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Identification of Nutrient Deficiency Based on Leaf Image Data Using Machine Learning

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***Abstract*— The world population has been growing significantly during the last few decades. The demand for rice is constantly increasing with the ever-increasing global population, as rice crops are one of the primary food sources for humans. Increased fertilizer use in recent years has helped farmers to raise their rice production rapidly. Adding too much of fertilizers will have a negative effect on the soil. To boost the rice production, it is necessary to ensure that each paddy plant is healthy. This study makes use of a very practical method to identify nutrient deficiencies (NPK) in rice plants, using leaf imaging and machine learning techniques. The study proposes a framework in which the color and texture features of the image are extracted and then combined to get a single robust feature representation of the image. Classification of the image is done for identifying macro nutrient deficiencies using the Random Forest model, which when compared with Naive Bayes gave better accuracy.**

Index Terms*— *Machine Learning, Naïve Bayes, NPK, Nutrient deficiency, Random Forest

I. Introduction

The agriculture industry of India is the single most important contributor to the overall economy of the country. According to the most recent data, this industry accounts for 17.9% of the overall contribution to the country's GDP [1]. Plant growth is dependent on many different nutrients. Rice needs 16 different nutrients, but the most important are nitrogen (N), Phosphorous(P) and Potassium(K).

Magnesium, Calcium and Sulphur are minor macronutrients [1], while Zinc, Iron, Manganese, Copper, Molybdenum and Chlorine are micro nutrients[2].It is essential for the long-term survival of crops to receive a significant supply of NPK and other nutrients. The role of different nutrients in the the growth of the rice plant is listed below.

Nitrogen:Nitrogen promotes plant growth, including increased height and the number of roots. It is essential in the synthesis of virtually every known biomolecule, including enzymes, proteins, hormones, nucleic acids, alkaloids, and vitamins.

Phosphorous(P): Phosphorus is important for healthy plant growth and efficient energy transfer. Nucleotides, sugar phosphates, nucleic acids, and phospholipids are all biomolecules that rely on it in some way during their creation.

Potassium (K): Safeguards against crop failures and diseases. Also required for activating enzymes and to help in maintaining osmotic and ionic balance.

Magnesium (Mg): Plants require magnesium in order to carry out their functions correctly.

Calcium (Ca): Essential for maintaining cell division and the health of cell membranes. Calcium, in the form of pectate, is a vital element of the cell wall.

Sulphur (S): Necessary for the generation of cellular energy and in the synthesis of lipids and proteins.

Zinc (Zn): Crucial to the functioning of numerous enzyme-based systems.

Iron (Fe): Plays a catalytic role as a necessary part of many plant enzymes. Several photochemical and respiratory oxidation process depends on it.

Chlorine (Cl): Being an enzyme catalyst, it aids in the osmotic dehydration of plants in salty soils and is required for photosynthesis.

This study aims to identify nutrient deficiency (NPK) based on rice leaf image data using machine learning.

II. SYMPTOMS OF DEFICIENCY

While there are various warning signs for nutritional deficiencies, this study will focus on those seen in the leaf of the rice plant in particular. Multiple symptoms are typical for rice that is lacking in NPK.

Nitrogen Deficiency (N): Nitrogen deficiency's earliest symptoms are mature leaves are noticeably lighter than typical. When nitrogen is lacking, the tips of older leaves, and sometimes all of the leaves, turn pale green and chlorotic. Defective leaves are thin, short, erect and lemon yellow, except for young leaves which are greener [3][4].

Phosphorus Deficiency (P): When a plant doesn't get enough phosphorus, it slows or stops growing new shoots. In extreme cases of shortage, the leaves may turn a sickly yellow or white tint. An increase in anthocyanin production results in reddish, reddish-violet, or violet coloring. It is the older sections of the plant that show symptoms initially.[4].

Potassium Deficiency (K): Potassium insufficiency causes leaves to be thin, and short, with yellowish-brown leaf tips. Older leaves typically become brown as they age. Plants would be dark green overall but have necrotic patches that are a dark brown at first and then gradually spread outwards. The tips of older leaves are affected. The figure illustrates many characteristics of rice leaves that can be observed when there are NPK shortages.

Fig. 1. Different characteristics of rice leaves under NPK deficiencies [4]

Nutrient deficiency in plants is a major problem that reduces productivity and profits.Most of the time, farmers cannot detect nutrient deficiencies and therefore cannot take preventive measures. Lack of proper nutrition in plants is a big problem that threatens production and earnings. Usually, farmers have no way of knowing that their crops have nutritional shortage and, as a result, productivity will be reduced. Classifying rice plants with nutrient shortages is therefore greatly aided by image processing and machine learning methods. This work presents the application of ML techniques like Random Forest for detecting and labelling nutrient deficiencies in rice plant leaves (Shah, et al., 2018). As a result, farmers may fine-tune the plant's nutrition supply and achieve a higher yield.

III. LITERATURE SURVEY

Rice plants' leaves are a good place to look for signs of nutritional deficits, thus Xu et al. [19] made an effort in that direction. Therefore, vitamin deficits in rice can be diagnosed by observing the leaf color and form. Here, the performance of many different deep convolutional neural networks (DCNNs) is performed in identifying nutritional deficits in rice. Hydroponic experiments yielded a total of 1818 leaf images, spanning full nutrition and 10 classes of nutritional deficits. Mohanty et al. [20] adopted the AlexNet and GoogLeNet constructs to examine the feasibility of DCNNs for crop disease diagnosis.

Asad Ali et al. [21] created an automated system for detecting the nutritional deficiencies. The author used CNN classifier with an average of 77.97% individual accuracy for nutrient deficiencies. Nitrogen and potassium deficit diagnosis in maize is an effort made by Sridevy Sridarane et al.[22] using image mining, and color response. This study shows the relationship between nitrogen and potassium deficiency and spectral reflectance values in green and red.B.Liu.et al [23] proposed an improved CNN model for detecting leaf disease.

The authors of [24],[25] created a framework for rice plant disease identification. Four background removal and three segmentation strategies were tested on the leaf images. To extract features accurately from a leaf image, centroid feeding-based K-means clustering is used by the author. It improves K-means clustering by deleting disease-related green pixels. Color, form, and texture are extracted. Multi-class classification uses SVM.

IV. SYSTEM ARCHITECTURE

This work introduces a method that uses image processing and a machine learning approach to help farmers in identifying nutrient deficiencies in rice plants. Nutrient deficit (NPK) is assessed using CEDD and FCTH characteristics. The Random Forest (RF) classifier is trained using images of rice leaves with nutrient shortages such as nitrogen, potassium, and phosphorus.

Accuracy is then evaluated using training and test data sets. System working involves the following steps.

A. Image acquisition:

Rice NPK deficiency dataset from Kaggle having three types of shortages- N, P, K with 440, 333, and 383 images for each type, respectively are used. Each of the three categories has images of different sizes [14].

B. Image pre-processing:

Noise, blur, unwanted objects, poor contrast, and glare from weather and environmental changes are common in the resulting images [16][17]. Farmers' field images include such noises.

Pre-processing includes color space conversion, cropping, filtering, and enhancement. Image pre-processing removes unwanted distortions.

Pre-processing will improve the accuracy of image analysis. Image-enhancing noise reduction and contrast adjustment are pre-processing operations. Following is the formula for RGB Normalization:

$$r = \frac{R}{R+G+B}; g = \frac{G}{R+G+B};$$
$$b = \frac{B}{R+G+B}$$

Contrast adjustment: At this stage, the contrast of the images is adjusted in order to ensure that the foreground objects can be distinguished from the backdrop and any other foreground elements.

Noise Removal: Noise in the original image can cause negative results. Several distinct image filters may be used to reduce noise and improve edges.

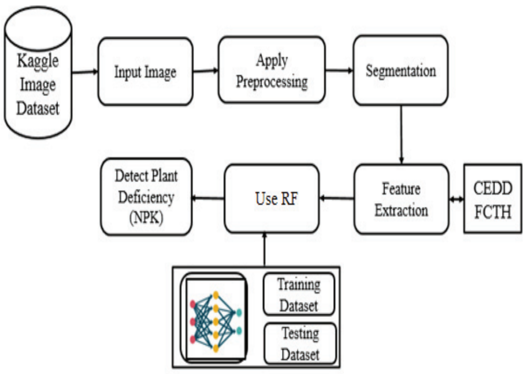

Fig. 2. Block Diagram of the Proposed System

C. Segmentation:

In the field of image processing, segmentation is crucial. Here, the image after pre-processing is broken down into several smaller images. Those are the good and unhealthy parts of the input. As a result, segmentation is required to identify features like spots, edges, and color differences. The first segmentation removes the background, while the second segmentation obtains the area of the leaf with the lesion.

D. *Feature Extraction:*

The extraction of features is the main aspect of texture analysis[18]. A variety of visual descriptors, including the Fuzzy Colour and Texture Histogram (FCTH) and the Colour and Edge Directivity Descriptor (CEDD), are applied to leaf images of paddy in order to extract useful features. CEDD includes color and texture in a histogram. Using these features requires relatively little processing power. This 54-byte descriptor is suited for large image databases. Alternatively, FCTH can accurately retrieve images despite anomalies, distortion, and smoothness, with a 72-byte image size limit. These traits aid recognition precision by combining color and texture data.

Color features from the image can be extracted by following these steps:

1. The input image is first split into non-overlapping blocks.
2. For every image, CEDD computes the color histogram of the block. The color histogram represents the frequency of occurrence of different color values in the block.
3. CEDD then applies a color quantization step to reduce the number of colors used in the histogram.
4. The histogram is then normalized to make it robust to changes in illumination and contrast.
5. CEDD calculates the edge orientation histogram for each block. This represents the frequency of occurrence of different edge orientations in the block. The histograms of each block are concatenated to form the final CEDD descriptor for the image.

The resulting CEDD descriptor is a compact representation of the color and edge information of the image, which can be used for efficient image retrieval.

Texture Features are extracted by FCTH with the following steps:

1. The image is split into blocks.
2. For each block, FCTH calculates the gray-level co-occurrence matrix to capture the spatial relationships between the pixel values in the block
3. Fuzzy clustering is applied to gray level co-occurrence matrix to obtain a set of texture clusters that represent different types of textures in the block
4. Colour information of each block is also extracted by calculating the color histogram of the block
5. Colour histogram and Texture clusters are combined to get the FCTH descriptor.
6. Descriptors of all blocks are combined to form the final FCTH descriptor of the image.

Once the color features and texture features are extracted, these are combined to get a robust feature representation of the image ie. concatenating these features to get a single feature vector.

E. *Classification:*

Extracted features are stored in a .csv file. Classification of the image is done for identifying deficiencies of nitrogen, phosphorous, and potassium by making use of the Random Forest model. The model has two steps -training and testing. 10-fold cross-validation is applied to the dataset. A confusion matrix is used for evaluating the accuracy of the classifier.

F. *Dataset Used*

This study makes use of the Kaggle rice plant nutrients deficiency dataset. There are 440 images in the "N" category, 333 in the "P" category, and 383 in the "K" category, all illustrating various forms of deficiency. The images in each of the three groups have different sizes.

- Nitrogen-deficient Images – 440 Images
- Phosphorus-deficient Images - 333 Images
- Potassium-deficient Images – 383 Images

V. EXEPERIMENTAL RESULTS

Random Forest classifier was used to classify the dataset.

Confusion Matrix

The suggested method uses a huge rice plant nutrient deficit dataset. Where accuracy and precision are calculated based on false positives and false negatives

TABLE I. CLASS WISE DISTRIBUTION OF IMAGE

Class	TP	TN	FP	FN
0	403	463	83	37
1	175	691	78	158
2	288	578	129	95

The three classes considered in this approach are
0 – Nitrogen Deficient
1 – Phosphorus Deficient
2 – Potassium Deficient

Accuracy and precision are calculated for the classes 0,1 & 2

$$Precision = \frac{TP}{TP\ X\ FP} \qquad Recall = \frac{TP}{TP\ X\ FN}$$

TABLE II. SYSTEM PERFORMANCE BASED ON THE CLASSES IDENTIFIED

Class	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)
0	94.66	92.46	94.77	94.59
1	89.63	83.96	80.18	93.58
2	89.71	84.5	85.38	91.94

Altogether 1156 images were evaluated with 440, 333, and 338 images respectively for classes 0,1 & 2 using Random Forest. The accuracy graph is shown in the figure below

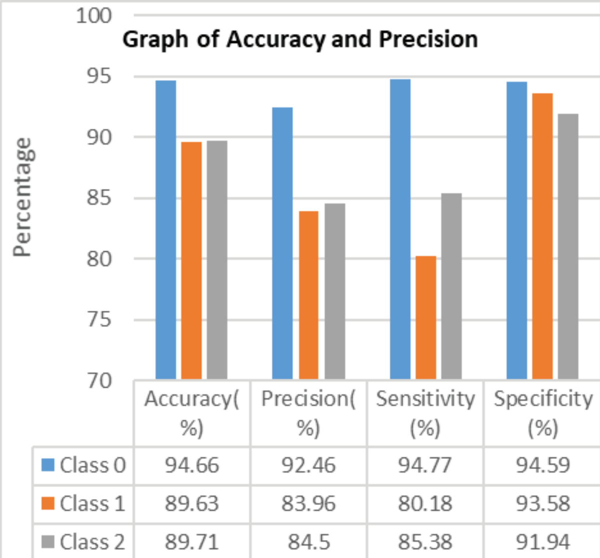

Fig. 3. Class-wise Accuracy and Precision Comparative graph

Naïve Bayes

The same data set of a total of 1156 images for classes 0, 1, and 2, with 440, 333, and 338 for each class respectively were tested for the Naïve Bayes classifier.

Confusion Matrix

TABLE III. CLASS WISE SYSTEM PERFORMANCE

Class	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)
0	87.83	82.92	91.59	84.8
1	78.58	69.17	52.55	89.86
2	79.45	69.06	75.2	81.75

The accuracy graph for Naïve Bayes is as shown in Figure 4

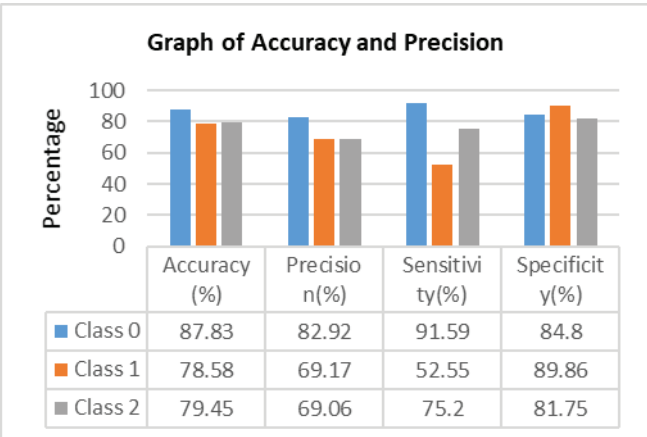

Fig. 4. Class-wise Accuracy and Precision Comparative graph

It has been observed that when Random forest is compared to Nave Bayes, the accuracy of deficiency detection is greater for the random forest for classes 0,1, and 2, which are 94%, 89%, and 89%, respectively, compared to 87%, 78%, and 79% for Nave Bayes.

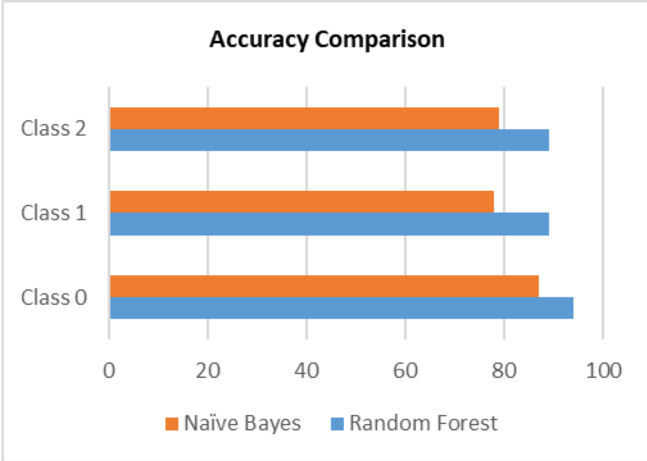

Fig. 5. Algorithm Comparison

This leads one to conclude that the Random forest is superior for identifying NPK deficiencies. The similarity is depicted in Figure 5.

VI. DISCUSSION

Visual indications/patterns can be used to identify a nutrient deficiency in plants. Features are extracted from the image using visual descriptors. The accuracy of Random Forest was more as compared with Naïve Bayes for identifying deficiency of nutrients on a labeled data set of rice plant leaf images.

In crops nutrient deficiency symptoms can overlap with other biotic and abiotic stresses like environmental factors, pests, and diseases which can confound the accuracy of nutrient deficiency identification using image processing and machine learning. Distinguishing between overlapping symptoms and accurately attributing them to nutrient deficiencies can be difficult.

The framework may be enhanced by incorporating sensor technology, which helps in the precise monitoring of nutrients present in the soil, for the enhanced crop yield.

VII. CONCLUSION

In order to keep plant development at its optimal level, it is essential to make an accurate diagnosis of any nutritional deficiencies. In this study, we present a method that is effective for identifying nutrient (NPK) deficiencies in rice plants. Image processing machine learning techniques, such as Random Forest (RF), allow for more precise fault identification. It has been found that CEDD and FCTH features are sufficient for detecting a new low-level feature that provides a unique image of the leaf's color and texture. This system aids farmers in making educated decisions about how to address nutritional shortfalls at the right time.

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