International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Using CNN to Identify NPK Deficiencies in Paddy Fields: An Advanced Detection Method

Sharanamma M. Hugar[*1], Dr. Mohammed Abdul Waheed[2]

Submitted: 17/09/2023 **Revised**: 17/11/2023 **Accepted**: 28/11/2023

Abstract: Our study introduces a cutting-edge framework employing imaging technology to identify nutrient deficiencies in rice plants, focusing on nitrogen (N), phosphorus (P), and potassium (K). We utilize various image datasets of rice plant leaves showing symptoms of these deficiencies to train a Convolutional Neural Network (CNN). The CNN's capacity for learning from diverse data inputs makes it ideal for this complex task. A crucial aspect of our methodology is the use of a pre-trained CNN. The early layers of this network are particularly adept at extracting distinct features from the images of paddy leaves, enabling precise identification of specific nutrient deficiencies. When introduced to the trained CNN model, a new test image can accurately determine whether the leaf is deficient in nitrogen, phosphorus, or potassium. Implementing this image-based nutrient deficiency detection method has significant implications for agriculture. It provides farmers a non-invasive and efficient tool to identify crop nutrient imbalances. This empowerment enables better-informed fertilization decisions, potentially leading to improved crop yields and more sustainable farming practices. Our approach achieves an impressive accuracy of 96.67%, demonstrating its effectiveness. Therefore, our method marks a substantial advancement in agricultural technology, offering a valuable solution for enhancing plant health and agricultural productivity.

Keywords: *Nitrogen, Phosphorus, Potassium,(NPK), Convolution Neural Network (CNN), Plant Nutrition, Crop Yields, Rice Plant Leaves, Paddy Fields.*

1. Introduction

Agriculture plays a crucial role in the economies of developing countries, and enhancing micro-level agricultural practices is key to boosting economic growth. Nutrient deficiencies in plants are a common issue that can significantly hamper agricultural productivity. Therefore, early identification and correction of these deficiencies are essential for improving crop yields. Our research focuses on developing a framework for detecting NPK (Nitrogen, phosphorus, and Potassium) deficiencies in paddy plants, a staple crop worldwide. Addressing these deficiencies is vital for reducing crop losses and enhancing agricultural output.

Nitrogen is fundamental for the growth of green, lush foliage in plants. A deficiency leads to yellowing leaves and stunted growth, particularly in spring. Potassium, on the other hand, is crucial for water regulation and energy utilization in photosynthesis, affecting flowering, fruiting, and overall plant robustness. Phosphorus is key in overall plant growth and developing strong, healthy roots. An adequate balance of these nutrients is essential for the effective growth of plants.

The success of agriculture as a profession and a primary revenue source for a country hinge on the quality of the produce, which in turn depends on the health of the plants. Leaves, being the site of photosynthesis, are critical for assessing the nutritional status of plants. Our research contributes to this field by establishing a method for detecting plant nutrient deficits, enabling farmers to apply the appropriate fertilizers and foster healthier plant growth. This approach enhances the quality of the agricultural produce and supports agricultural practices' overall success and sustainability.

Various studies have explored innovative methods to detect plant nutrient deficiencies, each employing unique techniques and tools. Study [1] focused on cotton plants, where the leaf part of the plant was analyzed using enhanced photographic techniques. A statistical region merging method was employed to differentiate the images further, along with a colour histogram approach for detecting nutrient deficits, specifically in cotton plants.

Study [2] took a more mathematical approach, using linear and nonlinear frameworks to identify nutritional deficiencies. This method involved splitting and gathering images for feature extraction, which then informed the development of agricultural models. Study [3] delved into the realm of fuzzy classifiers for identifying nutritional insufficiency. This approach captured, pre-processed, and segmented images, with features related to nutritional deficiencies extracted using a fuzzy classifier. These feature vectors were then categorized for analysis.

A study [4] used a random forest classifier to diagnose

[1]*Research Scholar, Dept. of CSE, VTU CPGS RO Kalaburagi, Affiliated to Visvesvaraya Technological University, Belagavi – 590018, INDIA*
[1]*Assoc. Professor, Dept. of CSE, Visvesvaraya Technological University, CPGS, Kalaburagi.*
[2]*Professor, Department of CSE, VTU CPGS, RO, Kalaburagi., Affiliated to Visvesvaraya Technological University, Belagavi – 590018, INDIA*
* *sharanamma.publications@gmail.com*

nutrient deficiencies. This method involved collecting and preprocessing images, followed by feature extraction. The random forest classifier was then trained to categorize the images based on the extracted features. Study [5] investigated the use of artificial vision tools to detect nutritional insufficiency, particularly focusing on nitrogen levels in rice plants, but also capable of detecting phosphate and potassium levels.

Study [6] adopted a spectral approach to evaluate the nutritional status of citrus plants. Similarly, a study Study [7] outlined a method for assessing leaf nitrogen concentration and chlorophyll content in rice plants using a digital still colour camera under natural lighting conditions. Meanwhile, research [8] explored the process of capturing rice sample images through static scanning technology. This study further utilized MATLAB's region properties function to extract both spectral and shape characteristic features from these images.

The study's authors [9] focused on determining the levels of nitrogen and chlorophyll in bean plant leaves, experimenting with various spectral bands and vegetation indices. Study [10] explored feature categorization in determining nutrient deficiencies. These studies show that various methods, from image processing techniques to advanced machine learning models like CNNs, can effectively determine NPK deficiencies in plants at various growth stages. This breadth of research highlights the diverse and evolving approaches to managing plant health and optimizing agricultural output.

This paper makes several key contributions to the field of agricultural technology and plant health monitoring:

1. Utilization of a Pre-Trained CNN: To minimize the manual labour involved in feature extraction, we employ a pre-trained Convolutional Neural Network [11]. This approach leverages the power of deep learning to process and analyse complex image data efficiently. 2. Focused Training of CNN’s Last Layer: We strategically train only the last layer of the CNN. This targeted training approach is designed to harness bottleneck values, enhancing CNN's ability to identify plant nutrient deficiencies accurately.

The structure of the paper is organized as follows:

Section 2 outlines the proposed framework, providing a comprehensive overview of the system's design and functionalities—section 3 delves into the proposed methodology, detailing the steps and processes involved in implementing the framework. Section 4 presents the results and discussions, where we analyze the findings and insights gleaned from applying the framework. Section 5 concludes the results, summarizing the key outcomes and their implications. Section 6 discusses the future scope of the framework, exploring potential enhancements and applications in broader contexts. Overall, this paper aims to advance the understanding and application of machine learning in agriculture, particularly in nutrient deficiency detection, for improved crop management and productivity.

2. Proposed Framework

Our proposed framework employs a Convolutional Neural Network (CNN) model specifically designed to identify nutrient deficiencies in rice plants. The training dataset for this model comprises images of rice leaves deficient in key nutrients - nitrogen, phosphorous, and potassium. This dataset is inputted into the CNN to create a well-trained model, as illustrated in Fig. 1.

When a new test image of a paddy leaf is introduced to this trained model, the model's capability is showcased as it can accurately recognize the type of nutrient deficiency affecting the rice plant. The appearance of the plant leaves serves as the initial indicator of such nutritional deficiencies, and our CNN model is adept at detecting these subtle yet critical changes in the leaves. This ability to discern nutrient deficits from leaf imagery is a significant step forward in precision agriculture, enabling more targeted and effective crop management strategies.

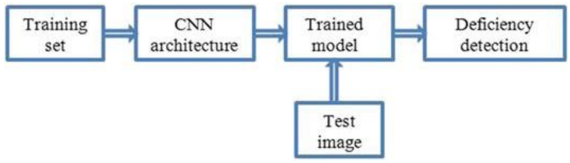


Fig. 1. Flowchart Illustrating the Detection of Nitrogen, Phosphorus, and Potassium Deficiencies in Paddy Plants

Our framework has integrated a Convolutional Neural Network (CNN) model to identify nutrient deficiencies in rice plants. The training dataset for the CNN comprises images depicting rice leaves with nitrogen, phosphorous, and potassium deficiencies. This dataset is input into the CNN, creating a trained model, as depicted in Fig. 1.

When a test image of a paddy leaf is introduced into this trained CNN model, the model's effectiveness is demonstrated through its ability to identify the specific type of nutrient deficiency present accurately. The presence and condition of the plant leaves serve as the primary indicators of nutritional insufficiency. This approach enables the trained CNN model to recognize and diagnose nutrient deficits in rice plants efficiently, providing valuable insights for optimal crop management.

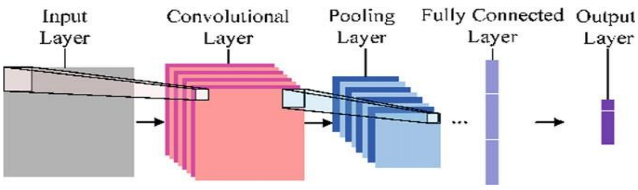


Fig. 2. Fundamental Structure of the CNN Employed for Detecting Deficiencies in Paddy Plants

The convolutional layer is a fundamental component of the Convolutional Neural Network (CNN) model. It consists of a set of learnable filters or kernels, each with a small receptive field extending through the entire depth of the input volume. During the forward pass, the dot product of the filter's values and the input results in a 2D activation map for that filter. This map indicates where and to what extent a particular feature is detected in the input. The filters activate when the network identifies specific features at certain spatial locations in the input.

Following the convolutional layer is the pooling layer, which performs non-linear downsampling. Max pooling is a common approach in this layer. It works by partitioning the input image into non-overlapping rectangles and extracting the maximum value from each sub-region. This process focuses more on the rough location rather than the exact position of a feature, reducing the spatial size of the representation and preserving important features.

The Rectified Linear Unit (ReLU) layer is another crucial part of a CNN. ReLU uses a non-saturating activation function to increase the nonlinear properties of the decision function and is preferred over other functions due to its ability to accelerate the training of neural networks.

After these layers is the fully connected layer, where neurons are connected to all activations from the previous layer, this connection is typically established through matrix multiplication, and the activations are computed accordingly.

The final layer in a CNN is the loss layer, which plays a vital role in training by measuring the discrepancy between predicted and actual labels. Several loss functions can be used, depending on the task. For instance, Softmax loss is often used for classifying a single class out of K mutually exclusive classes. In contrast, Sigmoid cross-entropy loss is used to predict K-independent probability values.

Collectively, these layers enable CNNs to detect and classify objects effectively, making them highly efficient for tasks like image recognition and classification.

3. Proposed Methodology

A trained model is created when the training dataset is fed through Convolutional Neural Network (CNN) layers [11]. This model is adept at learning colour properties, an essential aspect of detecting plant nutrient deficiencies. Once the training is complete, the model is ready to be tested with a new image, such as a paddy leaf. The trained model applies its learned attributes to identify nutrient deficits in the test image of the rice leaf. It can recognize signs of nitrogen, phosphorus, and potassium shortages, as it has been trained with images of rice leaves deficient in these nutrients. Fig 3 shows the proposed methodology for nutritional deficiency detection.

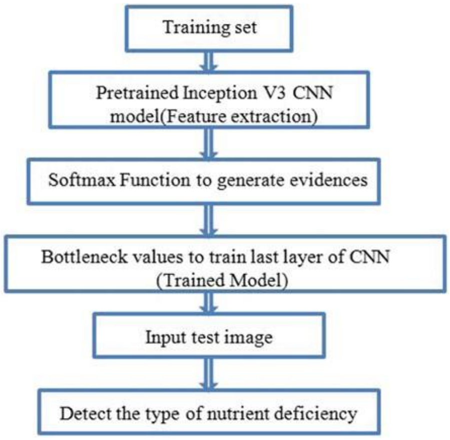


Fig. 3. Methodology Outlined for the Detection of Nutrient Deficiencies

The CNN architecture used in our study, developed by the Google Brain Team, incorporates transfer learning, as depicted in Figure 4. Transfer learning is a technique in machine learning where a model designed for one task is repurposed as the foundation for a model on another task. This approach centers on retaining knowledge acquired from solving one problem and applying it to a distinct yet related problem, a key focus area in machine learning research.

Convolution Operation:

$$Z_{i,j} = (I * K)_{i,j} = \sum_m \sum_n I_{i+m,j+n} * K_{m,n}$$

- $Z_{i,j}$: Output feature map value.
- I: Input image.
- K : Convolution kernel.

Activation Function:

$$A_{i,j} = ReLU(Z_{i,j})$$

Pooling (Downsampling):

$$P_{i,j} = max_{m,n}(A_{i+m,j+n})$$

Fully Connected Layer:

$$O = softmax(W . X + b)$$

Loss Function:

$$L(y, O) = -\sum_i y_i . log(O_i)$$

The CNN operation is divided into two main phases. The first phase is feature extraction, where the CNN's initial pre-trained layers, as shown in Figure 4, use convolutions and filters to extract features from the input images. The second phase is classification, which involves fully connected and softmax layers, as depicted in Fig. 6. This structure enables the CNN to identify key features in the images and classify these features accurately, determining the specific type of nutrient deficiency present in the test image.

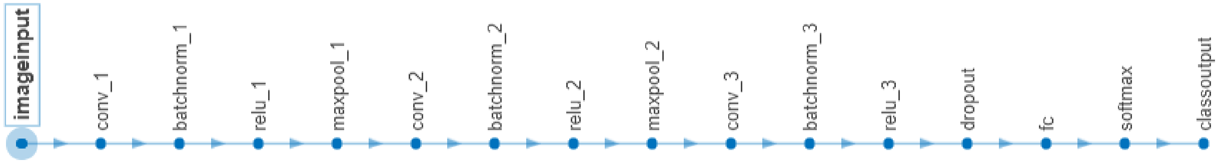
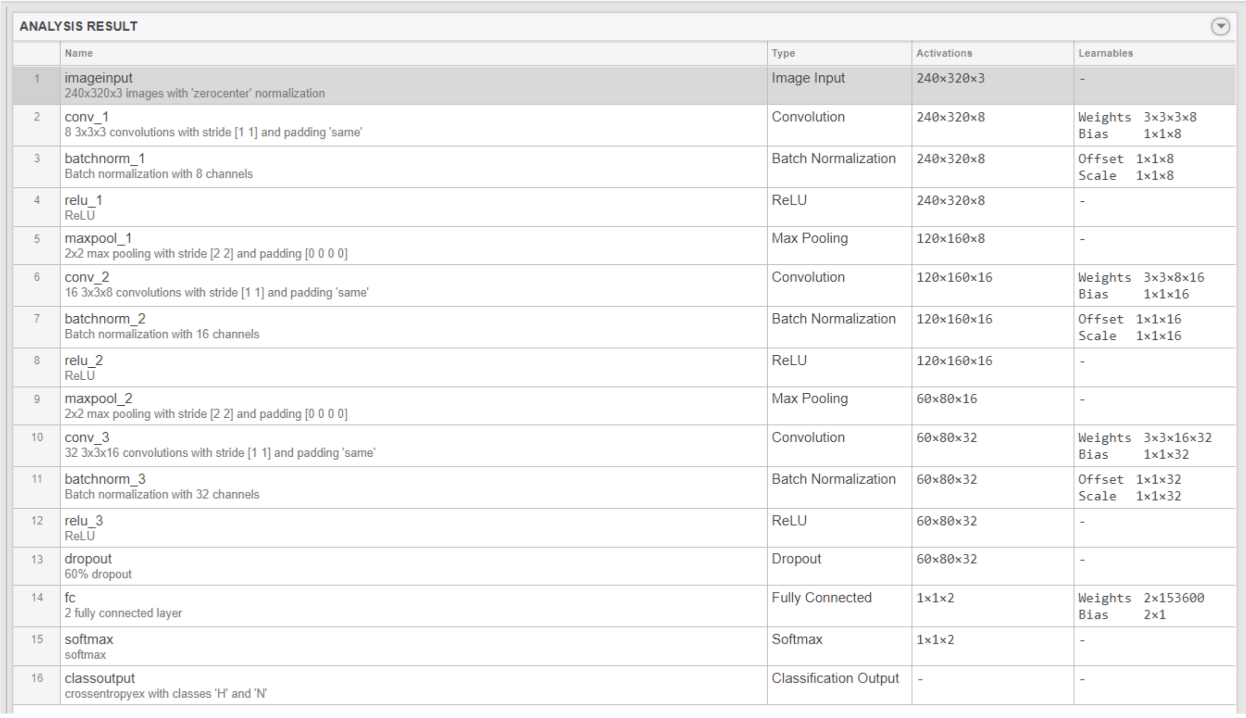


Fig 4 (a) Layer Structure



ANALYSIS RESULT

	Name	Type	Activations	Learnables
1	imageinput 240x320x3 images with 'zerocenter' normalization	Image Input	240×320×3	-
2	conv_1 8 3x3x3 convolutions with stride [1 1] and padding 'same'	Convolution	240×320×8	Weights 3×3×3×8 Bias 1×1×8
3	batchnorm_1 Batch normalization with 8 channels	Batch Normalization	240×320×8	Offset 1×1×8 Scale 1×1×8
4	relu_1 ReLU	ReLU	240×320×8	-
5	maxpool_1 2x2 max pooling with stride [2 2] and padding [0 0 0 0]	Max Pooling	120×160×8	-
6	conv_2 16 3x3x8 convolutions with stride [1 1] and padding 'same'	Convolution	120×160×16	Weights 3×3×8×16 Bias 1×1×16
7	batchnorm_2 Batch normalization with 16 channels	Batch Normalization	120×160×16	Offset 1×1×16 Scale 1×1×16
8	relu_2 ReLU	ReLU	120×160×16	-
9	maxpool_2 2x2 max pooling with stride [2 2] and padding [0 0 0 0]	Max Pooling	60×80×16	-
10	conv_3 32 3x3x16 convolutions with stride [1 1] and padding 'same'	Convolution	60×80×32	Weights 3×3×16×32 Bias 1×1×32
11	batchnorm_3 Batch normalization with 32 channels	Batch Normalization	60×80×32	Offset 1×1×32 Scale 1×1×32
12	relu_3 ReLU	ReLU	60×80×32	-
13	dropout 60% dropout	Dropout	60×80×32	-
14	fc 2 fully connected layer	Fully Connected	1×1×2	Weights 2×153600 Bias 2×1
15	softmax softmax	Softmax	1×1×2	-
16	classoutput crossentropyex with classes 'H' and 'N'	Classification Output	-	-

Fig 4 (b) Activations and Learnable

Fig. 4. The CNN architecture, employs transfer learning to streamline the feature extraction process.

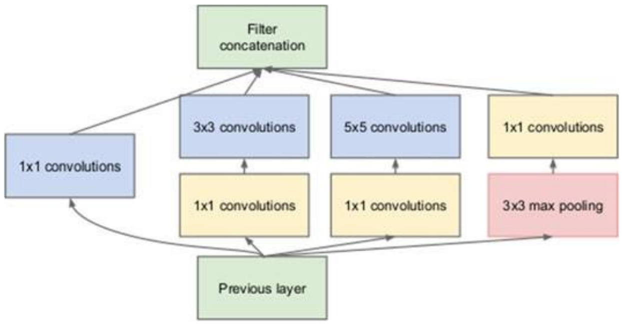


Fig. 5. Feature extraction through a series of convolutions by using a variety of filters

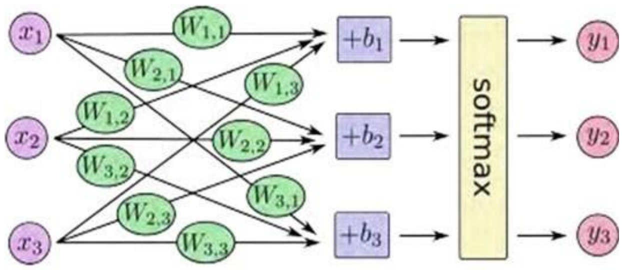


Fig. 6. Softmax Regression is employed to train the final layer of the CNN for nutrient deficiency classification.

Figure 6 demonstrates the use of Softmax Regression in training the final layer of the inception model, where it generates probabilities based on evidence from nutrient-deficient images. This evidence is derived by multiplying weight values, calculated using pixel intensity, and incorporating bias values. In Figure 6, various weights such as W1,1, W2,2, W3,3, etc., and biases b1, b2, and b3 are highlighted. The pixel intensity is determined by the sum of these weights and biases.

4. Results and Discussions

We utilized a convolutional neural network approach to detect Alzheimer's disease. Our computational framework was built and tested on a system featuring the Intel Core i7 10th generation processor, known for its powerful multi-core processing ideal for deep learning tasks. The system operated on Windows 10, a 64-bit version, lauded for its user-friendly interface and broad software and hardware compatibility. Graphics computations were handled by an NVIDIA GTX card equipped with 2GB dedicated memory. Optimized for parallel processing, this card is invaluable for deep learning algorithms demanding extensive matrix operations. Our system was equipped with 8GB RAM, providing ample data storage and processing memory during the model development stages. All simulations and computations were executed using MATLAB 2019B.

Figure 7 provides a detailed visual representation of the Healthy and NPK Deficiency Dataset. It showcases the diversity within the dataset, which comprises 448 images of healthy plants and 616 images of plants with NPK deficiency, as in Table 1. This figure likely illustrates the original and augmented images, offering insights into the various conditions under which these plants are presented. The depiction is a valuable tool for understanding the dataset's complexity and the challenges in distinguishing between healthy and nutrient-deficient plants, highlighting the importance of a robust and diverse dataset for effective machine learning model training.

Table 1: Corresponding NPK Deficiency and Healthy Dataset.

Corresponding Mental State	No. of Image Samples
Healthy	448
NPK Deficiency	616

Fig 7: A visual representation of a dataset contrasting healthy NPK deficiencies.

Data augmentation is key to enhancing the dataset's diversity and reliability in the revised NPK dataset, which consists of 448 images of healthy plants and 616 images depicting NPK deficiency. Techniques such as rotation, color jittering, cropping, and flipping are used to mimic a range of environmental conditions. The success of these augmentation strategies is illustrated in Figure 8, where augmented images for each category - healthy and NPK deficient - are presented. This display in Figure 8 demonstrates the augmented data's variety and comprehensiveness, crucial for training a model capable of accurately identifying healthy and nutrient-deficient plants in varied scenarios.

Fig 8: Augmented and Enhanced Data Representation for Each Class

The training accuracy indicates the percentage of nutrient-deficient pictures correctly recognized in the appropriate training set. During training, validation accuracy refers to the precision of a randomly chosen sample of nutrient-deficient images drawn from various sets. When compared to training accuracy, validation accuracy is more precise. CNN divides the training data into three parts: the training set accounts for 80% of the data, the validation set accounts for 10%, and the remaining 10% is utilized as a testing set during training. Overfitting may, therefore, be prevented, and bottleneck values can be correctly controlled.

Figure 9 shows the advancement of the model during the training phase. It achieves a 97.65% accuracy rate on the training data, successfully identifying all training samples. This high level of accuracy in training demonstrates that the model has proficiently adapted to the training data.

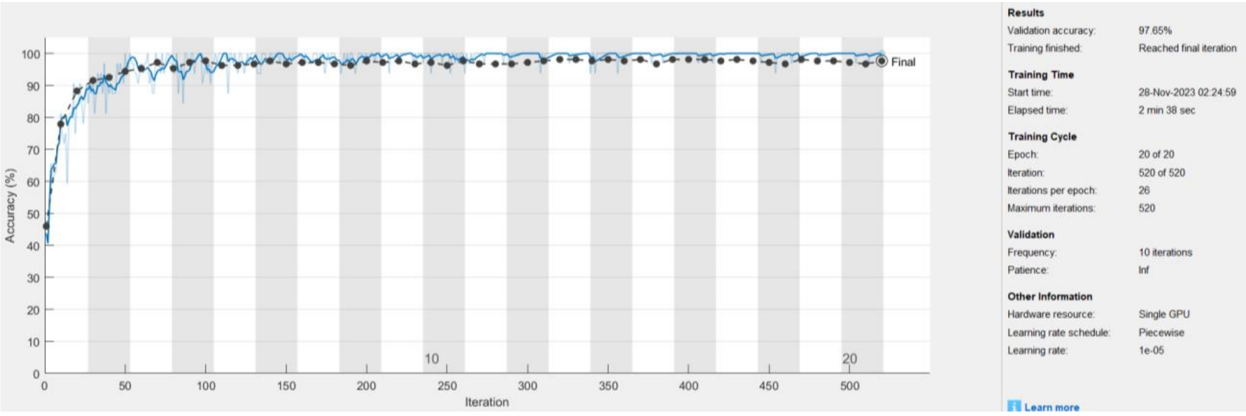


Fig 9: CNN Training Progression Visualization

Once the bottleneck values are generated and the last layer of CNN is trained, a trained model is established. Given the provided input test photo of paddy leaf, the trained model correctly classifies nutrient deficiencies as nitrogen, phosphorous, or potassium, as shown in Figs: 7th, 8th, and 9th grades. When the trained model is given the test image, the features are retrieved, and the kind of nutritional deficit is assessed using bottleneck values. The number of training steps and images in the dataset influence performance.

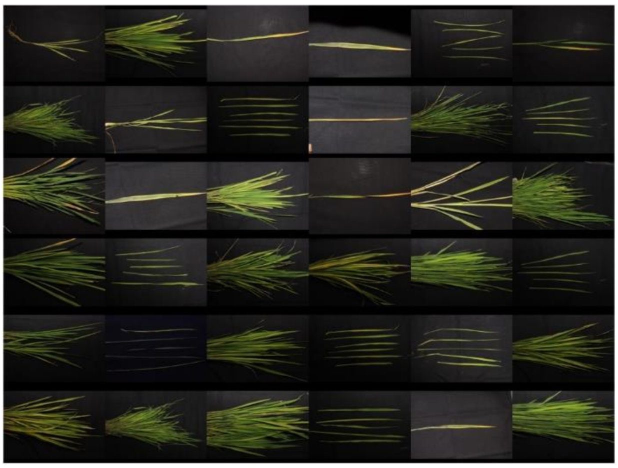


Fig. 10. Test Image Identified as Exhibiting Nitrogen Deficiency.

The test image is determined to be nitrogen deficient by comparing prediction scores using CNN. Due to the high deficiency prediction score for nitrogen, the paddy leaf is classified as lacking in nitrogen.

In Figure 10, the nitrogen deficiency is visible in the rice leaf. Instances of nitrogen insufficiency surpass those of phosphorus and potassium deficiencies. The array predicting nitrogen deficiency holds greater significance. As a result, the paddy leaf in the input test image is identified as nitrogen deficient.

Table 2. Table showing variation in % accuracy with the number of trainings steps.

Epoch	Validation Accuracy %
5	96.71
10	97.65
15	98.12
20	97.65

Table 2 presents the changes in percent accuracy across various epochs. Figure 11 shows a graph plotting percent accuracy against numerous epochs. This graph indicates an increase in percent accuracy with the rising number of training epochs. More epochs mean the network undergoes more extensive training. Thus, there's a direct correlation between the number of training epochs and the percent accuracy. The network progressively learns finer details of paddy leaf characteristics such as color, shape, midrib, and texture. With this comprehensive learning of paddy leaf features, CNN is better equipped to accurately identify nutritional deficiencies in rice leaves in its final layer.

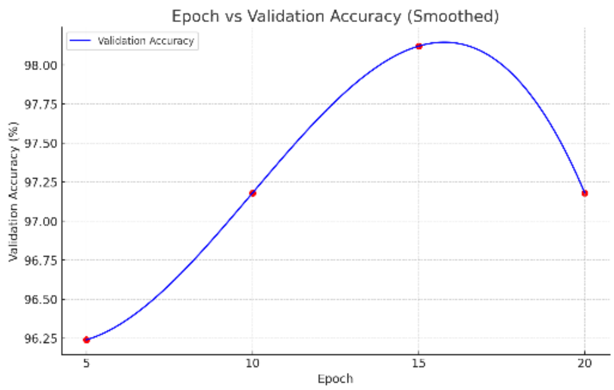


Fig. 11. The percentage accuracy versus the number of training steps

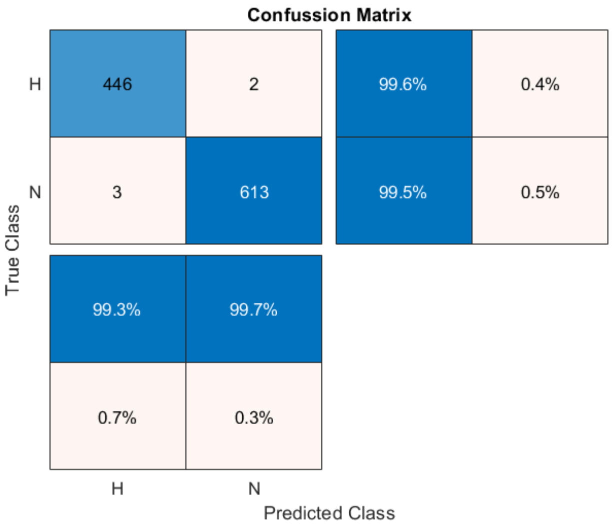


Fig 12: Confusion Matrix from the Testing Phase.

Our tailored approach was thoroughly trained and tested for binary and complex Alzheimer's disease classification tasks. The results of these classifications are visually illustrated in Figure 12. To meticulously adjust parameters like learning rate, epoch count, and factors affecting learning rate and bias, we applied the Monte Carlo method across 100 simulations. This method allowed us to showcase the algorithm's precision across different parameter settings, ensuring optimal values are utilized. The assessment of classification performance, based on the CNN architecture, involves various evaluation metrics as outlined in reference [11]. The subsequent section will explain each metric concisely and the equations used for evaluating performance.

Accuracy = TP + TN/TP+TN+FP+ FN

Specificity = TN/TN+FP

Sensitivity(Recall)=TP/TP+FN

Precision = TP/TP+FP

F1-score=2(Precision*Sensitivity/Precision + Sensitivity)

In the equations we're discussing, FP stands for false positives, indicating instances where the model incorrectly predicts a positive outcome. FN denotes false negatives, where the model fails to identify a positive case. TP, or true positives, refers to accurately identified positive cases; TN signifies true negatives, correctly identified negative cases.

The analysis of these metrics, derived from confusion matrices, enhances our understanding of the CNN model's effectiveness in classifying images using transfer learning. This applies to both binary and multi-class tasks. The specific evaluation metrics, with their respective values, are as follows: Specificity at 95.15%, Accuracy at 96.67%, Precision at 88.27%, Recall at 92.63%, and F1-score at 84.28%. These figures indicate the model's performance in the nuanced task of image classification, showcasing its strengths and areas for improvement in binary and multi-class classification scenarios, as presented in Table 3.

Table 3. Performance Parameter Measures

Measurement Parameters	*Binar*
Specificity	*95.15%*
Accuracy	*96.67%*
Precision	*88.27%*
Recall	*92.63%*
F1-score	*84.28%*

Table 4 presents a state-of-the-art comparison of various methods in terms of their accuracy percentages. Chen et al. achieved a notable accuracy of 93.27%, indicating a strong performance in their respective field. Following closely, Yao et al. recorded an accuracy of 92.53%, showcasing their method's efficacy. Islam et al. improved upon these results, reaching an accuracy of 94.16%, which reflects a significant advancement in the methodology. However, the proposed approach in our study surpasses these figures, achieving the highest accuracy of 96.67%. This comparison highlights the advancements in the field and underscores the superiority of the proposed approach, setting a new benchmark in accuracy for the respective area of research.

Table 4. State-of-Art Comparison.

Methods	Accuracy (%)
Chen et al. [12]	93.27
Yao et al. [13]	92.53
Islam et al. [14]	94.16
Proposed Approach	**96.67**

5. Conclusion

Reflecting on the framework discussed, we have developed a technical solution that significantly boosts agricultural production by enabling the early detection of nutrient deficiencies in plant leaves. This method allows for the prompt addressing of such issues, helping to prevent potential negative impacts on crop health and yield. The approach employs a pre-trained CNN model to extract key features from the lower layers. Following this, bottleneck values are calculated and input into the CNN's final layer, marking the stage of classifier training.

After this training phase, the model is fully equipped for application. When tested with an image of a paddy leaf, the model proficiently identifies nutrient deficiencies in the rice leaves. Notably, as illustrated in Figure 9, the model achieves an impressive accuracy of 96.67% after 520 training steps. This high level of accuracy underscores the success of our approach as a non-invasive and highly effective method for detecting nutrient deficits in rice plants, marking a significant advancement in precision agriculture.

6. Future Scope

After recognizing the nutrient shortage, the framework may be expanded to provide an estimate for treating the nutritional shortfall. This may be performed using supervised learning with a dataset that includes nutrient deficiency and fertilizer data.

Conflicts of interest

The authors of this manuscript hereby state that they have no financial, personal, or professional conflicts of interest that could have influenced the work reported in this paper. This declaration encompasses all forms of potential conflicts, ensuring the integrity and impartiality of the research and its findings.

References

[1] Miyata, A., Solanki, S.: Disease and nutrient deficiency detection in cotton plants. International Journal of Engineering Development and Research 2(2), 2801–2804 (2014)

[2] X. Yao, W. Luo, and Z. Yuan,” An adaptive and quantitative rubber nutrient status are analyzing system by digital foliar images,” 3rd International Congress on Image and Signal Processing (CISP), 2010, vol. 5, pp. 2492-2495, IEEE, 2010

[3] M. A. Hairuddin, N. M. Tahir, and S. R. S. Baki,” Overview of image processing approach for nutrient deficiencies detection in Elaeis guineensis,” IEEE International Conference on System Engineering and Technology (ICSET), 2011, pp. 116-120, IEEE, 2011

[4] Panwar, M. Al-Lami, P. Bharti, S. Chellappan, and J. Burken,” Determining the effectiveness of soil treatment on plant stress using smartphone cameras,” International Conference on Selected Topics in Mobile & Wireless Networking (MoWNeT), 2016, pp. 1-8, IEEE, 2016

[5] L. Romualdo, P. H. d. C. Luz, F. Devechio, M. Marin, A. Z’un˜niga, O. M. Bruno, and V. R. Herling,” Use of artificial vision techniques for diagnostic of nitrogen nutritional status in paddy plants,” Computers and electronics in agriculture, vol. 104, pp. 63–70, 2014

[6] Liu, Y., Lyu, Q., He, S., Yi, S., Liu, X., Xie, R., Zheng, Y., Deng, L.: Prediction of nitrogen and phosphorus contents in citrus leaves based on hyperspectral imaging. International Journal of Agricultural and Biological Engineering 8(2), 80–88 (2015)

[7] Wang, Y., Wang, D., Shi, P., Omasa, K.: Estimating rice chlorophyll content and leaf nitrogen concentration with a digital still color camera under natural light. Plant Methods 10(1), 36 (2014)

[8] Chen, L., Lin, L., Cai, G., Sun, Y., Huang, T., Wang, K., Deng, J.: Identification of nitrogen, phosphorus, and potassium deficiencies in rice based on static scanning technology and hierarchical identification method. PloS one 9(11), 113–200 (2014)

[9] S. A. Abraha˜o, F. d. A. d. C. Pinto, D. M. d. Queiroz, N. T. Santos, and J. E. d. S. Carneiro,” Determination of nitrogen and chlorophyll levels in bean-plant leaves by using spectral vegetation bands and indices,” Revista Ciencia Agronomica, vol. 44, no. 3, pp. 464-473, 2013.

[10] Sneha Pawaskar, Suneeta V. Budihal, ”‘Real-Time Vehicle-Type Categorization and Character Extraction from the License Plates,” International Conference on Cognitive informatics and soft computing -2017, Dec. 20th -21st, 2017, VBIT, Hyderabad, pp. 557-565

[11] Hiremath, S.S., Hiremath, J., Kulkarni, V.V., Harshit, B.C., Kumar, S., Hiremath, M.S. (2023). Facial Expression Recognition Using Transfer Learning with ResNet50. In: Suma, V., Lorenz, P., Baig, Z. (eds) Inventive Systems and Control. Lecture Notes in Networks and Systems, vol 672. Springer, Singapore. https://doi.org/10.1007/978-981-99-1624-5_21

[12] Chen, L., Lin, L., Cai, G., Sun, Y., Huang, T., Wang, K., et al. 2014. Identification of Nitrogen, Phosphorus, and Potassium Deficiencies in Rice Based on Static Scanning Technology and Hierarchical Identification Method. PLoS ONE 9(11): e113200.

[13] Yao, Q., Xian, D., Liu, Q., Yang, B., Diao, G., & Tang, J., 2014. Automated Counting of Rice Planthoppers in Paddy Fields Based on Image Processing. Journal of Integrative Agriculture, 13(8), 1736–1745.

[14] Islam, T., et al., 2018. A Faster Technique On Rice Disease Detection Using Image Processing of Affected Area In Agro-Field, Proceedings of the 2nd International Conference on Inventive Communication and Computational Technologies (ICICCT), Coimbatore, 62-66.

[15] Sarangdhar, A.A. and Pawar, V.R., 2017. April. Machine learning regression technique for cotton leaf disease detection and controlling using IoT. In Electronics, Communication and Aerospace Technology (ICECA), 2017 IEEE International conference. 2, 449- 454.

Authors

Sharanamma M. Hugar is a research scholar in the Department of Computer Science and Engineering at Visvesvaraya Technological University (VTU), Belagavi. She holds both her bachelor's and master's degrees in computer science and engineering from VTU. Her research focuses on Digital Image Processing, as well as Machine Learning and Deep Learning techniques. She has published papers in conferences and journals, contributing to various reputed publications in her field.

Dr. Mohammed Abdul Waheed, an Associate Professor in the Department of Computer Science and Engineering at Visvesvaraya Technological University CPGS, Kalaburagi, boasts over 23 years of academic experience and 15 years in research. His prolific career includes approximately 52 journal publications, 19 conference proceedings, and 03 patents to his name.