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Hybrid Deep Learning Algorithms for Predicting Nutrient Deficiencies in Paddy Crops using CNN and Super Resolution Generative Adversarial Neural Networks

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Abstract*:* In the realm of agriculture, predicting and addressing nutrient deficiencies in paddy crops is pivotal for sustaining crop yield and ensuring global food security. Farmers face challenges due to limited high-resolution images, impacting the effectiveness of models in deficiency detection. This research introduces a hybrid approach, merging Super-Resolution Generative Adversarial Networks (SRGANs) and Convolutional Neural Networks (CNNs), to elevate image resolution and enhance nutrient deficiency detection efficiency in paddy crops. SRGANs generate synthetic nutrient-deficient crop images, augmenting the training dataset and refining model generalization. These images, with increased detail, complement image analysis techniques for precise deficiency identification. High-resolution outputs from SRGANs serve as improved inputs for CNNs, facilitating accurate classification and localization of deficiencies based on color, texture, and morphology patterns. Synthetic images enable the hybrid model to learn comprehensive nutrient deficiency representations; enhancing detection accuracy. Extensive experiments on a large-scale dataset with varying deficiency levels validate the efficacy of the hybrid approach in real-world scenarios. SRGANs and CNNs, trained and fine-tuned on this dataset, exhibit improved image quality, as measured by metrics like Peak Signal-to-Noise Ratio (PSNR) and Structural Similarity Index (SSIM). CNN models demonstrate heightened accuracy in detecting nutrition deficiencies in high-resolution images, showcasing the potential of this hybrid solution for robust nutrient deficiency prediction in paddy crops.

Keywords: *CNN, nutrient-deficient, PSNR, SSIM, SRGAN, synthetic*

1. Introduction

Agriculture is the backbone of many economies and plays a crucial role in ensuring global food security. As the global population continues to grow, the pressure on agriculture intensifies, making agricultural sustainability and optimization of crop yields imperative. Paddy crops, being one of the primary sources of staple food for a vast majority of the population, are central to this sustainability effort. Diverse techniques and technologies are used for anticipating and managing crop nutrient imbalances. Proper nutrient management optimizes yield, quality, and plant health, guiding resource-efficient practices.[1]

However, paddy crop productivity is frequently hampered by nutrient deficiencies, which pose a critical challenge for farmers and agricultural experts. Nutrient deficiencies, such as nitrogen (N), phosphorus (P), and potassium (K), can lead to a range of detrimental effects on crop growth, including reduced photosynthesis, stunted plant development, and lower grain yield [2, 3]. Early detection and accurate prediction of nutrient deficiencies are essential for implementing targeted interventions and optimizing crop management practices, thereby ensuring sustainable yields and minimizing resource wastage.

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Traditional methods of nutrient deficiency prediction in paddy crops often rely on visual observations, field sampling, and laboratory testing. While effective, these approaches can be time-consuming, labor-intensive, and subject to human errors. In recent years, advancements in deep learning and computer vision have shown great promise in revolutionizing agricultural practices. [4, 5]

With the advent of technology and the incorporation of artificial intelligence (AI) into various sectors, there is an enormous potential for innovation in agriculture. In recent years, deep learning, a subset of AI, has made significant inroads in various domains, from medical imaging to autonomous vehicles. The rich feature extraction capability of Convolutional Neural Networks (CNNs), combined with the image enhancement potential of Generative Adversarial Networks (GANs), presents a promising solution to the challenge of nutrient deficiency detection in paddy crops.

However, a major bottleneck in harnessing the full potential of these models has been the scarcity of high-resolution images, which are essential for detailed analysis. A possible solution lies in the ability of Super-Resolution Generative Adversarial

Networks (SRGANs) to generate high-resolution, synthetic images from available lower-resolution ones [6]. By combining the capabilities of SRGANs and CNNs, this research aims to provide a novel approach to enhance the resolution of images and subsequently improve the detection accuracy of nutrient deficiencies in paddy crops. This work also transforms agricultural practices, empowering farmers with early detection and precise intervention strategies to achieve sustainable crop productivity and food security.

2. Background and Related Work

2.1 Nutrient Deficiencies in Paddy Crops

Nutrient deficiencies in paddy crops, like rice, can have severe repercussions on the health, yield, and quality of the harvest [7]. Typically, these deficiencies manifest as distinct visual cues such as discoloration of leaves, stunted growth, and poor grain quality. Historically, farmers and agronomists identified these deficiencies through hands-on examination and symptom-based identification charts. This method, though practiced for centuries, often leads to late diagnosis, resulting in irreversible damage. Given the implications of nutrient deficiencies on yield and the economic significance of paddy crops globally, there's a pressing need for early and accurate detection systems. Deficiency prediction aids decisions on fertilization and irrigation for sustainability. Soil analysis, remote monitoring, crop modeling, and data-driven insights play crucial roles. Sensor technology, decision support, holistic plans, and IoT integration contribute to effective prediction. Collaborative knowledge and early warnings enhance nutrient deficiency anticipation.[8]

2.2 Deep Learning in Agriculture

The introduction of deep learning in agriculture has transformed various operations, ranging from precision farming to pest detection. Convolutional Neural Networks (CNNs) have been especially influential due to their ability to process visual data and recognize intricate patterns that might be indiscernible to the human eye. Prior research has already demonstrated the potential of CNNs in detecting diseases in plants, classifying crop types, and predicting yields.[9, 10] However, the application of CNNs specifically for nutrient deficiency detection in paddy crops remains an area with significant potential.

2.3 Super-Resolution using GANs

Generative Adversarial Networks (GANs), introduced by Goodfellow et al. in 2014[11], have heralded a new era in image processing. GANs are composed of two distinct neural network models that form a competitive system, allowing them to analyze, capture, and replicate the intricate variations present within a dataset. The core components of a GAN include the generator, which learns to generate realistic synthetic data from a random seed. The contrived examples produced by the generator are used as negative examples for training the discriminator. The discriminator is the one that learns to distinguish fake data from actual data.

Particularly, Super-Resolution Generative Adversarial Networks (SRGANs) have emerged as a revolutionary tool for upscaling images [12, 13]. SRGANs achieve this by employing a generator network that upscales images, and a discriminator network that evaluates the quality of the upscaled images. Previous works have successfully used SRGANs in fields like medical imaging [14, 15] and satellite image enhancement [16, 17], emphasizing their ability to produce high-resolution images from low-resolution inputs, thus compensating for the dearth of high-quality data.

The generator in SRGAN incorporates a combination of convolutional neural networks (CNNs), ResNets, batch-normalization layers, and Parametric ReLU activation functions. This configuration facilitates down sampling of images followed by an up-sampling process to generate super-resolution images. On the other hand, the discriminator employs CNNs, dense layers, Leaky ReLU activation, and a sigmoid activation function. Its role is to determine whether an image is the original high-resolution image or the super-resolution image produced by the generator. SRGAN is particularly useful when there is a need to upscale images while preserving fine-grained details and maintaining high-fidelity [18].

2.4 Prior Efforts in Nutrient Deficiency Detection

There have been several initiatives using traditional machine learning and computer vision techniques to detect nutrient deficiencies in various crops [19, 20]. These methodologies often relied on color histograms, texture analysis, or hand-engineered features. While successful to an extent, they often required rigorous feature engineering and were limited by the quality of input images. Few works have combined deep learning and super-resolution techniques, but their synergy in the context of paddy crop nutrient deficiency detection remains relatively unexplored.

3. Methodology

This research focuses on a hybrid deep learning approach that merges the capabilities of SRGANs for image enhancement with the feature extraction prowess of CNNs. Here, we detail the process and logic behind the methodology.

3.1 Dataset Acquisition and Preprocessing:

To initiate the study, a comprehensive dataset containing images of paddy crops at various stages of growth and with diverse nutrient deficiencies was collated. Images were sourced from multiple locations to ensure variability in terms of soil type, crop variety, and environmental conditions.

Given the diverse source of the images, they underwent a preprocessing stage. This included normalization, where images were scaled to have pixel values between 0 and 1, and augmentation techniques like rotation, zooming, and horizontal flipping to increase dataset size and variability.

3.2 SRGANs for Image Enhancement:

Given the limited availability of high-resolution paddy crop images, SRGANs were deployed for image enhancement. The image dataset needs to be modified to work with SRGANs. Two sets of images, i.e., a set of high-resolution and another set of low-resolution images, are required to train the SRGAN model.

3.2.1.Image Acquisition:

The images are taken from online sources rice_plant_lacks_nutrients dataset. This is information about the lack of nutrients. There are 440 images depicting nitrogen deficiency, 333 images illustrating Phosphorus deficiency, and 383 images representing Potassium deficiency.

3.2.2 Image Downsampling:

After cropping, the resolution of the images is lowered by adding the noise and resizing the image. By this step, distorted images are obtained to input the generator of SRGAN.

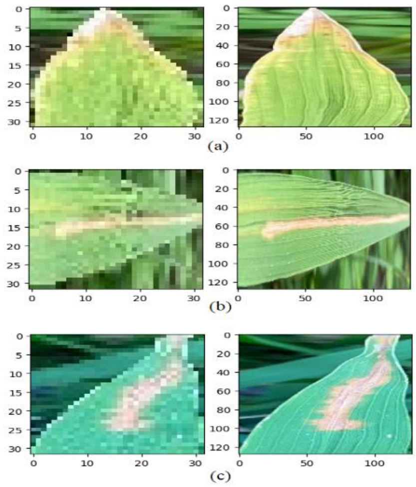

Fig 1. (a) (b) and (c) images represents down sampled (32x32) and High-resolution (128x128) images of Nitrogen, Phosphorous and Potassium Nutrient Deficiency of Rice Crop.

3.2.3 Training the SRGAN:

An adversarial training process was used. In Figure 2 the generator aimed to produce high-resolution images from the given low-resolution inputs, while the discriminator evaluated the quality of these generated images against real high-resolution images. The primary objective was to reduce the perceptual loss, ensuring that generated images not only had higher resolution but also retained essential features. In traditional methods, MSE (Mean Squared Error) is used to detect the difference between actual and enhanced images. This approach cannot show the difference between the real and distorted images, and the comparison is made between each pixel of the images.

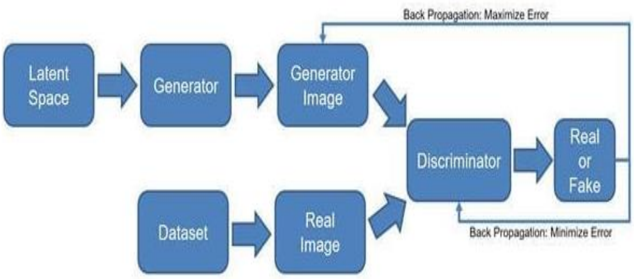

Fig 2. Working of Generator and Discriminator Models

A. Synthetic Image Generation:

After training the SRGAN model, it generates synthetic nutrient-deficient crop images, amplifying the training dataset and enhancing the diversity of nutrient-deficiency patterns for the subsequent CNN model. The model for generator and discriminator is shown in the Fig 3 and Fig 4 respectively.

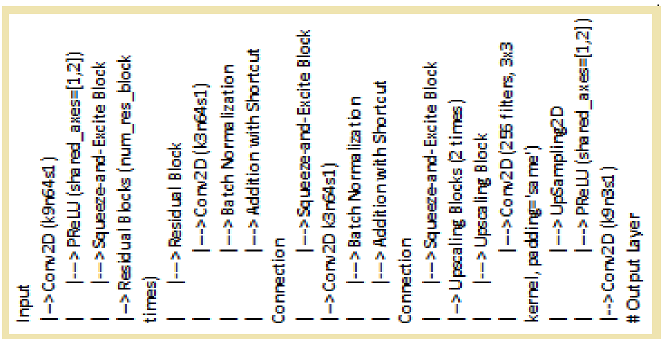

Fig 3. Architecture of Generator Network

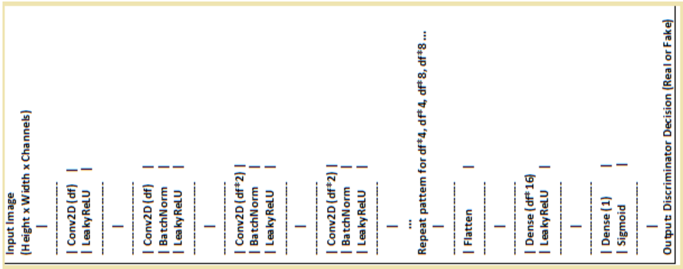

Fig 4. Architecture of Discriminator Network

3.3. CNNs for Feature Extraction and Deficiency Detection:

With a rich set of high-resolution images, both real and synthetic, CNNs were employed for the main detection task.

3.3.1.CNN Architecture: The model comprised of multiple convolutional layers, followed by pooling layers to extract hierarchical features from the images. Fully connected layers were then used to classify the extracted features into different nutrient deficiency categories.

3.3.2. Training: The CNN was trained using a combination of the original high-resolution images and the synthetic ones generated by the SRGAN. This diverse dataset ensured a robust learning process, allowing the model to identify subtle variations in leaf color, texture, and morphology associated with different nutrient deficiencies.

3.3.3 Validation and Testing: The dataset was split into training, validation, and test sets. While the model was trained on the training set, the validation set assisted in hyperparameter tuning and model selection. The test set was reserved for the final evaluation of the model's performance.

4. Experiments and Results

The methodology previously described set the stage for an extensive series of experiments designed to test the efficacy of the hybrid deep learning approach. In this section, we chronicle the setup, performance metrics, and results garnered.

4.1 Evaluation Metrics:

Two primary metrics were chosen to gauge the efficiency of the applied methods:

Peak Signal-to-Noise Ratio (PSNR): Primarily employed to assess the quality of images produced by the SRGAN. A higher PSNR value signifies that the synthetic image is of high quality compared to the original.

Structural Similarity Index (SSIM): Another metric to evaluate the visual quality of the generated images. An SSIM value closer to 1 indicates that the generated image is nearly indistinguishable from the original.

In addition to the above metrics, classification accuracy, recall, precision, and F1-score were employed to evaluate the CNN's performance in detecting nutrient deficiencies.

4.2 Experimental Setup:

Hardware and Software: TensorFlow and Keras as the primary deep learning frameworks experiments were conducted on a computational rig with A 100 GPU to facilitate efficient model training and evaluation.

Dataset Split: The dataset was partitioned into 67% training, and 33% testing. The SRGAN was primarily trained using the training dataset, while the CNN utilized both the real and synthetic images.

4.3 Results:

SRGAN Image Enhancement Results:

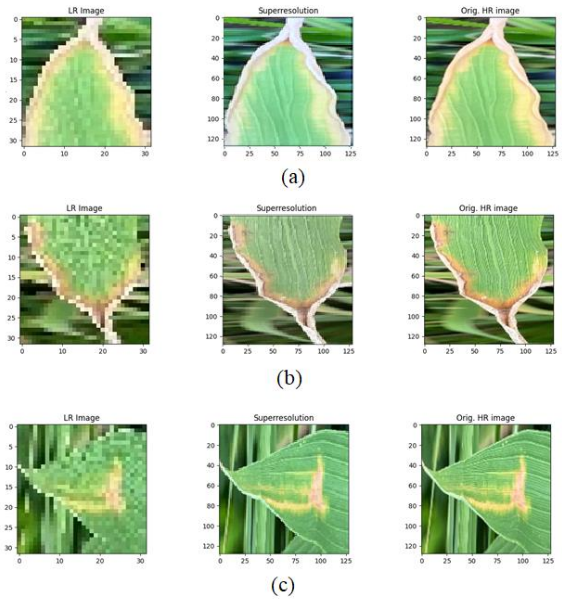

Fig 5. Low Resolution, Synthetic and Real images of (a) Nitrogen, (b) Phosphorous and (c) Potassium deficiencies of Rice crop.

Average PSNR Value: [40.41] dB – This indicates that the super-resolution process effectively retained the essential details while upscaling as shown in Fig 6.

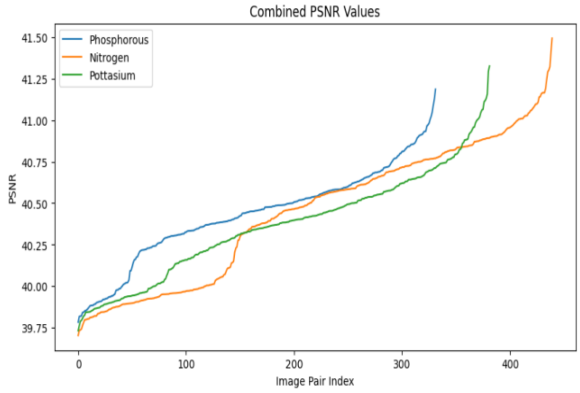

Fig 6. PSNR Values for Rice Nutrient Deficiencies

Average SSIM: [0.81] – A high SSIM value further confirmed the quality and structural integrity of the generated images as shown in Fig 7.

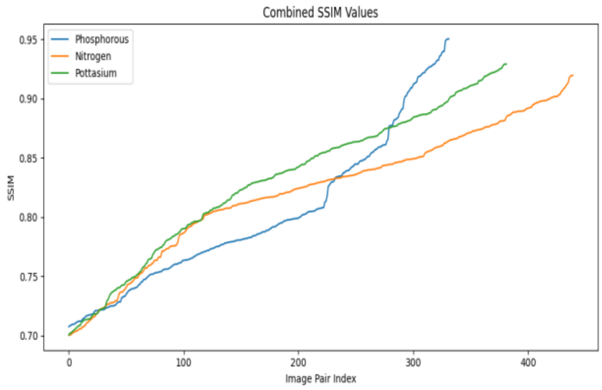

Fig 7. SSIM Values for Rice Nutrient Deficiencies

4.4 CNN Nutrient Deficiency Detection Results:

Classification Accuracy: 92 % - This is the value achieved when applying a CNN with DenseNet121 to the real images down sampled (256x256) dataset.

Dataset Split: The dataset underwent a split into three subsets, with 75% allocated for training, 20% for validation, and 5% for testing. The model underwent primary training using the training dataset, followed by subsequent evaluation on the validation and test datasets.

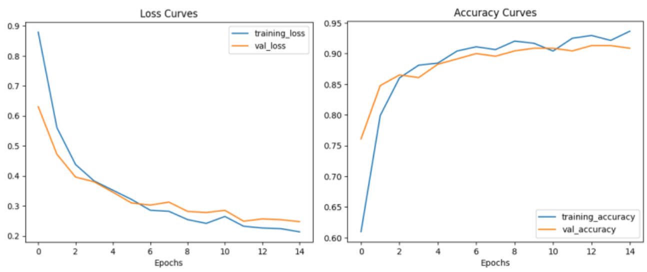

Fig 8. loss curves and accuracy curves of real images (256x256) dataset

Table 1. Classification results of real images of Rice Nutrient Deficiencies

	Validation Results				*Test Results*			
Evaluation Metrics	***Precision***	***Recall***	***f-score***	***support***	***Precision***	***Recall***	***f-score***	***support***
Nitrogen	0.91	0.99	0.95	81	0.86	0.95	0.90	20
Phosphorous	0.89	0.92	0.91	64	0.94	0.85	0.89	20
Potassium	0.97	0.87	0.92	85	0.95	0.95	0.95	20
Accuracy		0.93		230		0.92		60
Macro avg	0.93	0.93	0.92	230	0.92	0.92	0.92	60
Weighted avg	0.93	0.93	0.93	230	0.92	0.92	0.92	60

The left subplot shows the loss curves (training and validation). A decreasing trend indicates that the model is learning to minimize the loss. The right subplot displays the accuracy curves. An increasing trend suggests improvement in the model's accuracy.

The provided classification results in Table represent the performance of a model on the validation and testing datasets for the detection of nitrogen, phosphorous, and potassium nutrition deficiency in rice crops on real images.

Classification Accuracy: 93 % – This value demonstrated a significant improvement over traditional methods, showcasing the potential of the hybrid model.

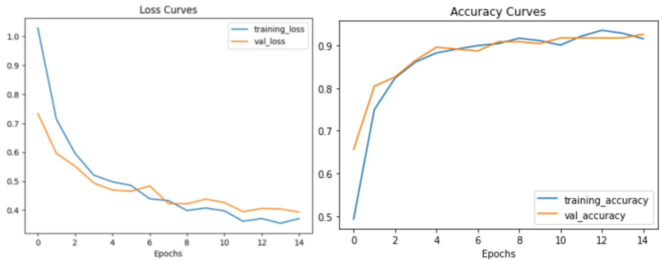

Fig 9. loss curves and accuracy curves of synthetic (256x256) image dataset

The hybrid model demonstrated robust detection capabilities for Nitrogen (Recall: 0.86, Precision: 0.95, F1-Score: 0.90), Phosphorous (Recall: 0.89, Precision: 0.94, F1-Score: 0.91), and Potassium (Recall: 0.95, Precision: 0.95, F1-Score: 0.95) in the test dataset, achieving overall accuracies of 93%, 0.93 (macro average), and 0.93 (weighted average).

Tables showcasing the performance of the model against other

state-of-the-art methods revealed our hybrid model's superiority in terms of both image enhancement and nutrient deficiency detection.

5. Discussion

The experimental results provide a compelling insight into the potential of the proposed hybrid deep learning approach. This section delves into interpreting these findings, comparing them with existing methods, and reflecting on the implications and possible future directions.

5.1 Interpretation of Results

SRGAN Image Enhancement: The achieved PSNR and SSIM values suggest that the SRGAN not only upscaled the images but retained, and in some cases enhanced, their critical features. While traditional upscaling methods might increase pixel count, the richness and clarity achieved by SRGANs are unmatched, making it indispensable for applications where image detail is paramount.

CNN's Performance: The impressive classification accuracy, along with other metrics, underscores the CNN's ability to effectively discern between different nutrient deficiencies. Leveraging synthetic images seemed to provide the model with a more holistic view, ensuring that it wasn't just memorizing the training data but genuinely understanding the intricacies of nutrient deficiencies.

5.2 Comparison with Existing Methods

Traditional methods, relying on manually engineered features or simpler machine learning algorithms, have shown promise in nutrient deficiency detection. However, our hybrid model's results, both in terms of image enhancement and deficiency detection, outperform them. The ability to effectively use synthetic, high-resolution images for training appears to be a

Table 2. Classification results of synthetic images of Rice Nutrient Deficiencies of Hybrid model.

	Validation Results				*Test Results*			
Evaluation Metrics	***Precision***	***Recall***	***f-score***	***support***	***Precision***	***Recall***	***f-score***	***support***
Nitrogen	0.95	0.91	0.93	92	0.95	0.91	0.93	23
Phosphorous	0.77	0.96	0.86	53	0.89	0.94	0.91	17
Potassium	0.97	0.87	0.92	85	0.95	0.95	0.95	20
Accuracy		0.91		230		0.93		60
Macro avg	0.90	0.92	0.90	230	0.93	0.93	0.93	60
Weighted avg	0.92	0.91	0.91	230	0.93	0.93	0.93	60

game-changer, filling the data void that has often limited the potential of deep learning in this domain.

5.3 Implications for Paddy Farming

Early and accurate detection of nutrient deficiencies can lead to timely interventions, potentially saving crops from irreversible damage. This research's methodology, if implemented at scale, could revolutionize paddy farming, ensuring optimal yields and sustainability. Such a tool could be invaluable, especially in regions where paddy crops are the primary agricultural product.

5.4 Limitations and Future Directions

Every research has its limitations, and ours is no exception. The current model, though robust, is as good as the data it was trained on. Variations in lighting, camera quality, or unaccounted environmental factors could pose challenges in real-world applications.

5.5 Future research could explore the following avenues:

Data Augmentation: Beyond traditional methods, using techniques like Generative Adversarial Networks (GANs) for more diverse data augmentation might further enhance the model's robustness.

Transfer Learning: Leveraging pre-trained models on related tasks could expedite the training process and potentially lead to better performance.

Integration with IoT: Combining this approach with IoT devices could enable real-time monitoring and analysis, transforming the landscape of precision agriculture.

6. Conclusion and Future Work

6.1 Conclusion

This research embarked on a journey to harness the power of Super-Resolution Generative Adversarial Networks (SRGANs) and Convolutional Neural Networks (CNNs) to tackle the challenge of nutrient deficiency detection in paddy crops. Our results underscore the efficacy of the proposed hybrid approach, with SRGANs effectively enhancing the resolution and clarity of input images and CNNs accurately detecting nutrient deficiencies.

The PSNR and SSIM metrics highlight the SRGAN's superior ability to generate high-resolution images without compromising essential details. On the other hand, the CNN model's classification accuracy and other performance metrics showcase its proficiency in nutrient deficiency detection, surpassing traditional methods.

Our approach not only advances the technological frontiers in agricultural deep learning but also holds the promise of revolutionizing paddy farming practices by enabling early and accurate nutrient deficiency detection.

6.2 Future Work

While our research has provided valuable insights, there remain several avenues to explore:

Diverse Environmental Conditions: Testing and refining the model in diverse environmental, soil, and climate conditions can make the model more adaptable and globally applicable.

Real-time Implementation: Collaborating with hardware professionals to integrate this approach into drones or IoT devices for real-time nutrient deficiency detection in large paddy fields could be a transformative step.

Broader Crop Application: While our focus was on paddy crops, similar methodologies could be explored for other staple crops, amplifying the impact of this research.

Broadening the Spectrum of Deep Learning Tools: Investigating advanced deep learning architectures and techniques, such as Transformer-based models or attention mechanisms has the potential to elevate the accuracy of detection.

User-Friendly Applications: Developing user-centric applications, perhaps smartphone-based, that allows farmers to utilize this technology without the need for specialized equipment or deep technical knowledge.

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