Image Classification of Philippine Rice (*Oryza sativa*) Diseases Using Deep Convolutional Neural Networks

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ABSTRACT

Rice is a staple food in the Philippines. However, the Philippine Rice Plant (*Oryza sativa*) is vulnerable to diseases that affect crop quality and yield, resulting in significant crop losses. Filipino farmers generally have limited access to crop protection experts for early disease diagnosis. Meanwhile, existing automated diagnosis methods have inadequate accuracy and capacity. In response, this study employed machine learning and computer vision to accurately detect and classify 13 types of rice diseases: bacterial leaf blight, bacterial leaf streak, bakanae, blast, brown spot, false smut, grassy stunt, narrow brown spot, ragged stunt, sheath blight, sheath rot, stem rot, and tungro virus. With the aid of *fast.ai* deep learning library, popular deep convolutional neural networks (DCNNs) were explored as the potential vision model architecture. Ultimately, with its best-in-class scores, the *ConVNeXt* architecture was adopted. The model was trained on 7,820 stratified image inputs. Optimal model performance was achieved by transforming the images in the size of 192px × 192px with a 1:1 aspect ratio, and with reflection scaling. The model trained for 13 epochs and initially attained 98.32% accuracy. By augmenting the data during testing time, the model's accuracy was improved, and finalized, to 98.71%

KEYWORDS

Rice Plant Diseases, Computer Vision, Convolutional Neural Networks, ConVNeXt

1 INTRODUCTION

Rice is the most important staple in Southeast Asia as it provides 50% of the calorie intake for its population [10, 19]. This has always been the case in poor countries and even relatively wealthier countries. In developing countries alone, more than 3.3 billion people depend on rice for more than 20% of their calories. One-fifth of the world's population, more than 1 billion people, depends on rice cultivation for livelihood [25]. Rice is paramount for millions of small-scale farmers cultivating it across extensive hectares in the region. It is equally vital for numerous landless laborers who depend on these farms for their livelihoods [24]. According to IRRI, 48 million ha in Asia is used for rice production, this equates to almost 30% of the world's rice harvest. The Philippines alone recorded 4.81 million hectares of area harvested for rice and a total production of 19.96 million metric tons, with a value of Php 403.89 billion [20]. The Philippines continues to hold its position as one of the leading rice producers globally, securing the 8th spot, trailing behind countries such as China, Indonesia, India, and other Southeast Asian nations [16].

However, some of the produce is wasted in the process of distribution. Numerous destructive diseases afflict rice plants, including sheath rot, narrow brown spot, grassy stunt, ragged stunt, bacterial leaf streak, brown spot, blast, sheath blight, false smut, stem rot, bakanae, bacterial leaf blight, and tungro. These diseases, caused by various phytopathogens such as fungi, bacteria, and viruses, lead to significant crop losses, impacting both yield and crop quality. The estimated yield loss in rice due to these pathogens ranges from 15% to 30%, resulting in an annual cost of approximately 33 billion USD [15]. These diseases are widespread, highly infectious, and cause significant damage, posing a major challenge to agricultural development.

To minimize these losses on agricultural production, monitoring and early detection of pests and diseases are necessary to decrease disease spread and facilitate effective management practices. The traditional method of identifying rice diseases involves visual inspection by plant protection experts [26]. Expertise is essential for accurate visual observations, but interpretations can vary among individuals, potentially introducing errors [23].

This method is time-consuming and relies heavily on subjective judgment, making it difficult to promptly prevent and control rice diseases [26]. Moreover, plant protection experts are limited and are rather costly. Additionally, the reliance on manual assessment is prone to inconsistencies and may result in delayed responses to emerging threats. Compounding these challenges, the pool of plant protection experts is limited and often associated with high costs, further impeding the widespread implementation of effective disease management strategies.

To address these challenges, researchers have turned to computer vision for the early detection of these diseases. This approach is more cost-effective and less labour-intensive, as it significantly reduces the time required for diagnosis. Furthermore, the utilization of computer vision technology enhances the accuracy of disease detection, allowing for prompt intervention and better treatment outcomes. However, these intervention models a machine that detects a selected few only. Studies by Mirandilla & Paringit (2019) and Bari et al. (2021) automated a machine that detects three diseases only[3, 14]. Although both studies detect varying diseases, using two machines to detect rice diseases is counterproductive. Alternatively, other researchers developed models using bigger datasets. Consequently, the accuracy suffers. One model from Sengupta (2022) only has an accuracy of 88.19% with the MapReduce approach[21]. Moreover, a study by Deng et al. (2021) rendered a

91% accuracy using the ensemble model consisting of DenseNet-121, SE-ResNet-50, and ResNeSt-50[4].

Overall, deep learning through computer vision is a promising technology. Existing research has paved the way for others to use and improve. Accordingly, the group decided to create a model that uses computer vision to detect and classify rice diseases. This study aimed to increase the accuracy, efficiency, and convenience of rice disease diagnosis.

2 METHODOLOGY

2.1 Framework

Since the 1980s, convolutional neural networks (CNNs) were already used for computer vision-related tasks such as object identification and classification. [18] Much of the use of CNNs has been left behind over the years due to advances in other machine-learning fields. However, recent advances in big data and computing power have paved the way for the resurgence of CNNs working in tandem with deep learning models to form new technologies called deep convolutional neural networks (DCNNs).

Figure 1 illustrates how DCNNs become more advantageous over traditional CNNs– convolutional layers learn and improve upon the feature representations of previous epochs through deep learning, allowing convolutional neural networks to better identify and classify objects. In this study, different modern deep learning models, such as DCNNs, are explored to determine the best-fit model for classifying different Philippine rice diseases.

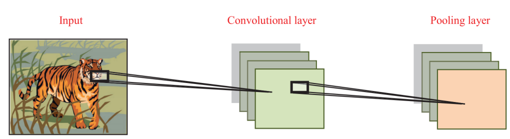

Figure 1: Deep Convolutional Neural Networks (DCNNs) (Rawat & Zhang, 2017)

To assist the researchers in model exploration, *fast.ai* [8], a modern deep-learning library was used for several computer vision and deep learning processes. Such processes include splitting the dataset into training and validation groups, creating disease classifiers for the training data, and training and fitting the training data against various deep-learning models. *Fast.ai* also provided additional functionality through image augmentation (i.e. *scale*, *rotate*, and *reflect* scaling methods), which was later used to augment the training data and increase the overall accuracy of the model.

Figure 2 shows an example of a deep learning model (*ResNet*) fitted using the Oxford IIT Pets dataset. In the figure, the *fast.ai* library was used to train the model to then display the true label (above) and the predicted label (below) for each image. In this paper, the *fast.ai* library was used to obtain the *Pytorch* image models that were then used to train and fit the dataset for Philippine rice disease classification.

2.2 Training and Validation Data

The data used in this study were obtained from two different sources, the *Philippines Rice Diseases* dataset (1,380 224px × 224px images)

Figure 2: Deep Learning Model *ResNet* Data Fitting Using FastAI (Howard & Gugger, 2020)

by Shruti Argwal, researcher at the Computer Science & Artificial Intelligence Laboratory, Massachusetts Institute of Technology [1], and the *Paddy Doctor: Paddy Disease Classification* dataset (10,407 480px × 640px images) by the Department of Computer Science and Engineering, Manonmaniam Sundaranar University [17].

Table 1 shows the 14 different categories that were labelled in the *Philippines Rice Diseases* dataset. Images in the *Paddy Doctor* dataset were classified into 10 categories. However, only 6 of the 10 categories were endemic to the Philippines and overlapped with the *Philippines Rice Diseases* dataset (6,440 images). Heance, images belonging to these categories were combined with the first dataset, while the rest were discarded.

Stratified random sampling was used to ensure that each disease in the dataset was represented in the training and validation sets. For each disease, 80% of the images were randomly selected as part of the training set and 20% as part of the validation set.

Table 1: Distribution of the *Philippines Rice Diseases* (PRD) and *Paddy Doctor* (PD) Datasets

Category	PRD	PD	Total	%Total	Train	Valid
Bacterial Leaf Blight	97	382	479	6.17	383	96
Bacterial Leaf Streak	99	477	576	7.42	461	115
Bakanae	100	-	100	1.29	80	20
Blast	98	1,738	1,836	23.65	1469	367
Brown Spot	100	965	1,065	13.72	852	213
False Smut	98	-	98	1.26	78	20
Grassy Stunt	100	-	100	1.29	80	20
Narrow Brown Spot	98	-	98	1.26	78	20
Normal/Healthy	100	1,775	1,875	24.15	1500	375
Ragged Stunt	100	-	100	1.29	80	20
Sheath Blight	98	-	98	1.26	78	20
Sheath Rot	92	-	92	1.19	74	18
Stem Rot	100	-	100	1.29	80	20
Tungro	100	1,103	1,203	15.50	962	241
Total	1,380	6,440	7,820	100.00	6,255	1,565
%Total	17.65	82.35	100.00	-	79.99	20.01

2.3 Model Selection

Howard & Capelle (2022) explored different *Pytorch* Image Models on the Oxford IIT-DP dataset to determine the fastest and most accurate pre-trained deep learning models for fine-tuning using a combination of GPU memory consumption, error rate, and total fitting time [11].

Table 2 shows a comparison of the different deep learning models and shows that *ConvNeXt* (7.7949) [13] yielded the highest score rating followed by *Swin* (8.9773) [12] and *ViT* (8.8091) [5] . The *ResNet* (9.5975) [7] CNN was then added in this paper as a control variable. *ConvNeXt* was therefore tentatively selected as the best deep learning model for the dataset. However, the dataset was still trained on the various models for further confirmation.

Table 2: Comparison of Different Pre-Trained Deep Learning Models for Fine-Tuning for Model Selection (Howard & Capelle, 2022)

Family	*Model*	Score
ConVNeXt	convnext_tiny_in22k	7.7949
Swin	swin_s3_tiny_224	8.9773
ViT	vit_small_r26_s32_224	8.8091
ResNet	resnet26d	9.5975

The dataset was trained on four (4) different deep-learning models for comparison. The models were selected based on similar computing power (number of floating-point operations per second or FLOPs) in their model family. Images were down-sampled to a 224px × 224px resolution to maintain compatibility with *Swin* which only accepts such resolution. The images also used the *squish* scaling method and were trained across only five (5) epochs to reduce the overall training time between comparisons.

Figure 3 shows that *ConVNeXt* yielded the lowest error rate on the dataset at 2.78%, followed by *Swin* at 2.85%, *ViT* at 3.01%, and *ResNet* at 4.85%. Therefore, *ConVNeXt* was selected as the deep learning model for this paper.

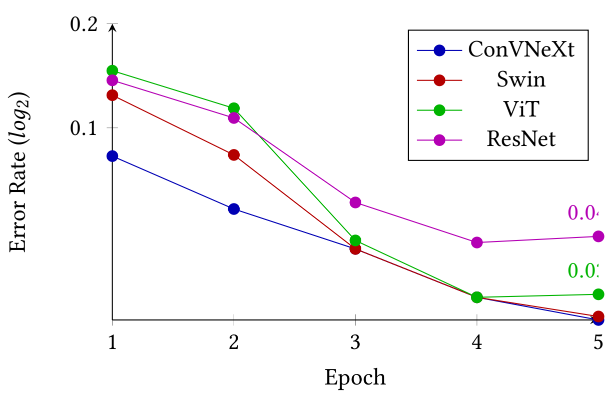

Figure 3: Line Graph of Error Rate Across Epochs per Deep Learning Model – 224px × 224px, *Squish* Scaling, 5 Epochs

2.4 Image Resolution

To determine the best image resolution for the model, four (4) different setups were tested. The resolutions were selected based on whether reducing the image resolution (37K vs. 50K) resulted in a different error rate and whether using the *Philippines Rice Diseases* dataset aspect ratio (1:1) or the *Paddy Doctor* dataset aspect ratio (3:4) resulted in a difference in error rate. Figure 4 shows the four different setups.

Figure 4: Comparison of Sample Image in the Dataset with Varying Resolutions – *Squish* Scaling

Table 3 shows that there was no significant difference in the model's error rates by varying the image resolution and aspect ratio. However, the table showed that a 192px × 192px image resolution resulted in the least fitting time and lowest error rate at 2.46%. Therefore, it was selected as the image resolution for the model.

Table 3: Train Loss, Valid Loss, Fit Time, and Error Rates of Different Image Resolutions – *ConVNext*, *Squish* Scaling Method, Five (5) Epochs)

Resolution	Train	Valid	Time	Error
192px × 192px (37K, 1:1)	0.0742	0.1012	7:32	0.0246
224px × 224px (50K, 1:1)	0.0692	0.1041	7:51	0.0278
168px × 224px (37K, 3:4)	0.0661	0.1048	8:07	0.0278
192px × 256px (50K, 3:4)	0.0701	0.1100	8:26	0.0265

2.5 Scaling Method

To determine the best scaling method for the model, four (4) different scaling methods were explored. The scaling methods were selected based on their frequency of use in DCNNs. Figure 5 shows the four different setups.

Table 4 shows that the *Reflection* scaling method yielded the lowest error rate at 2.00%, followed by *Squish* at 2.59%, *Crop* at 2.98% and *Zeros* at 3.11%. Therefore, *Reflection* was selected as the scaling method for the model.

From these tests on deep learning architectures and image preprocessing, the optimal parameters for the model implementation were identified. First, the model will make use of the *ConVNeXt* deep learning architecture as justified by optimal runtime performance and accuracy in the earlier tests. Secondly, the image dataset

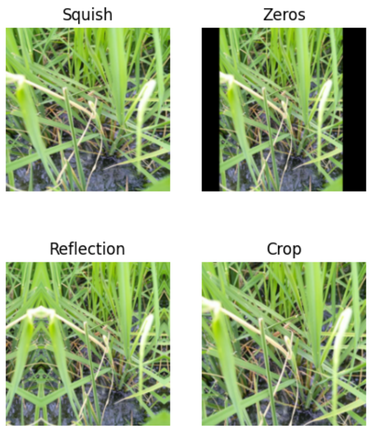

Figure 5: Comparison of Sample Image in the Dataset with Varying Scaling Method, 192px × 192px Image Resolution

Table 4: Train Loss, Valid Loss, Fit Time, and Error Rates of Different Scaling Methods – *ConVNeXt*, 192px × 192px Resolution, 5 Epochs

Method	Train	Valid	Time	%ER
Squish	0.0742	0.1012	7:32	0.0246
Zeros	0.0789	0.1152	8:48	0.0311
Reflection	0.0826	0.0761	9:55	0.0200
Crop	0.0939	0.0869	6:20	0.0298

will be loaded with a resolution of 192px × 192px and a 1:1 aspect ratio and scaled using the reflection method.

Table 5: Summary of the Model Parameters

Model Architecture	ConVNeXt
Image Resolution	192px × 192px
Image Aspect Ratio	1:1
Scaling Method	Reflection

3 RESULTS

3.1 Learning Iterations

To develop a deep learning model that detects and classifies Philippine rice diseases, the *ConVNeXt* architecture will be used on an image dataset that is transformed using optimal parameters. Then, to maximize the model's accuracy, it must undergo several training iterations. Limiting the iterations to the number where the model remains a good fit is important. The model is said to be a good fit if there is minimal difference between the training loss and validation loss [2]. This means the model should have roughly the same accuracy during training and validation.

Figure 6 suggests that the number of epochs (or iterations) should be between 9 and 13–*after* the values stabilized and *before* the learning curves diverged. Accordingly, a maximum of 13 epochs

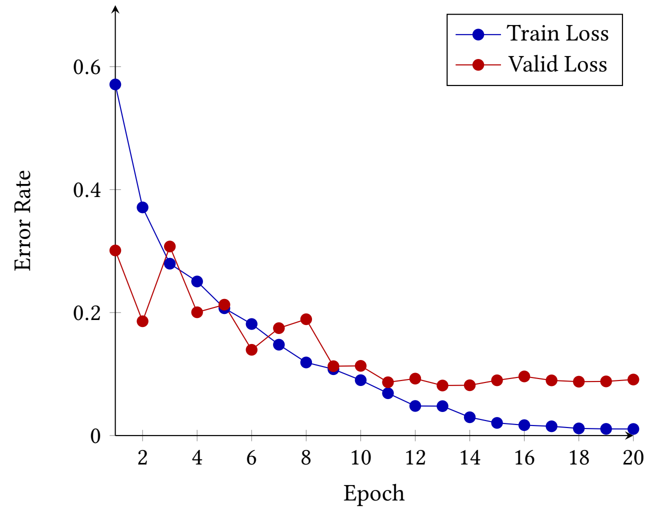

Figure 6: Learning Curves of Training Loss vs Validation Loss of the Model after 20 Epochs

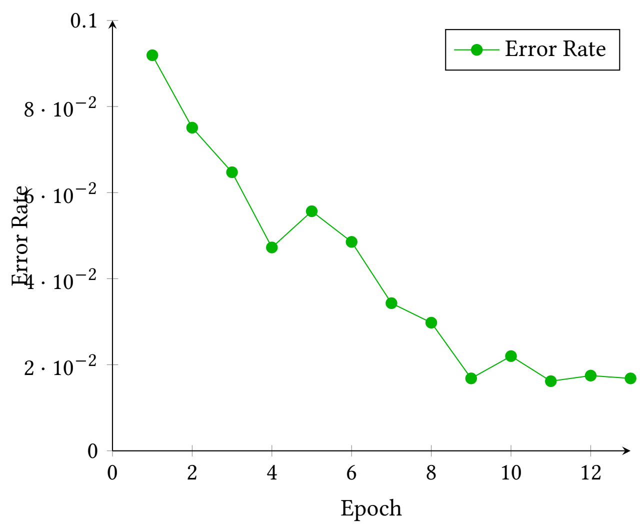

Figure 7: Line Graph of Error Rate of the Model after 13 Epochs

was defined in training the model. At this epoch, the difference between the training loss and validation loss is only 0.060836.

3.2 Training Time and Error Rate

The model completed its training in under 27 minutes and 7 seconds. On average, each training epoch lasted 2 minutes and 5 seconds. After the 13th epoch, the error rate is at 0.016828 or 1.6828%. This means that the model achieved 98.3172% accuracy in detecting and classifying 13 Philippine rice plant diseases.

3.3 Data Augmentation

To further improve these results, a *Test Time Augmentation* (TTA) may be performed. During TTA, the dataset is expanded by appending transformed variations of an input dataset, and then, the predictions are aggregated [22]. Image transformations may involve warping, brightening, or flipping to increase the input size.

Table 6: Effects of TTA to the Model's Error Rate/Accuracy

Augmentation	%ER	Accuracy
With TTA	0.0168	0.9832
Without TTA	0.0129	0.9871

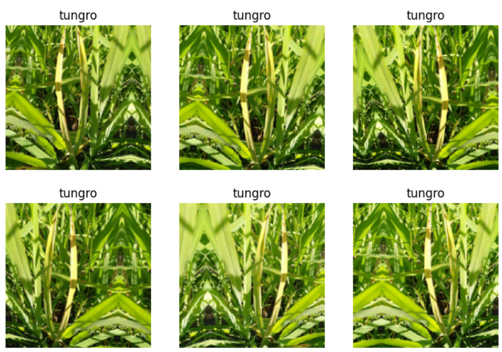

Figure 8: A Sample of the Transformations Applied to an Image of *Tungro* Disease during Test Time Augmentation

Table 6 shows that by applying TTA, the accuracy of 98.32% can be further increased to the final accuracy value of 98.71%.

4 DISCUSSIONS

To detect and classify common Philippine rice plant (*Oryza sativa*) diseases, a deep learning model that uses the *ConVNeXt* architecture was developed. This architecture was used because it performs best and results in the highest accuracy during preliminary testing. *ConVNeXt* is a vision backbone that is based upon convolutional neural networks (CNN or *ConvNets*). In recent years, CNNs were overtaken in performance and popularity by other hierarchical vision Transformers such as the *Swin Transformer*. In turn, *ConVNeXt* was developed by *Meta* under their *Facebook* AI Research department. Later benchmark suggests that this new architecture can scale with top-performing hierarchical vision Transformers while being much simpler in design [13]. Consequently, *ConVNeXt* was used as the vision architecture of the model, which was trained and validated using a stratified image dataset of 13 rice plant diseases.

The model is determined to give optimal scores when the images are loaded in a 1:1 aspect ratio. It is important to note that not all images in the dataset are uniformly in this aspect ratio. This means there will be empty spaces or missing information when the images are resized. Thus, several scaling methods were tested and it was determined that reflection scaling results in the highest accuracy for the model. Computer vision relies heavily on the quality and quantity of the data [9]. From this, it can be inferred that transforming the images into an aspect ratio of 1:1 with the reflection scaling method will likely result in the best performance because the original data is retained, and pixel information is also increased for every image input.

Then, to ensure the goodness of fit of the model, it was trained under 13 epochs or iterations. The model initially achieved 98.32% accuracy. Through *Test Time Augmentation*, this was improved to 98.71%. This increase in accuracy resulted from dataset augmentation, which allowed the model to train on a bigger input size. It is important to note that TTA does not always boost a model's performance as it is still dependent on the dataset [6]. However, as evident in this case, TTA was effective in improving the model's performance, resulting in a very high accuracy in classifying rice plant diseases.

5 CONCLUSIONS

Rice is a staple food in the Philippines, and local rice plants (*Oryza sativa*) are exposed to various diseases. Given the low availability of experts and the high cost of detecting the presence of these diseases, it is important to consider an accessible and effective technological intervention. This paper aimed to develop an optimal model in detecting the presence of—and subsequently classifying—these rice plant diseases using computer vision and machine learning. The *ConVNeXt* architecture was employed as it proved to be the most efficient in detecting and classifying Philippine Rice Plant diseases. In particular, the model with *ConVNeXt* achieves the best performance when the images of the rice diseases have a resolution of 192px × 192px in a 1:1 aspect ratio and are scaled with reflection padding. In addition, it was determined that using dataset augmentation during testing improves the result by 0.39%. Altogether, with Test Time Augmentation, these input parameters provide a computer vision model with 98.71% accuracy. Ultimately, very high accuracy suggests that this model can reliably assist Filipino rice farmers, with limited access to plant protection experts, in detecting and classifying the thirteen aforementioned Philippine Rice Plant diseases.

5.1 Limitations

The image datasets used in this study are obtained from two different sources. Consequently, the two datasets vary in properties and quality. In addition, the researchers utilized basic image transformations to process the image dataset. There are more complex and possibly lengthier image processing algorithms available. These can be broadly categorized into *Morphological*, *Gaussian*, *Fourier Transform*, *Edge-Detection*, and *Wavelet* image processing. Lastly, the model training was performed in an environment with limited resources, thus restricting the researchers to certain computer vision architectures and transformations. With more powerful machines, more updated and robust architecture and image processing can be adopted.

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REFERENCES

[1] Shruti Argwal. 2023. *Philippines Rice Diseases.* Retrieved Dec 18, 2023 from https://www.kaggle.com/datasets/shrupyag001/philippines-rice-diseases/data
[2] Baeldung. 2023. What Is a Learning Curve in Machine Learning? https://www.baeldung.com/cs/learning-curve-ml. Accessed: 2023-12-28.
[3] Bifta Sama Bari, Md Nahidul Islam, Mamunur Rashid, Md Jahid Hasan, Mohd Azraai Mohd Razman, Rabiu Muazu Musa, Ahmad Fakhri Ab Nasir, and Anwar P P Abdul Majeed. 2021. A real-time approach of diagnosing rice leaf disease using deep learning-based faster R-CNN framework. *PeerJ Computer Science* 7, e432 (2021), 105.
[4] Ruoling Deng, Ming Tao, Hang Xing, Xiuli Yang, Chuang Liu, Kaifeng Liao, and Long Qi. 2021. Automatic diagnosis of rice diseases using deep learning. *Frontiers in Plant Science* 12, 70 (2021), 38.
[5] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, and Neil Houlsby. 2021. An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale. arXiv:cs.CV/2010.11929
[6] fast.ai. n.d.. Training a State-of-the-Art Model. https://nbviewer.org/github/fastai/fastbook/blob/master/07_sizing_and_tta.ipynb#Test-Time-Augmentation. Accessed: 2024-1-09.
[7] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2015. Deep Residual Learning for Image Recognition. arXiv:cs.CV/1512.03385
[8] Jeremy Howard and Sylvain Gugger. 2020. Fastai: A layered API for deep learning. *Information* 11, 2 (2020), 108. https://doi.org/10.3390/info11020108
[9] IBM. n.d.. What is computer vision? https://www.ibm.com/topics/computer-vision. Accessed: 2023-12-28.
[10] International Rice Research Institute. 2023. Transitioning toward equitable, profitable, and environmentally sound rice agri-food systems. https://www.irri.org/where-we-work/countries/southeast-asia. Accessed: 2024-1-09.
[11] Jeremy Howard and Thomas Capelle 2022. *The best vision models for fine-tuning.* Retrieved Dec 18, 2023 from https://www.kaggle.com/code/jhoward/the-best-vision-models-for-fine-tuning
[12] Ze Liu, Yutong Lin, Yue Cao, Han Hu, Yixuan Wei, Zheng Zhang, Stephen Lin, and Baining Guo. 2021. Swin Transformer: Hierarchical Vision Transformer using Shifted Windows. arXiv:cs.CV/2103.14030
[13] Zhuang Liu, Hanzi Mao, Chao-Yuan, Wu, Christoph Feichtenhofer, Trevor Darrell, , and Saining Xie. 2022. A ConvNet for the 2020s. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR).* 11976–11986.
[14] Jean Rochielle F. Mirandilla and Enrico C. Paringit. 2019. Detection and Differentiation of Selected Rice Diseases Using Hyperspectral Data. In *The 40th Asian Conference on Remote Sensing.* 9.
[15] Shubhransu Nayak, Soma Samanta, Chandan Sengupta, and Soumya Sephalika Swain. 2021. Rice crop loss due to major pathogens and the potential of endophytic microbes for their control and management. *Journal of Applied Biology & Biotechnology* 9, 5 (2021), 166–175.
[16] DA Press Office. 2022. From Business Mirror: Philippine rice production, varieties and research: What we know so far. https://www.da.gov.ph/from-business-mirror-philippine-rice-production-varieties-and-research-what-we-know-so-far/. Accessed: 2024-1-09.
[17] Pandarasamy Arjunan Petchiammal. 2022. *Paddy Doctor: A Paddy Disease Classification.* Retrieved Dec 18, 2023 from https://kaggle.com/competitions/paddy-disease-classification
[18] Waseem Rawat and Zenghui Wang. 2017. Deep convolutional neural networks for Image Classification: A Comprehensive Review. *Neural Computation* 29, 9 (2017), 2352–2449. https://doi.org/10.1162/neco_a_00990
[19] Roehlano M. Briones. 2018. The rice economy and the role of policy in Southeast Asia. https://www.searca.org/pubs/discussion-papers?pid=398. Accessed: 2024-1-09.
[20] PCAARRD's Industry Strategic Science and Technology Plans. n.d.. Rice Industry Profile. https://ispweb.pcaarrd.dost.gov.ph/isp-commodities/rice/. Accessed: 2024-1-09.
[21] Shampa Sengupta, Abhijit Dutta, Shaimaa A. M. Abdelmohsen, Haifa A. Alyousef, and Mohammad Rahimi-Gorji. 2022. Development of a Rice Plant Disease Classification Model in Big Data Environment. *Bioengineering (Basel, Switzerland)* 9, 12 (2022), 758.
[22] Divya Shanmugam, Davis Blalock, Guha Balakrishnan, and John Guttag. 2021. Better Aggregation in Test-Time Augmentation. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV).* 1214–1223.
[23] Vimal K. Shrivastava, Monoj K. Pradhan, Sonajharia Minz, and Mahesh P. Thakur. 2019. Rice Plant Disease Classification Using Transfer Learning of Deep Convolution Neural Network. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences* 42, 3 (2019), 631.
[24] Jayco Valmon. 2015. Essential food for the poor - Rice Today. https://ricetoday.irri.org/essential-food-for-the-poor/. Accessed: 2024-1-09.
[25] Mary Williams. 2017. Importance of rice science and world food security. https://plantae.org/robert-zeigler-importance-of-rice-science-and-world-food-security/.. Accessed: 2024-1-09.
[26] Nanxin Zeng, Gufeng Gong, Guoxiong Zhou, and Can Hu. 2021. An Accurate Classification of Rice Diseases Based on ICAI-V4. *Journal of Plants* 12, 11 (2021), 2225.