Optimizing Rice Disease Classification: A Comparative Study of Different Color, Shape and Texture Features

Joshua R. Dela Cruz
College of Engineering
University of the Philippines Diliman
Quezon City, Philippines
jrdelacruz12@up.edu.ph

Vince Raphael R. Miranda
College of Engineering
University of the Philippines Diliman
Quezon City, Philippines
vrmiranda@up.edu.ph

Prospero C. Naval, Jr.
Department of Computer Science
University of the Philippines Diliman
Quezon City, Philippines
pcnaval@up.edu.ph

Abstract—Rice holds significant importance as a staple food across Asia. Despite its crucial role, the rice industry grapples with challenges in disease classification. Current approaches utilizing ANN and SVM often rely on pre-processing and segmentation of the diseased portion of the rice plant before classification, which prevents automation. This study presents an automated, more efficient method by eliminating pre-processing and segmentation steps as well as utilizing the whole image. Leveraging features such as color histogram, GLCM, color moments, Zernike moments, and Legendre moments, the study trains SVM and ANN models—recognized for their effectiveness—to classify thirteen rice diseases, achieving accuracies of 86.23% and 83.93% respectively.

Index Terms—computer vision, image classification, rice plant diseases, artificial neural network, support vector machine

I. INTRODUCTION

Rice, often referred to as the "staple of life" in many Asian countries, holds unparalleled significance deeply rooted in the country's culture and sustenance [5].

While highly significant, 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 [26]. 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 [3].

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 [13]. 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 and ultimately ensure a stable food supply.

Previous research in this field often focused on using classical machine learning models to classify only one to three diseases. These approaches usually involved multiple pre-processing steps, such as background removal and isolation of the diseased portion of the rice plant, before feature extraction. This complexity made classification difficult to automate. In contrast, deep learning models, while effective in image classification without the need for the classical feature vector, require large amounts of data and computational resources [12]. The objective of the study is to create a simpler, more efficient, and cheaper solution by introducing a method that leverages Artificial Neural Network (ANN) and Support Vector Machine (SVM), both classical models known for their strength in classification problems [4], [25]. By utilizing multiple global features of an image, primarily the color histogram, the researchers eliminate the need for image preprocessing, and by utilizing the SVM, they address the high computational costs and data demand of deep learning models. In the study, the researchers also further expand the classification scope by including a wider range of common Asian rice diseases.

II. RELATED STUDIES

Machine learning techniques for rice disease identification have been utilized since the late 2000s. In a comprehensive survey by Shah, J. P. et al. [25], 19 papers were analyzed, providing insights into the landscape of research on rice plant diseases. The survey compared various criteria, including the size of the image dataset, the number of classes or diseases considered, preprocessing and segmentation techniques, and the input features used. Different classifiers were employed and achieved accuracies ranging from 75% to 100%.

On the other hand, numerous studies have explored the potential of deep learning models, particularly Convolution Neural Networks (CNN) often favored for image classification. CNNs can process images directly, eliminating the need for certain image processing steps such as segmentation, feature selection, and feature calculation [16]. In a study which compared four well known pre-trained models to classify six

rice diseases through 6330 natural photographs of rice leaves taken from fields of planting areas, the highest mean-average precision obtained was 79.19% [15].

Meanwhile in a comparison of six CNN-based models, three models with transfer learning approach, and an ensemble model consisting of three CNN-based models, a maximum accuracy of 97.00% was achieved. However, this required a dataset of 14,118 zoomed rice leaf images on a white background, which was then increased through positional and color augmentation to create 34,992 training images and 7,884 testing images [1]. However, while these results are promising, as comprehensively outlined in a recent survey of machine learning models [22], deep learning models face potential challenges in deployment especially due to computational cost and complexity [6]. Additionally, as evident in the literature, these deep learning models require thousands of images and annotations. This presents challenges when the model aims to identify new or regional rice diseases with limited images. This situation increases labor and data gathering costs related to image capturing and annotation.

In a Philippines-based study, the research focused on three prevalent diseases. The methodology employed MATLAB functions, implementing a two-step image enhancement process for noise removal and a five-step segmentation technique to isolate the diseased portion before feature extraction. The chosen features encompassed color moments in both RGB and HSV color spaces while the classification model used was a traditional Neural Network. Utilizing a database of 134 disease images of leaf samples acquired using a controlled-light module box which was designed with specific dimensions to capture the required length of rice leaf, ensured controlled lighting for image acquisition, the model successfully achieved 100% accuracy in disease identification [20].

III. METHODOLOGY

A. Dataset

The dataset was obtained from kaggle[1] containing diverse images of rice plants (paddy images, zoomed-in images, processed images). All images are standardized to a dimensionality of 224×224 pixels. The dataset consists of original images for all 14 balanced classes, including 13 diseases and 1 healthy class. This subset has undergone cleaning and evaluation by other users, ensuring the removal of near-duplicate images from different classes.

For the experiment proper, three different datasets were created from the original data.

1) First Dataset - Main dataset partitioned into training and testing sets. 80% of the dataset, comprising 1024 diseased and 80 non-diseased rice images, was allocated for training. The remaining 20%, consisting of 256 diseased and 20 non-diseased rice images, was designated for testing.

2) Second Dataset - Contains only three classes: brown spot, bacterial leaf blight, and rice blast; created for the

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

purpose of comparing the performance of this study's ANN and SVM results relative to the previous Philippine study conducted. To create a similar setting as will be discussed in Section III.C, the same amount of images focusing on the rice plant were randomly selected for each class, removing paddy images in the dataset resulting in 50 images per class. The total images were then partitioned into an 80-20 ratio for training-testing, similar to the First Dataset.

3) Third Dataset - Similar to the first dataset, 14 classes will be classified but in order to mimic a similar setting to most papers that only used similar types of images per class, 50 randomly selected images will be selected for each class, focusing on only either zoomed-in or paddy shot images per class.

B. Image Feature

An image feature is a value derived from a predefined image-processing algorithm and characterizes the content of an image. For this experiment, color, texture and shape features are explored. Details of the features are discussed in the following subsections and the analysis of their individual contribution to the classification is presented in Section IV.A.

1) Color Features: Crucial in computer vision, color ranks among the most significant and widely utilized low-level features. In the realm of computer vision, numerous color descriptors are available for extracting the color features of an image. A table from a literature [28] offers an overview of various color methods, outlining their respective strengths and weaknesses. This was referenced in selecting the Histogram method for its computational simplicity and intuitiveness, and Color Moment method for its compactness and robustness to noise.

Color histogram is a type of line graph, where each peak represents a particular color of the color space being used. The peaks in a color histogram are referred to as bins which are dependent on the colors in an image, represents the x-axis. The y-axis denotes the number of pixels there are in each bin or of a particular color [19].

Color moments offer computational simplicity and minimal storage. The mathematical meaning of this approach is that any color distribution can be interpreted as a probability distribution [14]. In this paper, the moments such as the mean (first order), standard deviation (second order), skewness (third order), and kurtosis (fourth order) represent the feature vector.

2) Texture Features: For this study, textural features were derived from the Grey Level Co-occurrence Matrix (GLCM), commonly known as Haralick features [8]. GLCM incorporates an offset value (D) to define pixel adjacency based on a specific distance, and in this case, the offset value is set to 1.

3) Shape Features: Shape features were obtained through image moments. Image moments serve as comprehensive descriptors capturing the global features of an image, offering insights into various geometrical characteristics. In computer vision, moments prove effective for characterizing diverse geometric attributes of an object, including its area, border,

location, and orientation. The utilization of moments in image analysis and pattern recognition found inspiration in the work of Hu [10]. Over the years, the field of computer vision has delved into multiple moment descriptors, Moment Invariants, Geometric Moments, Rotational Moments, Orthogonal Moments, and Complex Moments [18].

The two most common orthogonal moments, Zernike Moment and Legendre Moment are utilized due to their 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. This is basically seen as an inner product between the image's function and the Zernike polynomials [21].

Legendre Moment is first presented by Teague [27] which introduces the Legendre polynomials that form a complete orthogonal set inside the unit circle. The kernel of the Legendre moments are therefore defined as products of Legendre polynomials defined along rectangular image coordinate axes inside a unit circle.

C. Experimental Setup

1) Experiment: To assess the effectiveness of global features obtained without preprocessing the images, two classification models: ANN and SVM will be employed. The performance of both models will then be evaluated under the following conditions:

1) Generalizability of the models across 14 classes (13 diseased and 1 non-diseased rice images) and diverse image types (paddy images, zoomed-in images, processed images) using the first dataset. This will also investigate whether the selected attributes are sufficient for ANN and SVM, considering the dataset's diversity.

2) Using the second dataset, a comparative evaluation with the Philippine literature [20] which achieved 100% accuracy using ANN for three rice diseases (brown spot, rice blast, and leaf blight) which serves as the benchmark for the modes of this study.

3) Test under the third dataset to compare the performance of the ANN and SVM models to common dataset settings used by international literatures wherein there is less variability in the image magnification for each class.

2) Implementation: The general high-level overview of the implementation for each experiment that was performed are shown in Figure 1.

Data Preparation. In implementing the project, the researchers first imported the images which were translated to BGR images before converting to RGB, which is often the input data used to extract the aforementioned image moments, color, and texture features.

Feature Extraction

Texture. Texture extraction was achieved by first converting the RGB image data into grayscale with CV2 [2], [24]. The

researchers then utilized the Mahotas Feature[2] library to get the haralick features from each image which were all appended to form a GLCM feature dataframe.

Histogram. Histogram was calculated by converting the RGB images to HSV and LAB color spaces using CV2. Once converted, the researchers then proceed to split 3-dimensional tensor color spaces by their three respective channels as a similar method was done in a study by Pugoy, et al. [23]. For each channel the minimum and maximum values were taken and the number of bins parameters was set [7], [23]. The regions, which is the difference of the minimum and maximum values divided by the number of bins, then became the features with their values being the counts of numbers in each channel that fit within the range. As the 'number of bins' parameter affects the number of histogram features created with more bins leading to more histogram color features for each channel, different values ranging from zero to one hundred was tested to determine the the optimal and final number of bins to be used in the model.

Color Moments. Color moments were also computed using the RGB, HSV, and LAB channels. A similar approach was also employed by Prajapati et al., which this study expounded by also calculating the kurtosis and skewness of the HSV and LAB color spaces [25].

Image Moments. Libraries were also used to extract the Zernike Moments and Legendre Moments. Traditionally, various degrees of order are evaluated to determine the optimal value for each, but multiple literatures suggest that the performance of a model plateau after reaching a certain point of order for the Zernike and Legendre Moments [9], especially if there are minimal smooth color changes [11]. Additionally, computing for higher order moments is computationally expensive and does not align with the objective of this research [18]. Hence for this study, a fixed value was chosen as referred to the literature for these features.

Artificial Neural Network. For the implementation of the ANN, Keras from Tensorflow[3] was used. Preliminary architecture settings and hyperparameters were set arbitrarily to create a simple model. This was then trained using the training data that was split into 95%-5% training-validation sets and evaluated using the test data with complete features. Subsequently, Principal Component Analysis (PCA)[4] was used to select a subset of best features from the initial dataframe which were used for the second evaluation of the model. Finally, the hyperparameters were then tuned using kerastuner's hyperband[5] [17] and the model with the tuned parameters was tested after training on the training data with refined features.

Support Vector Machine. An SVM model is built using the scikit-learn[6] and evaluated. Once trained, the researchers proceeded to feature selection using PCA experimenting with a range of variances and number of features [7]. These sets

---

[2]https://mahotas.readthedocs.io/en/latest/features.html
[3]https://www.tensorflow.org/guide/keras
[4]https://scikit-learn.org/stable/modules/generated/sklearn.decomposition.PCA
[5]https://keras.io/api/keras_tuner/tuners/hyperband/
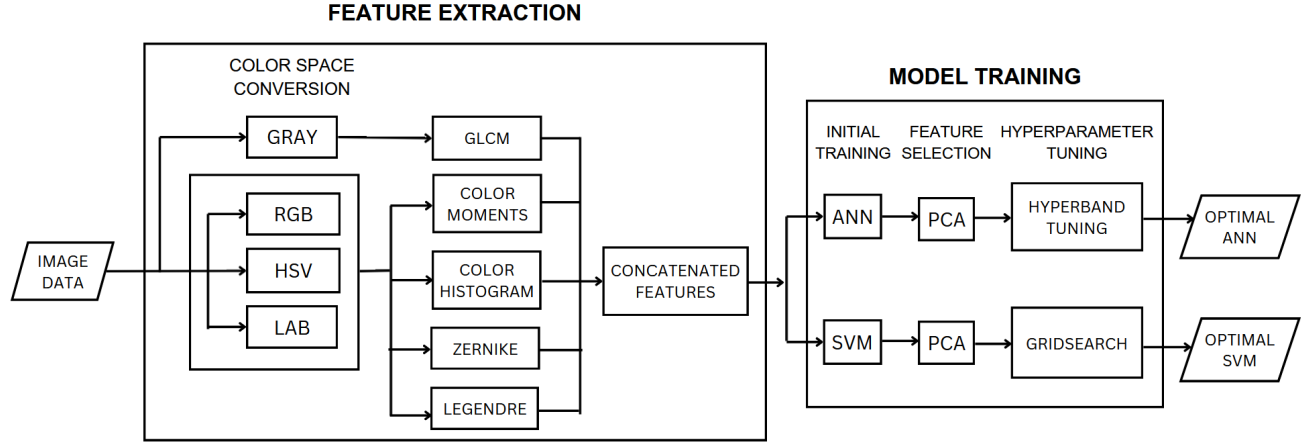[6]https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html

Fig. 1. Experiment Implementation

of features are then used to build multiple models which are trained and evaluated using the parameters of the initial SVM model and the model features with the best test accuracy are then used for hyperparameter tuning. Hyperparameter tuning is then done with gridsearch[7]. The best model is then selected after evaluating each model by their accuracy.

IV. DISCUSSION AND ANALYSIS OF RESULT

A. Experiment 1: Assessing Generalizability Across Diverse Dataset and Multiple Classes

To categorize the images into diseased and non-diseased classes, the ANN and SVM classifiers were used. As an initial assessment, the performance of both models was evaluated using individual sets of features. Each run focused on either histogram, color moment, texture, Legendre moments, or Zernike moments only, with the result presented in the Table I. Accuracies are based on models with selected best features for each set and tuned parameters.

TABLE I
PERFORMANCE OF ANN AND SVM USING INDIVIDUAL SETS OF FEATURES

Feature	ANN (%)	SVM (%)
Histogram	78.62	85.14
Color Moment	76.09	55.79
GLCM	60.87	59.78
Zernike	13.04	13.85
Legendre	38.41	41.3

1) Artificial Neural Network: The result of the three evaluations under ANN is presented in Table II, showing that with the complete set of extracted features and unrefined hyperparameters, the model could already achieve a good accuracy of 80.79%. After using PCA to reduce the dimensionality of the data, minimal changes were obtained on the metric.

[7]https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html

Finally, tuning the hyperparameters with hyperband creates 186 trial combinations wherein the top 10 best results for tuned parameters are shown in Table III, a small increase on the accuracy resulting in 83.33% was obtained. This implies that either the features obtained for all the 14 classes or that the feature selection performed were not sufficient.

TABLE II
MODEL COMPARISON FOR ANN

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

TABLE III
TOP 10 TRIALS FOR THE ANN HYPERPARAMETER TUNING

Trial Number	Nodes per Hidden Layer	Activation Function	Learning Rate	Accuracy (%)
0070	480-320-480	relu-tanh-relu	0.1	83.93
0076	480-320-480	relu-tanh-relu	0.1	83.93
0080	192-32-512	sigm-tanh-relu	0.1	83.93
0106	480-352-224	relu-tanh-tanh	0.01	83.93
0119	64-512-64	tanh-tanh-tanh	0.1	83.93
0165	384-384-320	sigm-relu-sigm	0.3	83.93
0172	192-96-512	tanh-sigm-relu	0.5	83.93
0066	512-128-320	sigm-sigm-tanh	0.1	82.14
0067	512-128-320	sigm-sigm-tanh	0.1	82.14
0073	512-128-320	sigm-sigm-tanh	0.1	82.14

2) Support Vector Machine: The findings of training the SVM on the three datasets are shown in Table IV. In the initial training the study found an accuracy of 78.62%. Similar to the ANN, even with the absence of hyperparameter tuning and feature selection the model is already adequate at classifying rice diseases. This accuracy, however, was further improved after feature selection via PCA where the SVM reduced the features to 194 from 933 while still achieving a higher accuracy of 84.05%. The highest accuracy was then achieved via hyperparameter tuning making use of gridsearch with the

top results presented in Table V which tested the outcomes of different kernels, c, and gamma values. The final accuracy of the model was 86.23%.

TABLE IV
MODEL COMPARISON FOR SVM

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

TABLE V
TOP 10 TRIALS FOR THE SVM HYPERPARAMETER TUNING

Trial Number	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	82.24
27	100	0.1	poly	82.15
5	1	0.01	linear	82.06
2	1	0.001	linear	82.06

B. Experiment 2: Comparative Evaluation with the Philippine Study

In the second experiment, using the dataset comprising randomly selected zoomed-in images, a new dataframe of features was extracted, yielding an initial set of 933 features. Similar to Experiment 1, the initial ANN and SVM models were employed to evaluate the features through PCA. Subsequently, each model was tuned to obtain optimal parameters then utilizing these models, the accuracy results for individual rice diseases and overall performance are presented in Table VI below.

TABLE VI
COMPARISON OF ACCURACY (IN %) RESULTS FOR ANN OF PHILIPPINE LITERATURE (PL) VS ANN AND SVM OF PROPOSED METHOD (PM)

Disease	ANN (PL)	ANN (PM)	SVM (PM)
Brown Spot	100	100	100
Rice Blast	100	100	90.91
Leaf Blight	100	100	100
Overall	100	100	96.77

It can be observed that for both Philippine literature and this study's proposed method, a 100% accuracy was obtained when classifying the three classes of rice disease. On the other hand, SVM only attained a 90.91% accuracy when classifying rice blast images.

C. Experiment 3: Comparative Evaluation with International Studies

For this experiment, performance for both ANN and SVM revealed very high results as presented in Table VII, as compared to the models of experiment 1 which utilized the dataset with varied types of images for each class, This highlights the effectiveness of the model when classifying single variation of images for each label.

TABLE VII
PERFORMANCE OF ANN AND SVM WITH DIFFERENT MODELS FOR EXPERIMENT 3

Model	ANN (%)	SVM (%)
1	90.07	88.65
2	91.49	93.61
3	93.62	93.61

Model 1: Complete features, untuned parameters
Model 2: Selected features, untuned parameters
Model 3: Selected features, tuned parameters

As can be seen, ANN with all the extracted features and untuned parameters, already obtained a 90.07% accuracy, subsequently performing evaluation on selected features resulted in slight increase resulting to 91.49%. Finally tuning the parameters, the hypermodel obtained 93.62%.

On the other hand, SVM were also able to obtain a very high accuracy of 88.65% immediately even with all the features and untuned parameters. It was increased to 93.61% after selecting the best features and more, reaching a great value of 93.63% after performing gridsearch for its parameters.

V. CONCLUSION AND RECOMMENDATIONS

A. Conclusion

In this study, the researchers sought to develop a simple machine-driven classification method that eliminates the necessity for pre-processing diverse rice images while using classical machine learning models. The focus was on leveraging multiple global features of an image, specifically Haralick Texture Features, Color Histogram, Color Moments, and the Orthogonal Image Moments, Legendre and Zernike Moments. While numerous studies have addressed rice disease classification, efforts were made to broaden the scope by classifying prevalent rice diseases in Asia. The classification included a total of 13 classes representing rice diseases affecting various parts of a rice plant, in addition to images of healthy rice plants.

To assess the explanatory power of the features, an initial checking for individual sets of each feature was conducted showing the effectivity of the color features.

ANN and SVM models were then employed to classify the full set of 933 features and comparing the results of this with just using the features selected by PCA, resulted in minimal difference for ANN but a substantial change for SVM increasing the initial accuracy of 78.62 to 84.05%. Ultimately, using the subset containing the best features and tuned models for both ANN and SVM, an accuracy of 83.33% for ANN and 86.23% for SVM were obtained confirming the effectiveness of SVM in classifying high-dimensional datasets.

Though examining the result of Experiment 2 outlined in Section IV.B, it is evident that the proposed methodology in this study demonstrates success particularly when dealing with a limited number of classes and less variability in images,

comparable to the Philippine study that utilized multiple steps to remove noise and isolate the disease portion of rice plant.

Finally, looking at Experiment 3 which was performed as a supplementary assessment; to align with other international rice disease image classification studies that often utilize pre-processed and segmented images, a test was conducted on randomly selected and balanced of either zoomed-in or whole rice field images for each of 14 classes revealing a final result of 93.62% test accuracy for ANN and 93.61% for SVM, highlighting the great potential of the selected features and emphasizing the impact of diverse image types on classification accuracy.

In summary, the proposed method underscores its significant potential in classifying a diverse dataset of rice disease images, including those that include paddy shots which are actually more common in the real world. Remarkably, this classification is achieved with no pre-processing, eliminating the need for intricate steps and complex computations usually associated with common approaches.

B. Recommendations

As seen in experiment 1, despite conducting feature selection and optimizing the models with tuned hyperparameters, achieving an accuracy of over 90% was not possible suggesting that the extracted features may be insufficient or that a more effective feature selection method is essential, especially when dealing with a complex dataset with numerous classes. Further exploration of other global features and feature selection techniques are recommended to enhance the model's performance and potentially achieve perfect accuracy in classifying diverse sets of rice disease images.

Given that the study performed better in classifying a dataset of only zoomed in rice diseases images, future studies may want to explore the models performance on a dataset composed solely of whole rice plant or paddy images.

Furthermore, while less efficient, prior studies employing rice disease image segmentation before feature extraction and classification have demonstrated promising outcomes. Hence, prospective researchers may want to explore the extraction of features used in this study on pre-segmented rice images.

References

[1] M. T. Ahad, Y. Li, B. Song, and T. Bhuiyan. Comparison of cnn-based deep learning architectures for rice diseases classification. *Artificial Intelligence in Agriculture*, 9:22–35, 2023.

[2] A. Chaugule and S. N. Mali. Evaluation of texture and shape features for classification of four paddy varieties. *J. Ind. Eng.*, 2014:1–8, 2014.

[3] C. Cruz, I. Ona, N. Castilla, and R. Opulencia. Bacterial blight of rice. Retrieved from http://www.knowledgebank.irri.org/decision-tools/rice-doctor/rice-doctor-fact-sheets/item/bacterial-blight.

[4] T. Gayathri Devi and P. Neelamegam. Image processing based rice plant leaves diseases in thanjavur, tamilnadu. *Cluster Computing*, 22(Suppl 6):13415–13428, 2019.

[5] M. Gumapac. Rice: A filipino constant. *Bar Digest*, 25(10):1337–1342, 2011.

[6] M. Haldar, M. Abdool, P. Ramanathan, T. Xu, S. Yang, H. Duan, Q. Zhang, N. Barrow-Williams, B. C. Turnbull, B. M. Collins, et al. Applying deep learning to airbnb search. In *proceedings of the 25th ACM SIGKDD international conference on knowledge discovery & Data Mining*, pages 1927–1935, 2019.

[7] H. Hamdani, A. Septiarini, A. Sunyoto, S. Suyanto, and F. Utaminingrum. Detection of oil palm leaf disease based on color histogram and supervised classifier. *Optik (Stuttg.)*, 245(167753):167753, Nov. 2021.

[8] R. M. Haralick, K. Shanmugam, and I. Dinstein. Textural features for image classification. *IEEE Transactions on Systems, Man, and Cybernetics*, SMC-3(6):610–621, 1973.

[9] S. J. Hosaini, S. Alirezaee, M. Ahmadi, and S. V.-A. D. Makki. Comparison of the legendre, zernike and pseudo-zernike moments for feature extraction in iris recognition. In *2013 5th International Conference and Computational Intelligence and Communication Networks*, pages 225–228, 2013.

[10] M.-K. Hu. Visual pattern recognition by moment invariants. *IRE Transactions on Information Theory*, 8(2):179–187, 1962.

[11] T. Hupkens. Legendre moments of colour images. 2009.

[12] F. Jiang, Y. Lu, Y. Chen, D. Cai, and G. Li. Image recognition of four rice leaf diseases based on deep learning and support vector machine. *Computers and Electronics in Agriculture*, 179:105824, 2020.

[13] R. Kaundal, A. Kapoor, and G. Raghava. Machine learning techniques in disease forecasting: A case study on rice blast prediction. *BMC bioinformatics*, 7:485, 02 2006.

[14] N. Keen. Color moments, 2005.

[15] K. Kiratiratanapruk, P. Temniranrat, A. Kitvimonrat, W. Sinthupinyo, and S. Patarapuwadol. Using deep learning techniques to detect rice diseases from images of rice fields. In *Trends in Artificial Intelligence Theory and Applications. Artificial Intelligence Practices*, pages 225–237, Cham, 2020. Springer International Publishing.

[16] A. Krizhevsky, I. Sutskever, and G. E. Hinton. Imagenet classification with deep convolutional neural networks. In *Advances in Neural Information Processing Systems*, volume 25. Curran Associates, Inc., 2012.

[17] L. Li, K. Jamieson, G. DeSalvo, A. Rostamizadeh, and A. Talwalkar. Hyperband: a novel bandit-based approach to hyperparameter optimization. *J. Mach. Learn. Res.*, 18(1):6765–6816, jan 2017.

[18] S. Liao. *Image Analysis by Moments. The Department of Electrical and Computer Engineering*. The University of Manitoba, Winnipeg, Manitoba, Canada, 1993.

[19] C. Novak and S. Shafer. Anatomy of a color histogram. In *Proceedings 1992 IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pages 599–605, 1992.

[20] J. W. Orillo, J. Dela Cruz, L. Agapito, P. J. Satimbre, and I. Valenzuela. Identification of diseases in rice plant (oryza sativa) using back propagation artificial neural network. In *2014 International Conference on Humanoid, Nanotechnology, Information Technology, Communication and Control, Environment and Management (HNICEM)*, 2014.

[21] M. Oujaoura, B. Minaoui, and M. fakir. *Image Annotation by Moments*, pages 227 – 252. 07 2014.

[22] A. Paleyes, R.-G. Urma, and N. D. Lawrence. Challenges in deploying machine learning: A survey of case studies. *ACM Comput. Surv.*, 55(6), dec 2022.

[23] R. A. D. L. Pugoy and V. Y. Mariano. Automated rice leaf disease detection using color image analysis. In *Third International Conference on Digital Image Processing (ICDIP 2011)*. SPIE, Apr. 2011.

[24] K. Robert Singh and S. Chaudhury. Comparative analysis of texture feature extraction techniques for rice grain classification. *IET Image Process.*, 14(11):2532–2540, Sept. 2020.

[25] J. P. Shah, H. B. Prajapati, and V. K. Dabhi. A survey on detection and classification of rice plant diseases. In *2016 IEEE International Conference on Current Trends in Advanced Computing (ICCTAC)*, pages 1–8, 2016.

[26] A. M. Shew, L. L. Nalley, A. Durand-Morat, K. Meredith, R. Parajuli, G. Thoma, and C. G. Henry. Holistically valuing public investments in agricultural water conservation. *Agricultural Water Management*, 252(C), 2021.

[27] M. Teague. Image analysis via the general theory of moments. *J. Opt. Soc. Am*, 70(8), 1980.

[28] D. Zhang, M. M. Islam, and G. Lu. A review on automatic image annotation techniques. *Pattern Recognition*, 45(1):346–362, 2012.