Classification Nutrient Deficiency of Maize Plant Leaf Using Machine Learning Algorithm

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Abstract

The development and productivity of maize, an important crop worldwide, may be stunted by several nutritional deficiencies. If we want to increase maize output, we need to find these problems quickly. This study suggests a thorough method for identifying nutritional deficits in maize plants by analyzing leaf photos. Our approach combines deep learning algorithms with conventional machine learning methods to analyze and extract information from these pictures. The four types of nutritional deficiencies that were examined are zinc (Zn), potassium (K), nitrogen (N), and phosphorus (P). The standard machine learning method uses Gabor, Discrete Wavelet Transform, Local Binary Pattern, and Gray-Level Co-occurrence Matrix (GLCM). Then, classification is done using algorithms like Support Vector Machine (SVM), Decision Tree, and Gradient Boosting. According to our experimental data, machine-learning algorithms successfully diagnose nutritional deficits in maize plants. The results of this study highlight the promise of machine learning algorithms for improving agricultural yields via better plant nutrition management. Farmers and agricultural specialists may greatly benefit from automated image analysis that can identify nutritional deficits in maize plants quickly and correctly. This technology has the potential to contribute to the sustainability and security of food on a worldwide scale.

Keywords: Nutrient deficiency; Maize plant; Deep learning; Image classification; Agriculture

1. Introduction

Technology is vital to all developing-world enterprises. Human existence depends primarily on agriculture. Our agricultural methods are traditional. Farmers still struggle to diagnose crop nutrient shortages, which consumes time and money. Misdiagnosis may cost time, money, and production. Skilled farmers and agricultural labs find deficiencies. Several environmental variables may make manual nutritional deficiency estimations erroneous. We utilize the leaf to find crop nutritional deficits since they are found in the stem, flowers, fruits, and other plant components. Plants require around twelve nutrients to grow. A leaf is used to identify crop nutritional deficits. Plants require around twelve nutrients to grow. Nitrogen, phosphorus, potassium, magnesium, calcium, iron, molybdenum, sulphur, and chloride.

Maize (Zea mays) is a fundamental crop globally, serving as a staple food source and a critical component of livestock feed. With a growing global population and increasing demand for food security, enhancing maize production is paramount. However, several factors heavily influence maize productivity, including nutrient deficiencies in the soil. Nutrition deficiencies, such as inadequate levels of nitrogen (N), phosphorus (P), potassium (K), and Zinc (Zn), can severely limit maize growth and yield. These deficiencies manifest as distinct physiological symptoms, often visible in the leaves, and addressing them swiftly is essential for sustainable agriculture.

A plant's ability to absorb water, sunshine, and nutrients is crucial to the agricultural system. The nutrients, which may be categorized as either macronutrients or micronutrients, those plants need vary in quantity. Macronutrients

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rank higher than micronutrients because of their importance in cellular and tissue development. Micronutrients include Ferrum, Zinc, Cuprum, and Manganese. The process of leaf development interferes with the creation of food, which in turn affects micronutrient deficiencies. Dwarf plant syndrome, poor blooming and fruiting, and other growth problems are associated with inadequate food generation. The changes in leaf color and the rate of foliage development are the first signs of nutrient deficiencies; Table 1 lists the symptoms in detail.

Table 1: Macronutrient deficiency symptoms

Macronutrients	Symptoms
Nitrogen (N)	Light green top leaves, yellow bottom leaves
Potassium (K)	Yellow and purple leaves with brown edges and mediocre flowers and fruit.
Phosphorus (P)	Slow growth and yellow foliage
Magnesium (Mg)	Early leaves fall and are yellow-red-brown between the veins.

The leaves of agricultural plants may reveal nutrient deficiencies by symptoms such as shrinkage, changes in color, deformities along the margins, necrosis, black spots, etc. The farmer must uproot the plants and send them to the appropriate lab for testing in order to identify the nutritional deficiencies. Because of this effort, nutrient deficits and the plants' responses to them may be better understood.

Detecting and diagnosing nutrient deficiencies in maize plants traditionally involves visual inspection by agronomists or field experts. This method, while effective, is labor-intensive and subject to human error. Additionally, the increasing demand for food necessitates the development of more efficient and accurate methods for nutrient deficiency diagnosis in maize plants. In this context, using machine learning and deep learning techniques provides a promising avenue for modernizing and enhancing the efficiency of nutrient deficiency classification.

This study focuses on classifying nutrient deficiencies in maize plants using a combination of traditional machine learning and deep learning algorithms. Specifically, we explore the use of advanced image analysis techniques to assess the nutrient status of maize plants by analysing images of their leaves. Our dataset consists of images from maize plants exhibiting deficiency symptoms in the four key nutrients - nitrogen, phosphorus, potassium, and zinc. By leveraging the distinctive visual cues of nutrient deficiencies, we aim to develop a robust and automated system for nutrient deficiency detection.

Applying machine and deep learning to agriculture has gained momentum in recent years. These technologies can revolutionize how we monitor and manage crop health and nutrition. The utilization of computer vision techniques for the analysis of plant imagery is a particularly promising development. Our research seeks to contribute to this emerging field by comprehensively analysing the performance of various machine and deep learning algorithms for nutrient deficiency classification in maize plants. Ultimately, our goal is to offer farmers and agricultural experts a valuable tool to enhance nutrient management and, by extension, maize production.

2. Related Work

About 20% of the calories consumed in Sub-Saharan Africa come from maize. Unfortunately, Sub-Saharan African farmers have not been able to harvest enough food to meet human needs. The main causes are outdated agronomic practices and the need for more nutrients. A major contributor to this low maize harvest yield is nitrogen shortage. Unfortunately, many smallholder farmers lack the knowledge to spot this nitrogen deficiency in its early, reversible stages, protecting their maize crops from potential harm. This research aims to discover how to make an app for older Android phones that can diagnose nitrogen deficiency using a machine-learning model. Our technique utilizes Keras's built-in Image Augmentation algorithms to augment our datasets with more photographs. The produced model has achieved an accuracy of 81%. Using this Android app, a smallholder farmer may monitor and assess the soil health of many farms and then apply fertilizer as needed to make up for the nitrogen deficit. For the convenience of interested academics, we have also highlighted prospects in this study area. [1]

The main reason agricultural productivity is low is because of plant diseases. The detection and control of plant diseases is a common challenge for farmers. Therefore, farmers can benefit from early illness diagnosis to prevent additional losses. This work uses supervised machine learning methods to diagnose diseases in maize plants using plant photos. The classification methods are studied and contrasted to find the most accurate model for predicting

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plant diseases. The RF algorithm achieves the best results with a 79.23% accuracy rate compared to other classification methods. As a preventative strategy, farmers will employ the trained models mentioned earlier to identify and categorize new image diseases as soon as they appear. [2]

Improving crop yield relies on identifying nutritional deficits in plants. As farmers notice signs of nutrient inadequacy in their plants, they can implement effective nutrient management measures to remedy the situation. Novel opportunities for non-destructive field-based analysis of nutritional deficiencies have emerged with computer vision and machine learning approaches. Shape and color are crucial parameters for feature extraction. This study employs two approaches to picture segmentation and feature extraction to create distinct feature sets from identical image sets. Classification using various machine-learning approaches is subsequently performed on these. In order to determine which method works better with the two sets of features, we examine the experimental data and compare them according to the classification accuracy. [3]

This work introduces a machine-learning method for detecting brown spot disease, bacterial leaf blight, and leaf smut in rice. The accuracy of the algorithms in predicting illnesses affecting rice leaves varied. With an accuracy of 97.9167 percent on test data, the decision tree was determined to be the top performer. Having found a nearly perfect algorithm, we intend to continue this research when better datasets become available. [4]

Regarding agricultural importance, maize ranks second in Indonesia, right behind rice. Maize productivity will rise annually, extending the expected lifespan. Injuries and illnesses might hinder efficiency. Hence, an automated system is required to classify and identify maize diseases in images. The classification of diseases in maize is reviewed in this article. Classification issues are addressed by algorithms such as machine learning and deep learning, which employ a variety of methodologies. Three phases comprise machine learning: preprocessing, segmentation, and classification. Currently, the most effective substitute is deep learning, particularly CNN. Common convolutional neural network (CNN) architectures used for picture classification include Alexnet, VGG, ResNet, and GoogleNet. The following project will use CNN CAM and Grad-GAM to generate visual explanations. Using primary data, convolutional neural network (CNN) architecture, and parameter adjustment are innovative features. Unfortunately, deep learning has its limitations when it comes to processing data. It necessitates prerequisites for high-speed computation and a substantial volume of data. Thanks to a new Google collaboration, deep learning can be trained using very fast computers. [5]

Diseases that affect rice plants have reduced yields by 37% every year. One possible explanation is that we still need to learn more about rice plant diseases to identify and control them effectively. Another reason is that no suitable application has been developed to help with this. Using Convolutional Neural Networks (CNN), an application can detect diseases in rice plants. Because of CNNs' precision in picture identification and classification, many researchers have employed them to detect plant diseases. However, some studies on rice plant disease identification still need to be completed. This study delves into contemporary rice plant illnesses and the Deep Learning methods employed for disease detection. Additionally, it thoroughly evaluates several methods used in the literature, noting the advantages and disadvantages of each. This research has found the most accurate methods in the picture identification procedure at every stage, which will be useful for identifying diseases in rice plants. [6]

Sustainable development is becoming more important, and with it comes a slew of information technologies that can boost agricultural output. In particular, certain advances in machine learning applications—a subfield of artificial intelligence—have the potential to improve and even transform current methods of plant pathology significantly. Classification of leaf diseases using machine learning has recently gained popularity in academia and industry. Consequently, getting a bird's-eye view of the latest advancements in machine learning and its uses for detecting leaf diseases is incredibly beneficial for researchers, engineers, managers, and entrepreneurs. This study's comprehensive overview will cover information, methods, and practical uses. To begin, the datasets used in the article are available to the public. Traditional (shallow), deep and enhanced learning are popular machine learning approaches. We will next provide a brief overview of each. We wrap off by talking about some similar applications. The information presented in this publication could be valuable for researchers interested in smart agriculture, machine learning, and disease classification in leaves. [7]

In Indonesia, chili peppers are a highly valuable horticultural crop. One of the reasons why the country's chile production is outpacing its consumption is because of malnutrition. The quantity of macro- and micronutrients needed to sustain plant growth and development varies from one plant to another. Chili plants exhibit varying visible signs when deficient in or have excess macronutrients. One non-destructive approach to plant health problem diagnosis based on visual symptoms of chili leaf is digital image processing. To find a nutritious solution, digital image processing and learning technologies like the SVM work together to categorize the many kinds of macronutrient shortages. Image capture, preprocessing, feature extraction, and classification using support vector machines (SVMs) with multiple kernels are the steps in this study's methodology for identifying micronutrient

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shortages in chili plants. This study's experimental results suggest that SVM, combined with a Polynomial kernel, can assist modern farmers in non-destructively determining a plant's health status with an accuracy of 97.76 percent. Precision agriculture in Indonesia is anticipated to be advanced with this method when applied to an intelligent farming system [8].

This study has covered every angle of machine learning techniques for smart data analysis and its applications. Our goal has been accomplished; we have provided a brief overview of how SN Computer Science can apply machine learning to solve various real-world problems. The next step for the system to help with smart decision-making is to train the advanced learning algorithms using the real-world data and information associated with the intended application. Additionally, we covered several well-known application domains to demonstrate the practicality of machine learning techniques. We have concluded by outlining the problems, possible solutions, research possibilities, and future directions in this field. Therefore, effective solutions in diverse application areas are required to handle the identified issues and generate interesting research possibilities. It can be a technical resource for academics, businesspeople, and policymakers interested in this study area. [9]

One of the world's most vital food crops, maize is also one of the most difficult for planting staff to diagnose based on their experience alone due to the variety of corn illnesses. Even with the incorrect diagnosis, output quality could be improved. An emerging field of study in plant disease detection is the application of deep learning and image recognition technologies, made possible by the rapid advancements in computer technology. After data, augmentation improves the model's generalizability and accuracy, the approach constructs a convolutional neural network model based on transfer learning. After that, it trains the model, speeds up the convolutional neural network's training, and uses the test dataset's feedback network results. We conducted this study by classifying corn leaf photos in PlantVillage into four categories: healthy leaves, corn with grey spots, maize with common rust, and corn with northern leaf blight. We initially achieved our optimization model by modifying the optimizer and learning rate parameters of the GoogLeNet pre-training network. Next, we compared the outcomes of training the optimization model using several transfer learning networks, such as the original GoogLeNet, ResNet18, Vgg16, and Vgg19. The maximum accuracy rate is 5.9% higher than the baseline GoogLeNet model. Beyond that, the result is superior when contrasted with other transfer-learning networks. We hope that our model will lead to some novel approaches to the problem of corn and other crop pest and disease identification. [10]

We used machine learning and digital image processing to categorize and identify micronutrient deficits in maize plants. The researchers also employed optimization strategies for reducing features to improve the classifiers' accuracy. The results show that both GA and SOS, the optimization algorithms, do a good job of choosing the best feature collection to improve classification accuracy. Using SOS as the optimization strategy, a support vector machine classifier achieved the greatest classification accuracy of 90%. Plant diseases and micronutrient shortages can be better understood and treated with these methods. [11]

The global population relies on maize as a primary source of sustenance. Hence, the crop's output must keep multiplying to meet consumer demand. Because it is a vigorous feeder, maize requires many nutrients. The deep green coloration of healthy plants shows the presence of sufficient nutrients. Now, a laboratory test detects nutritional deficiencies in maize leaves. It necessitates agricultural expertise and takes much time. Hence, an image processing method has been implemented to enhance laboratory tests and avoid identification errors caused by humans. Researchers, farmers, and agriculturists will be able to use this study's findings to understand the causes of maize nutritional deficiencies better and develop effective solutions. This study used image-processing methods to identify the specific nutrient deficit shown on plant leaves. Since the classifiers were successful in achieving 78.35% accuracy, the random forest technique was employed. Random forests may effectively handle nutrient deficit detection in maize leaves. The testing of more machine learning algorithms will improve current accuracy. [12]

Several illnesses negatively affect agricultural output, even though maize is a crucial commodity for global food security. It takes much time and is highly subjective to diagnose these disorders. Automating this process is crucial in agricultural applications, and computer vision techniques make it possible; we validated all trials before evaluating these CNNs on the PlantVillage dataset's maize leaf images. We found that data augmentation affected pre-trained models and that there was a correlation between the different types of maize leaves. All the convolutional neural network (CNN) models tested achieved a 97% accuracy rate in maize leaf disease classification. Finally, our method opens new avenues for computer vision-based leaf disease detection. [13]

Image classification involves categorizing images according to shared characteristics. Image classification relies heavily on the feature extraction step. Typical features in traditional picture categorization include morphology, color, texture, and several derivative aspects. The classification's accuracy depends on the features used and the quantity of suitable features. This research looks at picture categorization using the feature-generating Bag of Features (BOF) approach. Each of the four steps—using the grid approach to locate feature points, Speed Up

Robust Feature (SURF) to extract features, k-means to cluster word-visual vocabularies, and Support Vector Machine for classification—makes up the whole process (SVM). The data set includes three picture formats: RGB, grayscale, and segmentation. Cercospora, common rust, healthy, and northern leaf blight are the four classes that make up each type. Every class has fifty photos. We ran two sets of tests for every data type: one for training and one for validation. We used 70–80% of the photos and the remaining data for validation in the latter. [14]

The major goal of this research is to use the Random Forest classification method to solve the problem of disease detection in maize crops. This algorithm is used to improve the accuracy of disease detection in maize plants because of its reputation for handling complex datasets and producing reliable predictions. Scientists want to build a reliable model that can tell healthy maize plants apart from diseased ones using machine-learning techniques, specifically the Random Forest algorithm. The study looks at new ways to detect crop diseases and highlights how machine learning may improve farming techniques for more efficient crop management and reliable food supplies. [15].

3. Feature Extraction Techniques

By combining DWT, Gabor, GLCM, and LBP methods, this strategy allows for feature extraction.

A. DWT

The decomposition of data or images into various frequency components is accomplished using the DWT, a powerful technique for signal processing. Picture analysis sometimes employs DWT for feature extraction, which may help identify nutritional deficits in maize plant leaves by providing details about patterns, textures, and other traits.

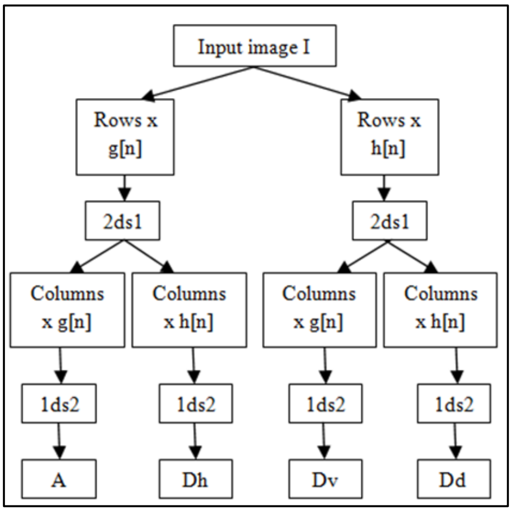

Figure 1. 2-D DWT Decomposition

The proposed method extracts texture information from the picture segment comprising the area of interest using discrete 2-D wavelet transforms. DWT takes a signal's frequency and other characteristics into consideration. For accurate texture feature extraction, this quality is a boon. A 2-dimensional discrete wavelet transform (DWT) with fewer coefficients can retain signal information. In image processing, DWT maintains the picture's two-dimensional signal with rows and columns. The finer details of a picture, including its diagonal, horizontal, and vertical subbands, are investigated using wavelet transforms. The decomposition of an image using 2-D DWT is shown in Figure 1.

B. GLCM

One measure of a surface's quality is its texture. Where grey levels are located in a given area defines it. Pixel positions and pixel values reveal texture properties. As a result, texture classification is rather flexible. Changing the display's size or resolution changes the texture of a picture. At larger sizes, textures that seem distinct at smaller ones tend to blend.

A texture's attributes may be conveyed using statistical texture analysis by looking at the distribution of pixel intensities at a certain location. Creates first-, second-, and higher-order statistics according to the pixel or dot

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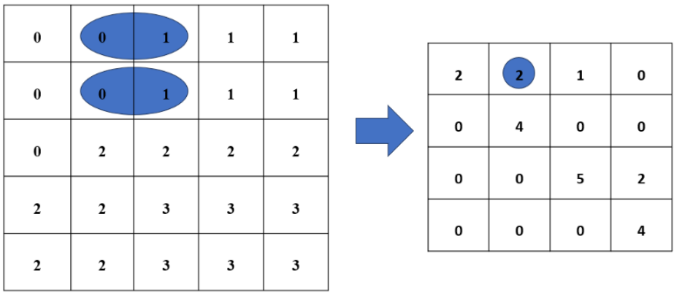
count for each possible combination. Using second-order statistics for GLCM-based feature extraction, a picture may be assessed as a texture.

The GLCM table shows how frequently an image pixel brightness combination occurs. Figure 2 illustrates the GLCM of a four-level image at 1 distance and 0° direction.



(a) (b)

Figure 2. Image with 4 gray levels b. GLCM for distance 1 and orientation 0°.

Features are the statistical data found in an image. GLCM is a way to get special information from black-and-white pictures. Following the given steps, the following GLCM properties are acquired.

- Contrast: Contrast is used to assess the local GLCM disparities.

$$Contrast = \sum_{i,j} |i-j|^2 p(i,j) \quad (1)$$

- Homogeneity: The homogeneity is high if the GLCM element distribution is near the GLCM diagonals.

$$Homogeneity = \sum_{i,j} \frac{1}{1+(i-j)^2} p(i,j) \quad (2)$$

- Energy: The consistency of the pixels is quantified.

$$Energy = \sum_{i,j} p(i,j)^2 \quad (3)$$

- Dissimilarity: One way to measure, the dissimilarity between two images is by looking at the number of grey-level pairings.

$$Dissimilarity = \sum_{i,j} |i-j| p(i,j) \quad (4)$$

Where, $p(i,j)$ = image pixel to be processed

- ASM: As such, it stands for how consistently the image's greyscale values are distributed.

$$ASM = \sum_{i=1}^{G} \sum_{i=1}^{G} (P(i,j))^2 \quad (5)$$

The features of all directions (0^o, 45^o, 90^o, and 180^o) were extracted in the proposed approach.

C. Gabor Filter

The process of feature extraction using the Gabor filter is explained below.

- Filter Bank Construction: To leverage the diverse capabilities of Gabor filters, constructing a filter bank with different orientations and frequencies is essential. We describe the process of filter bank construction, highlighting the importance of a well-designed set of filters.

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- Filtering Process: The convolution of Gabor filters with the input image generates a set of filtered images, each emphasizing different spatial frequencies and orientations. This step forms the basis for subsequent feature extraction.
- Feature Maps: For each filtered image, feature maps are computed, representing the response strength of the Gabor filter at each pixel. We discuss how these feature maps accentuate the image's specific texture patterns, edges, and orientations.
- Pooling and Subsampling: Pooling operations like max pooling may be applied to the feature maps to reduce dimensionality and enhance robustness to scale and position variations. This section explores the benefits of pooling in the feature extraction process.
- Feature Vector Formation: The final step involves flattening and concatenating the filtered and pooled feature maps into a comprehensive feature vector. This vector serves as the representation of the original image in the Gabor feature space.

D. LBP

The process of feature extraction using LBP is explained below.

- Local Pixel Comparison: LBP operates by comparing each pixel in an image with its surrounding neighbors. A circular or square neighbourhood is defined around each pixel.
- Binary Code Generation: Find the difference between the intensity values of the nearby pixels and the ones in the middle. Assign a binary value of 1 if the intensity of a neighbouring pixel is equal to or higher than the centre pixel and 0 otherwise. This procedure generates each neighbourhood's binary code.
- Rotation Invariance: Enhance LBP's robustness by considering rotation-invariant patterns. For each binary code, find its equivalent circular rotation with the minimum decimal value, ensuring that patterns with similar textures are represented consistently.
- Histogram Calculation: Divide the image into non-overlapping local regions, and for each region, create a histogram of the LBP codes. This histogram reflects the distribution of different texture patterns within that region.
- Concatenation of Histograms: Concatenate the histograms from all local regions to form a feature vector. This vector represents the distribution of LBP patterns across the entire image.

4. Machine Learning Algorithms

Three well-known deep learning algorithms are used in the suggested method. This section comprehensively summarizes the Gradient Boosting, Decision Tree, SVM, and KNN algorithms.

A. SVM

SVM is a powerful and extensively used machine learning method often used for regression and classification tasks. Many applications rely on it for picture and text classification and medical diagnostics (e.g., nutrient shortage diagnosis in maize plant leaves) because it handles complex datasets well. The main purpose of support vector machines (SVMs) is to locate the optimal hyperplane that, in a high-dimensional space, divides data points into different classes. This hyperplane maximizes the class difference by improving generalizability and performance on new data.

The support vector machine (SVM) searches for a hyperplane those best splits the data points of two classes in a binary classification situation. Margin is the space between the hyperplane and the nearest data point for each class. SVM strives to optimize this margin to boost the accuracy of fresh data classifications.

When the initial feature space does not provide linear separability of the data, SVM may use the kernel technique. Kernels in support vector machines (SVMs) implicitly project data into a higher-dimensional space where separation is potentially possible. Linear, polynomial, sigmoid, and radial basis functions are kernel functions.

The regularisation parameter C finds a happy medium by maximizing the margin and minimizing classification error on training data. A smaller margin is possible with a minor C, although some misclassifications are possible. While a higher quality C reduces misclassification, it may also reduce the margin. These data points are located closest to the decision border, the hyperplane. They are the ones who first used the name "Support Vector Machine," and they are crucial for finding the hyperplane. Although SVM was originally designed to be a binary classifier, it may be customized to handle multiple classes by implementing the One-vs.-Rest (OvR) or One-vs.-One (OvO) strategies.

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Standard support vector machines (SVMs) are well known for their generalizability, efficiency with small datasets, and ability to handle high-dimensional data. On top of that, they have a lower risk of overfitting. The parameters and kernel choices, in addition to the scale of input features, might affect SVM performance. When classes are very imbalanced, SVMs cannot work very well.

B. KNN

It is used for photo classification, recommendation systems, and anomaly detection because of its simplicity. KNN is a non-parametric method that assumes no data distribution. In KNN, related data points are classified together. The technique finds the k-nearest neighbors in the training dataset and gives the most common class to a new data point.

- Distance Metric: Data point similarity depends on distance metrics. Distance measures feature space "closeness" between two places.
- Forecasting parameters "k" include the number of neighbors. A small k may provide noisy results, while a large k may over-smooth and overlook local patterns.
- Weighted Voting: Some KNN variations may weight neighbors by their closeness to the new data point. Closer neighbors may affect the prognosis more than further away.
- Choosing k: Choosing k correctly is crucial. Small k may make the algorithm noise-sensitive, whereas big k may overgeneralize. Cross-validation and other validation methods may assist in choosing k.
- Multiclass Classification: KNN can classify several classes using majority or distance-weighted voting. The class with the most occurrences among the k-nearest neighbors is allocated to the new data point.

KNN is simple, does not assume data distribution, and works well with complicated and non-linear decision limitations. The distance measure, k neighbors, and data distribution affect KNN performance. Due to determining distances to all training sites, huge datasets might be computationally costly.

KNN may be useful for multiclass classification of maize plant leaf nutrient deficit studies. Its simplicity and absence of data distribution assumptions may help it capture complicated MRI patterns. However, preprocessing data and adjusting k and distance parameters are essential for KNN success.

C. DT

Decision Trees are flexible and interpretable classification, regression, and feature selection algorithms. Leaf nodes give classification class labels or regression prediction values, while core nodes make feature-based decisions.

- Splitting Criteria: The method chooses the best data-partitioning feature at each internal node. Classification and regression use Gini impurity or variance reduction to identify the "best" feature. The characteristic with the greatest class separation or variance reduction is chosen.
- Recursive Partitioning: Data is partitioned by feature values after selection. This procedure repeats on each subset until a stopping requirement, such as a maximum depth, minimal node samples, or pure classes, is satisfied.
- Easily known and understandable decision rules come from the tree structure. Every journey from root to leaf is a sequence of choices leading to a prediction.
- Overfitting: Decision when training data contains noise and irrelevant patterns, trees may overfit. Establishing a limit depth and pruning are typical approaches to lessen this.
- Handling Decision Trees handles category and numerical data. The tree may divide category characteristics into binary or multiway depending on categories.

Decision trees can capture non-linear data connections, are straightforward to read, and need little data preprocessing. Their feature scaling sensitivity is lower. Decision Trees may be unstable (little data changes can alter tree architectures) and may struggle with difficult tasks without regularization. This study on multiclass categorization of maize plant leaf nutrient shortage may benefit from Decision Trees' interpretability and ability to collect significant characteristics. Hyperparameters like maximum depth and splitting criteria may be tuned to balance model complexity with generalization performance. Consider ensemble approaches like Random Forest to improve classification accuracy.

D. GB

Classification and regression are effectively using gradient-boosting ensemble learning. Like Random Forest, Gradient Boosting creates a strong predictive model from several weak learners (typically decision trees). Gradient

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Boosting builds trees sequentially, fixing the faults of the previous tree. Gradient Boosting builds trees sequentially, unlike Random Forest. Each ensemble is taught to fix the previous one.

- A loss function compares projected and actual goal values. Gradient Boosting builds a decision tree for each ensemble iteration to reduce this loss function.
- Gradient Boosting employs gradient descent optimization to identify the new tree's direction and number of changes to reduce loss function.
- A learning rate parameter determines how each new tree affects the ensemble. A lower learning rate makes the model more robust but may need more trees for optimal performance.
- Gradient Boosting uses weak learners like decision trees. These shallow trees prevent overfitting and improve generalization.
- Data Weights: Gradient Boosting weights data points per iteration. Higher weights for misclassified or poorly forecasted data pieces direct future trees to these difficult instances.
- Each new tree addresses the ensemble's faults in additive training. This additive method enhances model performance progressively.
- Gradient Boosting terminates when a preset number of trees is achieved or the loss function improvement is minimal.
- Hyperparameters: Tree number, learning rate, maximum depth, and loss function are crucial.
- Regularization: Gradient Boosting may use subsampling and shrinkage to avoid overfitting.

Gradient Boosting generally outperforms Decision Trees and Random Forests. Complex connections and noisy data are no problem for it. Gradient Boosting's capacity to successively repair mistakes and adapt to complicated data patterns should make it a promising prediction model for maize plant leaf nutrient shortage multiclass classification. Tuning hyperparameters and adjusting the learning rate ensures model convergence and accurate classification results.

5. Proposed System

Figure 3 shows the suggested system block diagram. Input, preprocessing, feature extraction, training, and classification are included.

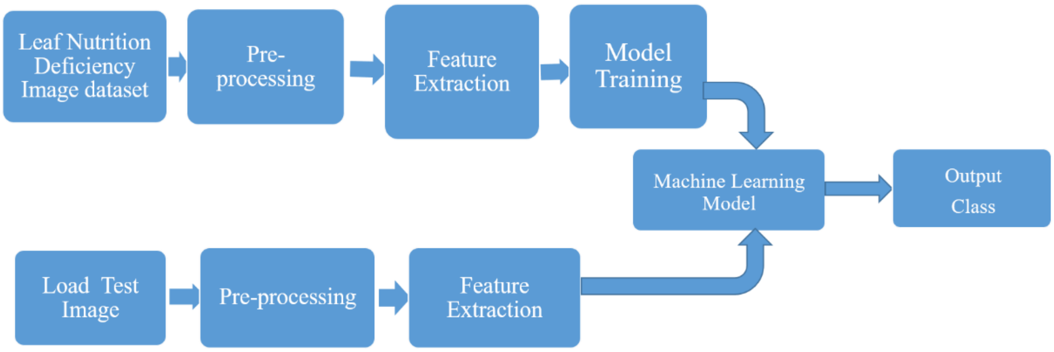

Figure 3. Block diagram of the proposed system

A. Maize Leaf Nutrition Image Database

The system starts with collecting a self-generated dataset of images of maize leaves. These images represent different nutrient deficiency categories. The images serve as the input data for the nutrient deficiency classification task. The dataset generation process outlined is for identifying nutrient deficiencies and diseases in plants, specifically focusing on four essential nutrients for maize: Nitrogen (N), Phosphorus (P), Potassium (K), and Zinc (Zn). Here is a breakdown of each step in the dataset creation process:

- Step 1: Identification of Important Nutrients: The essential nutrients critical for maize plant growth and productivity are identified as Nitrogen (N), Phosphorus (P), Potassium (K), and Zinc (Zn). These nutrients play a key role in plant health and development.

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- Step 2: Artificial Nutrient Deficiency Generation: 16 treatment conditions are created to simulate nutrient deficiencies. These treatments represent a combination of nutrient deficiencies and serve as experimental conditions for studying the impact of nutrient scarcity on plant growth.
- Step 3: Creation of Three Different Environments: Three distinct environments are established for conducting the experiments: Pot, Field, and Greenhouse. Each environment may have unique characteristics, including soil conditions, lighting, and climate control.
- Step 4: Commencement of Photography: The photographic data collection from the maize plantation starts after 20 days. This timing allows observing plant responses to nutrient deficiencies under varying environmental conditions.
- Step 5: Climate Condition Data Collection: Climate conditions are monitored alongside image capture. Multiple climate-related readings, such as temperature, humidity, and other relevant factors, are recorded daily. This data can help correlate environmental conditions with plant responses.
- Total Number of Plants per Day: The dataset includes 3 different environments, each with 16 treatments and 2 replications for each treatment. This results in 96 plants under observation per day.
- Image Collection: Expecting to capture 5 photographs of each plant per day, the dataset generation process results in 480 images per day. Over 75 days, this totals 36,000 images for the entire dataset.
- Total Database Size: The final dataset size, comprising 36,000 images, is a comprehensive resource for studying how nutrient deficiencies affects maize plants in various environmental conditions.
- Sorting of Images: The images from the collected dataset are processed and stored with the images with the proper resolution, camera angle, and background.

The sample images of plants grown in pot and field are shown in Fig.4:

(a) (b)

Figure 4. Sample images grown for dataset creation in (a) Pot and (b) Field

The dataset distribution for the implementation of machine learning algorithms is shown in Table II.

Table 2: Dataset distribution

Nutrition deficiencies	Total Number of Images	Number of Training Images	Number of Testing Images
ALL PRESENT	1470	1176	294
ALLAB	2430	1944	486
KAB	4301	3441	860
PAB	2970	2376	594
ZNAB	2545	2036	509
NAB	1535	1228	307
Total	15251	12201	3050

B. Image Preprocessing

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Image preprocessing enhances picture quality before processing and analysis. The given photos are originally RGB. RGB pictures are first grayscaled. Noisy photos were acquired. Image color and brightness are determined by color transformation. Median filters increase picture quality.

C. Feature Extraction

In the proposed approach, several image processing and feature extraction techniques, i.e., GLCM (with four angles 0^o, 45^o, 90^o, and 45^o with distance. These techniques are vital in preparing the data for subsequent analysis, such as nutrient deficiency classification or disease detection. A detailed explanation of each technique is given below.

- GLCM is a texture analysis method used to quantify the spatial relationships between pixel values in an image. It calculates the frequency of pixel pairs at a given distance and angle. In this case, GLCM is computed using four different angles (0°, 45°, 90°, and 135°) with a distance of 1 pixel. The GLCM provides information about the texture and patterns in the image, which can indicate nutrient deficiencies or other plant health issues.
- DWT is a signal-processing technique for decomposing an image into different frequency components. It is particularly useful for capturing variations in the image at multiple scales. DWT can help identify structures and features in the Maize plant leaves that might not be apparent in the original image. This technique is often used for feature extraction and dimensionality reduction.
- LBP: A texture analysis method that encodes local texture patterns in an image. It works by comparing the intensity of a pixel with its surrounding neighbors. LBP is robust against changes in illumination and provides information about the texture and patterns within the Maize plant leaves, which can be relevant for identifying nutrient deficiencies or diseases.
- Gabor Filter: These are used for image texture and feature analysis. They are designed to capture spatial frequency information, crucial for understanding patterns and structures. Gabor filters are particularly effective in extracting features related to plant leaf textures and fine details that may indicate nutrient deficiencies.

D. Classification using a machine learning algorithm

In our study's training and classification phase, SVM, KNN, DT, and GB are applied to brain MRI feature sets. Every categorization algorithm has its strengths. SVM uses a kernel technique to create an optimum hyperplane to separate classes with non-linear bounds. KNN predicts class labels for the k-nearest neighbors based on feature space closeness. DT creates interpretable decision trees that may capture complicated connections by recursively splitting data by feature values.

Conversely, GB progressively constructs decision trees to repair previous mistakes, improving predicting accuracy. We evaluate each method on our fused feature set and optimize hyperparameters using cross-validation.

E. Evaluation

Precision, recall, F1 score, and accuracy evaluate our classification models. These measurements demonstrate our trained algorithms' maize plant nutrient deficiency classification. Accurately.

- Precision is the ratio of successfully predicted positive cases (true positives) to the model's total positive predictions. It shows the model's ability to prevent false positives, which is helpful when costly. Precision is mathematically determined as:

$$Precision(P) = \frac{TP}{TP + FP} \tag{6}$$

- Recall: Recall, sensitivity, or true positive rate is the percentage of true positives the model correctly detects out of all positives. It shows that the model captures all-important positives. The math behind the recall is:

$$Recall\ (R) = \frac{TP}{TP+FN} \tag{7}$$

- F1 Score: Well-balanced models have a harmonic mean of accuracy and recall, called the F1 score. It considers false positives and negatives and helps when class distribution is unbalanced. We compute the F1 score as follows:

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$$F1\ Score = \frac{2 \times P \times R}{P + R} \qquad (8)$$

- Accuracy: Accuracy is the ratio of successfully predicted occurrences to the dataset's total instances. In unbalanced datasets, accuracy is crucial but not always ideal when one class greatly outnumbers the other. Accuracy is the ratio of successfully predicted occurrences to the dataset's total instances. In unbalanced datasets, accuracy is crucial but not always ideal when one class greatly outnumbers the other. Accuracy is the ratio of successfully predicted occurrences (including true positives and negatives) to the dataset's total instances. In unbalanced datasets, accuracy is crucial but not always ideal when one class greatly outnumbers the other.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \qquad (9)$$

6. Results and Discussion

This section presents the results of the proposed Nutrient Deficiency of Maize Plant Leaf Using a Machine Learning Algorithm with DWT, Gabor, GLCM, HoG, and LBP feature extraction techniques. In this study, we aimed to classify nutrient deficiency in maize plant leaf into six distinct categories: All nutrient Present (ALL Present), All nutrient Absent (ALLAB), Nitrogen Absent (NAB), Phosphorous Absent (PAB), Potassium Absent (KAB), and Zn absent (ZnAB). We used feature-rich DWT, Gabor, GLCM, HoG, and LBP features from the self-generated dataset to fuel machine learning algorithms. Below are our categorization experiment results:

A. DWT

Different machine learning classifiers were used to assess Discrete Wavelet Transform (DWT) characteristics from the self-generated Maize plant leaf Dataset in Table II. This study classifies maize nutritional deficits by nitrogen, phosphorus, potassium, and no deficiency. Different machine learning classifiers were used to assess Discrete Wavelet Transform (DWT) characteristics from the self-generated Maize plant leaf Dataset in Table 3. This study classifies maize nutritional deficits by nitrogen, phosphorus, potassium, and no deficiency.

Table 3: Comparative analysis of different ML algorithms with DWT features

Classifier	Attribute	Precision	Recall	F1_Score	Accuracy
SVM	Rbf	0.7155	0.6765	0.6567	0.6765
	Poly	0.6726	0.4728	0.4199	0.4728
	sigmoid	0.3886	0.4135	0.3632	0.4135
KNN	k=3	0.4884	0.4889	0.4468	0.4889
	k=5	0.3991	0.4001	0.34440	0.4001
	k=7	0.3573	0.3777	0.3138	0.3777
DT		0.6731	0.6826	0.6755	0.6826
GB		0.7594	0.7437	0.7334	0.7437

Table III presents a comparative analysis of various machine learning algorithms using Discrete Wavelet Transform (DWT) features for classification. The table provides precision, recall, F1 score, and overall accuracy metrics for each classifier and corresponding attribute configuration. For instance, SVM with a linear kernel achieves a precision of 0.7155, recall of 0.6765, F1 score of 0.6567, and an accuracy of 0.6765. Similarly, other classifiers and their attribute variations are evaluated, comprehensively comparing their performance in utilizing DWT features for classification tasks.

B. GLCM

The evaluation of various machine learning classifiers using GLCM features at 0o, 45o, 90o, and 135o orientations for the classification of maize plant nutrient deficiencies in t self-generated Maize plant leaf Dataset is outlined in Tables 4, 5, 6, and 7. The classifiers are employed to categorize nutrient deficiencies, providing insights into the distinctive patterns associated with specific deficiencies in maize plants.

Table 4: Comparative analysis of different ML algorithms on GLCM features with 0^o

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GLCM 0 degree					
Classifiers	Attributes	Precision	Recall	F1_Score	Accuracy
SVM	Rbf	0.4261	0.4504	0.3761	0.4504
	Poly	0.3719	0.4293	0.3424	0.4293
	sigmoid	0.2564	0.1428	0.1697	0.1428
KNN	k=3	0.7025	0.7107	0.7045	0.7107
	k=5	0.6387	0.6552	0.6432	0.6552
	k=7	0.6245	0.6454	0.6290	0.6454
DT		0.8954	0.8953	0.8951	0.8953
GB		0.7487	0.7470	0.7398	0.7470

Table 4 presents a comparative analysis of machine learning algorithms applied to GLCM features at a 0^{o} orientation for classifying maize plant leaf nutrient deficiencies. The table provides performance metrics such as Precision, Recall, F1 Score, and Accuracy for each classifier and attribute combination. Decision Tree (DT) exhibits high precision, recall, and accuracy, displaying its effectiveness in accurately classifying nutrient deficiencies in maize plant leaves based on GLCM features at a 0^{o} orientation.

Table 5: Comparative analysis of different ML algorithms on GLCM features with 45^{o}

GLCM 45 degree					
Classifiers	Attributes	Precision	Recall	F1_Score	Accuracy
SVM	Rbf	0.31113	0.4364	0.3439	0.4364
	Poly	0.3601	0.4318	0.3290	0.4318
	sigmoid	0.1779	0.0925	0.1151	0.0925
KNN	k=3	0.7436	0.7484	0.7444	0.7484
	k=5	0.6868	0.6951	0.6880	0.6951
	k=7	0.6554	0.6686	0.6577	0.6683
DT		0.8914	0.8912	0.8911	0.8912
GB		0.7738	0.7711	0.7658	0.7711

Table 5 presents a comparative analysis of various machine-learning algorithms applied to GLCM features at a 45-degree orientation to classify maize plant leaf nutrient deficiencies. The performance metrics such as precision, recall, F1 score, and accuracy are reported for each classifier and attribute set. For instance, the Decision Tree classifier exhibits high precision, recall, and accuracy values across the board, indicating its effectiveness in accurately classifying maize plant nutrient deficiencies based on GLCM features at a 45-degree orientation. The table provides valuable insights into the comparative performance of different machine learning algorithms for this classification task.

Table 6: Comparative analysis of different ML algorithms on GLCM features with 90^{o}

GLCM 90 degree					
Classifiers	Attributes	Precision	Recall	F1_Score	Accuracy
SVM	Rbf	0.4389	0.4414	0.3539	0.4414
	Poly	0.3683	0.3434	0.3446	0.4348
	sigmoid	0.2297	0.1152	0.1422	0.1152
KNN	k=3	0.6962	0.7041	0.6976	0.7041
	k=5	0.6425	0.6571	0.6456	0.6571
	k=7	0.6215	0.6408	0.6249	0.6408
DT		0.8897	0.8899	0.8891	0.8899
GB		0.7522	0.7495	0.9454	0.7495

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Table 6 presents a comparative analysis of machine learning algorithms applied to GLCM features at a 90-degree orientation to classify maize plant leaf nutrient deficiencies. The evaluation metrics for each classifier and attribute combination are provided for precision, recall, F1 score, and overall accuracy. For instance, the Decision Tree (DT) exhibits high precision, recall, and F1 score, indicating robust performance in accurately classifying nutrient deficiencies in maize plant leaves. Conversely, SVM with a polynomial kernel (poly) performs less based on the specified metrics. This comprehensive comparison aids in identifying the most effective machine-learning algorithm for maize plant nutrient deficiency classification based on GLCM features at a 90-degree orientation.

Table 7: Comparative analysis of different ML algorithms on GLCM features with 135°

GLCM 135 degree					
Classifier	Attribute	Precision	Recall	F1_Score	Accuracy
SVM	Rbf	0.4377	0.4411	0.3534	0.4411
	Poly	0.3683	0.4348	0.3446	0.4348
	sigmoid	0.2297	0.1152	0.1422	0.1152
KNN	k=3	0.6959	0.7039	0.6973	07039
	k=5	0.6425	0.6571	0.6456	0.6571
	k=7	0.6208	0.6402	0.6243	0.6402
DT		0.9008	0.9013	0.9007	0.9013
GB		0.7470	0.7448	0.7394	0.7448

Table 7 presents a comparative analysis of machine learning algorithms applied to GLCM features at a 135-degree orientation to classify maize plant leaf nutrient deficiencies. The classifiers include Support Vector Machine (SVM) with RBF, poly, and sigmoid kernels, K-Nearest Neighbors (KNN) with k values of 3, 5, and 7, Decision Tree (DT), and Gradient Boosting (GB). The table displays precision, recall, F1-score, and overall accuracy for each classifier and attribute combination. Decision Tree (DT) notably exhibits high performance across all metrics, with precision, recall, F1-score, and accuracy consistently exceeding those of other classifiers. The results provide insights into the effectiveness of different machine learning algorithms in identifying and classifying maize plant leaf nutrient deficiencies based on GLCM features at a 135-degree angle.

C. Gabor

Table 8 compares machine-learning techniques for maize plant leaf nutrition identification Gabor feature categorization.

Table 8: Comparative analysis of different ML algorithms on Gabor features

Classifiers	Attributes	Precision	Recall	F1_Score	Accuracy
SVM	Rbf	0.7155	0.6765	0.6567	0.6765
	Poly	0.6726	04728	04199	04728
	sigmoid	0.3886	0.4135	0.3632	0.4135
KNN	k=3	0.4884	0.4889	0.4468	0.4889
	k=5	0.3991	0.4001	0.3440	0.4001
	k=7	0.3573	0.3777	0.3138	0.3777
DT		0.6731	0.6826	0.6755	0.6826
GB		0.7594	0.7437	0.7334	0.7437

In Table 8, a comparative analysis of various machine-learning algorithms is conducted to classify maize plant leaf nutrient deficiencies based on Gabor features. The evaluation metrics such as precision, recall, F1 score, and overall accuracy are reported for each classifier and attribute set. For instance, SVM with an rbf kernel exhibits precision, recall, F1 score, and accuracy of 0.7155, 0.6765, 0.6567, and 0.6765, respectively. The table provides insights into the performance of these machine-learning algorithms in discerning and classifying maize plant leaf nutrient deficiencies based on the extracted Gabor features.

D. LBP

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The comparative analysis of different machine learning algorithms for the classification of LBP features of maize plant leaf nutrition recognition is presented in Table VIII.

Table 9: Comparative analysis of different ML algorithms on LBP features

Classifiers	Attributes	Precision	Recall	F1_Score	Accuracy
SVM	Rbf	0.8249	0.8068	0.8050	0.8068
	Poly	0.7902	0.7943	0.7908	0.7943
	sigmoid	0.2761	0.2179	0.1435	0.2179
KNN	k=3	0.5605	0.5859	0.5528	0.5859
	k=5	0.4957	0.5178	0.4812	0.5178
	k=7	0.4981	0.5042	0.4632	0.5042
DT		0.6455	0.6615	0.6512	0.6615
GB		0.7705	0.7593	0.7511	0.7593

Table 9 presents a comparative analysis of various machine-learning algorithms applied to classify maize plant leaf nutrient deficiency using Local Binary Pattern (LBP) features. The table reports precision, recall, F1 score, and overall accuracy for each classifier and attribute configuration. The results display the performance of these algorithms in accurately identifying and classifying nutrient deficiencies in maize plant leaves based on the extracted LBP features. Notably, SVM with a linear kernel demonstrates high precision, recall, and accuracy, while Decision Tree and Gradient Boosting algorithms also exhibit competitive performance in this context.

As presented in Tables 2 to 8, the analyses of the various approaches to maize plant nutrient deficiency classification offer insights into the performance of different machine learning algorithms and feature extraction methods.

In Table 3, SVM with a linear kernel classifies Discrete Wavelet Transform (DWT) features with good precision, recall, and accuracy. This implies that DWT characteristics may reliably diagnose maize plant nutritional deficits, with SVM performing well. Tables III-VI show GLCM characteristics at 0°, 45°, 90°, and 135° orientations. These statistics show that the Decision Tree is a top precision, recall, F1 score, and accuracy classifier. GLCM characteristics processed by Decision Tree show promise for finding and categorizing maize nutritional deficits. The Decision Tree performs well across orientations, proving its applicability. Table VIII classifies nutritional deficiencies using Gabor characteristics. SVM with a linear kernel performs competitively, indicating Gabor features might help classify. However, this technique may need further research and improvement to improve other classifiers.

The findings show that maize plant nutrient deficit classification requires proper feature extraction techniques and classifiers. Decision Tree excels in GLCM features, whereas SVM with a linear kernel excels in DWT and Gabor. These results may guide precision agriculture machine learning research for crop health monitoring and management.

7. Conclusion

This paper presents the classification of nutrient deficiency using machine-learning algorithms. The features were extracted using different methods: DWT, GLCM, Gabor, LBP, and features were classified using SVM, KNN, DT, and GB algorithms. The comprehensive analysis of various approaches to maize plant nutrient deficiency classification using machine learning algorithms and different feature extraction methods has provided valuable insights into their respective performances. The utilization of Discrete Wavelet Transform (DWT) features demonstrated the effectiveness of a Support Vector Machine (SVM) with a linear kernel, suggesting its suitability for accurate classification in this context.Furthermore, exploring Grey Level Co-occurrence Matrix (GLCM) features at different orientations revealed Decision Tree as a consistently high-performing classifier across 0o, 45o, 90o, and 135o orientations. This emphasizes the robustness of the Decision Tree in capturing distinctive patterns associated with nutrient deficiencies in maize plants using GLCM features.

Applying Gabor features for nutrient deficiency classification also displayed competitive performance with SVM employing a linear kernel. While this approach holds promise, further refinement and exploration of other classifiers may enhance its effectiveness. These findings underscore the importance of carefully selecting feature extraction methods and classifiers to achieve accurate and reliable maize plant nutrient deficiency classification. The identified strengths of SVM with a linear kernel and Decision Tree across different feature sets and orientations provide valuable guidance for researchers and practitioners in precision agriculture. As technology advances, the integration of machine learning into crop health monitoring holds great potential for improving agricultural practices and ensuring global food security.

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