parameters (4,864). Progressive convolution and pooling reduced dimensionality, producing flattened outputs of 32 (LeNet4×4) and 128 (LeNet8×8). Dense layers enabled higher-level abstraction, resulting in total parameters of 70,390 and 81,910, respectively. At higher resolutions (16×16 and 32×32), feature representation expanded substantially. Flatten outputs increased to 512 and 2,048, reflecting improved capacity to capture spatial variability. Correspondingly, dense layer parameters rose sharply, with total parameters reaching 1,27,990 and 3,12,310. Across all models, trainable parameters aligned with total parameters, indicating efficient learning. Feature map representations are illustrated in Figure 1.

TABLE 1. Max-pooling output-shape (P_{Max}) and total parameters (TPs) and number of trainable parameters (NTPs) for the LeNet model of low (4x4 pixels) to moderate (32x32 pixels) spatial variability for identifying sheath blight of rice.

Layer type	**LeNet$_{4x4}$**		**LeNet$_{8x8}$**	
	P_{Max}	**NTPs**	**P_{Max}**	**NTPs**
Conv#2D	(None, 4, 4, 64)	4,864	(None, 8, 8, 64)	4,864
Average_pooling#2D	(None, 2, 2, 64)	0	(None, 4, 4, 64)	0
Conv2#D-1	(None, 2, 2, 32)	51,232	(None, 4, 4, 32)	51,232
Average_pooling#2D_1	(None, 1, 1, 32)	0	(None, 2, 2, 32)	0
Dropout	(None, 1, 1, 32)	0	(None, 2, 2, 32)	0
Flatten	(None, 32)	0	(None, 128)	0
Dense	(None, 120)	3,960	(None, 120)	15480
Dense-1	(None, 84)	10,164	(None, 84)	10164
Dense-2	(None, 2)	170	(None, 2)	170
TPs	--	70,390	--	81,910
NTPs	--	70,390	--	81,910
	LeNet$_{16x16}$		**LeNet$_{32x32}$**	
Conv#2D	(None, 16, 16, 64)	4,864	(None, 32, 32, 64)	4,864
Average_pooling#2D	(None, 8, 8, 64)	0	(None, 16, 16, 64)	0
Conv2#D-1	(None, 8, 8, 32)	51,232	(None, 16, 16, 32)	51,232
Average_pooling#2D_1	(None, 4, 4, 32)	0	(None, 8, 8, 32)	0
Dropout	(None, 4, 4, 32)	0	(None, 8, 8, 32)	0
Flatten	(None, 512)	0	(None, 2048)	0
Dense	(None, 120)	61,560	(None, 120)	2,45,880
Dense-1	(None, 84)	10,164	(None, 84)	10,164
Dense-2	(None, 2)	170	(None, 2)	170
TPs	--	127,990	--	3,12,310
NTPs	--	127,990	--	3,12,310

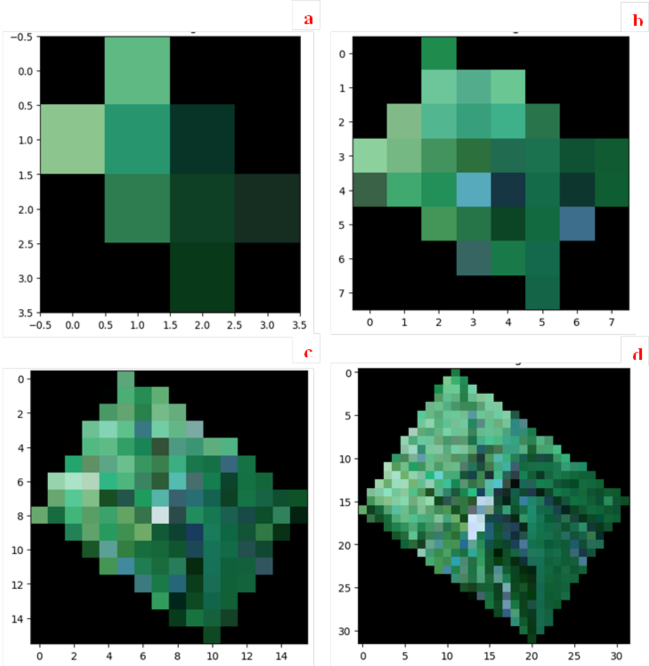

Fig 1. Grid (or matrix layout) representing feature maps or activations from specific layers of the LeNet model of low (4x4 pixels) to moderate (32x32 pixels) resolution for identifying sheath blight of rice. (Lenet$_{4x4}$ (a), Lenet$_{8x8}$ (b), LeNet$_{16x16}$ (c) and LeNet$_{32x32}$ (d)).

Training metrics for LeNet models

Training performance demonstrated strong scalability across resolutions (Table 2; Figure 2). Lower-resolution models stabilized quickly. Training time declined sharply after the first epoch, averaging ~1.5–2.1 seconds. Higher-resolution models required longer computation, with LeNet$_{32\times32}$ stabilizing around 16 seconds per epoch.

TABLE 2. Training set metrics for LeNet models of low (4x4 pixels) to moderate (32x32 pixels) resolution for identifying sheath blight of rice.

Model acronym	**Optimal epochs to train the model**	**Time to train (in sec)**	**Average training loss**	**Training loss after attaining optimal epochs**
LeNet$_{4x4}$	10	1.60	0.0336	0.0196
LeNet$_{8x8}$	7	2.11	0.0223	0.0125
LeNet$_{16x16}$	10	5.30	0.0123	0.0019
LeNet$_{32x32}$	9	15.94	0.0357	0.0133
	TAM[a]	**Training accuracy**	**PPCr[b,c] for training vs. validation accuracy**	**Training F-1 score**
LeNet$_{4x4}$	0.9918	0.9897	0.534^{NS}	0.9947
LeNet$_{8x8}$	0.9947	0.9964	0.8250*	0.9986
LeNet$_{16x16}$	0.9957	0.9955	0.8967**	0.9987
LeNet$_{32x32}$	0.9941	0.9967	0.8973**	0.9984

[a]TAM=Training average matric, [b] PCCr=Pearson's coefficient of correlation, [c] Significance at $p<0.05$, $p<0.01$ and non-significant are marked as *, ** and NS, respectively.

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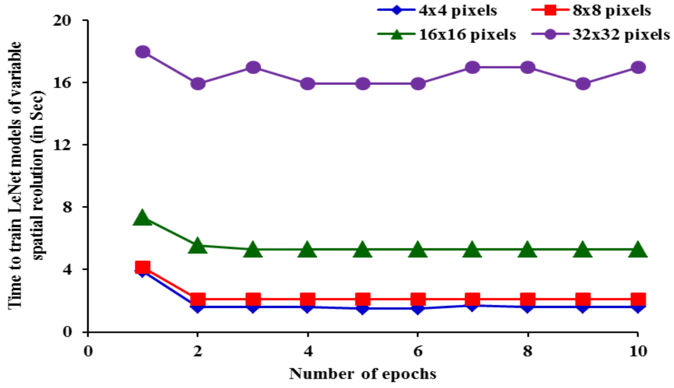

Fig 2. Time to train LeNet model of low (4x4 pixels) to moderate (32x32 pixels) resolution for identifying sheath blight of rice across epochs.

All models converged within 7–10 epochs. The LeNet$_{4\times4}$ model achieved 0.9897 accuracy and an F1-score of 0.9947 with minimal loss. The LeNet$_{8\times8}$ model further improved performance, reaching ~0.9964 accuracy and 0.9986 F1-score, with significant correlation between training and validation metrics. Higher-resolution models (16×16 and 32×32) showed marginal gains in precision. F1-scores approached ~0.999, with highly significant correlation coefficients. These results confirm consistent accuracy, low loss, and strong generalization across all resolutions. Confusion matrices are presented in Figure 3.

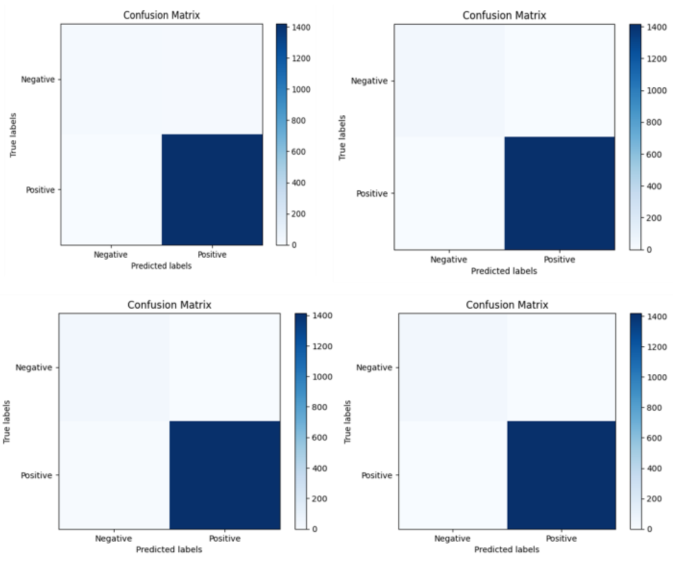

Fig 3. Confusion matrix of the LeNet model of low (4x4 pixels) to moderate (32x32 pixels) resolution for identifying of sheath blight of rice. (LeNet$_{4x4}$ (a), LeNet$_{8x8}$ (b), LeNet$_{16x16}$ (c) and LeNet$_{32x32}$ (d)).

Validation metrics for LeNet models

Validation metrics indicated excellent predictive performance (Table 3). Accuracy exceeded 98% for all models, with the highest (~99.69%) in LeNet$_{32\times32}$. Precision remained consistently high, reaching ~99.87% in higher-resolution models. Sensitivity values ranged from 99.64% to 100%, confirming reliable detection of diseased samples. Specificity improved with resolution, increasing from 55.88% (4×4) to above 91% in higher models. False positive rates declined accordingly, particularly in LeNet$_{8\times8}$. Overall, higher resolutions ensured better balance between sensitivity and specificity, enhancing classification reliability.

TABLE 3. Validation set metrics for LeNet models for identifying of sheath blight of rice.

[a] FPR= Validation false positive rate, [b] TNR=Validation true negative rate, [c]FNR=Validation false negative rate.

Model	Loss	Acuracy	Precision	Sensitivity/Recall
LeNet$_{4x4}$	0.0240	0.9923	0.9895	1.0000
LeNet$_{8x8}$	0.0456	0.9929	0.991	0.9972
LeNet$_{16x16}$	0.0531	0.9889	0.9987	0.9964
LeNet$_{32x32}$	0.0555	0.9969	0.9987	0.9994
	Specificity	**FPR[a]**	**TNR[b]**	**FNR[c]**
LeNet$_{4x4}$	0.5588	0.4412	0.5682	0.00001
LeNet$_{8x8}$	0.9972	1.0000	1.0000	0.00280
LeNet$_{16x16}$	0.9742	0.9892	0.6669	0.00001
LeNet$_{32x32}$	0.9146	0.9972	0.6789	0.00001

Training and validation loss and accuracy vis-à-vis epochs

All models showed a steady increase in accuracy and a consistent decline in loss with epochs (Figures 4 and 5). The LeNet$_{4\times4}$ model achieved ~99.46% training accuracy with low validation loss, indicating stable learning. The LeNet$_{8\times8}$ model demonstrated rapid convergence and strong generalization. The LeNet$_{16\times16}$ and 32×32 models achieved near-perfect accuracy (>99.8%) with minimal loss, reflecting superior optimization. An inverse relationship between accuracy and loss was evident (Figure 6). Lower resolutions showed relatively higher validation loss, suggesting limited feature capture. In contrast, moderate resolutions achieved minimal loss (~0.0127), indicating better learning of disease patterns.

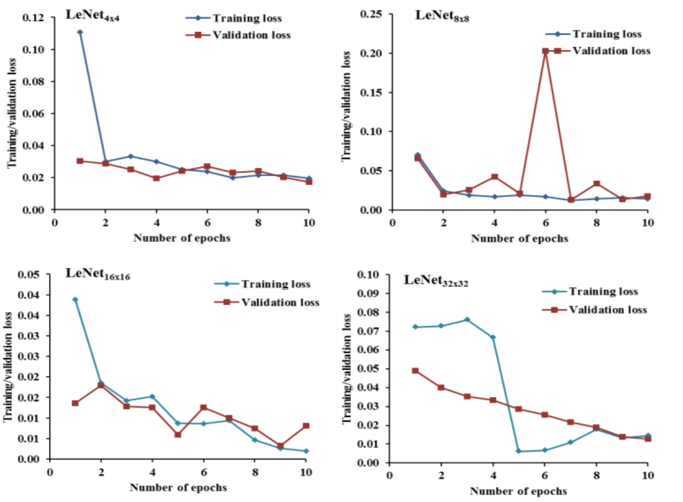

Fig 4. Training and validation loss for LeNet model of low (4x4 pixels) to moderate (32x32 pixels) resolution for identifying of sheath blight of rice across epochs.

Performance indices of LeNet models

Performance indices improved consistently with resolution (Table 4). The LeNet$_{4\times4}$ model achieved high overall accuracy (~99%) but showed lower precision for negative class detection. In contrast, the LeNet$_{32\times32}$ model delivered near-perfect performance. F1-scores approached 0.99 for both classes, with balanced precision and recall. Macro and weighted averages confirmed superior classification efficiency. These findings demonstrate that increasing spatial resolution enhances feature representation, leading to more accurate and reliable detection of sheath blight disease in rice.

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TABLE 4. Performance indicators of LeNet models for identifying of sheath blight of rice

	Precision	Recall	F1-score	Support
$LeNet_{4x4}$				
0	1.00	0.56	0.72	34
1	0.99	1.00	0.99	1419
Accuracy				1453
Macro-average	0.99	0.78	0.86	1453
Weighted average	0.99	0.99	0.99	1453
$LeNet_{8x8}$				
0	0.89	1.00	0.94	34
1	1.00	1.00	1.00	1419
Accuracy			1.00	1453
Macro-average	0.95	1.00	0.97	1453
Weighted average	1.00	1.00	1.00	1453
$LeNet_{16x16}$				
0	0.85	1.00	0.92	34
1	1.00	1.00	1.00	1419
Accuracy			1.00	1453
Macro-average	0.93	1.00	0.96	1453
Weighted average	1.00	1.00	1.00	1453
$LeNet_{32x32}$				
0	1.00	0.99	0.99	34
1	1.00	1.00	1.00	1419
Accuracy			1.00	1453
Macro-average	1.00	1.00	0.99	1453
Weighted average	1.00	1.00	1.00	1453

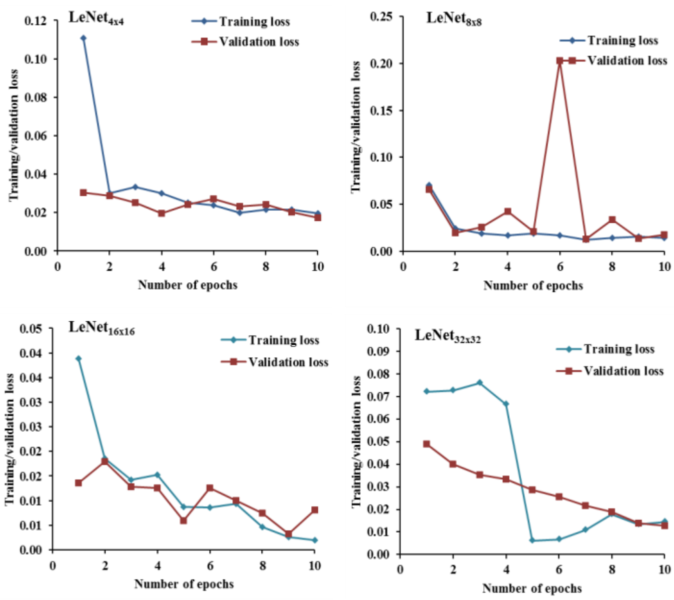

Fig 5. Training/validation accuracy for LeNet model of low (4x4 pixels) to moderate (32x32 pixels) resolution for identifying sheath blight of rice across epochs.

IV. Discussion

The swift and precise identification of rice diseases is crucial to sustaining rice production and safeguarding global food security [14]. It is essential to explore automated recognition methods for common rice diseases to enable early detection, and accurate diagnosis, thereby minimizing crop loss and enhancing crop yields [15-16]. Advances in computational power and the rapid expansion of data have pushed DL algorithms to impressive levels of performance, leading to widespread applications in fields such as speech recognition, image processing, and natural language processing [8, 17].

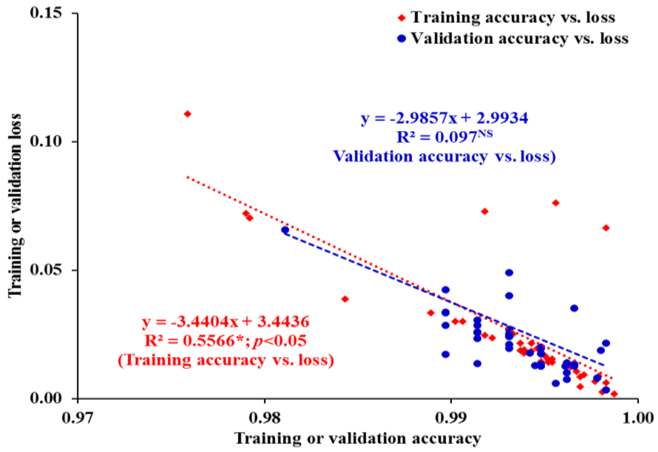

Fig 6. Relationship between training or validation accuracy vis-à-vis training or validation loss for LeNet model of low (4x4 pixels) to moderate (32x32 pixels) resolution *for identifying of sheath blight of rice*

Similar to these findings, earlier studies have consistently shown that training and validation accuracy tend to improve with an increasing number of epochs in DL models for rice disease detection [11]. For instance, Jayaraju and Banu [18] reported a similar trend using the VGG-16 model for rice disease recognition, and reported a steady increase in accuracy with training progression. Similarly, Rasjava et al. [19] observed a sharp rise in training accuracy in their CNN model tailored for rice plant disease identification. Li et al. [20] also reported a decrease in training loss alongside a rise in training accuracy for disease identification in rice ecosystems using images, affirming the model's learning efficiency. Further, Adi et al. [21] reported improvements in both training and validation accuracy with corresponding declines in loss using a CNN model for rice disease identification. Latif et al. [10] similarly found that DL models achieved higher accuracy in both training and validation phases when using an improved CNN for detecting rice plant diseases, underscoring the robustness of DL approaches in precision agriculture. Bhattacharya et al. [22] developed a CNN models using 2 hidden-layers aimed at categorizing 3 diseases viz. bacterial-blight, blast-and brown-spot using a two-stage classification approach. Inititally, model partitioned 1500 rice leaf images into healthy and diseased categories, and subsequently, the second stage, classified 500 images per disease type, and achieved ~94% accuracy for healthy vs. infected leaves and ~78.44% accuracy in identifying the three specific diseases. In another study, Shrivastava et al. [23] assessed the effectiveness of various pre-trained DL-CNN models for classifying rice plant diseases from a data-set of 1216 real-world images using 10 different models viz. Xception, MobileNet, DenseNet169, ResNet152V2, Inception_V3, InceptionResNet_V2, AlexNet, VGG-16, NasNetMobile and NasNetLarge, focusing on eight disease classes plus a healthy category. Among these, VGG-16 achieved the highest classification accuracy at 93.11%, suggesting its potential utility as a diagnostic tool in agricultural advisory systems.

The results of the present study which developed LeNet models using *Kaggle* data-set comprising large data-set (7075 disease + 2970 healthy) partitioned into a training: validation ratio of 80:20 showed model particularly at highest spatial resolution ($LeNet_{32x32}$) exhibited strong classification performance (F1-score=0.99; accuracy=99.67%). These results revealed outstanding performance with higher accuracy rates by ~21.5% over the SVM based supervised learning applied for classifying rice diseases [24]. Rozaqi and Sunyoto [25] developed a method to accurately detect early and late blight in potato leaves using deep learning with CNNs, by training data-set after splitting in 70: 30 for training and validation phases and, processing images in batches of 20 across 10 epochs.

Their [25] approach achieved an accuracy of ~92%, showing lower rates of accuracy than the application of $LeNet_{32x32}$ model developed and executed for rice sheath blight disease detection in the present study. Jiang et al. [26] pioneered a hybrid approach by combining CNNs to abstract comprehensive structures from rice disease images with SVM for classification and prediction of four rice diseases, and achieved an impressive accuracy of 96.8%. Shah et al. [27] conducted a relative study evaluating the performance of DL models, including Inception_V3, VGG-16, VGG-19 and ResNet50 on a data-set comprising rice blast and healthy leaf samples, and reported that amongst these architectures, ResNet50 exhibited the highest accuracy ~99.75%, indicating its superior effectiveness in distinguishing between diseased and healthy rice leaves in this classification task.

Mannepalli et al. [28] applied the VGG-16 model to classify 3 diseases of paddy ecosystems (viz. bacterial leaf blight/blast/brown spot) and attained cataloguing accuracy of ~97.7% on a public data-set. Similarly, Mohapatra et al. [29] developed a DL-CNN architecture to identify 4 diseases of paddy (viz. brown spot/blast/bacterial blight/Tungro), and achieved high accuracy (~97.47%). Poorni et al. [30] engaged the Inception_V3 model to recognize bacterial blight, brown spot and bacterial leaf streak disease and attained accuracy level of 94.48%. Rahman et al. [31] adapted large models (e.g., VGG-16 and Inception_V3) for detecting rice diseases and pests, and introduced a compact CNN suitable for mobile applications, with this lightweight model attaining an accuracy of 93.3%. An overall accuracy achieved in these studies [28-31] on rice disease detection was substantially lower than the results of $LeNet_{32x32}$ model developed for sheath blight disease detection in rice ecosystems.

Tejaswini et al. [32] examined 3 diseases (hispa (500 images)/brown spot (400 images)/leaf blast (300 images)) vis-à-vis 400 healthy plant images using multiple DL models viz. VGG-16, VGG-19, ResNet, Xception and a custom 5-layer CNN. Among these models, the 5-layer CNN showed the highest accuracy at 78.2%, while VGG-16 achieved a lower accuracy of 58.4%. In a study by Shivam et al. [12], researchers combined two rice leaf image data-sets for disease identification. The first dataset contained 120 images spanning three disease classes viz. brown spot, bacterial leaf and leaf smut, while the second data-set included 2092 images with a healthy category and three infected classes. The merged data-set comprised 2212 images, divided into 523 healthy and 1689 infected samples was preprocessing involved normalization to ensure consistent pixel values, followed by an 80:20 split into training and validation sets using three DL models viz. VGG-19, LeNet5 and MobileNet-V2. Their [12] results indicated that VGG-19 and MobileNet-V2 outperformed LeNet5, achieving higher accuracy and lower loss rates in rice disease identification. However, a lower accuracy even with small dataset comprising 1600 images (disease + healthy) [32] and 2212 images (disease + healthy) underscores the robustness of $LeNet_{32x32}$ model developed on large data-set (7075+2970; disease + healthy images).

These results demonstrate that the $LeNet_{32x32}$ model, developed on an extensive data-set with high-resolution images, substantially outperformed prior deep learning approaches in rice disease detection. Achieving an accuracy of ~99.67% and an F1-score of 0.99, the $LeNet_{32x32}$ model exhibited superior precision in classifying rice sheath blight, significantly surpassing traditional SVM methods and various CNN architectures in previous studies. This model's performance underscores the efficacy of high-resolution, large-scale datasets and DL frameworks for advancing precision agriculture, offering a promising tool for rapid, reliable, and scalable disease diagnosis in rice ecosystems.

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