Bioinformatics and Data Mining Research Group

Improving Rice Leaf Disease Identification with Object Detection and Image Enhancement

FARIA AHMED	190041218
TASFIA TASNEEM ANNESHA	190041220
RAFI HASSAN CHOWDHURY	190041234

<u>Under the supervision of:</u>

Tareque Mohmud Chowdhury
Assistant Professor
Department of Computer Science and Engineering (CSE)
Islamic University of Technology (IUT), OIC

Rice Leaf Disease Identification

- Identification involves determining the specific disease affecting a crop based on observable symptoms or characteristics.

Object detection

- Object detection involves identifying and locating objects within an image.

Image Enhancement

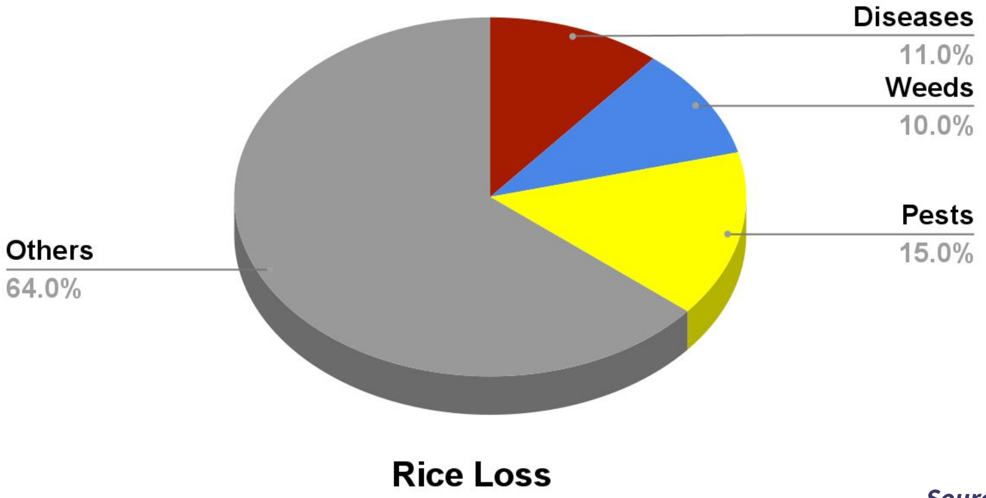
- Process that involves improving the quality or visual appearance of an image.
- Useful scenarios - Noisy Image, Low contrast Image, Low Resolution Image

Identification with Object Detection and Image Enhancement

- Input Image ➔ Image Enhancement ➔ Object detection model ➔ Disease Identification ➔ Output

Problem Statement

"The challenge lies in providing small-scale farmers with limited resources access to timely and accurate crop disease detection. Existing issues include low-quality images from mobile phones, a scarcity of quality data, and the need for mobile-compatible solutions."



Source : [7]

Current Challenges

- Limited Access to High-Resolution Devices
- Low Computational Power of Farmer's Devices
- Challenges in Data Collection
- Inadequate Size of Available Dataset
- Varied Environmental Conditions
- Biased images in available dataset
- Integration of Image Enhancement Techniques

Literature Review

"Identification and Recognition of Rice Diseases and Pests Using Convolutional Neural Networks "[1]

- by C. R. Rahman, P. S. Arko, M. E. Ali, M. A. I. Khan, S. H. Apon, F. Nowrin, and A. Wasif, Biosystems Engineering

Performance:

CNN Architecture	Training Method Used	Mean Validation Accuracy	Standard Deviation
VGG16	Baseline training	89.19%	10.28
	Transfer Learning	86.52%	5.37
	Fine Tuning	**97.12%**	2.23
InceptionV3	Baseline training	91.17%	3.96
	Transfer Learning	72.09%	7.96
	Fine Tuning	**96.37%**	3.9
MobileNetv2	Baseline training	78.84%	7.38
	Transfer Learning	77.52%	8.56
	Fine Tuning	**96.12%**	3.08
NasNet Mobile	Baseline training	79.98%	6.96
	Transfer Learning	78.21%	8.09
	Fine Tuning	**96.95%**	3.35
SqueezeNet v1.1	Baseline training	74.88%	8.18
	Transfer Learning	42.76%	9.12
	Fine Tuning	**92.5%**	3.75
Simple CNN	Two Stage Training	**94.33%**	0.96

Dataset:

- BRRI's Online Available Dataset
- total 1426 images of rice diseases and pests

Limitations:

- They have a large number of parameter
- Different symptoms at different stages of an attack

CNN Architecture	No. of Parameters
VGG16	138 million
InceptionV3	23.8 million
MobileNetv2	2.3 million
NasNet Mobile	4.3 million
SqueezeNet	0.7 million
Simple CNN	0.8 million

Literature Review

"Rice Disease Identification Method Based on Attention Mechanism and Deep Dense Network " [2]

- by M. Jiang, C. Feng, X. Fang, Q. Huang, C. Zhang, and X. Shi, Electronics, vol. 12

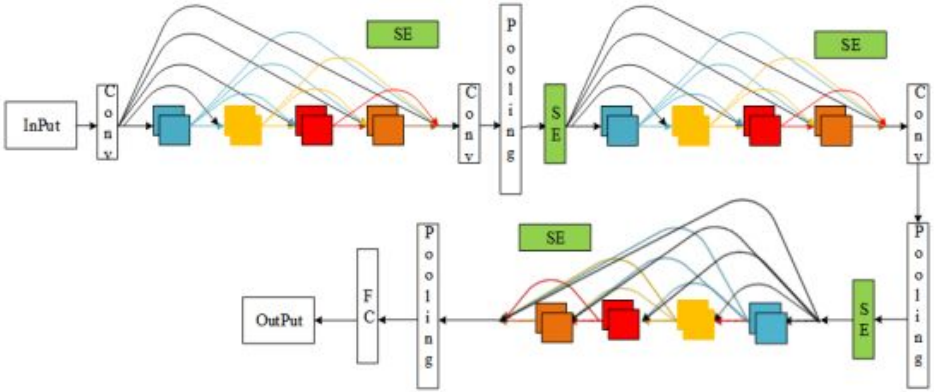


Fig: *SE DenseNet Model Architecture*

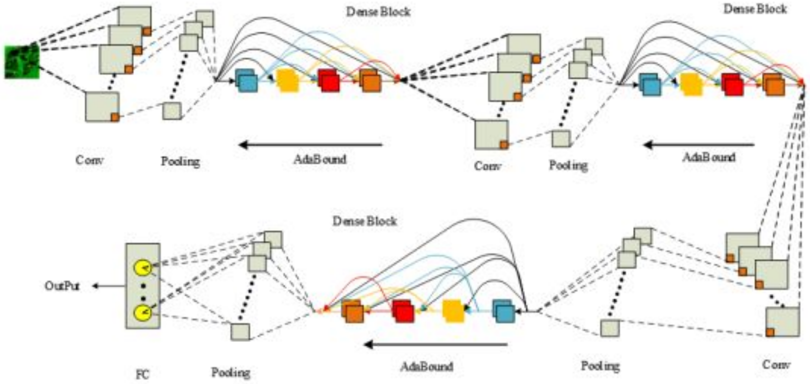


Fig: *AB-SE-DenseNet model architecture*

Literature Review

“RiceNet: A two stage machine learning method for rice disease identification” [3]

-by Z. Liu, S. Wang, Y. Zhang, Z. Li, Z. Li, X. Li, and X. Zhang, Biosystems Engineering

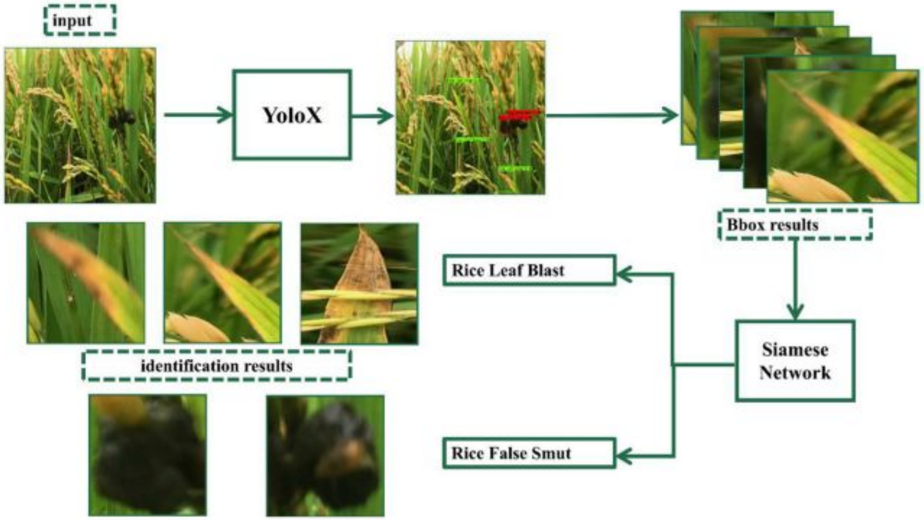


Fig: *Processing Flow*

Dataset:

Disease in image	Training dataset	Clipped patch dataset
Rice Panicle Neck Blast	50	120
Rice False Smut	50	180
Rice Leaf Blast	50	189
Rice Stem Blast	50	137
Total	200	626

Limitations:

- All the images taken here are high resolution (3024 x 4032 taken by iPhone 7 or Huawei P10) images. The model may not work very well on low resolution image.

Literature Review

[3]

“RiceNet: A two stage machine learning method for rice disease identification”

-by Z. Liu, S. Wang, Y. Zhang, Z. Li, Z. Li, X. Li, and X. Zhang, Biosystems Engineering

Standard Models.

Model	size	mAP^{val} 0.5:0.95	mAP^{test} 0.5:0.95	Speed V100 (ms)	Params (M)	FLOPs (G)
YOLOX-s	640	40.5	40.5	9.8	9.0	26.8
YOLOX-m	640	46.9	47.2	12.3	25.3	73.8
YOLOX-l	640	49.7	50.1	14.5	54.2	155.6
YOLOX-x	640	51.1	**51.5**	17.3	99.1	281.9
YOLOX-Darknet53	640	47.7	48.0	11.1	63.7	185.3

Fig: *YOLOX architecture performance*

Source : *Github* [5]

Literature Review

"Lite-SRGAN and Lite-UNet: Toward Fast and Accurate Image Super-Resolution, Segmentation, and Localization for Plant Leaf Diseases" [4]

-by H. S. El-Assiouti, H. El-Saadawy, M. N. Al-Berry, and M. F. Tolba, IEEE Access

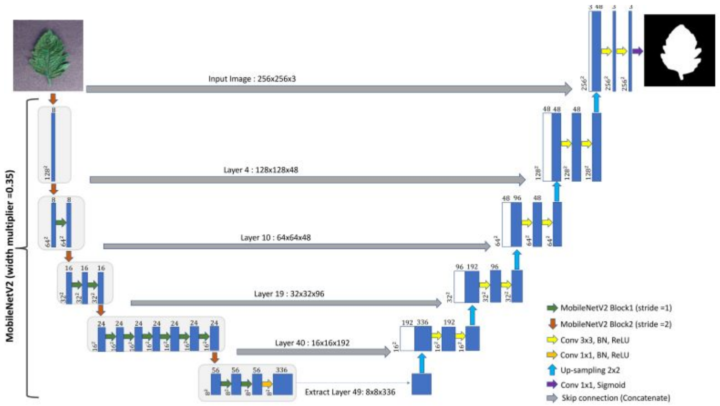


Fig: *Lite-UNet*

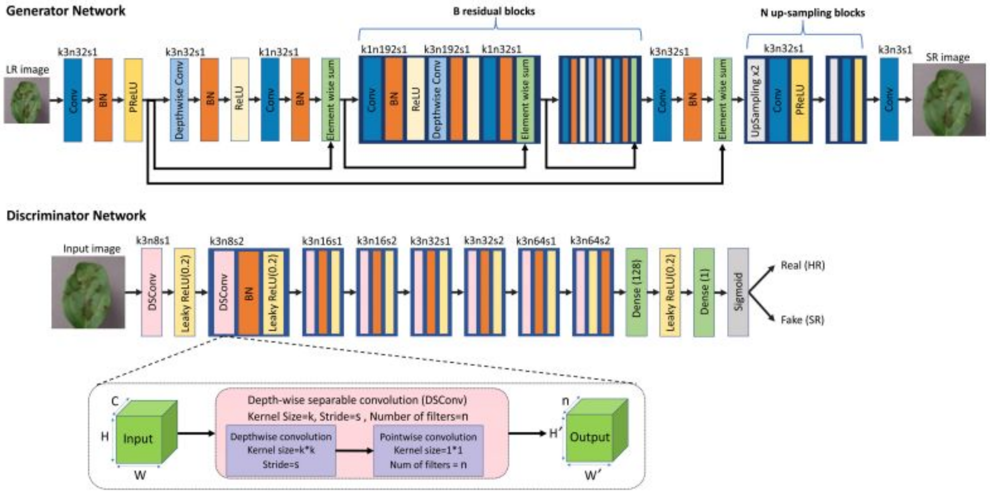


Fig: *Lite-SRGAN*

Literature Review

"Lite-SRGAN and Lite-UNet: Toward Fast and Accurate Image Super-Resolution, Segmentation, and Localization for Plant Leaf Diseases" [4]

-by H. S. El-Assiouti, H. El-Saadawy, M. N. Al-Berry, and M. F. Tolba, IEEE Access

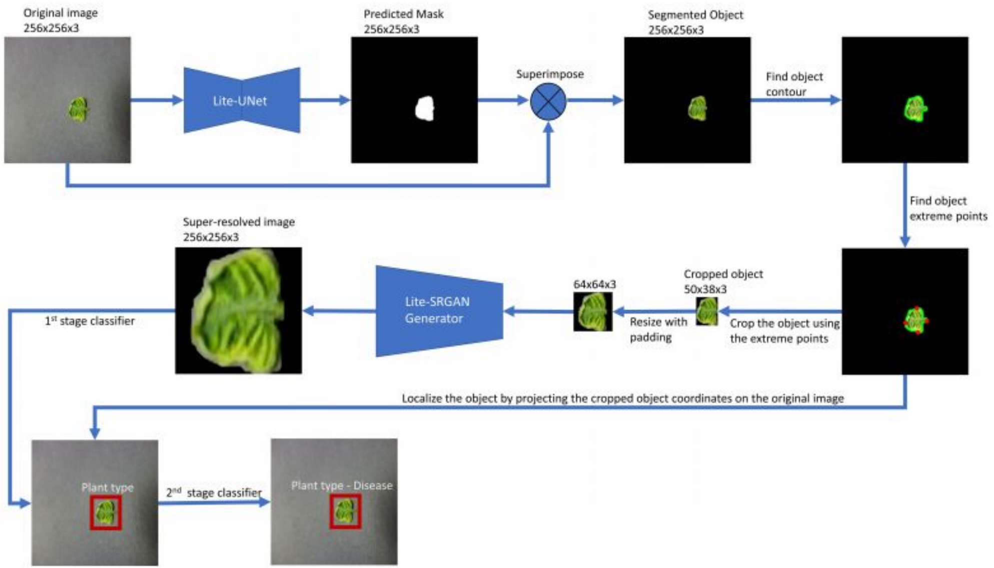


Fig: *Processing Flow*

Limitations:

- Training dataset has no background noise.
- Close-up shot
- Trained and tested on better resolution image



Research Aims and Objectives

Aim 1

Rice leaf image enhancement and object detection.

Objectives

➢ Determining the performance on low quality dataset.

➢ Use image enhancement method for better object detection.

➢ Evaluating the effects of data enhancement technique on the object detection performance.

➢ Ensuring mobile compatibility.

Research Aims and Objectives

Aim 2

Identify the input image in 10 different disease classes.

Objectives

- ➢ Identifying diseases with high accuracy using light architecture models.
- ➢ Developing an efficient system that combines image enhancement and disease detection techniques, specifically tailored for paddy crop disease identification.

Proposed Pipeline

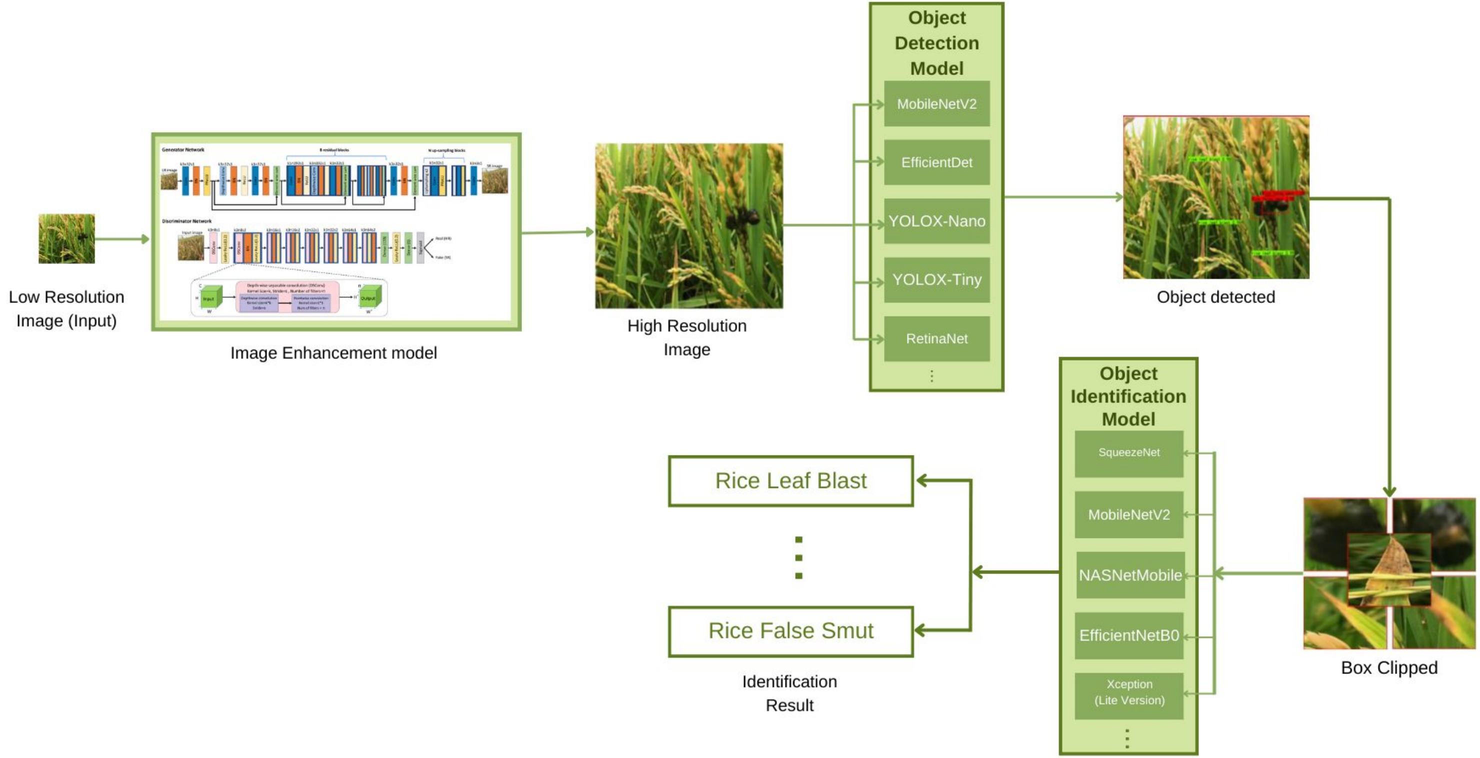


Fig: *Proposed Pipeline*

Source : *Ricenet*[3]

Enhancement

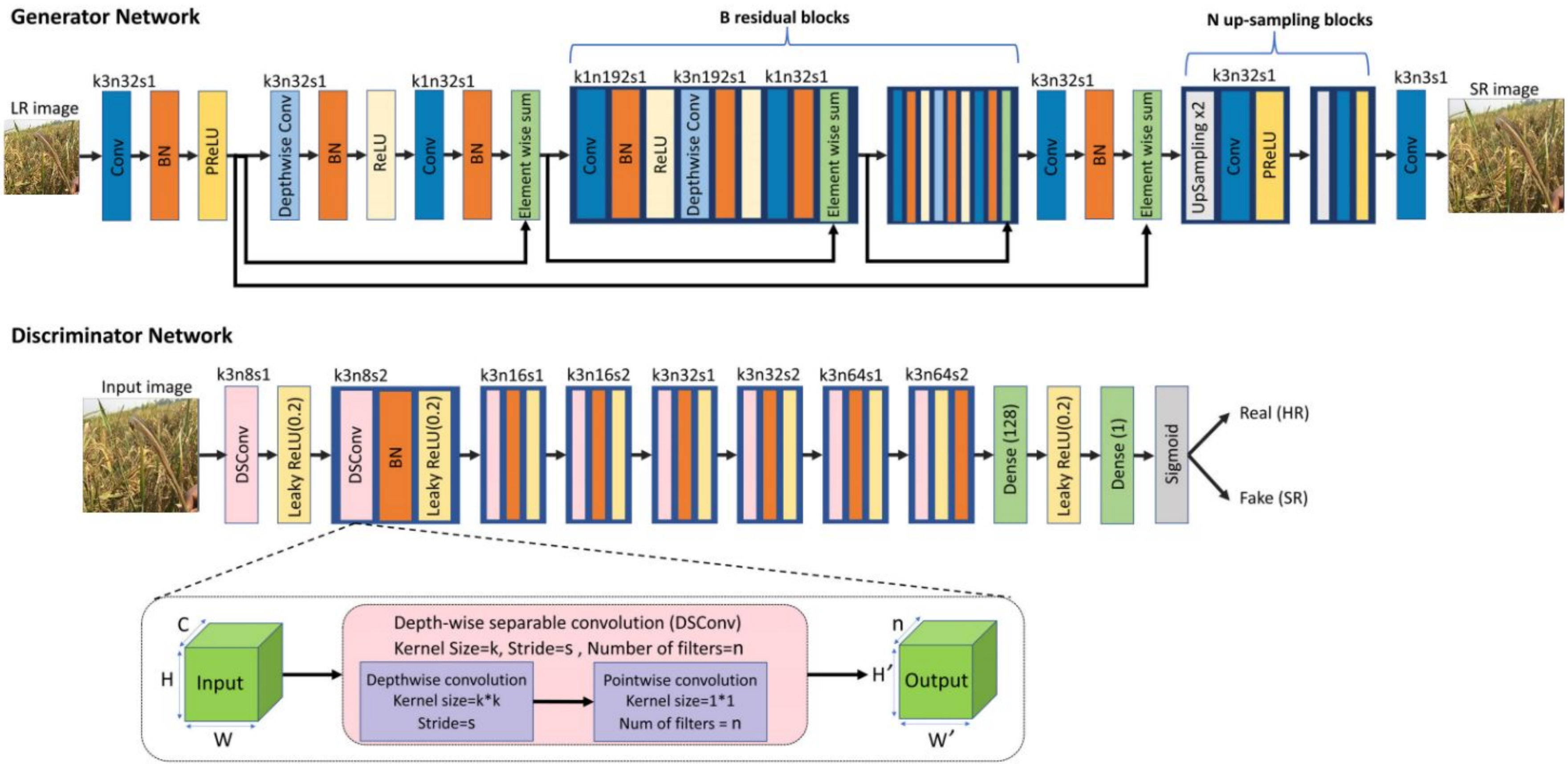
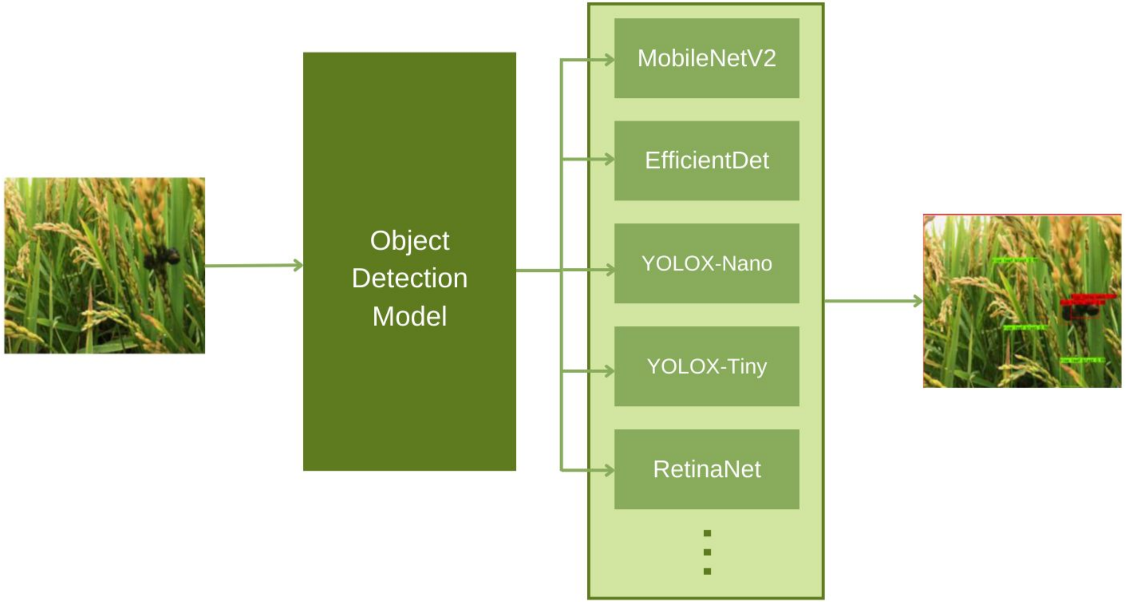


Fig: *Processing Flow*

Source : *Lite-srgan*[4]

Detection

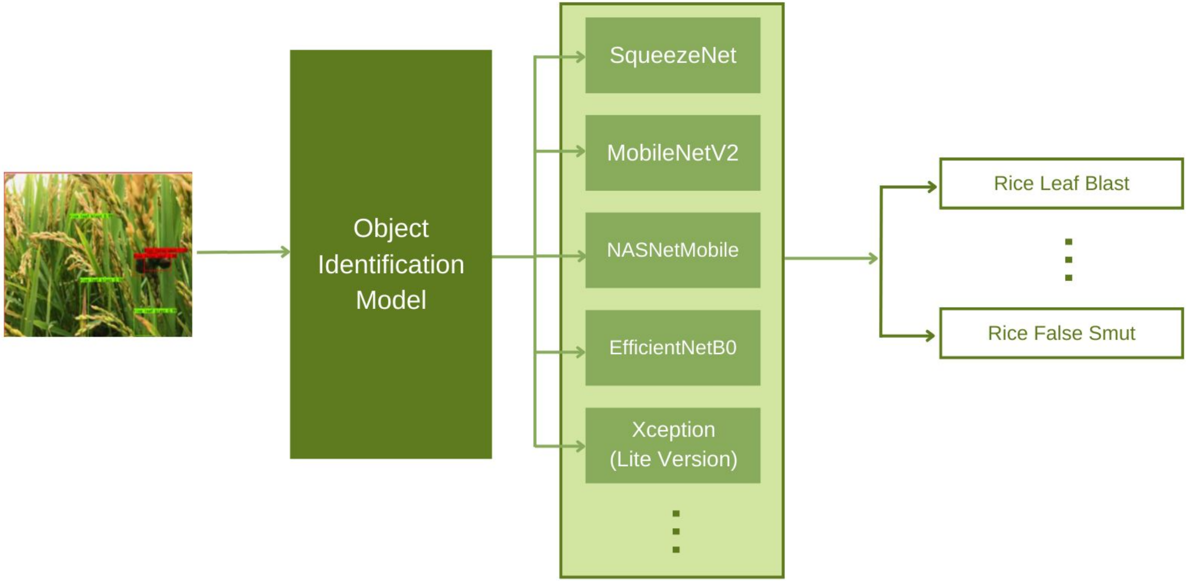


Name of Model	No. of Parameters
MobileNetV2	2.24M
YOLOX-Nano	0.91M
YOLOX-Tiny	5.06M

Fig: *Object Detection*

Source : *Ricenet*[3]

Identification



Name of Model	No. of Parameters
SqueezeNet	1.25M
MobileNetV2	~3.47M
NASNetMobile	~ 5.33M
EfficientNetB0	~ 5.3M

Fig: *Image Identification*

Source : *Ricenet*[3]

Dataset

Paddy Doctor: Paddy Disease Classification [6]

- Training dataset : 10,407 (75%) labeled paddy leaf images across **ten classes** (nine diseases and normal leaf).
- Test dataset : 3,469 (25%) paddy leaf images into one of the nine diseases or normal leaf

Dhan-Shomadhan: A Dataset of Rice Leaf Disease Classification for Bangladeshi Local Rice [8]

- **5 different** harmful diseases of rice leaf called Brown Spot, Leaf Scaled, Rice Blast, Rice Tungro, Sheath Blight.
- Dataset contains 1106 images.

Dataset

BRRI's Online Available Dataset [9]

- total 1426 images of rice diseases and pests

Class Name	No. of Collected Images
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

Table 1: Image Collection of Different Classes

Our Experiments

Dataset	# Classes	# Samples	Classifier	Accuracy
Original Dataset: Rice Leaf Diseases Dataset Customized Dataset: RLD_train_test	3	40 each class, splitted into training and testing set with 80:20 ratio	Basic CNN	76.56%
			MobileNet-v2	87.00%
			MobileNet-v3	33.33%
			VGG19	62.50%
			EfficientNet	80.00%

Dataset	# Classes	# Samples	Classifier	Accuracy
Original Dataset: Paddy Doctor: Paddy DIsease Classification Customized Dataset: PD_train_test	10	10.407 total image, splitted into training and testing set with 80:10:10 ratio	MobileNetV2	32.37%
			MobileNet-v3Large	7.50%
			VGG19	87.65%

Dataset	# Classes	# Samples	Classifier	Accuracy	Precision	Recall	F1-Score	Parameters
Original Dataset: Dataset Customized Dataset: BRRI_train_test	9	Total 1426 images in 10 classes with a maximum of 286 images and minimum of 71 images in a single class	MobileNet-v2	83.71%	84.2200	83.7100	83.9600	2.24M
			MobileNet-v3	81.61%	82.4200	81.6100	82.0100	4.21M
			MixNet	84.41%	84.6400	84.4100	84.5200	5.81M
			EfficientNet	78.81%	79.8200	78.8100	79.3100	4.02M
			XceptionNet	81.61%	81.7600	81.6100	81.6900	20.83M
			InceptionV3	67.62%	68.7300	67.6200	68.1700	21.80M

Our Experiments

HR(PSNR/SSIM)

SRGAN(28.306/0.899)

Lite-SRGAN(28.356/0.898)

Fig: *Image enhancement experiment*

Future Work

Data Collection

➢ Collect data from the field and make a dataset of our own.

Motivation:

- In some images the disease affected leaves are blurry.
- High Resolution training and testing Images.
- Test Set images are not labelled
- Close-up image
- The number of available field image is very small
- Biased dataset

***Fig:** Sample from Paddy Doctor dataset*

***Fig:** Sample from Dhan-Shomadhan dataset*

Neck Blast

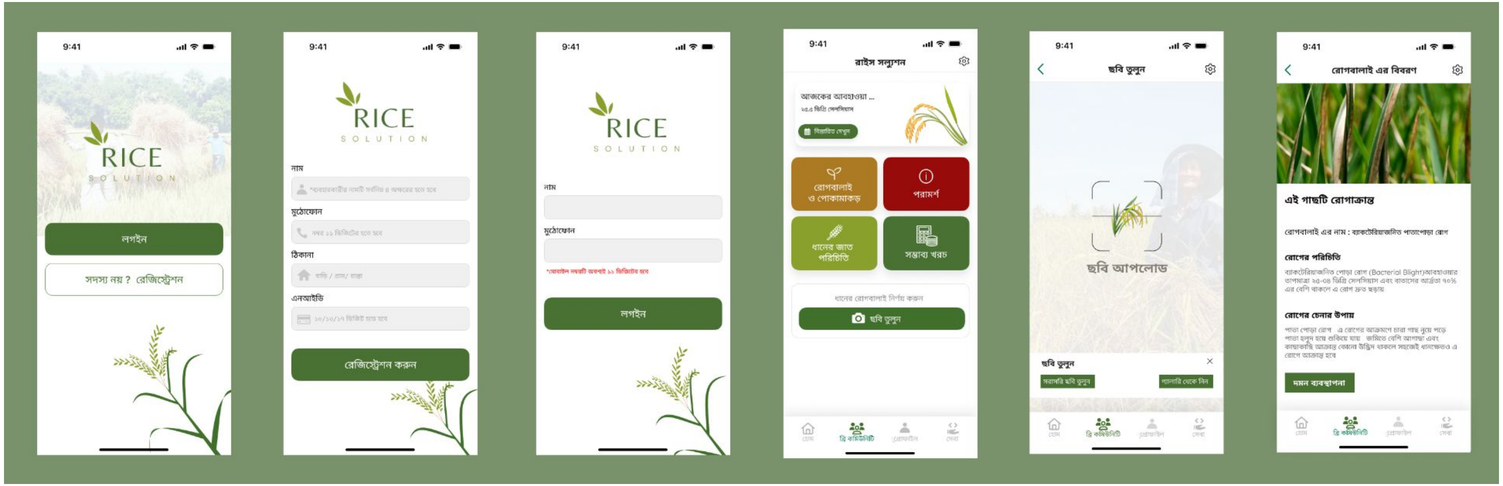
BLB

BPH

***Fig:** Sample from BRRI dataset*

Future Work

- ➢ Increase the efficiency of the model with high accuracy.
- ➢ Integrate the model in a mobile application for ease of disease detection.



References

[1]C. R. Rahman, P. S. Arko, M. E. Ali, M. A. I. Khan, S. H. Apon, F. Nowrin, and A. Wasif, “Identification and recognition of rice diseases and pests using convolutional neural networks,” *Biosystems Engineering*, vol. 194, pp. 112–120, 2020.

[2]M. Jiang, C. Feng, X. Fang, Q. Huang, C. Zhang, and X. Shi, “Rice disease identification method based on attention mechanism and deep dense network,” *Electronics*, vol. 12, p. 508, 01 2023.

[3]Z. Zhang, X. Wang, and Z. Wang, “Ricenet: A two stage machine learning method for rice disease identification,” *Biosystems Engineering,* vol. 209, pp.1–13, 2022.

[4]H. S. El-Assiouti, H. El-Saadawy, M. N. Al-Berry, and M. F. Tolba, “Lite-srgan and lite-unet: Toward fast and accurate image super-resolution, segmentation,and localization for plant leaf diseases,” *IEEE Access*, vol. 11, pp. 67 498–67 517, 2023.

[5]Megvii-BaseDetection. (Year of the GitHub repository’s last update) YOLOX: You only look once extreme. GitHub repository. [Online]. Available: https://github.com/Megvii-BaseDetection/YOLOX.git

[6]Kaggle. Paddy Doctor |Paddy disease classification dataset. Kaggle dataset. [Online]. Available: https://www.kaggle.com/c/paddy-disease-classification/data

[7]Oerke, E-C. “Crop losses to pests.” *The Journal of Agricultural Science*, vol.144, no. 1, pp. 31-43, 2006

[8]Dhan-shomadhan: A dataset of rice leaf disease classification for bangladeshi local rice. [Online]. Available: https://data.mendeley.com/datasets/znsxdctwtt/1

[9]Brri’s online available dataset. [Online]. Available: Dataset - Google Drive

Thank You!