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Capsule Networks for Rice Leaf Disease Classification

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Abstract

Deep Learning is a high-performance machine learning approach that combines supervised machine learning and feature learning. It is built of a sophisticated models with numerous hidden layers and neurons to create advanced image processing models. DL has proven its effectiveness and resilient in different fields including big data, computer vision, image processing, and many others. In agriculture, rice leaf infections are a frequent and pervasive issue that lower crop and output. This research proposed a reduced form of Capsule Network (Caps NET), a form convolutional neural network, for the classification of rice leaf disease. The goal of the suggested Caps NET model was to assess the suitability of various feature learning models and enhance deep learning models' capacity to learn about rice leaf disease classification. Caps NET was fed images of both healthy and infected leaves. High classification performance was obtained with the ideal configuration (FC1 (960), FC2 (768), and FC3 (4096)), which had 96.66% accuracy, 97.25% sensitivity, and 97.49% specificity.

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1. Introduction

Half of the world's population relies primarily on rice as their main source of food, particularly in Asia. Millions of smallholder farmers depend on rice production not only as a source of income but also as a crucial nutrient source [1]. However, there are several biotic and abiotic pressures that must overcome in order to produce rice sustainably. Rice infections are one of the most harmful aspects to the quality and yield of rice [2] [3]. Due to its significant effect on rice production and crop losses, rice leaf diseases are a serious concern for both researchers and farmers. Signs of leaf disease including sheath blight, bacterial leaf blight, blast, leaf spots, and others are among the most common rice leaf diseases [4]. Disease outbreaks in areas that cultivate rice are dynamic due to the intricate relationships that exist across viruses, host rice, and environmental variables [5].

Integrated data sources such as historical disease records, symptom patterns, environmental conditions, and growing conditions are combined to help build systems that produce precise forecasts and recommendations for a high quality and healthy rice production. These systems use machine learning algorithms to analyse large data and assist in the diagnosis and detecting of rice diseases. [5], [6]. Highly advanced computer-aided diagnosis methods for agricultural illnesses have been made possible by recent developments in Artificial Intelligence (AI)., AI has proved its efficiency in different applications including distinguishing animals, humans and other organisms such as plants, and many other applications [7]. Convolutional neural networks (CNNs), one type of deep learning algorithm, is used widely to identify and categorize illness signs from digital photos of crop leaves. CNNs have the ability to diagnose illnesses with great accuracy, often better than human specialists, by learning from enormous collections of annotated images [8].

Caps NETs, which are a form of CNNs, are able to identify diseases with a high degree of accuracy—often surpassing that of human [9] although automated diagnosis tools have demonstrated potential in a number of agricultural settings, there is still an absence of research on how to classify rice leaf diseases using these systems. The viability and efficacy of Caps NET in precisely diagnosing and classifying rice leaf diseases have not been thoroughly studied. A noteworthy investigation exhibited the capacity of deep learning methodologies for rice stress phenotyping, including the identification and categorization of illnesses in rice leaves. Future uses of Caps NET in the treatment of rice diseases made possible by the researchers' exceptional accuracy in illness categorization, which they attained by training CNNs on a sizable dataset of images of rice leaves[9]. Although the classification of rice leaf diseases by Caps NET may have benefits, more research is necessary to validate and improve these systems before they can be applied in actual agricultural settings [10]. This work aims to lessen this gap by evaluating whether it is practical to utilize Caps NET to classify prevalent illnesses of rice leave or not . By assessing the performance of Caps NET in practical and real-world environments, this study seeks to explore both the potential uses and the limitations of these systems in detecting diseases of rice [11][12]. This work includes numerous contributions as follows:

- It assesses how well rice leaf diseases can be classified using Caps NETs.
- Evaluating of such networks using a recent dataset. Furthermore, it research the benefit of using Caps NETs over the tradition Convolutional Neural Networks (CNNs).
- It has an important implication of the possibility of using deep learning networks in agriculture by providing a system capable of identifying diseases in rice leaves.

The rest of this research is organized as follows: Section Two examines relevant literature reviews. Section Three describes the methodology of the proposed work and includes information on data collection and Caps NETs. The experimental results are presented in Section Four. A discussion is provided in Section Five, and finally, the study is concluded in Section Six.

2. Related Work

Rice diseases affect both rice and other crops and pose a serious threat to global feeding security and farming. Recently, computer-aided diagnosis systems, such as those utilizing artificial neural networks (ANN) or Caps NETs, have gained attention as valuable tool. These tools proved its ability in classifying and detecting diseases in rice and related species [13]. This section provides an overview of research on using ANN to distinguish between various rice diseases, specifically those that affect rice leaves.

Wang et al. [15], they translated ABC spectral reflectance of infected rice leaves to CNN by training the model in this vision. Their approach has enabled them to query and collect comprehensive information that is required for the diagnosis and management of riceme disease, which can serve as a useful way to improve plant healthcare. Li et al. [16] applied machine learning techniques to classify rice bacterial leaf blight. These techniques were followed by developing a decision support system that combines phenotypic with genomic data. The proposed system was able to predict the potential rice diseases (disease-prone) as well as eco-epidemiological indicators of the path system for dimensional criteria. The proposed system helped breeders in selecting an ideal strategy to resist gene breeding based on disease ratios over complex environmental effects. The system was not only able to identify diseases around different situations, such as ornamental, fruit rice, and vegetable rice, but also detecting a few fastidious rice-diseases. The system was designed in such a way that it employs molecular diagnosis and image analysis techniques, coupled with remote sensing for precise symptom detection and identification. Zhang et al. [24] categorized different sorts of rice leaf diseases using the Convolutional Neural Network (CNN) model. Their research was able to predict disease with high accuracy comparing to many other proposed models. The research used a dataset with enough images of leaves affected by wide-range of rice illness. They trained the CNN model with this dataset and received a good classification accuracy. This study elucidated the prospective role of the model in helping us to timely identify and accurately diagnose rice leaf diseases leading to better disease management and minimal crop losing.

Singh, et al. [25] tackled the image classification problem of rice leaf disease so it is suggested that with respect to recognition and categorization this new classifier which was build using CNN model special for (RLD) might outperform them. Augmented Model This augmented model is deeper and employs more advanced optimization techniques. In conclusion, the proposed method outperforms conventional CNN models following large scale experiments on rice leaf dataset (providing a clear improvement in classification accuracy). Needs to improve models for agricultural disease detection with deeper and higher-solving problems. Chen, et al. [26]. The image classification problem of rice leaf disease so it is suggested that with respect to recognition and categorization this new classifier which was build using designed CNN model special for (RLD) might outperform them. Augmented Model This augmented model is deeper and employs more advanced optimization techniques. In conclusion, the proposed method outperforms conventional CNN models following large scale experiments on rice leaf dataset (providing a clear improvement in classification accuracy). Needs to improve models for agricultural disease detection with deeper and higher-solving problems.

3. Methodology

This section covers the thorough techniques employed in our investigations to assess the viability and efficiency of Caps NETS for the classification of rice leaf disease. The methodology of our proposed system is depicted in Figure 1.

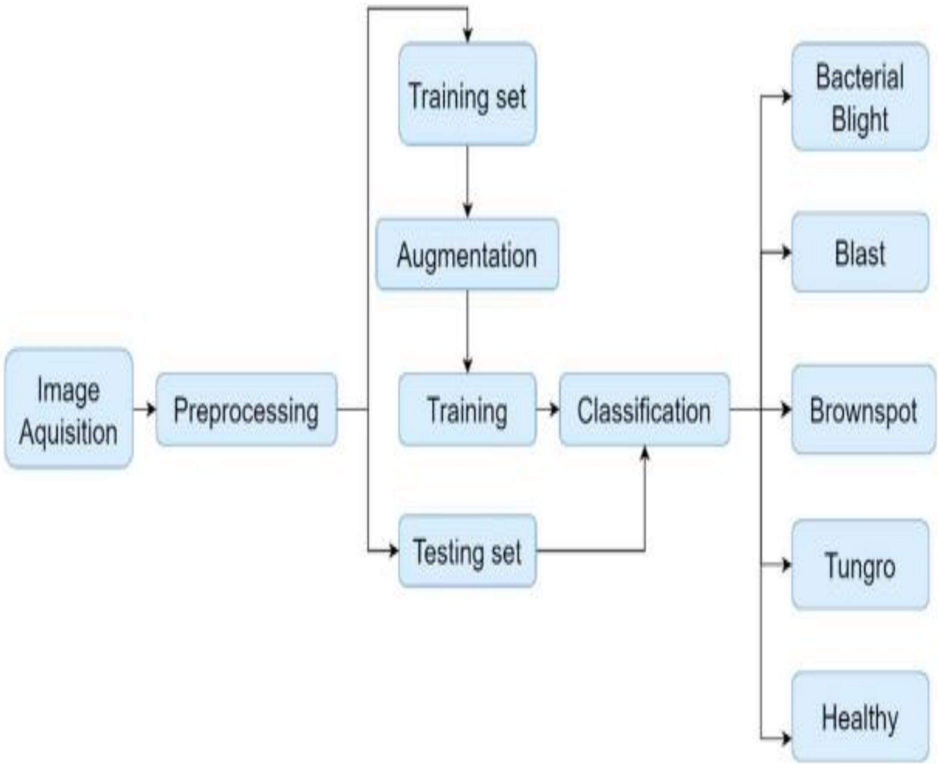


Figure 1. The Proposed system methodology

3.1 Data Collection

We started by compiling a large dataset of digital images of rice leaves having symptoms from common diseases including brown spot, bacterial leaf blight, blast, and sheath blight diseases. These images came from research repositories, field surveys, and publicly accessible databases. Further, the authors used handheld spectrometers or hyperspectral imaging devices to acquire spectral reflectance data of both healthy and diseased plants in rice, with distinct spectrum fingerprints related to different disease types [18]. Figure 2 illustrates the different types of rice leaf diseases.

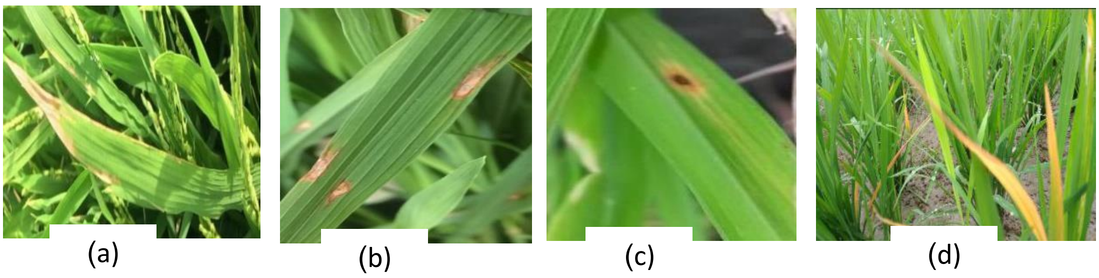


Figure 2. Types of rice leaf diseases: (a) Bacterial blight, (b) Blast, (c) Brown spot, and (d) Tungro.

3.2. Capsule Networks (Caps NET)

Gathering the randomization into a predetermined space is made possible by transfer learning. A primary factor contributing to the effectiveness of pre-trained CNN architectures is the comprehensive feature learning convolutional analysis stages (CONV layer). In light of this, regularization and factorization algorithms can optimize pre-trained weights more quickly. However, employing a pooling layer (down sampling) could result in a notable loss of data across feature maps. A unique deep learning technique called the Caps NETs (Capsule NET) eliminates the pooling layer from the design and used Caps NETs to move spatial data across layers. [19].

A Caps NET input is the CONV layer output at a predetermined number of filter sizes. The probability that instantiation parameters and feature maps, such as texture, pose, rotation, and details of deformation, will be encoded by Caps NET makes up a Caps NET output [20]. Transferring the acquired feature maps part-whole structure between low-level network caps made possible by the spatial information [19]. Capsule NETs primary advantages included geographical information, squashing function, and dynamic routing between Caps NETs, which defines the outcome as a probability at [0–1]. Similar to CNN, the Caps NETs containing the vector of ativity were transferred to the entirely interconnected layers (FC)[19][21]. Considering the activity vectors and location information, Caps NETs are robust against overfitting, even in tiny datasets, and can learn from partial hierarchies for images that are scaled and rotated. Additionally, by eliminating the neurons in FCs based on a similarity index at each FC, the dropout factorization expedites the training of Caps NET. [22]. In Caps NET, the CONV stands for creating various input data representations based on rectified-linear units (ReLUs) and feature maps. The suggested leaf disease's Caps NET structure is shown in Figure 3.

Figure 3. The structure of leaf disease's Caps NET

It is clear from Figure 3 that the pooling layer is absent. The degree of characteristics to be extracted determines how many CONVs are needed [26]. While the initial CONVs identify low-level variables, the main Caps NET conveys distinct changes in the depth of CONV, the quantity and size of filters, and ultimately classification factors including depth of FCs, number of neurons at each FC, learning rate, dropout index, and more [18]. The following equation explains the squashing function:

$$f_{\text{squashing(j)}} = \frac{\| Sj \| \; 2 \; Sj}{1 + \| \; Sj \; \| \; 2 \; \| \; Sj \; \|} \qquad (1)$$

Where s_j represents for jth individual primary Caps NET predictions.

The primary Caps NET, located at the lowest layer is responsible for extracting the spatial information. The subsequent Caps NET, referred to as the routing Caps NET follows instantiation parameters and higher level features. The geographical data for the low-level is mapping. As a result, creating a Caps NET requires choosing [20]

4. Experimental Results

These are shadows and sun beams in the photos of the rice leaves. Every image was meticulously regulated for the analysis because real-world situations of monitoring rice leaves which increased the dataset variability. The photos of the sick leaves show tiny bacterial specks in about half of them. In order to diagnose rice leaf diseases early, this instance assessed the Caps NET. As a result, we tested on a typical Caps NET layer in Capsule Network topologies. However, in the supervised training stage, we iterated through different depths and ranges of neurons and FCs to define the best model with the best classification efficacy for identifying bell rice leaf disease. In this work, we compared the latest advances on the RiceVillage dataset [18] with the best Caps NET topologies. The leaf photos were reduced to 64 x 64 in order to provide a Caps NET standard input size. Prior to analysis, the RGB images were converted to grayscale images. In order to prevent overfitting and allow the Caps NET model to get many rice leaf image representations. Data enhancement was also carried out. Applying both vertical and horizontal flipsboosted the number of studied rice image databases by four times. Figure 4 shows the leaf image during the pre-processing step. We obtained 2950 and 4960 rice leaf images for sick and healthy bell rice, respectively, using the data augmentation approach. FCs' adaptability allowed the experiments to be repeated on different Caps NET models. Rice leaf stratification was used to train the proposed model using 80% of the dataset.

Both the Caps NET training and testing phases did not include any data augmentation. The trained Caps NET performance was verified using the leftover dataset. Using the characteristics of independent testing, the test outcomes were assessed. The trained Caps NET model's confusion matrix was used to calculate accuracy, sensitivity, and specificity. [22]. Within the Caps NET CONV layer, the convolution kernel size was set to 9 x 9 and there were 256 filters. With a convolution kernel of 9 x 9 and a step size of 2, 32 primary Caps NET layers were generated consecutively. The output of each layer contains 24x24 Caps NETs (24x24x32). Every Caps NET is an eight-dimensional vector that holds spatial data. The class Caps NET layer outputs a 16-dimensional vector for each Caps NET. Using the encoder approach with weight matrix W_{ij}, the 8-dimensional vectors are transformed into a 16-dimensional leaf Caps NET. The layer for the "Caps NET" class, leaf Caps NET, creates a matrix of dimensions 2 × 16 (healthy-disease × spatial information).

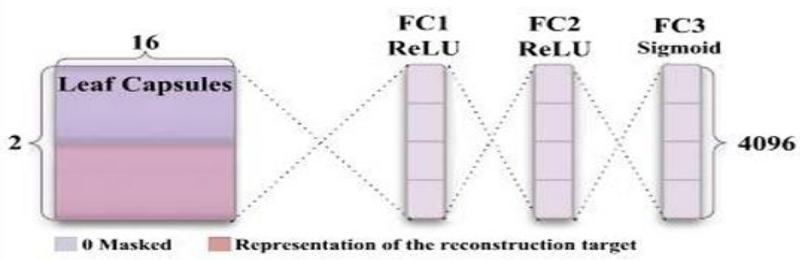


Figure 4. Caps NET decoding step [23]

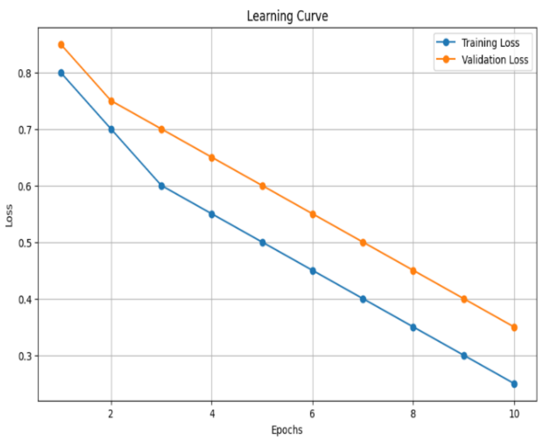
Figure 4 shows the FCs make for the decoder phase of the Caps NET. To construct the decoder model, the number of neurons in the final FC is equal to the number of pixels in the input sheet image (64 × 64 × 1 = 4096). The first FC (FC1) and second FC (FC2) both has 64 more neurons after each iteration, for a total count of 128 × 1024. FC has three different output functions: Softmax, ReLU, and ReLU.

Table1: The top five classification results (%) for different FC layer configurations in Caps NET topologies

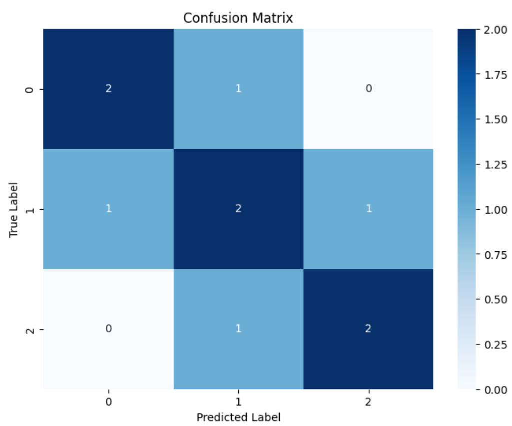
Architectures of Caps NET			Accuracy	Sensitivity	Specificity
FC1	FC2	FC3			
512	832	4096	92.98	93.13	93.34
1024	576	4096	95.16	95.61	96.59
384	896	4096	95.89	98.11	98.79
960	704	4096	95.94	98.32	98.80
960	768	4096	96.66	97.25	97.49

The best classification performance in rice leaf disease detection is shown in Table 1. The results show that the Caps NET model can provide accurate classification performance for rice leaf disease detection using simple FC with Caps NET information and spatial information. Although employing numerous neurons for FC1 and FC2, it failed to distinguish between images of healthy and diseased leaves. Increasing the number of neurons in each FC increased the detection performance. The optimal outcomes were achieved with 960 neurons in FC1 and 768 neurons in FC2, using the suggested Caps NET architecture. In terms of accuracy, sensitivity, and specificity, rates of 96.66, 97.25, and 97.49 were the best for rice leaf disease detection. For FC1, FC2, and FC3, the activation functions are Sigmoid, RELU, and RELU.

The training curve and confusion matrix demonstrate that the Caps NET has been trained effectively with a high level of accuracy, sensitivity, and specificity. These results underscore the model's capability in distinguishing between different types of rice leaf diseases. The choice of architecture, particularly the optimal configuration of fully connected layers (FC1(960), FC2(768), and FC3(4096)), has played a crucial role in achieving these results, making this a noteworthy contribution to the domain of rice disease classification using deep learning technique. Figure 5 shows learning rate curve and confusion matrix.



(a) Learning rate curve



(b) Confusion matrix

Figure 5. Learning rate curve and Confusion matrix of Capsule Net

5. Discussion

When we compare Caps NET topologies with traditional CNN algorithms for identifying rice leaf diseases, the results show significant improvements. After testing several Caps NET setups, we found that the one with FC1 (960), FC2 (768), and FC3 (4096) performed the best. The Caps NET configuration delivered impressive results, boosting 96.66% accuracy, 97.25% sensitivity, and 97.49% specificity. These results mark a notable improvement over previous CNN-based models. Table 2 shows previous studies proposed to identify rice diseases. Zhang et al. (2020) achieved 92.80% accuracy, 91.70% sensitivity, and 93.90% specificity, while Singh et al. (2021) reported 91.50% accuracy, 90.50% sensitivity, and 92.60% specificity. The new Caps NET setup outperforms these earlier studies. In another study, Chen et al. (2019) presented different metrics, with 90.70% accuracy, 89.80% sensitivity, and 91.80% specificity.

Table 2: The most cutting-edge technique for identifying rice leaf diseases.

Studies	Classifier	Accuracy	Sensitivity	Specificity
Zhang et al. (2020) [24]	CNN	92.80%	91.70%	93.90%
Singh et al. (2021)[25]	CNN	91.50%	90.50%	92.60%
Chen et al. (2019)[26]	CNN	90.70%	89.80%	91.80%
This study	CapsNET	95.76%	96.37%	97.47%

Caps Nets offers a new improvement compared to the regular CNNs. They have set a new field in image processing by preserving spatial relationships among parts more effectively than traditional CNNs. This ability allows Caps Nets to perform better in object detection under varying lighting conditions. Moreover, Caps Nets learn an interpretable feature representation with fewer layers achieving better interactions between parts and the whole.

6. Conclusion

This study highlights on Caps NETs, which significantly outperformed traditional CNNs in detecting rice leaf diseases. The different Caps Net configurations showed superior results with the most effective setup of FC1 (960), FC2 (768), and FC3 (4096) which achieved an accuracy of 96.66%, a sensitivity of 97.25%, and a specificity of 97.49%. These results represent a substantial improvement over previous CNN-based studies, as we mentioned in Table 2, which reported lower accuracy and sensitivity rates. The enhanced performance of Caps NETs is mainly due to their ability to capture hierarchical features and intricate spatial relationships more effectively. These findings suggest that Caps NETs have strong potential to improve automated disease detection systems, leading to more precise and reliable management of rice leaf diseases. In future research, we will focus on further refining of Caps NET architectures and investigating their application to other crops and types of diseases.

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