# Classification of Nutrient Deficiencies in Winter Wheat and Winter Rye

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## Abstract

*The CVPPA 2023 challenge seeks innovative methods to identify nutrient deficiencies in winter wheat and winter rye using RGB images captured by Unmanned Aerial Vehicles. In this study, our team, named as SWAT, which comprises members from the German Aerospace Center and the Technical University of Munich, has developed a pipeline that relies on soft vegetation indices extracted from RGB images, as well as a modified vision transformer called ViT-hybrid, for the purpose of nutrient deficiency detection. With our approach, we achieved an accuracy rate of* $91.9\%$ *for detecting nutrient deficiencies in both winter rye and winter wheat. This performance secured us the second position in the winter rye category and the fourth position in the winter wheat category on the public leaderboard of the challenge.*

## 1. Introduction

Food security, a global imperative, faces escalating threats. Altered weather patterns, extreme events, and rising temperatures disrupt crop yields and strain food supplies [1]. Concurrently, nutrient deficiencies in plants exacerbate the malnutrition crisis, compromising human health. Addressing these challenges, require a timely assessment of soil and crop conditions to minimize significant losses at the end of the season and safeguard food quality. Machine learning-driven plant phenotyping emerges as a pivotal solution. By harnessing artificial intelligence and advanced imaging techniques, it enables precise monitoring of plant growth, stress responses, and nutrient uptake. This data-driven approach can facilitate the understanding of complex relationships between crops and their environment to improve nutrient use efficiency.

Symptoms of nutrient deficiency are not always conspicuous until later stages of plant growth. Subsequently, nutrient deficiency types can be visually similar and not easily distinguishable. Thus, on-site surveillance of fertilizer treatment can be inefficient and impractical to scale.

Machine learning has been applied to several agriculture use cases including plant disease detection, crop classification and leaf segmentation. Nutrient deficiency detection in various crops have been tackled successfully using computer vision giving a general idea of its potential. [5] applied convolutional neural networks to recognise NPK deficiencies in sugar beets from RGB images. Their experimental results achieved an accuracy of $98\%$ using Dense-Net . [4] detect graduation color of okra leaves as a proxy of nutrient deficiency using Inception ResNet-v2. An accuracy of $96\%$ for training and $86\%$ on test set was realised.

In this paper, we present our solution to the CVPPA 2023 challenge which aims to solve on-site nutrient deficiency recognition in UAV-based RGB images. Seven types of deficiency are targeted. Our solution applies several data engineering and augmentation techniques and deep learning method to aid the recognition process. Section 2 describes the dataset provided. We detail the data processing strategies and our experimental setup in Section 3. In Section 4, we evaluate the performance of the proposed architecture and compare our findings with those obtained from various classical machine learning algorithms. Our findings are summarised in Section 5.

## 2. Dataset

The dataset provided in the competition is the DND-Diko-WWWR dataset; a UAV-collected RGB images over an experimental site in Dikopshof, Germany. A total number of 3600 samples are available, distributed evenly for winter wheat (harvested in 2020) and winter rye (harvested in 2021). The images are taken at several dates for seven soil and nutrient status namely **unfertilized**, **_PKCa**, **N_KCa**, **NP_Ca**, **NPK_**, N**PKCa**, and **NPKCa+m+**.

**N**, **P**, **K**, **Ca** denotes nitrogen, phosphorus, potassium, and lime nutrients and '_' signifies the exclusion of a particular nutrient in the fertilization plan. Supplementary application of mineral fertilizer and farmyard manure are represented by **m** and **s** respectively.

# 3. Experimental Framework

During our experiments, we employed two distinct pipelines: one grounded in classical machine learning (ML) principles and the other rooted in deep learning (DL) methodologies. In the subsequent sections, we will detail the specifics of each pipeline.

## 3.1. Data Processing

### 3.1.1 Feature Extraction

In the ML pipeline, we conducted feature extraction from our dataset. We employed a grid search to optimize individual features separately. Subsequently, we amalgamated feature groups to identify the most promising combination among them. The following feature groups were considered:

1. Histogram of soft vegetation indices:
   (a) *Visible Atmospherically Resistant Index (VARI)*:
   $$\text{VARI} = \frac{\text{Green} - \text{Red}}{\text{Green} + \text{Red} - \text{Blue}} \tag{1}$$
   (b) *Green-Red Vegetation Index (GRVI)*:
   $$\text{GRVI} = \frac{\text{Green}}{\text{Red}} \tag{2}$$
   (c) *Modified Green-Red Vegetation Index (MGRVI)*:
   $$\text{MGRVI} = \frac{2 \times \text{Green} - \text{Red} - \text{Blue}}{2 \times \text{Green} + \text{Red} + \text{Blue}} \tag{3}$$
   (d) *Triangular Vegetation Index (TVI)*:
   $$\text{TVI} = \sqrt{(NIR - \text{Red})(NIR - \text{Green})(NIR - \text{Blue})} \tag{4}$$
   (e) *Excess Green Index (ExG)*:
   $$\text{ExG} = 2 \times \text{Green} - \text{Red} - \text{Blue} \tag{5}$$
   (f) *Excess Green minus Excess Red (ExGR)*:
   $$\text{ExGR} = 3 \times \text{Green} - 2.4 \times \text{Red} - \text{Blue} \tag{6}$$
2. Color moments: channel mean, variance, skewness,
3. Histogram of oriented gradients,
4. Daisy feature descriptor,
5. Local binary patterns,
6. Gabor features,
7. Haralick features,
8. Histogram of channel entropies,
9. Histogram of Fast Fourier Transform,
10. Histogram of Wavelet Transform,

On the other hand, in the DL approach, rather than extracting histograms, we directly obtained soft vegetation indices and binary thresholded images using the Otsu method, along with the real part of Fast Fourier Transform (FFT) as auxiliary channels. Among these auxiliary channels, three were randomly selected to compose false-color channels alongside the original RGB channel, resulting in a 6-channel input for training and validation.

### 3.1.2 Data Augmentation

For data augmentation, we employed two strategies applicable to both the classical ML and DL pipelines:

- *Approach-1*: Training two separate models for the WW2020 and WR2021 datasets, respectively.
- *Approach-2*: Training a single model using combined WW2020 and WR2021 data.

In addition, for the DL pipeline, we applied several augmentation techniques, including mixup learning, random rotation, random flipping, and extraction of sub-patches from the original image. We then aggregated the model's decisions on these patches through majority voting or weighted summation.

## 3.2. Models

In our experimental setup, we harnessed the following ML techniques, Random Forest (RF), Support Vector Machines (SVM), and Light GBM. Conversely, in the DL domain, we leveraged the ViT-hybrid [2], and ConvNext [3] models. Notably, due to our augmented data containing a total of 6 channels in the DL approach, we horizontally expanded the chosen backbone model, with one branch processing the original RGB inputs and another handling the false RGB inputs. The embeddings from these branches were concatenated and jointly forwarded into the fully connected layers for subsequent classification, as illustrated in the Figure 1.

In the case of classical ML methodologies, the model was crafted using scikit-learn. However, in the DL approaches, PyTorch was employed, and the models were initialized utilizing pretrained weights sourced from the Imagenet dataset through the HuggingFace repository.

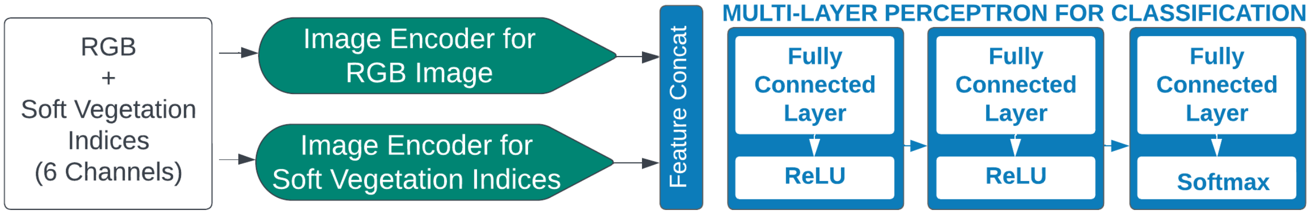

Figure 1. Deep Learning Pipeline processing true RGB and false RGB channels (namely soft vegetation indices) together.

### 3.3. Evaluation metrics

In our evaluation, we employed the following metrics to assess the performance of our models:

$$\text{Focal Loss} = -\alpha \cdot (1 - p_t)^\gamma \cdot \log(p_t) \tag{7}$$

Where: $\alpha$ is the balancing parameter, $p_t$ is the predicted probability of the true class, and $\gamma$ is a tunable focusing parameter.

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \tag{8}$$

These metrics were employed to quantitatively evaluate the performance of our models.

## 4. Results and Discussion

In this section, we discuss the results obtained through different approaches and augmentation techniques for detecting nutrient deficiencies in winter wheat and winter rye. Table 1 summarizes the achieved results.

Among the classical ML techniques, for nutrient deficiency detection in winter wheat and winter rye from UAV-based RGB images, SVM and RF delivered reasonable performance, achieving accuracy scores of $66.5\%$ and $70.0\%$, respectively, when trained on separate datasets. In contrast, when trained on a combined dataset, we observed a substantial improvement, as seen in the RF and Light GBM results, achieving accuracies of $77.9\%$ and $80.1\%$, respectively. On the other hand, DL approaches appear to outperform classical ML approaches. In particular, ViT-hybrid emerged as the top-performing model, especially when augmented with sub-cropping and majority voting, showcasing its potential for nutrient deficiency detection in winter wheat and winter rye from UAV-based RGB images. Further optimization and experimentation may provide opportunities for even higher accuracy.

Table 1. Applied methodologies and the achieved results.

| Approach | Augmentation | | | Accuracy on the Leaderboard (%) |
|---|---|---|---|---|
| | WR+ WW together | WR+ WW separate | Sub-cropping and majority voting size | |
| Support Vector Machines | | ✓ | 1 | 66.5% |
| Random Forest | | ✓ | 1 | 70.0% |
| Random Forest | ✓ | | 1 | 77.9% |
| Light GBM | ✓ | | 1 | 80.1% |
| ConvNext-tiny | | ✓ | 1 | 73.1% |
| ConvNext-tiny | ✓ | | 1 | 78.4% |
| ViT-hybrid | | ✓ | 1 | 75.7% |
| ViT-hybrid | ✓ | | 1 | 83.5% |
| ViT-hybrid | ✓ | | 5 | 87.7% |
| ViT-hybrid | ✓ | | 11 | 91.9% |

## 5. Conclusion

In this manuscript, we present our solution to the CVPPA 2023 challenge, which aimed to address on-site nutrient deficiency recognition in UAV-based RGB images. Our solution applied several data engineering and augmentation techniques, as well as deep learning methods, to enhance the recognition process. Our findings highlight the scalability and adaptability of ViT-hybrid when augmented with sub-cropping, establishing it as one of the top-performing approaches among all the submissions considered for this challenge. The accompanying codebase for our experiments is also available upon request; interested parties may contact the corresponding authors for access to the codes.

## References

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