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# Precision Nutrition Management and Fertilizer Optimization in Paddy Crops: A Hybrid Approach for Deficiency Detection and Recommendation Using Segmentation, Transfer Learning and Hyperparameter Tuning

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**Abstract:** The accurate and rapid diagnosis of nutrient deficiencies in crops is essential for effective agricultural management. Conventional methods, which rely on visual inspection of crop symptoms are limited by subjectivity and require significant expertise, making them impractical for widespread use by farmers. In this study, we propose a novel approach utilizing digital imaging and deep learning to quantitatively analyze crop symptoms for nutrient deficiencies, specifically targeting paddy crops. Our methodology involves segmenting the foreground of the crop image by removing background noise using GrabCut, refining the input image to enhance clarity and improve the accuracy of nutrient deficiency detection. We introduce a novel approach combining deep learning architectures, specifically MobileNet and a fine-tuned variant of MobileNet, for nutrient deficiency classification. To address overfitting, we integrate dropout layers and optimize hyperparameters, including learning rates and optimizers. The performance of these models is assessed using established metrics, including accuracy, precision, recall, and F1 score. Notably, the base MobileNet model achieves an accuracy of 89.65%, while the fine-tuned MobileNet variant attains 93.10%, demonstrating significant improvement and superiority. This integrated approach presents a promising solution for efficient nutrient management in paddy cultivation, contributing to increased yields and sustainable agricultural practices. Additionally, our system recommends appropriate fertilizers based on the nutrient deficiency findings, augmenting precision agriculture and crop management practices.

**Keywords:** *Nutrient Deficiency detection, Precision Agriculture, Image Segmentation, Deep Learning, MobileNet, Support Vector Machine (SVM), Fertilizer Recommendation*

## 1. Introduction

Rice is a crucial staple for many in Asia but faces numerous challenges due to urbanization, industrialization, environmental factors, an aging workforce, labor shortages, and outdated farming techniques. Effective management practices are vital for maintaining rice cultivation and boosting productivity. Deficiencies in nitrogen (N), phosphorus (P), and potassium (K) in rice manifest through specific symptoms, yet visual diagnoses are subjective and expertise-dependent. Digital imaging offers a more objective and precise method for detecting nutrient stress symptoms, making it more practical for widespread use by farmers[1,2,3].

Nitrogen plays a vital role in rice growth, but both insufficient and excessive nitrogen use can harm yields. Deficiency reduces grain count and weight, while overuse weakens stems and leaves. Proper nitrogen management is critical for optimal productivity and environmental protection [1,4,5]. Utilizing advanced image analysis and machine learning, we aim to create a diagnostic tool for accurately identifying nutrient deficiencies in rice. This involves using deep learning algorithms to analyze images and classify deficiency symptoms with high accuracy [2,3]. Field trials and experimental validation will assess our method's effectiveness, helping farmers make informed decisions about fertilizer use and crop management, thus enhancing the sustainability and resilience of rice production systems[1,3,5].

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## 2. Related Work

### 2.1 Segmentation of Agricultural Images

Semantic segmentation has significantly advanced image understanding in various fields, including agriculture[6]. Combining deep learning with traditional techniques has greatly improved agricultural image processing, transforming automation in crop analysis and pest identification. This paper reviews recent advancements in traditional and deep learning based semantic segmentation for agricultural images, highlighting challenges such as robustness, generalization, and limited labeled samples. Innovative solutions discussed include dataset augmentation and multimodal information integration.

### 2.2 Nutrient deficiencies in paddy crops

Nutrient deficiencies in rice pose significant threats to crop health, yield, and quality[7]. Symptoms like leaf discoloration and reduced grain quality have traditionally been identified through manual examination, often leading to delayed diagnosis and irreversible crop damage. Early and accurate detection systems are essential due to the significant impact on yield and the economic importance of rice. Predictive technologies are crucial for timely fertilization and irrigation decisions, ensuring crop sustainability. Key components include soil analysis, remote monitoring, crop modeling, and data-driven insights. Enhancing these strategies with sensor technology, decision support systems, IoT integration, and collaborative knowledge sharing improves deficiency detection and mitigation[8].

To address manual detection challenges, the model proposed in [9] uses an automatic robotic vehicle to detect nutrient deficiencies by capturing plant leaf images. This model is trained using images from various plants and locations, extracting features like edges and ridges. A Convolutional Neural Network (CNN) identifies nutrient deficiencies and their severity, providing fertilizer recommendations based on the detected deficiencies.

### 2.3 Deep Learning in Agriculture

Integrating deep learning into agriculture has revolutionized operations like precision farming and pest surveillance. Convolutional Neural Networks (CNNs) are especially impactful, analyzing visual data to detect patterns imperceptible to humans. CNNs have proven effective in identifying plant diseases, categorizing crop varieties, and forecasting yields[9,10]. However, using CNNs to detect nutrient deficiencies in rice crops remains a promising area for further exploration.

## 3.THE PROPOSED PADDY CROP NUTRITION DEFICIENCY DETECTION AND RECOMMENDATION MODEL

### 3.1 Framework Overview

Our research focuses on predicting nutrient deficiencies in paddy crops by integrating transfer learning and hyperparameter tuning. We present two novel approaches using digital imaging techniques, employing GrabCut[11] for foreground segmentation to remove background noise and improve image clarity. This preprocessing step enhances the accuracy of deficiency detection.

We evaluate MobileNet[12] architectures, with fine tuned MobileNet. To prevent overfitting, we integrate dropout layers and use GridSearchCV for hyperparameter tuning. MobileNet achieves 89.65% accuracy, while the optimized MobileNet attains 93.10%, outperforming other model. The system also recommends appropriate fertilizers based on detected deficiencies, supporting precision agriculture and crop management practices.

### 3.2 Overview of Models

Once the image is refined, MobileNet architecture model extract relevant features from the segmented crop images and classifies. MobileNet is a deep convolutional neural network, renowned for its ability to capture intricate patterns and details within images, making it highly suitable for identifying subtle symptoms of nutrient deficiencies.

### 3.3 Proposed Model

The Model introduces Two extra phases involving Initial training with frozen layers and Finetuning[14] . This additional step entails:

Fine-tuning a pre-trained model involves two main steps:

- **Initial Training with Frozen Layers:** Training the added custom layers while keeping the pre-trained layers (base model) frozen.
- **Fine-Tuning:** Unfreezing some layers of the pre-trained model and re-training the entire model (or parts of it) to fine-tune the pre-trained layers alongside the custom layers.

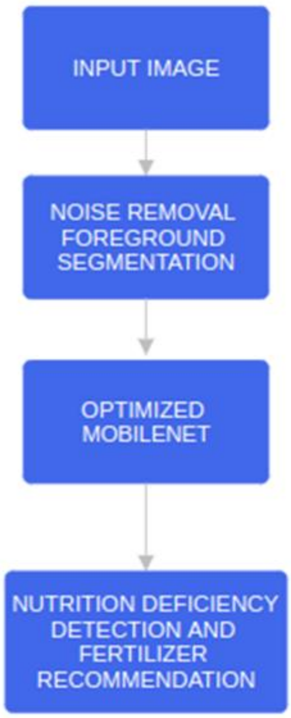



**Fig 1.** Proposed Model for Paddy crop nutrition deficiency detection and recommendation system

By incorporating these steps, proposed model significantly enhances the performance and accuracy of the nutrient deficiency detection. The optimized Mobilenet, equipped with the best parameters identified during tuning, delivers more precise detections. This provides farmers with a more reliable tool for diagnosing and managing nutrient deficiencies in paddy crops, contributing to better agricultural productivity and sustainability through precise nutrient management and fertilization strategies.

### 3.4 Introduction to the Models

GrabCut is an image segmentation algorithm that separates the foreground from the background using a combination of graph cuts and iterative energy minimization, starting with a bounding box and refining segmentation through color and edge information. MobileNet designed for mobile and embedded applications, uses depthwise separable convolutions to reduce parameters and computation, offering efficiency and speed while maintaining accuracy, making it suitable for real-time applications on devices with limited resources.

#### 3.4.1 Initial Training with Frozen Layers

In this step, we freeze the layers of the pre-trained MobileNet model to only train the custom layers added on top.

We load the MobileNet model with pre-trained weights (weights='imagenet') but without the top layers (include_top=False). We add a global average pooling layer, a fully connected layer with 512 units, a dropout layer, and a final dense layer for classification. We freeze all the layers of the MobileNet base model to ensure that only the custom layers are trained initially. We compile the model with a learning rate of 0.0001 and use categorical_crossentropy as the loss function since it's a multi-class classification problem. We train the model for 10 epochs, where only the custom layers are trained.

#### 3.4.2 Fine-Tuning

In this step, we unfreeze some of the deeper layers of the MobileNet model and re-train the entire model, including the previously frozen layers. We unfreeze the last 20 layers of the MobileNet base model. This allows the last 20 layers, along with the custom layers, to be trained. We re-compile the model with a smaller learning rate (0.00001) to fine-tune the weights without causing drastic changes that could disrupt the pre-trained weights. We continue training for another 10 epochs, this time fine-tuning both the previously frozen layers and the custom layers.

## 4. RESULTS AND DISCUSSION

In this study, the experiments were conducted using Google Colab, leveraging its resources such as GPU acceleration and ample memory. The coding environment utilized was Jupyter Notebook with Python 3.7. The dataset was processed and analyzed using MobileNet and fine tuned Mobilenet( Optimized Mobilenet). Subsequently, a comprehensive comparison and evaluation were carried out, assessing the performance of each model using key metrics such as accuracy, precision, recall, and F1 score.

### 4.1 Dataset

The dataset used in our study is sourced from Kaggle, this dataset comprises 1156 images focusing on nitrogen deficiency (N_deficiency), phosphorus deficiency (P_deficiency), and potassium deficiency (K_deficiency) in rice plants. These images are categorized based on the type of nutrient deficiency, providing a diverse dataset for training and evaluating our models. The dataset is publicly available on Kaggle [16] and has been utilized in various research papers, including the referenced paper [17].

**Table 1.** Image Dataset Description

| Dataset | Classes | Size |
|---|---|---|
| Rice | Potassium deficiency ( K_deficiency) | 383 |
| | Nitrogen deficiency (N_deficiency) | 440 |
| | Phosphorus deficiency ( P_deficiency) | 333 |

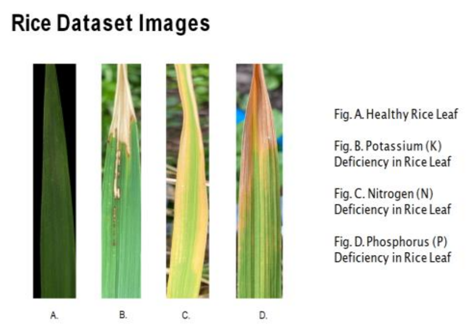



**Fig 2.** The different characteristics of rice leaves under NPK deficiencies.

### 4.2 Experimental findings

#### 4.2.1 Experimental outputs of Foreground segmentation :

The table demonstrates the effectiveness of GrabCut segmentation, an advanced image processing technique. In the "Image Before Segmentation" column, original images show complex scenes with foreground objects amidst cluttered backgrounds. However, in the "Image After Segmentation" column, GrabCut segmentation meticulously extracts foreground objects, resulting in clean and precise delineation from background noise. This process enhances image clarity and focus, making them suitable for applications like object recognition, image editing, and medical image analysis. GrabCut segmentation proves valuable for enhancing visual understanding and facilitating advanced image processing tasks.

| Real time Field image before segmentation | Image after segmentation |
|---|---|
|  (a) |  (b) |
|  (c) |  (d) |
|  (e) |  (f) |

**Fig 3.** Sample results of segmentation

### 4.2.2 Hyperparameter Tuning

**Table 2:** Hyperparameters Descriptors

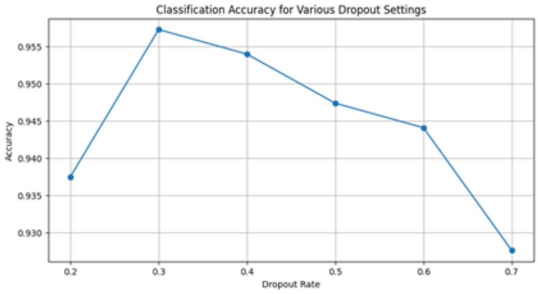
Hyperparameter Descriptors and Their Chosen Values

| Parameter | Value |
|---|---|
| Epochs | 10 |
| Batch Size | 32 |
| Learning Rate | 0.0001 |
| Optimizer | Nadam |
| Dropout | 0.3 |

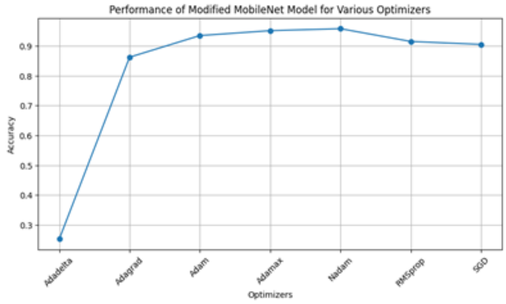
In our proposed model, the hyperparameters are set as follows: epochs - 10, batch size - 32, learning rate - 0.0001, optimizer - Nadam, and dropout - 0.3. These parameters play a crucial role in training the model and optimizing its performance.

### 4.2.3 Optimizing Model Performance: Dropout Settings and Optimizer Analysis

The plotted data highlights that a dropout rate of 0.3 consistently yields high accuracy, demonstrating its efficacy in preventing overfitting[20]. Furthermore, the Nadam optimizer consistently outperforms other optimizers in terms of accuracy. These results emphasize the critical role of hyperparameter selection in optimizing model performance.




*(a)*



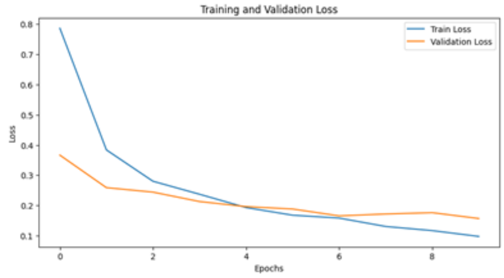

*(b)*

**Fig 4.** a & b Optimizing Model Performance: Dropout Settings and Optimizer Analysis

### 4.2.4 Model Performance Analysis: Training and Validation Metrics

The plotted data reveals the dynamic progression of model training and validation across epochs. In Plot 1, the accuracy steadily increases with each epoch, reflecting the model's improved performance over training iterations. Meanwhile, Plot 2 illustrates a consistent decrease in both training and validation loss as epochs advance, indicating the model's ability to minimize errors and converge effectively during training. These trends underscore the iterative nature of model optimization, wherein successive epochs contribute to refining the model's performance and enhancing its predictive capabilities.


*(a)*




*(b)*

**Fig 5.** a & b Model Performance Analysis: Training and Validation Metrics

### 4.3 Comparative analysis of Proposed Models

To evaluate the performance and generalizability of our proposed models, experiments were carried out using a dataset consisting of 1156 images of paddy. This dataset consists of 9 classes, including 8 diseased classes and 1 healthy class. All images are standardized to a size of 256x256 pixels with 3 channels. The dataset is partitioned into training and testing sets at a ratio of 8:2. Evaluation metrics encompass precision, recall, F1-score, and the number of parameters[18].

Accuracy = $(T_n+T_p) / (T_n+F_p+T_p+F_n)$ , Precision = $T_p / (T_p+F_p)$ , Recall = $T_p / (T_p+F_n)$,

F1 Score= 2 * ( Precision * Recall ) / ( Precision + Recall )

In binary classification, technical terms such as Tp (True Positive), Tn (True Negative), Fp (False Positive), and Fn (False Negative) are utilized to assess classifier performance. True Positive (Tp) denotes correctly classified positive samples, True Negative (Tn) indicates correctly classified negative samples, False Positive (Fp) represents misclassified positive samples, and False Negative (Fn) signifies misclassified negative samples.

#### 4.3.1 Analyzing the Performance Metrics of Two Models for Paddy Crop Nutrition deficiency detection

The experimental comparison results are presented in Table 2. These experiments were conducted using a designated experimental environment, ensuring consistency and reproducibility in the results obtained.The results offer valuable insights into the efficacy of the proposed models for the given task. Here, we provide a comparative analysis of their performance.

**Table 3**.The Metrics from the Comparison Experiments

| Dataset | Indicator | MobileNet | Proposed Model |
|---|---|---|---|
| Rice | Accuracy | 89.65 | 93.10 |
| | Precision | 90.39 | 93.11 |
| | Recall | 89.65 | 93.10 |
| | F1 Score | 89.57 | 93.09 |

The histograms provided in the report offer a visual representation of the performance metrics of all the models aforementioned in diagnosing nutrient deficiencies in paddy crops. Each histogram depicts the distribution of scores across key metrics, including accuracy, precision, recall, and F1-score.

### 4.4 Comparative Analysis: Histograms Illustrating the Performance of Two Models

These histograms provide valuable insights into the performance consistency and variability of each model, enabling stakeholders to make informed decisions regarding agricultural management strategies and crop health optimization. **Fig 6**

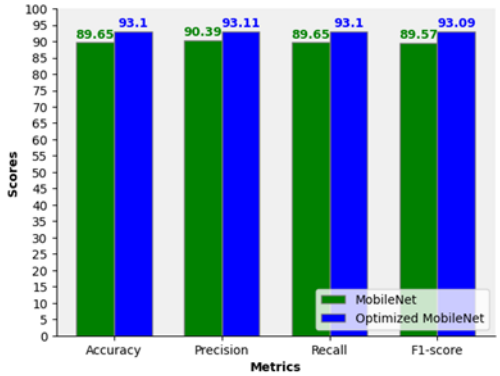



**Fig 6**. Histogram of Performance Before vs. After Optimization

### 4.5 Model Comparison: Confusion Matrices for Comprehensive Evaluation

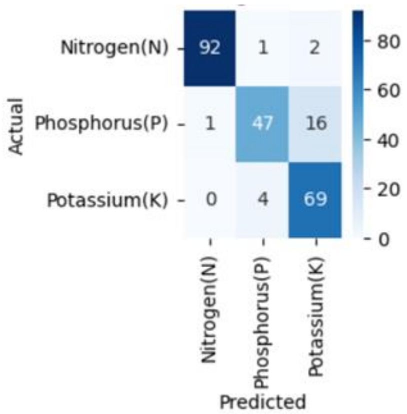



**Fig 7.** Confusion Matrix Generated Using MobileNet

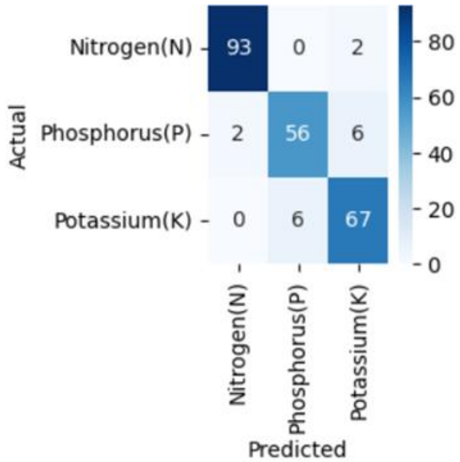
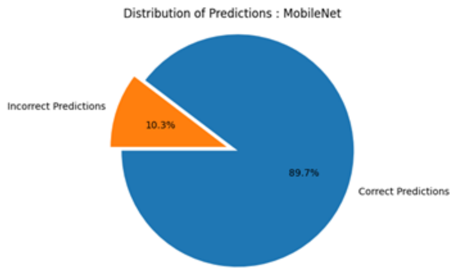



**Fig 8.** Confusion Matrix Generated Using Proposed Model

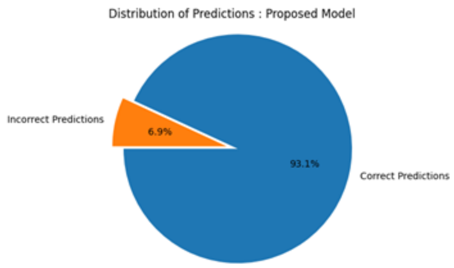
The confusion matrices demonstrate that proposed model provides better classification performance across most classes compared to other Model.

### 4.6 Pie Chart Analysis: Comparing Overall Model Performance for Comprehensive Insight

The below depicted pie charts represent the detection accuracy of MobileNet, and the Proposed Model. MobileNet demonstrates a significant increase in correct detections. However, the Proposed Model exhibits the highest proportion of correct detections, indicating superior accuracy.



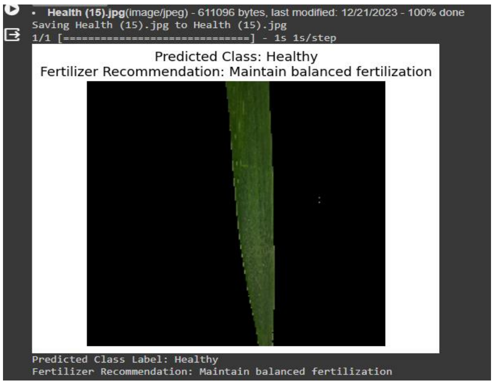

*(a)*




*(b)*

**Fig 9**. a & b Pie Chart Analysis: Comparing Overall Model Performance for Comprehensive Insight

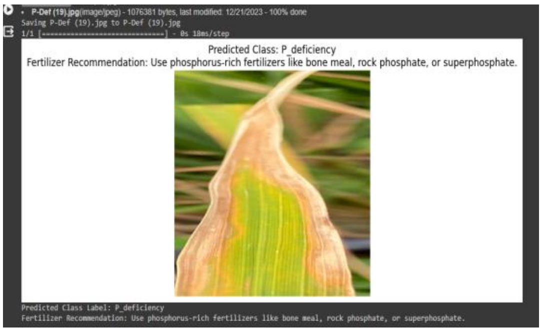
## 5. PROPOSED MODEL OUTPUT IMAGES AND RECOMMENDATIONS




*(a)*


*(b)*


*(c)*




*(d)*

**Fig 10.** a,b,c & d Sample out put results of the proposed model

Displayed above are the output results showcasing the outputs for the Proposed model. Sample Images are given with Healthy, K_deficiency( Potassium deificiency) , N_deficiency(Nitrogen Deficiency), and P_deficiency( Potassium Deficiency), and predicted the nutrition deficiency and recommended accordingly.

## 6. Conclusion

In conclusion, this study introduces innovative digital imaging methods for quantitative symptom analysis, addressing limitations of conventional visual inspection techniques in diagnosing crop nutrient deficiencies. Leveraging GrabCut segmentation and deep learning, particularly with MobileNet architecture, we achieve notable accuracy. The Finetuned MobileNet outperforms other model, attaining a remarkable accuracy of 93.10%. Notably, MobileNet model achieves an accuracy of 89.65% highlighting the comparative performance of these models. The integrated approach not only enhances nutrient deficiency classification but also recommends appropriate fertilizers, supporting precision agriculture and sustainable crop management practices. These findings underscore the potential of advanced imaging and machine learning techniques in revolutionizing agricultural practices for increased efficiency and productivity.

## 7. Future Scope

Future research could focus on optimizing hyperparameters and exploring additional deep learning architectures to further improve accuracy and efficiency across various models. Integrating real time monitoring systems and IoT technologies could enable automated nutrient management systems for timely interventions. Expanding this research to other crops and agricultural contexts could provide valuable insights for sustainable agricultural practices on a broader scale, ultimately contributing to global food security and environmental sustainability.

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