Optimizing rice disease classification: A comparative study of different color, shape and texture features

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Introducing the problem

RICE, often referred to as the staple of life in the in the Philippines, holds unparalleled significance deeply rooted in the country's culture and sustenance [2]. The reliance on rice in the Philippines is immense, with the nation's daily diet revolving around its consumption. In 2023 alone, the domestic consumption for milled rice reached a staggering 16.5 million metric tons [8].

But despite its importance, **rice's global production continuously faces substantial challenges due to the impact of rice diseases**. A 2016 study conducted in the United States reveals that approximately 30% of rice crop production losses worldwide can be attributed to diseases, creating a significant deficit equivalent to the sustenance of about 60 million people [28]. Diseases such as bacterial blight, can inflict up to a staggering 70% yield loss, with the severity increasing especially if it strikes early in the crop's life cycle [1].

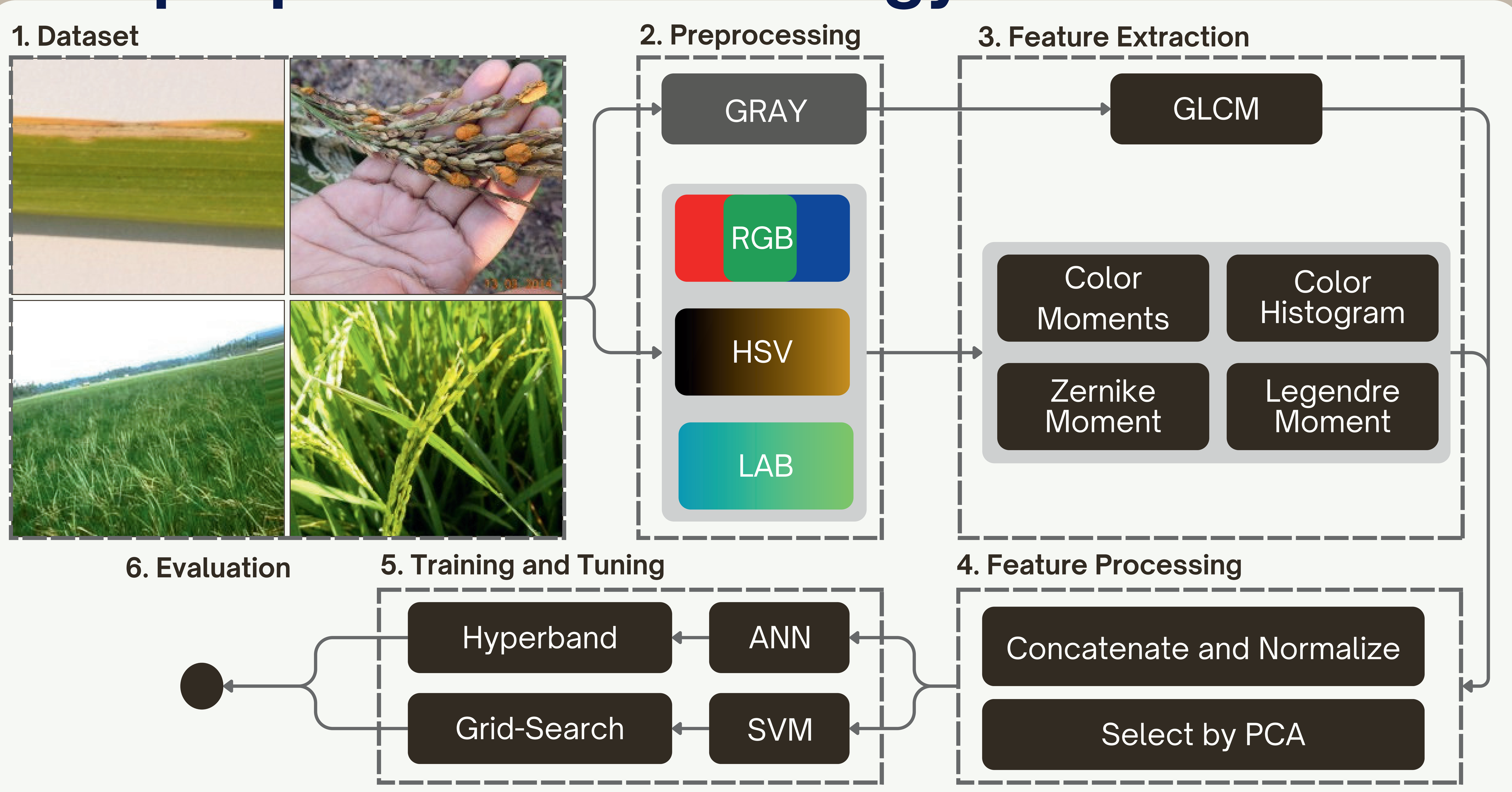
To address the challenge of yield loss, rice disease management strategies are crucially employed, involving intricate processes of detection, classification, and treatment. Early classification and forecasting systems, essential for managing rice diseases like rice blast, guide farmers in strategic decision-making for fungicide applications, fertilization practices, and yield prediction. Robust early-warning systems can prevent explosive disease outbreaks, reducing both yield losses and environmental impacts [5].

The primary hurdle lies in accurately classifying rice diseases, especially in vast fields with non-native pathogens thus prompting a shift towards the adoption of image processing for precise identification [4]. **Application of machine-driven systems can also reduce expert and labor costs by lowering the need for farmers to manually check the health condition of their crops**. All in all, this will contribute to the sustainable agriculture efforts in the Philippines and ultimately ensure a stable food supply for the nation

Goal of the study

1. Explores the use of classical machine learning models in classifying rice disease images by utilizing the whole image, and removing image pre-processing and segmentation steps (often performed by multiple studies [21, 27]) altogether which creates a more efficient and automated method that has the potential to be easily deployed in the future; and,
2. Extends the scope of classification to encompass a broader range of common rice diseases.

Our proposed methodology



methodology details

1
- Dataset is retrieved from *https://www.kaggle.com/datasets/shrupyag001/philippines-rice-diseases* containing diverse images of rice plants (paddy images, zoomed-in images, processed images).
- There are **13 distinct rice diseases and 1 healthy class**. All images are standardized to a dimensionality of **224 x 224 pixels**.
- Partitioned into an **80-20 ratio for training-testing**.

2
Images were converted to RGB, HSV and LAB which are often the input data used to extract the color moments and histogram and image moments. For GLCM texture features, gray channel was used.

3
For each respective color spaces, the following are computed:
- **Gray-Level Co-occurence Matrix (GLCM)**, a **texture analysis method** that quantifies the relationships between pixel intensities in an image, capturing information about contrast, and spatial dependencies [3];
- **Color moments** which convey that that any color distribution can be interpreted as a probability distribution [6]. This is computed by obtaining the mean, variance, skewness, and kurtosis of each color channel of an image;
- **Color Histogram** represented by a line graph, where each peak (referred to as bins) denotes a particular color of the color space. the range of values for each channel of a color space divided into n equal sized bins which become the features and their values are the count of channel values that fit in each bin [9].
- The two most common image moments, **Zernike Moment** and **Legendre Moment** producing the shape features. These have the desirable property of orthogonality, which ensures their effectiveness in describing images with mutually independent descriptors, minimizing information redundancy. They are also invariant to translations and rotation. Zernike Moment is the mapping of an image onto a set of complex Zernike polynomials [10] while Legendre polynomials is the projection of an image as it form a complete orthogonal set inside the unit circle [11].

4
- All the feature dataframes along with their labels are then **concatenated into a single dataframe and normalized.**
- **Principal Component Analysis (PCA)** was used to select a subset of best features from the initial dataframe. Variances ranging from 0.97 to 0.99 were surveyed to find the optimal variance and set of features for the final model.

5
- Hyperparameters affects the generalization of a model. For ANN, **hyperband search** (variation of random search with some explore-exploit theory to find the best time allocation for each of the configurations) [7] was used to determine the optimal setting while for the SVM, **grid-search** (algorithm that tests the performance of all possible combinations of listed hyperparameters) was used. Hyperarameters tuned for each model are shown in **Table 1 and 2**.
- Using the training data, the models were trained on three configurations: 1) default hyperparameters and complete set of features; 2) default hyperparameters and reduced features; and, 3) tuned models and reduced features.

6
- Using the models trained on different configurations, tests were performed under the three different experimental setup using their respective testing data.
- **Accuracy was used as the evaluation metric**. This measures how often the classifier correctly predicts and calculated as the ratio of the number of correct predictions and the total number of predictions.

Table 1. Hyperparameters for ANN

Hyperparameter	Values
Nodes per Hidden Layer	32 to 512 (by 32)
Activation Functions	relu, tanh, sigm
Learning Rate	0.001, 0.01, 0.1, 0.3, 0.5

Table 2. Hyperparameters for SVM

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

Experiments done . . .

Experiment 1: Assessing generalizability across diverse dataset and multiple classes

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

Use only three classes: brown spot, bacterial leaf blight, and rice blast; created for the purpose of comparing the performance of this study's models relative to a local study conducted [21] which achieved 100% accuracy using ANN for the three rice diseases.

Experiment 3: Assessing model performance on a controlled dataset

Evaluate on 14 classes but in order to mimic a similar setting to most papers that only used similar types of images per class, 50 randomly selected images were utilized for each class, focusing on only either zoomed-in or paddy shot images per class reducing variability.

. . . and their results

Table 3. Accuracy result (in %) of ANN and SVM with different models on diverse dataset

Model	ANN	SVM
Complete Features, Untuned Parameters	80.79	78.62
Selected Features, Untuned Parameters	80.72	84.05
Selected Features, Tuned Parameters	83.33	86.23

Table 4. Accuracy result (in %) for ANN of Local Literatures vs ANN and SVM of proposed method

Class	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**

Table 5. Accuracy result (in %) of ANN and SVM with different models on controlled dataset

Model	ANN	SVM
Complete Features, Untuned Parameters	90.07	88.65
Selected Features, Untuned Parameters	91..49	93.61
Selected Features, Tuned Parameters	93.62	93.61

The conclusion

1. On experiment 1, initial models with selected features showed minimal change for ANN but a notable increase for SVM. **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, while using classical model 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.

The recommendations

Despite conducting feature selection and rigorous optimization, it was difficult to obtain an accuracy of more 90% considering the number of classes on top of the varied images. This initiate a recommendation of perhaps **using more global features or performing a more effective feature selection**. Additionally, utilizing the algorithm and deploying it may be tried.

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