Master of Engineering in Artificial Intelligence
College of Engineering
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Optimizing Rice Disease Classification: A Comparative Study of Artificial Neural Network and Support Vector Machine Using Image Color, Moment, and Texture Features for Improved Efficiency

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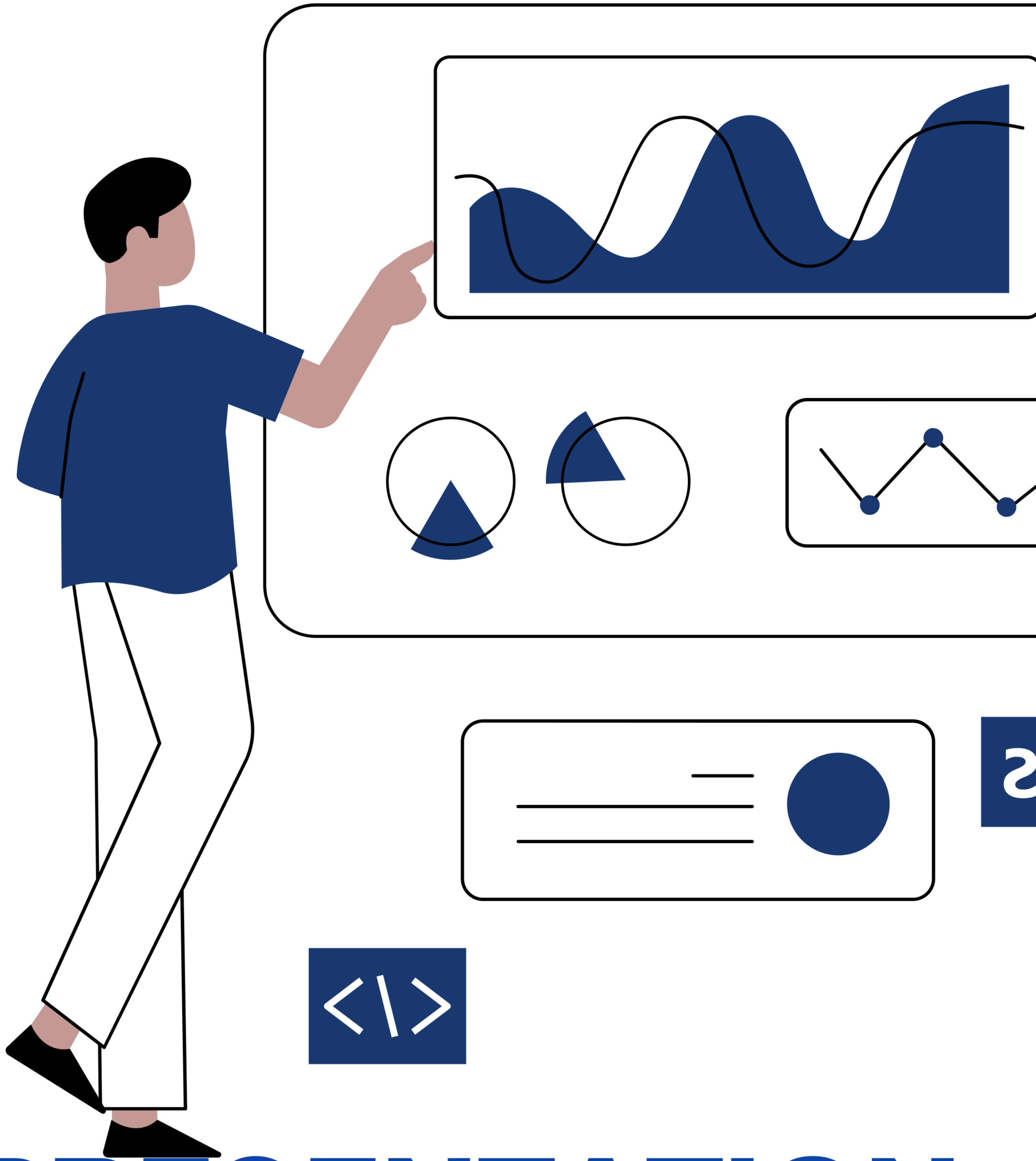
PRESENTATION OUTLINE



1. **INTRODUCTION**
   Problem Being Solved, Related Works, Relevance of the Study

2. **METHODOLOGY**
   Dataset, Features, Experimental Setup, Implementation

3. **RESULTS AND DISCUSSION**
   Extracted Features, Outcome of Experiments

4. **CONCLUSION AND RECOMMENDATION**
   Future for the study

1. INTRODUCTION

What is the problem being solved?

RICE, the staple of life in the Philippines

Impact of RICE DISEASE in yield

Early detection for DISEASE MANAGEMENT

Application of MACHINE-DRIVEN SYSTEM for early detection

Index Mundi. Philippines Milled Rice Domestic Consumption by Year, Retrieved: April 5, 2014.

Nalley, L., Tsiboe, F., Durand-Morat, A., Shew, A., Thoma, G. Economic and Environmental Impact of Rice Blast Pathogen (Magnaporthe oryzae) Alleviation in the United States. PLoS ONE, 11(12), e0167295. 2016.

1. INTRODUCTION

Related Works

- Usual Method

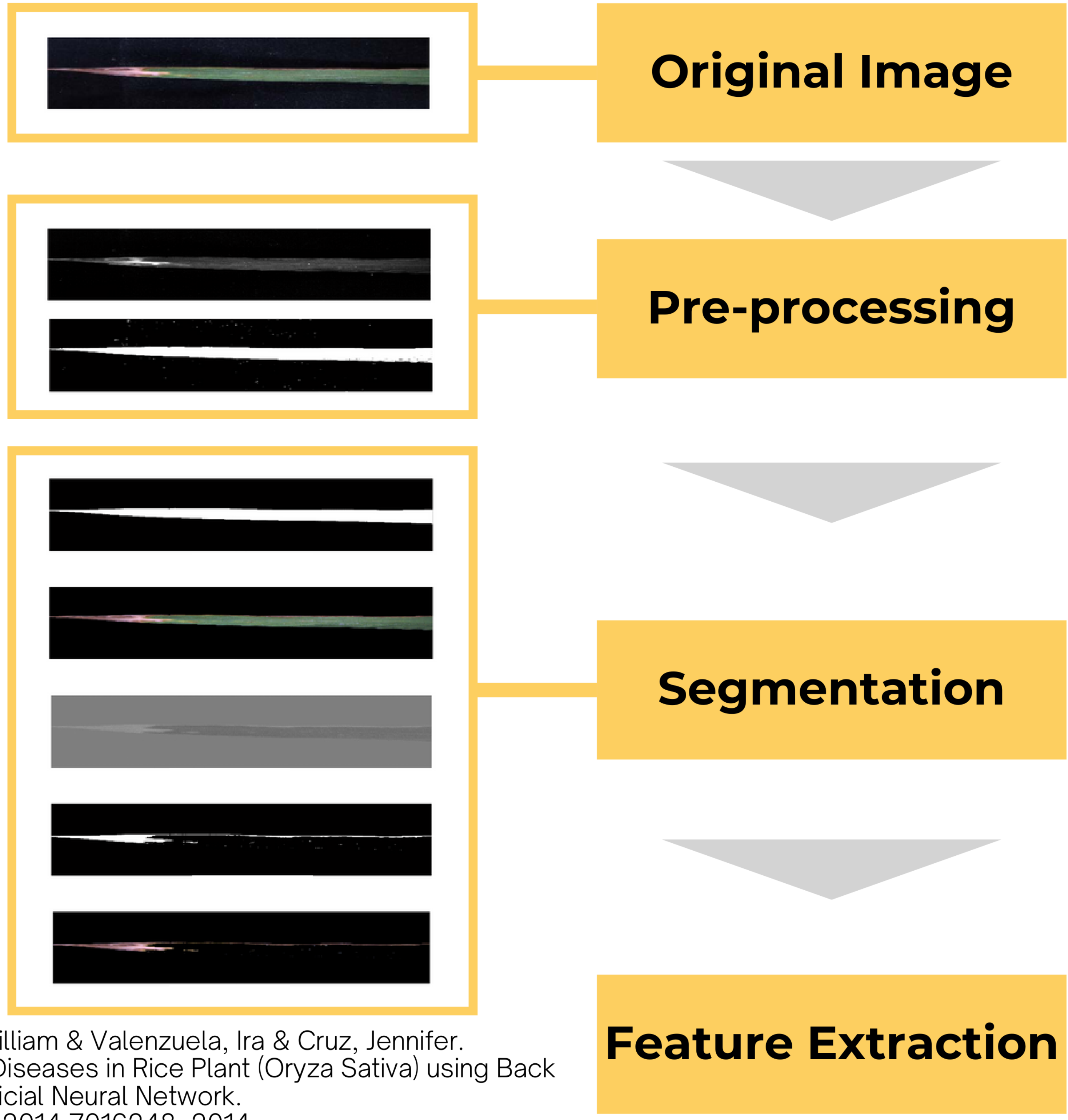


Image Source:

[1] Orillo, John William & Valenzuela, Ira & Cruz, Jennifer. Identification of Diseases in Rice Plant (Oryza Sativa) using Back Propagation Artificial Neural Network. 10.1109/HNICEM.2014.7016248, 2014.

- Common Results

Using different classifiers such as Nearest Neighbors, Support Vector Machines, and Neural Networks [2]:

- classification of 1-4 rice diseases
- accuracies ranging from 75% to 100%

[2]Shah, J. P., Prajapati, H. B., & Dabhi, V. K. A Survey on Detection and Classification of Rice Plant Diseases. In Department of Information Technology, Dharmsinh Desai University, Nadiad, Gujarat, India (Eds.), Proceedings of the IEEE (pp. 978-1-5090-1936-6/16/$31.00), 2016.

1. INTRODUCTION

Relevance of the Study

1. This study explores a more efficient and automated method in classifying rice disease images by utilizing the whole image, and removing image pre-processing and segmentation steps altogether by capitalizing on multiple global features of an image; and,
2. Extends the scope of classification to encompass a broader range of common Philippine rice diseases.

2. METHODOLOGY
Dataset

Pre-processed image

Zoomed-in Image

Paddy Shot

Source of Dataset:

https://www.kaggle.com/datasets/shrupyag001/philippines-rice-diseases

Details:

- 14 classes, balanced
- Uniform dimension of 224 x 224 pixels
- Varied shots: different magnifications and backgrounds

Divided into three:

1. Complete Dataset
2. 3 class Dataset
3. 14 class solely zoomed-in or whole rice plant images

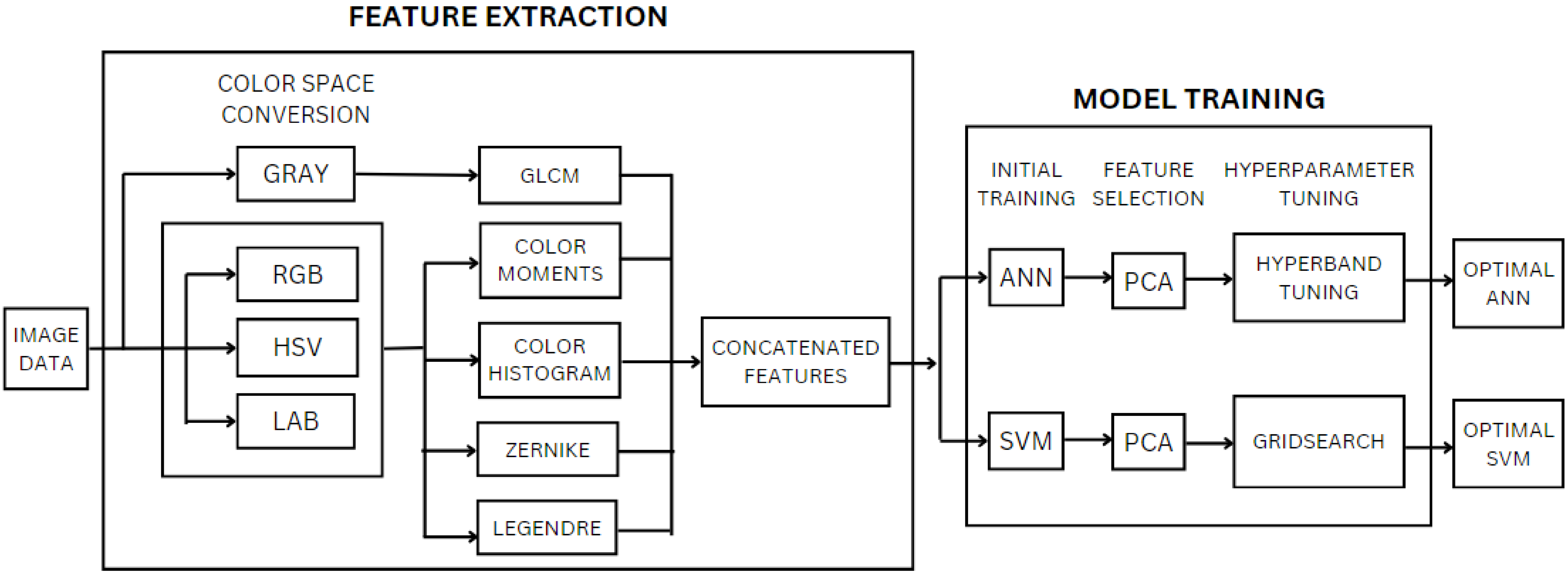
2. METHODOLOGY

Dataset

Label	Class Number	Number of Samples
bacterial leaf blight	0	97
bacterial leaf streak	1	99
bakanae	2	100
brown spot	3	100
grassy stunt virus	4	100
healthy rice plant	5	100
narrow brown spot	6	98

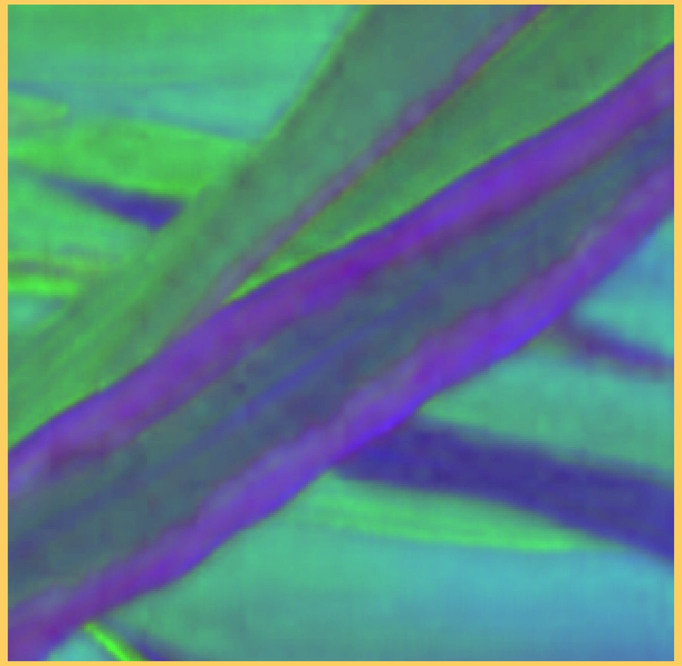
Label	Class Number	Number of Samples
ragged stunt virus	7	100
rice blast	8	98
rice false smut	9	100
sheath blight	10	98
sheath rot	11	91
stem rot	12	100
tungro virus	13	100

2. METHODOLOGY
Implementation



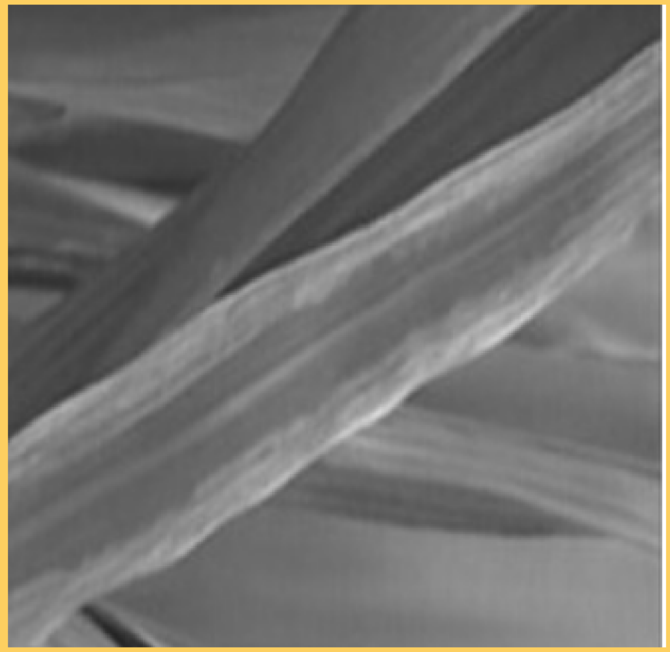
2. METHODOLOGY

RGB
original image



HSV
vividness
brightness

LAB
color separation
remove brightness
green to red
blue to yellow



GRAY
simplicity
reduced
dimensionality

2. METHODOLOGY

Color

1. For each channel of the **three color spaces (RGB, HSV, LAB)** the following color moments are computed: **mean, variance, skewness, and kurtosis**
2. **Color Histogram** the range of values for each channel of a color space are divided into **n equal sized bins** which **become the features** and their **values are the count** of channel values that fit in each bin.

2. METHODOLOGY

Texture Haralick Features

Texture

Image **texture features** refer to various characteristics that describe the **spatial arrangement** of **pixel intensities** in an image, providing information about its **visual pattern and structure**.

Gray-Level Co-occurrence Matrix (GLCM) is a texture analysis method that quantifies the relationships between pixel intensities in an image, capturing information about **texture, contrast, and spatial dependencies**, making it useful for tasks like image classification and segmentation.

Feature Name	Formula	Definition
'Angular Second Moment'	$\mathrm{ASM} = \sum_i \sum_j P(i,j)^2$	Represents the uniformity of distribution of grey level in the image
'Contrast'	$\mathrm{Con} = \sum_i \sum_j \lvert i-j \rvert^2 P(i,j)$	Local variations to show the texture fineness
'Correlation'	$\mathrm{Corr} = \frac{\sum_i \sum_j (i-\mu)(j-\nu)P(i,j)}{\sigma(i)\sigma(j)}$	Linear dependence in GLCM between different index
'Sum of Squares: Variance'	$\mathrm{SS{:}\ Var} = \sum_i \sum_j (i-\mu)^2 P(i,j)$	Higher weights that differ from the average value of GLCM
'Inverse Difference Moment'	$\mathrm{IDM} = \sum_i \sum_j \frac{1}{1+\lvert i-j \rvert} P(i,j)$	Inverse Contrast Normalized
'Sum Average'	$(\mathrm{Mean\ sum} = \sum_i \sum_{k=2}^{2N} k P_{x+y}(k)$	Higher weights to the higher index of the marginal GLCM
'Sum Variance'	$\mathrm{Var\ sum} = \sum_i \sum_{k=2}^{2N} (k-\mu_{x+y})^2 P_{x+y}(k)$	Higher weights that differ from the entropy value of the marginal GLCM
'Sum Entropy'	$\mathrm{H\ sum} = -\sum_i \sum_{k=2}^{2N} P_{x+y}(k) \log(P_{x+y}(k)+\epsilon)$	Higher weight on the higher sum of the index entropy value
'Entropy'	$\mathrm{H} = -\sum_i \sum_j P(i,j) \log(P(i,j)+\epsilon)$	Texture randomness producing a low value for an irregular GLCM
'Difference Variance'	$\mathrm{Var\ diff} = \sum_i \sum_{k=0}^{N-1} k^2 P_{x-y}(k)$	Average of the squared differences from the mean
'Difference Entropy'	$\mathrm{H\ diff} = -\sum_i \sum_{k=0}^{N-1} P_{x-y}(k) \log(P_{x-y}(k)+\epsilon)$	Higher weight on the higher difference of the index entropy value
'Informational Measure of Correlation 1'	$\mathrm{IMC1} = \frac{HXY1-HXY2}{\max(HX,HY)}$	Entropy measures
'Informational Measure of Correlation 2'	$\mathrm{IMC2} = \sqrt{1-\exp(-2(HXY2-HXY1))}$	Entropy measures

i and j represent rows and columns respectively, N is the number of distinct grey levels in the quantized image, $P(i,j)$ is the element from the normalized GLCM matrix, $P_x(i)$ and $P_y(j)$ are marginal probabilities of the matrix obtained by summing rows and columns of GLCM, respectively.

2. METHODOLOGY

IMAGE MOMENTS

- characterize diverse geometric attributes of an object, including its shape, area, border, location, and orientation.
- Zernike Moment and Legendre Moment are orthogonal moments which ensures their effectiveness in describing images with mutually independent descriptors, minimizing information redundancy. They are also invariant to translations and rotation

ZERNIKE MOMENT

Zernike Moment is the mapping of an image onto a set of complex Zernike polynomials. This is basically seen as an inner product between the image's function and the Zernike polynomials

$$R_{pq}(r) = \sum_{s=0}^{\frac{p-q}{2}} (-1)^s \frac{(p-s)!}{s!\left(\frac{p-2s+q}{2}\right)!\left(\frac{p-2s-q}{2}\right)!} r^{p-2s}$$

with $0_- < |p| < q$ and $p - |q|$ is given; $p > 0$.

LEGENDRE MOMENT

Legendre Moment uses a kernel for the Legendre moments that are described as products of Legendre polynomials defined along rectangular image coordinate axes inside a unit circle

$$\mathrm{P}_p(x) = \frac{1}{2^p} \sum_{k=0}^{\frac{p}{2}} (-1)^k \frac{(2p-2k)!}{(k)!(p-k)!(p-2k)!} x^{p-2k}$$

2. METHODOLOGY

EXPERIMENTAL SETUP

Hyperparameters to tune for:

ANN

Hyperparameter	Values	Step
Number of Hidden Layers	1 to 3	1
Nodes per Hidden Layer	32 to 512	32
Activation Functions	relu, tanh, sigm	N/A
Learning Rate	0.001, 0.01, 0.1, 0.3, 0.5	N/A
Batch Size	16, 32, 64, 128	N/A

SVM

Hyperparameter	Values
Kernels	rbf, linear, poly
C	0.001, 0.01, 0.1, 1
Gamma	1, 10, 100, 300

PCA	Values
Variance	.97 to .99

2. METHODOLOGY

EXPERIMENTAL SETUP

Experiment 1: Assessing Generalizability Across Diverse Dataset and Multiple Classes

Experiment 1 will be utilize **entire dataset 1** to explore the **generalizability of the models across 14 classes and various image types**. This aims to investigate whether the selected attributes are sufficient for ANN and SVM, considering the dataset's diversity.

Experiment 2: Comparative Evaluation with a Previous Local Study

Experiment 2 will use the dataset 2 to serve as a benchmark, aligning with the local literature [1]. This dataset comparison aims to **evaluate the model's performance against the local literature**, which achieved **100% accuracy using ANN** for **three rice diseases**.

Experiment 3: Assessing Model Performance on a controlled dataset

Experiment 3 will use the results of the initial dataset as a benchmark, and **determine the model's performance** when the there is **less variability** in the **image magnification** for each class. IE each class is **solely composed** of **zoomed in or whole rice plant images**

3. RESULTS AND DISCUSSION

EXPERIMENT 1: Assessing Generalizability Across Diverse Dataset and Multiple Classes

Total Extracted Features = 933

Descriptor	Color Channel	Dimension per channel	Total Features
Histogram	RGB	82	246
	HSV	82	246
	LAB	82	246
Color Moment	RGB	4	12
	HSV	4	12
	LAB	4	12
GLCM	Gray	13	13
Zernike	Gray	25	25
Legendre	Value	121	121

3. RESULTS AND DISCUSSION

EXPERIMENT 1: Assessing Generalizability Across Diverse Dataset and Multiple Classes

Result of different models for ANN

Model	Features	Hyperparameter	Accuracy (%)
ANN 1	933	untuned	80.79
ANN 2	246	untuned	80.72
ANN 3	246	tuned	83.33

untuned parameters:
Hidden Layers: 2
Nodes per Hidden Layer: 32-32
Activation Functions: relu-relu
Learning Rate: 0.001
Batch Size: 32

3. RESULTS AND DISCUSSION

EXPERIMENT 1: Assessing Generalizability Across Diverse Dataset and Multiple Classes

Top 10 results for ANN Hyperparameter Tuning

Trial	Number of Layers	Nodes per Hidden Layer	Activation Functions	Learning Rate	Batch Size	Accuracy (%)
70	3	480-320-480	relu-tanh-relu	0.1	32	83.93
76	3	480-320-480	relu-tanh-relu	0.1	32	83.93
80	3	192-32-512	sigm-tanh-relu	0.1	16	83.93
106	2	480-352-224	relu-tanh-tanh	0.01	16	83.93
119	3	64-512-64	tanh-tanh-tanh	0.1	128	83.93
165	3	384-384-320	sigm-relu-sigm	0.3	16	83.93
172	3	192-96-512	tanh-sigm-relu	0.5	128	83.93
66	3	512-128-320	sigm-sigm-tanh	0.1	128	82.14
67	3	512-128-320	sigm-sigm-tanh	0.1	128	82.14
73	3	512-128-320	sigm-sigm-tanh	0.1	128	82.14

3. RESULTS AND DISCUSSION

EXPERIMENT 1: Assessing Generalizability Across Diverse Dataset and Multiple Classes

Result of different models for SVM

Model	Features	Hyperparameter	Accuracy (%)
SVM 1	933	untuned	78.62
SVM 2	194	untuned	84.05
SVM 3	194	tuned	86.23

untuned parameters:
c: 1
gamma: scale
kernel: linear

3. RESULTS AND DISCUSSION

EXPERIMENT 1: Assessing Generalizability Across Diverse Dataset and Multiple Classes

Top 10 results for SVM Hyperparameter Tuning

Trial	C	Gamma	Kernel	Accuracy (%)
0	100	0.1	rbf	86.23
25	100	0.1	rbf	86.23
16	10	0.1	rbf	86.05
22	100	0.01	rbf	84.24
11	10	0.001	linear	82.25
17	10	0.1	linear	82.25
14	10	0.01	linear	82.25
27	100	0.1	poly	82.15
5	1	0.01	linear	82.06
2	1	0.001	linear	82.06

3. RESULTS AND DISCUSSION

EXPERIMENT 2: Comparative Evaluation with a Previous Local Study

Accuracy result (in %) for ANN of Local Literatures vs ANN and SVM of proposed method

	Local Literature	Proposed Method	
Disease	ANN	ANN	SVM
Brown Spot	100	100	100
Rice Blast	100	100	90.91
Leaf Blight	100	100	100
Overall	**100**	**100**	**96.77**

4. CONCLUSIONS

1. Initial models with selected features showed minimal change for ANN (**80.79% to 80.72% with 246 features**) but a notable increase for SVM (**78.62% to 84.05% with 194 features**). Subsequently, tuned models achieved **83.33% accuracy for ANN and 86.23% for SVM**, emphasizing SVM's effectiveness with high-dimensional datasets.
2. Result of Experiment 2 shows that the proposed methodology demonstrate **success particularly when dealing with a limited number of classes and less variability in images**.
3. Result of Experiment 3 revealed great results when ensuring that classes only have one type of image achieving a **95.74% accuracy for SVM and for 90.78% ANN**
4. The proposed method effectively classifies a diverse dataset of rice disease images, even common paddy shots, without pre-processing or complex computations by emphasizing global features such as **Haralick Texture, Color Histogram, Moments, and Orthogonal Image Moment**, showcasing its significant potential.

4. RECOMMENDATIONS

1. Identify other global features and feature selection techniques
2. Assess the models performance on a dataset composed solely of whole rice plant or paddy images
3. Utilize the presented features on pre-segmented rice images

END.
THANK YOU!