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Automated Recognition of Rice Grain Diseases Using Deep Learning

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Outline of the Presentation

- Research Problem
- Motivation
- Related Works
- Challenges Faced
- Methodology
- Dataset
- Experiment & Result
- Conclusion

Research Problem

✓ Automated Recognition of Rice Grain Diseases

❑ How can we implement that?

- Using Deep Learning Based Method

Motivation

01

Early Diagnosis

Early detection of disease can save tones of crops

02

Manual Observation

Manual disease observation procedure is time-consuming and laborious

03

Loss of Productivity

Loss of the crops create great impact on the economy

04

Complex Model Architecture

Existing models have complex architecture with huge parameters

Related Works

A Tabular Gist of the Reviewed Papers

Contributors	Reference Work
Rahman et al. 2020	Identification and Recognition of Rice Diseases and Pests Using Convolutional Neural Networks.
Ahmed et al. 2020	Rice grain disease identification using dual phase convolutional neural network-based system aimed at small dataset.
Devi et al. 2014	Analysis of Segmentation Scheme for Diseased Rice Leaves.
Liu et al. 2018	Identification of Apple Leaf Diseases Based on Deep Convolutional Neural Networks.
Dubey et al. 2017	Apple disease classification using color, texture and shape features from images.

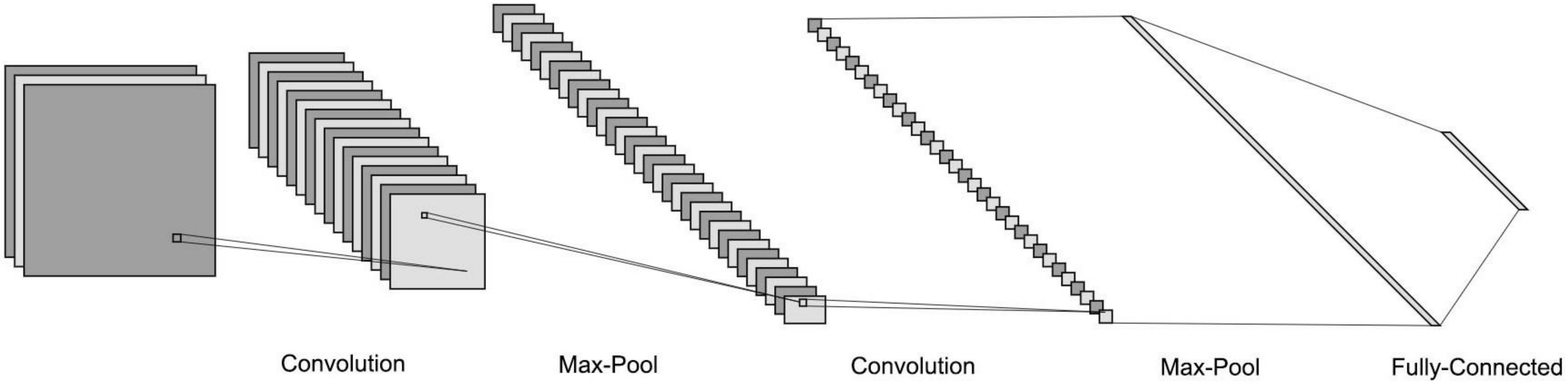
Challenges Faced

- Achieving Higher Accuracy through Lightweight Model
- Learning Complex Patterns of Diseases.
- Limitation of Availability of Large Dataset
- Ensuring the Memory-Efficient Architecture

Methodology

A custom Convolutional Neural Network (CNN) architecture is proposed namely RiceNet.

- Convolution Layer
- Pooling or Subsampling Layer
- Fully Connected Layer



Methodology

Proposed RiceNet Architecture

Layer Name	Function	Filter Size	Output Tensor
Input			$224 \times 224 \times 3$
Conv1	Convolutional	3×3	$222 \times 222 \times 16$
Pool1	Max-Pooling	2×2	$111 \times 111 \times 16$
Conv2	Convolutional	3×3	$109 \times 109 \times 32$
Pool2	Max-Pooling	2×2	$54 \times 54 \times 32$
Conv3	Convolutional	3×3	$52 \times 52 \times 64$
Pool3	Max-Pooling	2×2	$26 \times 26 \times 64$
Conv4	Convolutional	3×3	$24 \times 24 \times 64$
Pool4	Max-Pooling	2×2	$12 \times 12 \times 64$
Conv5	Convolutional	3×3	$10 \times 10 \times 32$
Pool5	Max-Pooling	2×2	$5 \times 5 \times 32$
Output	Softmax Regression		$9 \times 1 \times 1$
	No. of Parameters		**557, 389**

Dataset

For convenience, the two dedicated rice leaf datasets simply named as BdRice3 and BdRice9 respectively

Dataset	Class Name	No. of Images
BdRice9	False Smut	93
	Brown Plant Hopper (BPH)	71
	Bacterial Leaf Blight (BLB)	138
	Neck Blast	286
	Stemborer	201
	Hispa	73
	Sheath Blight and/or Sheath Rot	219
	Brown Spot	111
	Others	234
BdRice3	False Smut	75
	Neck Blast	63
	Healthy	62

Experiment & Result

Related Parameters of the Convolutional Neural Network (CNN)

CNN Architecture	Number of Parameters
VGG16	138 million
ResNet50	23 million
EfficientNetB0	5.3 million
NasNet Mobile	4.3 million
MobileNetv2	2.3 million
RiceNet	0.557 million

Experiment & Result

Performance of Different CNN Architectures Obtained from 5-Fold Cross Validation With BdRice9 Dataset

CNN Architecture	Weights	Accuracy
VGG16	imagenet	97.23%
ResNet50	imagenet	97.12%
EfficientNetB0	noisy-student	96.88%
MobileNetv2	imagenet	95.32%
NasNet Mobile	imagenet	95.58%
RiceNet	scratch	78.94%

Experiment & Result

Performance of Different CNN Architectures Obtained from 5-Fold Cross Validation With BdRice3 Dataset

CNN Architecture	Weights	Accuracy
VGG16	imagenet	98.82%
ResNet50	imagenet	98.01%
EfficientNetB0	noisy-student	97.94%
MobileNetv2	imagenet	96.43%
NasNet Mobile	imagenet	96.71%
RiceNet	pre-train	93.75%

Experiment & Result

F1-score of different CNN Architectures with BdRice3 Dataset

CNN Architecture	F1-Score
VGG16	68.32%
ResNet50	66.41%
EfficientNetB0	66.10%
NasNet Mobile	65.56%
MobileNetv2	65.57%
RiceNet	62.78%

Conclusion

- Achievements of the Proposed Approach
- Limitations
- Future Scopes

Question Answer (QA) Session