

DEEP LEARNING-BASED AUTOMATED IDENTIFICATION OF NPK DEFICIENCY IN EARLY GROWTH STAGE OF RICE (*Oryza Sativa L.*) USING SPATIAL ATTENTION MECHANISM

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ABSTRACT

Rice (*Oryza sativa L.*) is a staple food for nearly half of the world's population, and its productivity largely depends on the availability of essential nutrients such as nitrogen (N), phosphorus (P), and potassium (K), with deficiencies in these elements leading to reduced yield and food security risks. Traditional manual methods of diagnosing nutrient deficiencies are often inaccurate, time-consuming, and labor intensive, highlighting the need for automated, reliable solutions. This study proposes a deep learning based system for the automated identification of NPK deficiencies in rice leaves at early growth stages using a dataset of 1,155 images collected from Kaggle, where preprocessing involved resizing, normalization, augmentation, and class balancing with SMOTE. A baseline Convolutional Neural Network (CNN) was developed and compared with an enhanced CNN integrated with a Spatial Attention Mechanism (SAM), with the baseline achieving 96.5% accuracy and a 94.7% F1-score, while the CNN+SAM model significantly outperformed it, reaching 98.8% accuracy and a 98.2% F1-score. By enabling the model to focus on critical leaf regions, the attention mechanism improved feature discrimination and interpretability, demonstrating CNN+SAM as a robust and explainable solution for early detection of nutrient deficiencies and a valuable tool for advancing precision agriculture and sustainable rice production.

Keywords- *EfficientNet, Machine Learning Classifiers, Nitrogen (N), Phosphorus (P), and Potassium (K), Natural Language Processing, Nutrient Deficiency, Spatial Attention*

1.0 INTRODUCTION

Agriculture remains the backbone of many economies, particularly in developing countries, where it supports the livelihood of a significant portion of the population [1]. Nearly half of the world's population relies on rice as a primary food source and essential energy provider, making it one of the most important crops globally. This underscores its crucial role in sustaining a large portion of the global population and ensuring food security [2]. However, the productivity of rice is highly dependent on the availability of essential nutrients, particularly nitrogen (N), phosphorus (P), and potassium (K), which are crucial for the healthy growth and development of the crop. Deficiencies in any of these nutrients can lead to significant yield losses, adversely impacting food security and economic stability [3].

Despite its importance, rice cultivation faces numerous challenges that threaten yield and sustainability. Among the most pressing challenges are diseases that affect rice plants at different stages of growth. Diseases such as bacterial blight, blast, and sheath blight are widespread and have been identified as major contributors to reduced productivity worldwide [1]. These diseases, if left undetected or untreated, can cause devastating impacts on both smallholder farmers and large-scale agricultural systems. This makes early

detection and effective management strategies essential to protect crops and maintain stable yields.

In addition to plant diseases, environmental conditions also play a significant role in determining the productivity and resilience of rice crops. Factors such as temperature fluctuations, humidity, soil quality, and water availability directly influence the crop's vulnerability to diseases and nutrient deficiencies [4]. For example, prolonged periods of drought can exacerbate nutrient deficiencies, while excessive moisture may create favorable conditions for fungal infections. Climate change, with its associated extreme weather events, further complicates the stability of rice production systems, placing additional stress on global food supply chains.

The need for innovative solutions to address these challenges has led to the increasing adoption of advanced technological methods in agriculture. In particular, machine learning (ML) and deep learning (DL) approaches have shown great promise in the automatic detection and classification of rice diseases [5]. These models can analyze large datasets of plant images and identify subtle disease symptoms that may not be visible to the naked eye, thereby enabling early intervention. Moreover, such technologies offer scalable and cost-effective solutions that can be integrated into smart farming systems, making them accessible to farmers in both developed and developing regions.

This research work proposes a deep learning-based automated system for identifying nitrogen (N), phosphorus (P), and potassium (K) deficiencies in early-stage rice growth, utilizing a spatial attention mechanism. The spatial attention mechanism will enhance the model's ability to focus on critical areas of the image, improving the accuracy of nutrient deficiency identification. To minimize generalization error and reduce overfitting, we will train the model with a balanced dataset. Additionally, we will retrain the compressed model to maintain its accuracy, ensuring it remains effective while reducing computational complexity.

2.0 RELATED WORKS

Research shows that combining feature extraction techniques with deep learning significantly improves rice disease classification accuracy. These methods enhance the model's ability to distinguish between diseases and nutrient deficiencies, reducing misdiagnosis. AI-powered real-time monitoring systems also help farmers take timely corrective actions, boosting productivity and reducing excessive agrochemical use [2]. Several studies have proposed models to address these challenges.

Study [6] introduced a novel CNN-based method for rice disease detection using 500 images, achieving 95.48% accuracy across 10 common rice diseases. Another study used the VGG16 model with transfer learning on 40 images to detect rice and wheat leaf diseases, attaining accuracies of 97.22% and 98.75%, respectively. Additionally, enhanced deep learning models leveraging deep features showed improved classification performance. In a study using 5,932 field images of four rice diseases blast, brown spot, tangram, and bacterial blight a CNN combined with SVM via transfer learning demonstrated that SVM outperformed CNN in classification accuracy.

Study [8] introduced an AI-based Swarm system for monitoring and identifying rice diseases by analyzing color, shape, and position features with expert input. To reduce information loss and model complexity, rough set theory was employed for feature selection, followed by a rule-based classifier to categorize images as healthy or infected. Additionally, a support vector machine (SVM) with a polynomial kernel and Histogram of Oriented Gradients (HOG) was used for feature classification, demonstrating potential in addressing agricultural

challenges such as pest infestations that diminish rice crop quality and yield, especially in cases of limited domain expertise.

[9] proposed a model combining machine vision and a genetic algorithm to detect pest infections and plant growth stress from aerial imagery, achieving 92.5% accuracy using artificial neural networks and 87.5% with support vector machines. Meanwhile, new techniques have emerged for detecting and classifying rice diseases using image processing to analyze the RGB values of affected regions. A Naive Bayes classifier, focusing on these RGB values, has been employed to efficiently identify rice diseases such as bacterial blight, rice blast, and brown spot, with minimal computational cost.

[10] enhanced a deep learning based model for paddy rice disease identification and classification system. This study leveraging deep features, improve disease identification. For instance, classifies four rice leaf diseases using 5,932 field images, showing that combining SVM with CNN using transfer learning outperforms CNN alone. In Nigeria, rice a staple food requires specific growing conditions, such as hot, humid weather above 25°C and rainfall exceeding 0.1 mm. However, despite these favorable conditions, diseases hinder rice production.

Furthermore, [11] presents a framework closely related to our work, which integrates deep learning (DL)-based segmentation techniques with a bitwise logical AND operation and DL-based classification methods for diagnosing rice-infected leaves. Their model focuses on identifying common rice diseases such as bacterial leaf blight, brown spot, and leaf smut, while also addressing nutrient deficiencies including nitrogen (N), phosphorus (P), and potassium (K). Preliminary results suggest that the proposed DeepBatch framework offers improved diagnostic performance over conventional techniques, making it a potentially scalable solution for managing rice diseases and nutrient deficiencies in agricultural settings.

This study presents a computer vision-based deep learning system termed CAR-CapsNet, an upgraded capsule network (CapsNet) that uses contextual attention routing (CAR) to classify rice crop nutrient deficiencies. CAR-Capsnet's innovative use of contextual attention routing significantly enhances the model's ability to navigate and interpret complex visual features and patterns, leading to improved classification accuracy compared to previous routing methods.

3.0 METHODOLOGY

Dataset Description

In deep learning research, high-quality data is crucial for reliable deep learning results. This study used a **Kaggle dataset** containing **1,155 rice leaf images** categorized by nutrient deficiency **439 nitrogen**, **333 phosphorus**, and **383 potassium**. The dataset offers diverse samples suitable for analysis. To ensure uniformity and enhance model performance, **pre-processing steps** were applied to standardize image sizes and dimensions across all samples.

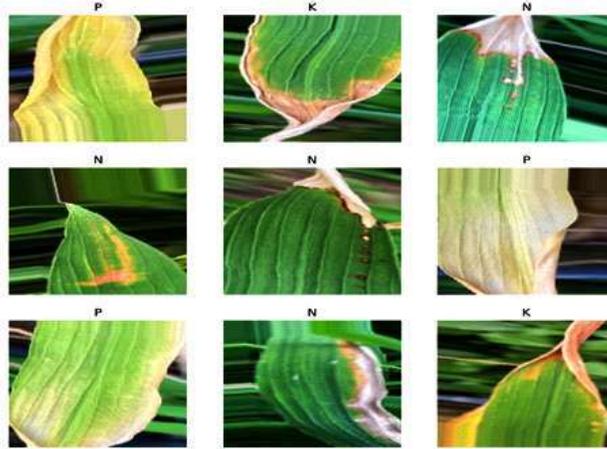


Fig. 1: Samples of images from the dataset

Models Architecture

This study utilized **EfficientNetB0** as the base architecture for classifying NPK deficiencies in rice crops, leveraging its balance of **accuracy and computational efficiency** through compound scaling and **transfer learning** with pretrained ImageNet weights to improve convergence and generalization. To further enhance feature extraction, a **spatial attention mechanism** was integrated after the final convolutional layers, allowing the model to focus on key regions of rice leaves exhibiting deficiency symptoms. This hybrid design effectively captured both global and localized patterns, resulting in **higher classification accuracy** and **better interpretability** demonstrated by attention heatmaps and performance metrics.

Research Framework

This illustrates a systematic approach to developing a deep learning model with spatial attention for detecting nutrient deficiencies (Nitrogen (N), Phosphorous (P), and Potassium (K)) in rice plants. Here's a breakdown of the key components:

Proposed Research Methodology Framework

The diagram below represent the research methodology we followed to achieve the research goals:

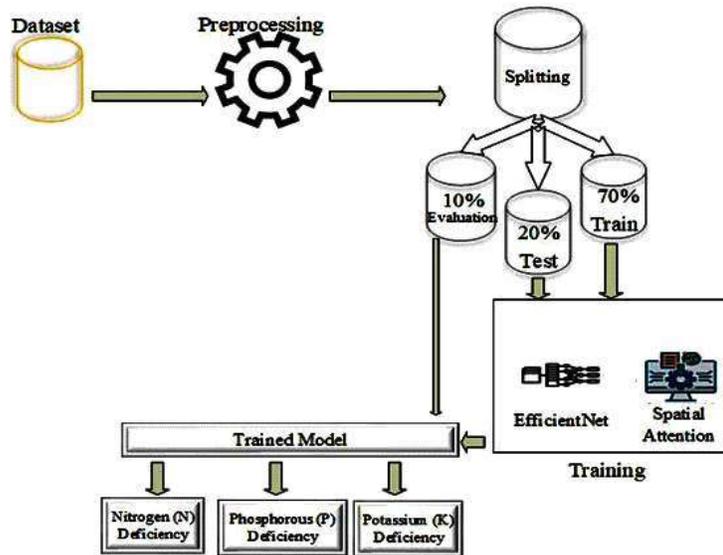


Fig. 2: Research Methodology Framework

Description of the Model Architecture

The core of this methodology involves designing a Convolutional Neural Network (CNN) model that integrates a spatial attention mechanism. The spatial attention helps the model focus on the most important regions of the image where nutrient deficiency symptoms appear.

Dataset

The process starts with a dataset, likely consisting of images of rice plants with varying nutrient deficiencies. This is the raw data required for training, testing, and evaluating the model.

Preprocessing

The preprocessing pipeline consisted of multiple stages: image resizing, normalization, noise removal, data augmentation, and synthetic oversampling using **Synthetic Minority Over-sampling Technique (SMOTE)**. Each stage aimed to enhance the quality of input data, mitigate overfitting, and balance the dataset for optimal classification results.

Data Class balancing

Initial analysis showed class imbalance among the three nutrient deficiency categories, which could bias the model. To correct this, **SMOTE** was applied in the **feature space** of extracted embeddings to generate synthetic samples for underrepresented classes. After augmentation, the dataset was re-evaluated and confirmed to have **balanced class distributions**, ensuring fairer model training as shown in Fig. 3 (a) and (b) represents the in balanced and balanced distribution respectively.

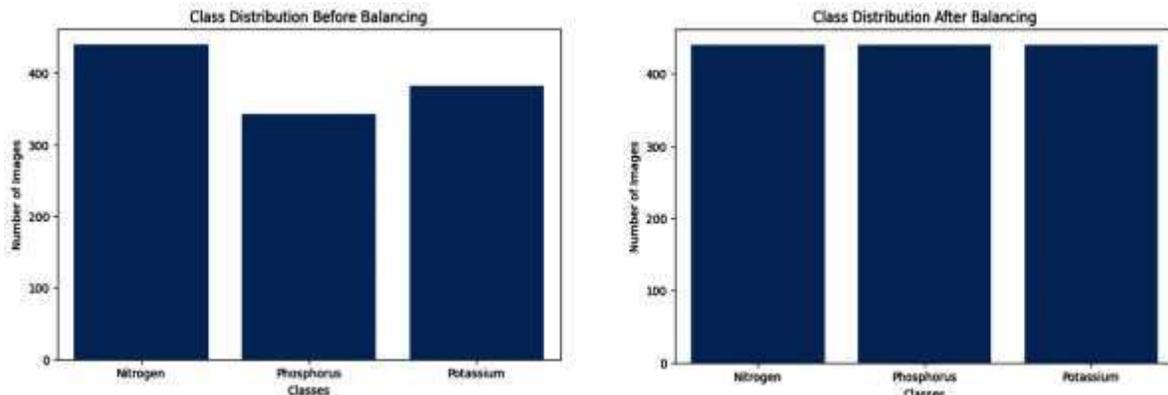


Fig. 3: (a) Before balancing

(b) After balancing

Data Augmentation

Given the limited dataset size, data augmentation techniques were employed to artificially expand the dataset and improve generalization. The following transformations were applied:

Rotation: Random rotations within $\pm 20^\circ$ to simulate different leaf orientations.

Flipping: Both horizontal and vertical flips to enhance model robustness.

Contrast Adjustment: Histogram equalization was applied to improve contrast, ensuring deficiency features remain visible under varying lighting conditions.

Data Splitting

The dataset is split into training, testing, and evaluation sets. This ensures that the model is trained on one subset (train), validated during training on another subset (evaluation), and tested on an unseen subset (test) to assess its performance.

Model Training

The proposed model was trained using the EfficientNetB0 backbone augmented with a spatial attention mechanism for enhanced focus on key regions of rice leaf images. The model was trained in a supervised setting with categorical cross-entropy as the loss function, appropriate for multi-class classification of nitrogen (N), phosphorus (P), and potassium (K) deficiencies.

Nutrients	Deficiency symptoms on Rice leaf	Example Image
Nitrogen	Leaves are narrow, short, erect growth and display a lemon yellowish coloration.	
Phosphorus	Red and purple color may develop in leaves.	
potassium	Yellowish-brown discoloration in leaves, with dark brown necrotic spots appearing first on the tips of older leaves.	

Fig. 4: Multi-class classification of NPK deficiencies

EfficientNet with Spatial Attention

The model being used is based on EfficientNet, a highly efficient convolutional neural network (CNN) architecture, known for its balance between accuracy and computational efficiency. The spatial attention mechanism is integrated into the model to enhance its ability to focus on important regions in the images that indicate nutrient deficiencies. This addresses the challenge of variability in agricultural images, such as lighting and background noise.

CNN Backbone

A CNN was chosen as the backbone of the model for its proven ability to learn rich visual features from images. The architecture incorporates the **EfficientNet** model as a pretrained feature extractor, enabling effective **transfer learning** on smaller datasets. The pretrained weights are fine-tuned for the specific task of **NPK deficiency detection** in rice crops. Within this setup, the CNN layers progressively extract **hierarchical features** beginning with low-level patterns such as edges and textures, and advancing to high-level features like leaf shape and discoloration facilitating accurate classification of nutrient deficiencies.

Spatial Attention Mechanism

A spatial attention module is integrated into the CNN to enhance its focus on specific regions that exhibit signs of nutrient deficiencies. The attention mechanism works as follows:

1. **Attention Map:** For each feature map generated by the CNN, an attention map is computed. This map assigns higher weights to the regions in the image that are more relevant to the detection of nutrient deficiencies (e.g., leaf edges, color patches, or areas of discoloration).
2. **Feature Recalibration:** The attention mechanism recalibrates the features by multiplying the attention map with the corresponding feature map, enhancing the important features while suppressing the irrelevant ones.

2. Result and Discussion

During training, key metrics such as **accuracy**, **loss**, and **precision-recall** were monitored. The inclusion of a **spatial attention mechanism** enhanced feature extraction by focusing on relevant image regions, leading to **faster convergence** and **better generalization** compared to the baseline CNN without attention. The following section presents and discusses the results obtained from both models.

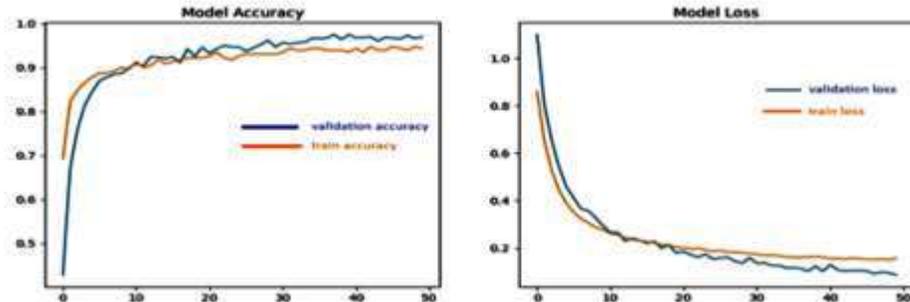


Fig. 5: (a) Training and validation accuracy (b) Training and validation loss

As illustrated in Fig. 5 (a) and (b) above, the CNN model without spatial attention achieved strong learning performance, with accuracy exceeding **95%** and losses dropping below **0.2**, showing effective feature extraction and minimal overfitting. These results establish a **robust baseline** for assessing the impact of spatial attention mechanisms.

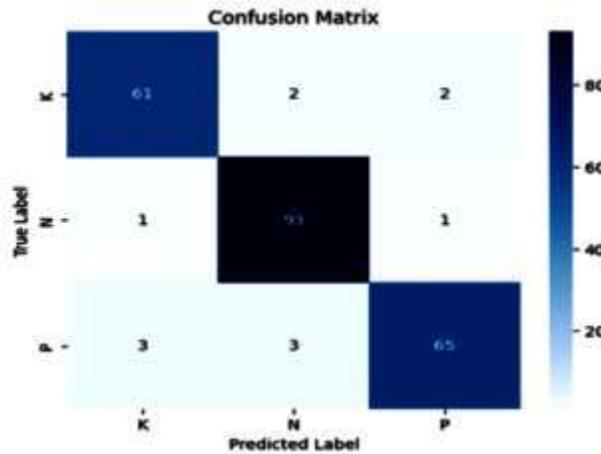


Fig. 6: Confusion matrix of EfficientNet

Fig. 6 above shows that the CNN model without spatial attention achieved 96.5% accuracy, performing best on nitrogen deficiency and slightly lower on potassium and phosphorus. Minor misclassifications between potassium and phosphorus indicate overlapping features, highlighting the potential benefit of spatial attention or more diverse data to improve feature distinction.

EfficientNet + Spatial Attention Training

The CNN with spatial attention was trained for **100 epochs** using the **Adam optimizer** (learning rate = 0.0001) and **categorical cross-entropy** loss. The attention module directed the model's focus to key leaf regions, enabling it to capture fine spatial patterns linked to nutrient deficiencies.

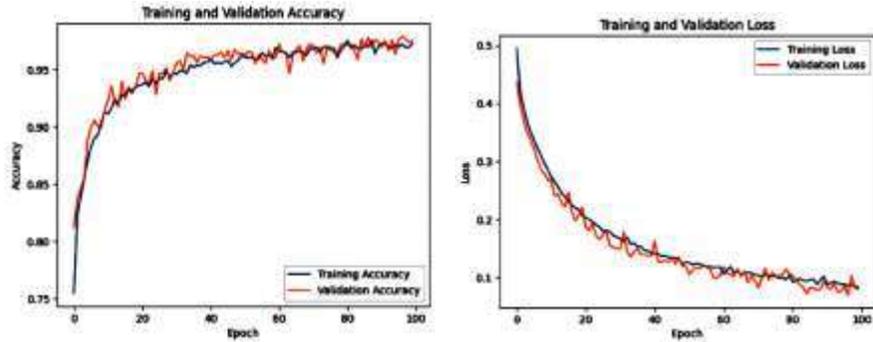


Fig 7: Training and validation accuracy and loss of EfficientNet + spatial attention

As shown in Fig. 7 above the training and validation plots, the model showed **excellent convergence and generalization**, achieving **98.6% training and 98.0% validation accuracy with low losses (<0.10)**, indicating minimal overfitting. This confirms that **spatial attention** significantly boosts CNN performance and feature discrimination for agricultural image classification.

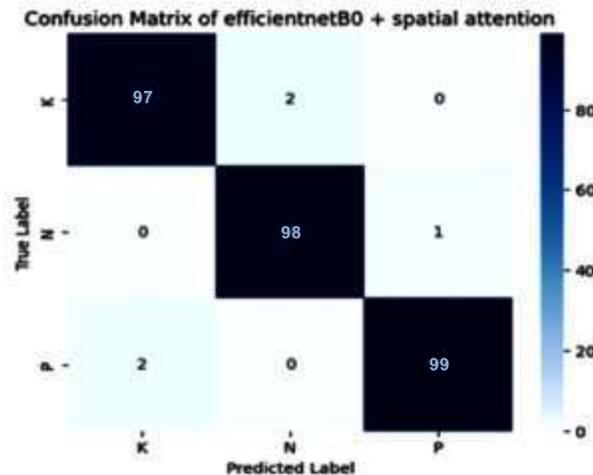


Fig. 8: Confusion matrix of EfficientNet + spatial attention

As illustrated in Fig. 8 above, the CNN model with spatial attention achieved an impressive **99% accuracy**, correctly classifying **294 out of 299 samples** across the three nutrient deficiency classes. It showed near-perfect predictions for nitrogen, phosphorus, and potassium deficiencies, demonstrating high reliability and confirming the effectiveness of the spatial attention mechanism in enhancing classification performance.

Attention heatmaps further revealed that the model focused on **key leaf regions** showing discoloration and irregular patterns, such as yellowing and reddish-brown areas features consistent with known NPK deficiency symptoms. This visual alignment provides strong evidence that the spatial attention module improved both **accuracy and interpretability**, making the model more transparent and trustworthy for **agricultural diagnostics** as shown in Fig. 9 below:

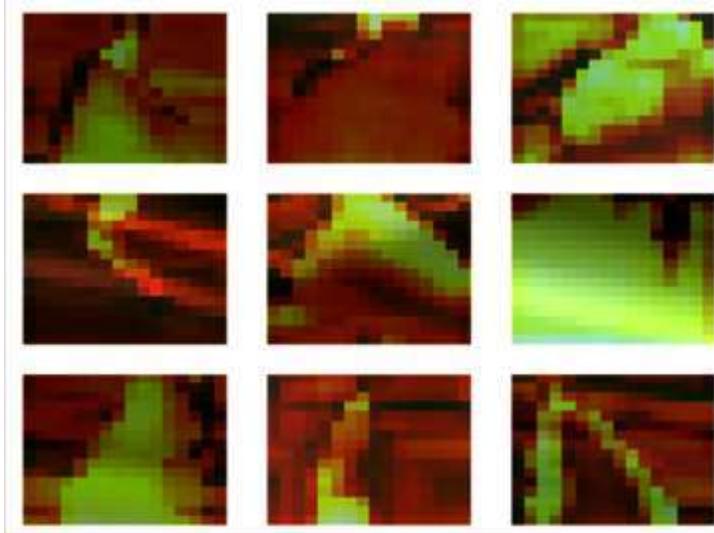


Fig 9: Feature heatmap

The table below summarize the results obtained after the two experiments and compared it to the state of the art model:

Table 1: Results Comparison

Aurthor(s)	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Amudha & Brinda(2024)	97.0	96.0	96.0	95.0
Proposed	96.5	94.8	94.5	94.7
Proposed + SAM	98.8	98.3	98.3	98.2

To assess the effectiveness of the proposed model, we compared its performance metrics accuracy, precision, recall, and F1-score with one of the existing state-of-the-art methods. As shown in Table 1, above Amudha & Brinda (2024) attained a higher performance, with an accuracy of 97% and consistent precision and recall values of 96%, yielding an F1-score of 95%. In comparison, our proposed Convolutional Neural Network (CNN)-based model without attention mechanisms achieved an accuracy of 96.5%, precision of 94.8%, recall of 94.5%, and F1-score of 94.7%, demonstrating a slide backward over earlier work. Furthermore, the integration of the Spatial Attention Mechanism (SAM) significantly enhanced the model’s performance. The CNN+SAM model achieved an outstanding accuracy of 98.8%, with precision and recall both at 98.3%, and an F1-score of 98.2%, outperforming all previously reported approaches. These results confirm that the incorporation of spatial attention not only improves model interpretability but also boosts classification effectiveness.

4.0 CONCLUSION

The findings of this study demonstrate that integrating a spatial attention mechanism into a CNN architecture significantly improves the performance of nutrient deficiency detection in rice crops. The enhanced model not only outperforms the baseline CNN in terms of accuracy and robustness but also introduces an interpretable feature that highlights the areas of interest used in decision-making. This added level of explain ability is critical for gaining user trust, especially in sensitive fields like agriculture where transparency in predictions is essential.

Furthermore, the improved performance of the CNN+SAM model positions it as a promising solution for real-world agricultural diagnostics. Its ability to accurately classify NPK deficiencies makes it a valuable tool for supporting timely and informed decisions in precision farming. By automating the detection process, this approach can help farmers identify nutrient issues earlier, reduce manual inspection efforts, and optimize fertilizer application, thereby increasing crop productivity and sustainability.

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