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Research Article

A Machine Learning-Based Framework for Detecting Crop Nutrients Deficiencies.

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ABSTRACT

Efficient nutrient management is critical to enhancing agricultural productivity while promoting sustainable practices. However, traditional methods for diagnosing nutrient deficiencies in crops such as soil testing and visual inspection are often costly, time-consuming, and limited in scalability. This study proposes a machine learning-based framework for the automated detection of crop nutrient deficiencies, focusing on the three essential macronutrients: Nitrogen (N), Phosphorus (P), and Potassium (K). Utilizing a dataset of 1,156 leaf images, the system extracts 26 colour, texture, and shape based features. Feature selection methods, including ANOVA, Mutual Information, Random Forest, XGBoost, and Recursive Feature Elimination (RFE), are employed to identify the most discriminative features. Seven machine learning models are evaluated K Nearest Neighbours (KNN), Support Vector Machine (SVM), Naïve Bayes, Logistic Regression, Multi-Layer Perceptron (MLP), Random Forest, and Decision Tree using accuracy and weighted F1-score. The results demonstrate that feature selection significantly improves model performance, with Random Forest achieving 87.62% accuracy and MLP yielding the highest F1 score of 81.84%. This research highlights the potential of machine learning for scalable, real-time nutrient deficiency detection, contributing to the advancement of precision agriculture and sustainable farming.

Keyword: Crop nutrient deficiency, Machine learning, Image-based feature extraction, Precision agriculture, Feature selection, , Crop health monitoring

1. Introduction

Nutrients are the backbone of plant growth and agricultural success, with Nitrogen (N), Phosphorus (P), and Potassium (K) serving as indispensable macronutrients. Nitrogen fuels photosynthesis and leaf development, Phosphorus underpins root systems and energy metabolism, and Potassium bolsters water regulation and resilience against stressors. Deficiencies in these nutrients present formidable challenges for farmers worldwide, leading to stunted growth, diminished crop yields, and poor produce quality. These setbacks not only erode farm productivity and economic viability but also threaten global food security as populations grow and arable land diminishes. For smallholder farmers and large-scale producers alike, nutrient imbalances translate into significant financial losses, reduced market competitiveness, and an increased reliance on costly corrective measures, amplifying the urgency for effective detection strategies [28].

Conventional methods for diagnosing nutrient deficiencies, such as visual inspection by trained agronomists or laboratory analysis of soil and plant tissue, have long been the standard. However, these approaches are fraught with limitations. Visual inspection is subjective, dependent on expertise, and impractical for monitoring expansive fields, while laboratory testing demands time, specialized equipment, and financial

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resources that many farmers cannot afford. Such inefficiencies hinder timely interventions, allowing deficiencies to escalate and exacerbate losses. In response, machine learning-based approaches have emerged as a transformative alternative, harnessing image-based analysis to automate and refine deficiency detection. By interpreting visual signatures of nutrient stress, these technologies promise rapid, objective, and scalable solutions tailored to modern agriculture's demands [29].

This research, titled "Crop Nutrient Deficiency Detection Using Machine Learning," seeks to develop an automated system to classify deficiencies of Nitrogen, Phosphorus, and Potassium. The study extracts 26 visual features from plant images—including RGB and HSV color statistics and Hu moments—and employs feature selection techniques such as ANOVA, Mutual Information, XGBoost, Random Forest, and Recursive Feature Elimination (RFE) to identify the most critical attributes. Seven machine learning models—K-Nearest Neighbours (KNN), Support Vector Machine (SVM), Naïve Bayes, Logistic Regression, Multi-Layer Perceptron (MLP), Random Forest, and Decision Tree—are trained and evaluated, with performance compared before and after feature selection to optimize accuracy, efficiency, and computational cost. This work advances precision agriculture by enabling early nutrient interventions, optimizing fertilizer application, and fostering sustainable farming practices, offering a scalable tool to enhance productivity and address global agricultural challenges.

My motivation for this research paper stems from the critical role of timely and efficient nutrient management in modern agriculture, which directly impacts crop yield, quality, and soil health. Essential macronutrients such as nitrogen (N), phosphorus (P), and potassium (K) are critical for plant growth, yet traditional diagnostic methods – such as soil testing and visual assessment – are often slow, expensive, and error-prone, limiting their effectiveness at scale. The growing need for sustainable and data-driven agricultural practices requires intelligent systems that can accurately detect nutrient deficiencies in a timely manner [23]. With recent advances in machine learning and image analysis, there is a promising opportunity to develop automated, scalable, and cost-efficient solutions. However, there is still a lack of practical, field-ready frameworks that effectively combine feature engineering and model optimization. This research aims to fill that gap by building a robust ML-based system to detect NPK deficiencies using image-derived features, leveraging advanced feature selection and multiple classifiers. The ultimate goal is to advance precision agriculture and contribute to global food security through sustainable practices [26].

1.1. Key contribution of this research work:

This paper presents a novel machine learning-based framework that aims to detect nutrient deficiencies in plants, specifically nitrogen (N), phosphorus (P) and potassium (K), through the analysis of leaf images. The method uses a structured feature extraction pipeline that analyses 26 different parameters related to the colour, texture, and shape of leaves. To optimize the performance, the study compares five feature selection techniques and evaluates seven different machine learning classifiers.

The experimental results show that the Random Forest classifier achieved the highest accuracy of 87.62%, while the Multi-Layer Perceptron (MLP) achieved the highest weighted F1-score of 81.84%, indicating strong predictive performance. This proposed framework is mobile-friendly, free to use, and designed for real-time applications, making it a practical and scalable solution for precision agriculture. It has significant potential to support farmers and agricultural stakeholders by enabling timely, accurate and automated detection of crop nutrient deficiencies.

This paper is structured into several major sections to present a comprehensive ML-based approach to detect nutrient deficiencies in crops. **Section 2** reviews related work using hyper spectral/multispectral imaging and ML models. **Section 3** outlines the proposed framework with a visual flow chart and describes an algorithmic. **Section 4** details the implementation of proposed framework. **Section 5**, results and performance of the various type of models. **Section 6** evaluation of the various feature selection techniques. **Section 7** concludes by confirming the feasibility, accuracy, and real-world applicability of ML in promoting sustainable agriculture.

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2. Related Research Work, Background Study, and Currently Available Technologies

2.1. Related Research

Nutrient deficiency detection in crops has been an area of active research, with traditional techniques like soil and tissue analysis being widely used. While these methods provide reliable results, they are often time-consuming, costly, and impractical for large-scale farming, especially for smallholder farmers [1].

To overcome these limitations, researchers explored remote sensing and imaging-based approaches. Patil et al. used hyper spectral imaging to detect nitrogen deficiency in wheat crops, achieving good accuracy but highlighting the challenge of high equipment costs [2]. Similarly, Zhao et al. applied multispectral imaging combined with deep learning (CNNs) to detect nutrient stress in maize, demonstrating the power of AI models in agricultural diagnostics [3].

Recent studies show growing interest in machine learning (ML) for automating deficiency detection. Sharma and Singh employed Support Vector Machines (SVM) for nitrogen and potassium deficiency classification in tomato plants, achieving high accuracy [4]. Kumar et al. implemented Random Forest (RF) and Decision Trees (DT) to classify multiple nutrient deficiencies from plant images, enhancing model interpretability and accuracy [5].

Moreover, feature extraction and selection have emerged as critical components in improving detection models. Li et al. combined RGB and HSV colour statistics with Hu moments to extract image features, improving detection performance while minimizing computational cost [6]. Techniques like ANOVA, Mutual Information, XGBoost, Random Forest, and Recursive Feature Elimination (RFE) were also found effective in selecting the most significant features for model training [7].

This current study builds upon these advancements by extracting 26 image features and comparing the performance of seven machine learning classifiers—KNN, SVM, Naïve Bayes, Logistic Regression, Multi-Layer Perceptron (MLP), Random Forest, and Decision Tree—in classifying Nitrogen, Phosphorus, and Potassium deficiencies. By integrating feature selection and model evaluation, this work enhances precision agriculture, aiming for scalable, cost-effective, and accurate nutrient deficiency detection systems.

2.2. Background Study

Agriculture remains the backbone of global economies and is essential for food security. One of the most critical factors influencing crop yield and quality is the balanced availability of essential macronutrients—Nitrogen (N), Phosphorus (P), and Potassium (K). Nitrogen drives photosynthesis and vegetative growth, Phosphorus strengthens root systems and energy transfer, while Potassium regulates water uptake and enhances plant resilience against biotic and abiotic stresses. Deficiencies in these nutrients can cause significant crop losses, and reduced produce quality, and ultimately threaten food supply chains, particularly in developing nations where agricultural productivity directly impacts livelihoods.

Traditionally, nutrient deficiencies are identified through visual inspections, soil tests, and plant tissue analyses. Although effective, these methods are costly, time-consuming, and often impractical for large-scale monitoring. They also require expert knowledge, which may not be available to smallholder farmers, further exacerbating yield gaps and contributing to environmental issues due to over-fertilization or nutrient mismanagement [8].

To overcome these limitations, researchers have increasingly focused on technology-driven solutions such as remote sensing, hyper spectral, and multispectral imaging. These technologies enable large-area monitoring but often demand expensive equipment, limiting their accessibility [9]. The rapid advancements in Artificial Intelligence (AI) and Machine Learning (ML) have opened new avenues for developing low-cost, scalable, and accurate nutrient deficiency detection systems using simple RGB images of leaves. Such systems can automate detection based on colour patterns, texture, and shape features, reducing dependency on expert manual inspections [27].

Recent studies have successfully integrated deep learning models like Convolutional Neural Networks (CNNs) for nutrient and disease detection in crops, achieving high accuracy [10]. For instance, Zhao et al. (2023) developed a CNN model using multispectral images to detect nutrient stress in maize, while Sharma and Singh (2023) applied SVMs and Random Forest classifiers for tomato plants [11][12]. Additionally, the emergence of Graph Convolutional Networks (GCNs) and explainable AI techniques offer promising directions for improving

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model interpretability and performance [13].

Furthermore, feature selection methods such as ANOVA, Mutual Information, Recursive Feature Elimination (RFE), and XGBoost are now widely used to optimize model performance by reducing computational complexity and improving classification accuracy [14]. This ensures that only the most relevant visual features contribute to nutrient deficiency predictions.

Despite these advancements, practical implementation at the farm level remains limited due to model generalization challenges, variable lighting conditions, and diverse crop varieties. Therefore, there is a growing need for robust, efficient, and scalable systems that farmers can use easily in real-world conditions.

This study addresses these challenges by developing a machine learning-based system that extracts 26 image features (colour statistics, texture, and shape descriptors) from plant leaf images and evaluates multiple classifiers (KNN, SVM, Naïve Bayes, Logistic Regression, MLP, Random Forest, and Decision Trees) for detecting N, P, and K deficiencies. By comparing model performance before and after feature selection, this research aims to contribute to the field of precision agriculture, enabling early nutrient interventions, optimized fertilizer usage, and enhanced crop productivity.

2.3. Currently Available Technologies for Nutrient Deficiency Detection

The agricultural sector has witnessed rapid technological advancements aimed at improving nutrient deficiency detection in crops. These technologies range from traditional manual methods to modern machine learning and artificial intelligence systems, offering farmers more accurate, efficient, and scalable solutions.

2.3.1. Traditional Methods

- **Soil Testing Laboratories:** Analysing soil samples for N, P, K, and micronutrient levels, is highly accurate but time-consuming, expensive, and not feasible for real-time monitoring.

Fig. 1. Soil Testing Labs, Soil Testing Laboratory in Delhi [15]

- **Plant Tissue Analysis:** Laboratory analysis of leaf samples to detect nutrient levels is accurate but labour-intensive and costly.

Fig. 2. Unlocking the Potential of Precision Agriculture [16]

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- **Visual Inspection by Agronomists:** Farmers or experts observe leaf colour, shape, and growth patterns to identify deficiencies and subjective, require expert knowledge, and impractical for large-scale farms.

Fig. 3. Visual Inspection by Agronomists [17]

2.3.2. Sensor-Based Soil and Plant Sensors

- Soil nutrient sensors, such as Teralytic Probes and NutriSense sensors, measure real-time soil nutrient levels but often come with high initial costs and maintenance requirements [18]. In contrast, leaf chlorophyll meters like the Minolta SPAD-502 Meter are portable devices that assess chlorophyll content as an indicator of nitrogen levels; however, their functionality is limited to detecting only nitrogen deficiencies [19].

2.3.3. Machine Learning and Deep Learning-Based Technologies [20]

- Leaf colour chart (LCC)-based nutrient deficiency detection models rely on manual comparison of leaf colour images to assess deficiencies, while image-based detection models use RGB and multispectral images processed through machine learning algorithms such as SVM, Random Forest, kNN, and CNN to automatically identify nutrient deficiencies with greater accuracy and scalability.

2.3.4. Summary: Advancing Nutrient Diagnosis in Agriculture: The Superiority of ML/DL-Enhanced LCC over Traditional Soil Testing and SPAD Meters: Table 1.

S. No.	Technology	Advantages	Limitation
1	Soil/Tissue Analysis	Highly accurate	Expensive, Time taken, slow, lab & Human dependency
2	IoT Sensors (SPAD Meter)	Real-time, portable	Limited nutrient scope, maintenance issues, Very Costly
3	LCC & ML/DL Models	Scalable, farmer-friendly, multi-nutrient	Needs image datasets, model training, Immediate & Real-time Results, Free of Cost

- **Revolutionizing Nutrient Assessment: From Manual Testing to Intelligent LCC Systems:** New technologies such as the Leaf Colour Chart (LCC) integrated with Machine Learning (ML) or Deep Learning (DL) models offer substantial improvements over traditional soil testing and SPAD meter-based assessments. Manual soil testing, although useful, is time-consuming, labour-intensive, and prone to errors due to variability in sampling, human interpretation, and laboratory limitations. In contrast, ML/DL-enabled LCC systems can process real-time leaf images captured using smartphones or portable devices, quickly diagnosing nutrient levels based on leaf color and patterns with high precision and consistency. This eliminates the need for physical sampling and laboratory work, making nutrient assessment faster and more scalable for large agricultural operations.
- **Data-Driven Decision Making: Enhancing Nutrient Management with ML/DL-Integrated**

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LCC Systems: Moreover, the integration of ML/DL models enhances the decision-making process through predictive analytics and continuous learning. These models can be trained on large datasets that include different crop types, growth stages, environmental conditions, and nutrient deficiencies, allowing them to provide more accurate and adaptive recommendations compared to fixed-threshold SPAD meters. While SPAD meters offer a non-destructive way to assess chlorophyll content, they are limited to point measurements and often require manual calibration and interpretation. In contrast, intelligent LCC systems can analyze entire crop fields using spatial imaging and generate comprehensive nutrient maps, enabling site-specific nutrient management (SSNM) that reduces fertilizer waste and improves yield [21].

- **Affordable and Accessible Solutions: Empowering Farmers with Smart LCC Technology:** Finally, the cost-effectiveness and user-friendliness of ML/DL-powered LCC systems make them more accessible to farmers, especially in resource-limited regions. Unlike SPAD meters and laboratory-based soil testing, which require expensive equipment and technical expertise, digital LCC solutions can be deployed through mobile applications. These apps can provide multilingual support, offline capabilities, and integration with other precision agriculture tools, thereby empowering farmers with timely and actionable insights. As a result, the shift from traditional methods to intelligent, data-driven solutions not only boosts productivity but also supports sustainable and environmentally friendly farming practices.

3. Proposed Algorithms and Framework:

3.1. Proposed Framework:

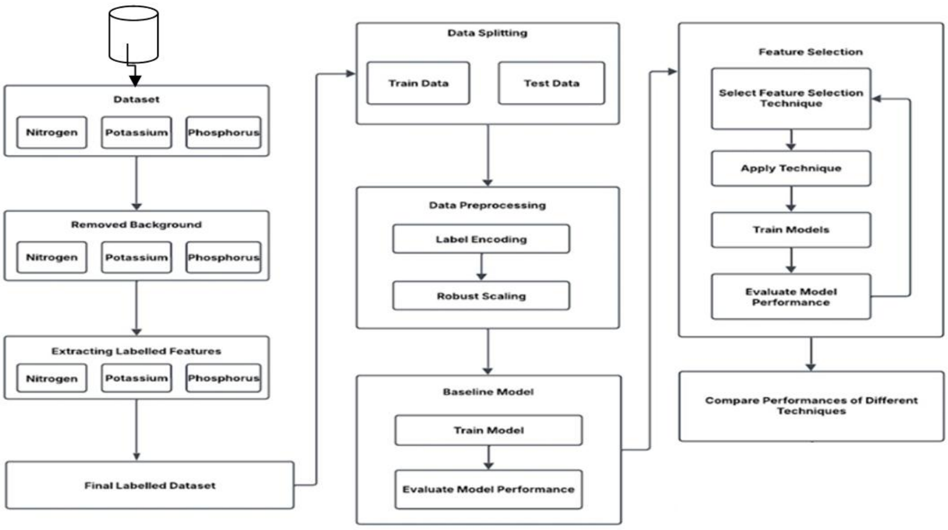

Fig. 4. Proposed Framework

3.1.1. Dataset Preparation: The process commences with dataset collection, comprising three essential agricultural nutrients: **Nitrogen, Potassium, and Phosphorus**. These nutrients play a pivotal role in determining soil fertility and, consequently, crop yield. The dataset may contain redundant or irrelevant background information, necessitating a pre-processing step to remove noise and enhance data quality before further analysis.

3.1.2. Background Removal: This step involves eliminating extraneous information from the dataset to ensure that only relevant attributes—**Nitrogen, Potassium, and Phosphorus**—are retained. Background removal is essential for reducing noise and potential bias, thereby improving the overall quality of extracted features. This refinement enhances model accuracy by focusing only on informative attributes for predictive analysis.

3.1.3. Feature Extraction & Labelling: Once the dataset has been cleansed of unnecessary information, relevant features are extracted and appropriately labelled. This process structures the dataset into a more meaningful form suitable for machine learning applications. Labelling ensures that the data is categorized systematically, facilitating efficient model training and performance evaluation.

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3.1.4. Data Splitting: To develop a robust predictive model, the dataset is divided into training and testing subsets. The training dataset is used to train the machine learning model, allowing it to learn underlying patterns, whereas the test dataset evaluates the model's generalization capability. A well-balanced split ratio, such as 80:20 or 70:30, ensures an optimal trade-off between training efficiency and model validation.

3.1.5. Data Pre-processing: Pre-processing involves two critical transformations: label encoding and robust scaling. Label encoding converts categorical variables into numerical representations, making them suitable for machine learning algorithms. Robust scaling is employed to normalize the feature values, minimizing the impact of outliers and ensuring a uniform data distribution. This step significantly enhances model stability and predictive accuracy.

3.1.6. Baseline Model Development: Before applying feature selection techniques, a baseline model is constructed using the pre-processed dataset. This initial model serves as a reference for evaluating subsequent improvements in performance. The baseline model is trained and assessed using standard performance metrics such as accuracy, precision, recall, and F1-score, providing a benchmark for further refinement.

3.1.7. Feature Selection: To enhance model efficiency and reduce computational complexity, a feature selection technique is chosen and applied. This process identifies the most influential features, eliminating redundant or insignificant variables. By retaining only the most relevant attributes, feature selection improves model interpretability and optimizes resource utilization without compromising predictive performance.

3.1.8. Model Training & Evaluation: Following feature selection, multiple models are trained using the refined dataset. Each model undergoes rigorous evaluation to assess its effectiveness. Performance metrics such as accuracy, precision, recall, and F1-score are computed to determine the most suitable model for the given problem. The comparative evaluation facilitates informed decision-making regarding the optimal approach for predictive analysis.

3.1.9. Comparative Performance Analysis: In the final phase, the performance of different models and feature selection techniques is systematically compared. The approach that yields the highest predictive accuracy and computational efficiency is identified as the optimal solution. This comparative analysis provides valuable insights into the most effective methodologies for soil nutrient-based predictive modelling, contributing to advancements in precision agriculture and data-driven decision-making.

3.2. Algorithm: Crop Nutrients Deficiency Algorithm

X, y = separate_features_target(Dataset)
$X_{train}, X_{test}, y_{train}, y_{test}$ = split(X, y)
dataProcessing:
    y'_{train}, y'_{test} = Label_Encoding(y_{train}, y_{test})
    X'_{train}, X'_{test} = Robust_Scaling (X_{train}, X_{test})
Models = {Model1, Model2, Model3, ..., Model7}
M = train_baseline_models (Models, X'_{train}, y'_{train})
y_{pred} = predict(M, X'_{test})
$Metrics_{all}$ = evaluate(y_{pred}, y'_{test})
T = {T1, T2, T3, T4, T5}
$Metrics_t$ = { }
For i = 1 to T:
    X''_{train}, X''_{test} = apply_FS($T_i, X'_{train}, y'_{train}, X'_{test}$)
    $Models^i_{trained}$ = train($Models_i, X''_{train}, y'_{train}$)
    y^i_{pred} = predict($Models^i_{trained}, X''_{test}$)
    $Metrics_i$ = evaluate(y^i_{pred}, y'_{test})
Compare the model performance

Step-by-Step Explanation of the Algorithm:

1. **Feature and Target Separation:** The dataset is split into features (X) and target labels (Y).
2. **Train-Test Split:** The data is split into training and testing sets.
3. **Data Reprocessing:** The target labels are encoded using label encoding and The features are scaled using Robust Scaling to handle outliers effectively.
4. **Baseline Model Training:** Multiple baseline models for example Logistic Regression, SVM, Decision

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Tree, etc. are trained on the reprocessed training data.

5. **Baseline Predictions and Evaluation:** Predictions are made on the test data using baseline models and the performance is evaluated using metrics like accuracy, precision, recall, F1-score, etc.
6. **Feature Selection and Model Re-Evaluation:** A set of feature selection techniques (T) are prepared for experimentation.
7. **Iterative Feature Selection and Training:** Apply it to the training and test data, Train the models again on the reduced feature set and predict and evaluate the model.
8. **Model Comparison:** Compare all trained models (with and without feature selection) to identify the best-performing model and technique.

4. Implementation

This research delineates a comprehensive methodology for detecting crop nutrient deficiencies using machine learning, with a specific focus on classifying Nitrogen (N), Phosphorus (P), and Potassium (K) deficiencies in crop leaves—an essential task for optimizing agricultural productivity and sustainability. The methodology integrates dataset collection, reprocessing, feature extraction, labelling, selection, consolidation, model training, and performance evaluation to create an automated, robust, and scalable diagnostic system. By leveraging a publicly available dataset from Kaggle and employing advanced computational techniques, this study addresses the pressing need for rapid and accurate nutrient deficiency detection, a challenge that traditional methods struggle to meet due to their labour-intensive and subjective nature. The approach is grounded in the analysis of visual symptoms captured in leaf images, harnessing machine learning's ability to discern subtle patterns indicative of nutrient stress. This work not only advances the technical framework for image-based agricultural diagnostics but also aligns with the broader objectives of precision agriculture, aiming to enhance crop management, reduce resource waste, and support sustainable farming practices amid growing global food demands. Each stage of the methodology is designed for reproducibility and efficiency, ensuring its potential for real-world deployment across diverse agricultural contexts, from smallholder farms to large-scale operations.

4.1. Data set Description

The dataset used in this study, titled "Crop Nutrient Deficiency Detection Using Machine Learning," was taken from Kaggle, a well-established platform for machine learning datasets, and contains 1,156 images of crop leaves showing nutrient deficiencies. It is organized into three folders, each of which belongs to a specific deficiency class: nitrogen (N), phosphorus (P), and potassium (K). The image distribution across these categories is as follows: 440 images for nitrogen (N), 333 images for phosphorus (P), and 383 images for potassium (K). These labelled images capture visible symptoms of nutrient stress — such as chlorosis (yellowing of leaves), discoloration, necrotic spots, and stunted growth — making the dataset highly suitable for supervised machine learning tasks focused on classifying nitrogen, phosphorus, and potassium deficiencies.

The dataset exhibits considerable diversity, including multiple plant species, lighting conditions, and backgrounds, reflecting real-world agricultural variability. This diversity presents challenges for model generalization, ensuring that classification algorithms are tested under conditions similar to field environments [22]. To address potential imbalances (e.g., images low in phosphorus (P)) and increase dataset variability, data augmentation techniques – such as flipping, rotation, and contrast adjustment – were considered to artificially expand the dataset, broadening the representation of deficiency patterns where applicable. These images provide the basis for pre-processing, feature extraction, and model training, supporting the development of an automated system for precise deficiency detection. By leveraging this trait-rich and diverse dataset, the study advances precision agriculture objectives, enabling early identification of nutrient deficiencies and promoting optimized crop management in various agricultural contexts.

4.2. Labelled Dataset Creation

The raw dataset obtained from Kaggle includes original images of crop leaves displaying clear symptoms of

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nitrogen (N), phosphorus (P) and potassium (K) deficiencies, such as chlorosis or stunted growth, captured under different conditions. These images are classified into three groups corresponding to each nutrient deficiency. Pre-processing was performed to refine the dataset for analysis. Background was removed to eliminate non-leaf elements (e.g., soil, sky), leaves were isolated to focus on deficiency-related features. The pre-processed images were organized into three separate sets representing nitrogen (N), potassium (K) and phosphorus (P) deficiencies

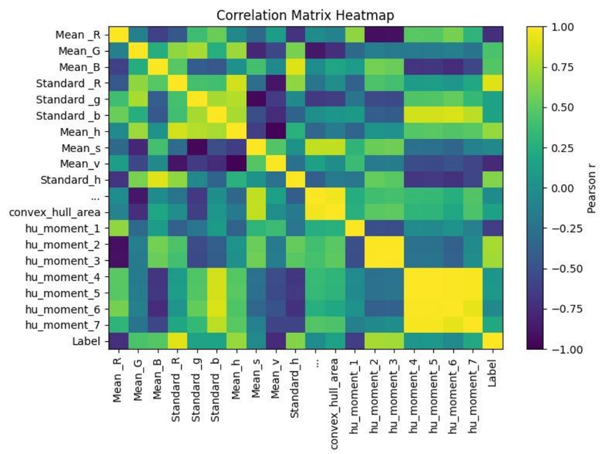

Fig. 5. Correlation s Matrix Heat map

4.3. Modelling and Feature Selection

This section delineates the sophisticated processes of feature selection and machine learning model development employed in the study "Crop Nutrient Deficiency Detection Using Machine Learning" to classify Nitrogen (N), Phosphorus (P), and Potassium (K) deficiencies in crop leaves. By integrating rigorous feature selection strategies with a comprehensive suite of predictive models, the methodology optimizes classification accuracy while minimizing computational overhead. This dual-phase approach—refining the feature set and evaluating predictive performance—underscores the study's commitment to delivering a scalable, automated solution for nutrient deficiency detection in precision agriculture.

Table 2.: Extracted Features for Crop Nutrient Deficiency Detection

S.No.	Feature Name	Description
1	Mean RGB (mean_r, mean_g, mean_b)	Average intensity of red, green, and blue colors.
2	Std RGB (std_r, std_g, std_b)	Variation in red, green, and blue color values.
3	Mean HSV (mean_h, mean_s, mean_v)	Average hue (color type), saturation (vividness), and value (brightness).
4	Std HSV (std_h, std_s, std_v)	Variation in hue, saturation, and brightness across the leaf.
5	GLCM Contrast	Measures intensity differences between neighbouring pixels.
6	GLCM Dissimilarity	Evaluates how different nearby pixel values are.
7	GLCM Homogeneity	Measures smoothness and uniformity in the texture.
8	GLCM Energy	Indicates consistency and repetition in texture patterns.
9	GLCM Correlation	Check how pixel values follow a predictable pattern.
10	LBP Mean	Captures small texture details like spots and edges.
11	Entropy	Measures randomness and complexity in texture.
12	Convex Hull Area	The area of the smallest enclosing shape around the leaf.
13	Hu Moments (hu_1 to hu_7)	Shape descriptors capturing rotation- and scale-invariant leaf features.

This step involved converting RGBA images to BGR format using OpenCV, followed by transformation to

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grayscale and HSV color spaces, thereby preparing the data for feature extraction while reducing noise and irrelevant variability. From these pre-processed images, 26 features were extracted to characterize leaf color, texture, and shape – key indicators of nutrient status. These include RGB color statistics (the average and standard deviation of the red, green, and blue channels), HSV color statistics (the average and standard deviation of the hue, saturation, and value channels), and seven Hu moments, which provide invariant shape and texture details.

These features were selected for their ability to capture deficiency symptoms, such as discoloration (e.g., yellowing from nitrogen deficiency) or morphological changes (e.g., from potassium deficiency). Each image was processed, and its features were associated with labels – namely "nitrogen," "potassium," or "phosphorus" – based on its deficiency category. The extracted features and labels were saved as three separate CSV files, one for each deficiency type. This automated labelling ensures data alignment with the associated nutrient deficiencies, structuring it for machine-learning tasks.

The three CSV files, each containing attributes and labels for a specific deficiency, were merged into a single, unified dataset stored as final_dataset.csv. This consolidated file integrates all extracted attributes and labels across the nitrogen, phosphorus, and potassium deficiency classes, providing a comprehensive dataset ready for model training and evaluation. Consolidation preserves the integrity of the labels ("nitrogen," "potassium," "phosphorus") and attribute data, thereby streamlining subsequent analysis.

4.4. Feature Selection: Identification and Optimization of Discriminative Features for Enhanced Classification Efficiency

The initial dataset encompassed 26 features extracted from pre-processed leaf images, including RGB and HSV color statistics (mean and standard deviation of each channel), texture attributes (e.g., GLCM-derived contrast, dissimilarity, homogeneity, energy, correlation; LBP mean; entropy), and shape descriptors (convex hull area, seven Hu moments). To enhance model performance, reduce dimensionality, and improve computational efficiency, five feature selection techniques were meticulously applied: Analysis of Variance (ANOVA), Mutual Information, eXtreme Gradient Boosting (XGBoost), Random Forest, and Recursive Feature Elimination (RFE). These methods were designed to isolate features most capable of distinguishing between Nitrogen (N), Phosphorus (P), and Potassium (K) deficiency classes [25] as shown in and Table 3 Fig 5 to 9.

Table 3.: Feature Selection Techniques Used

S.No.	Feature Selection Technique	Description
1	Anova	Examines variance across classes to identify statistically significant features offering maximal separation.
2	Mutual Information	Quantifies mutual dependency between features and labels, emphasizing predictive relevance.
3	RFE	Iteratively eliminates less impactful features through repeated model retraining, optimizing the subset.
4	XG Boost	A gradient-boosting framework that ranks features by their contribution to classification accuracy.
5	Random Forest	An ensemble technique assessing feature importance across multiple decision trees.

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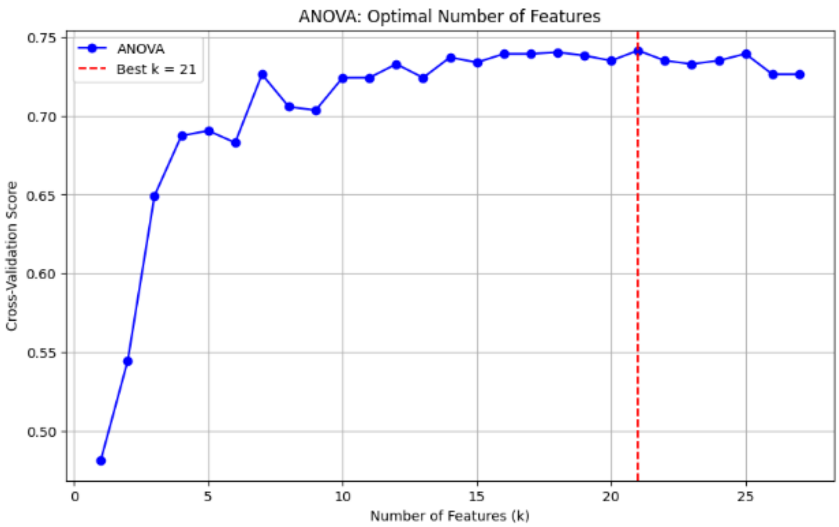

Fig. No. 6..: ANOVA feature selection Technique 21 Feature selected

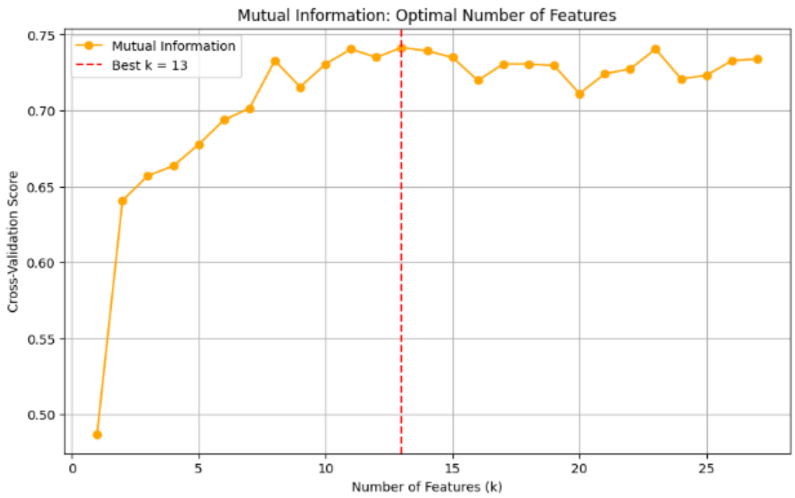

Fig. No. 7.: Mutual Information feature selection Technique 13 Feature selected

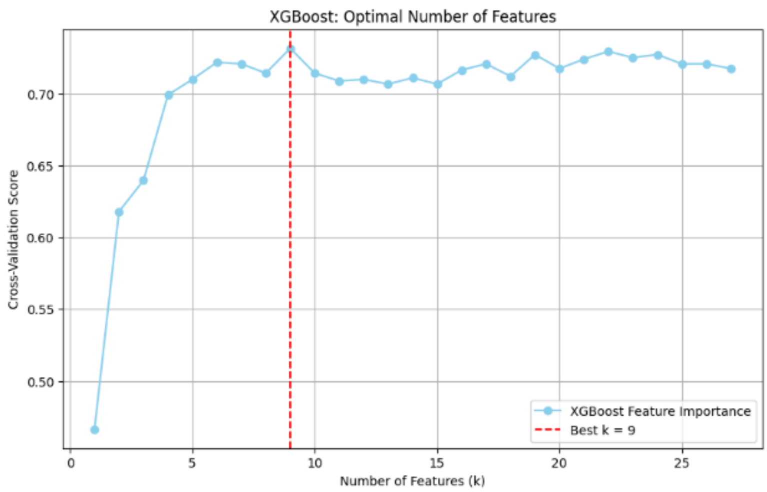

Fig. No. 8.: XGBoost feature selection Technique 13 Feature selected

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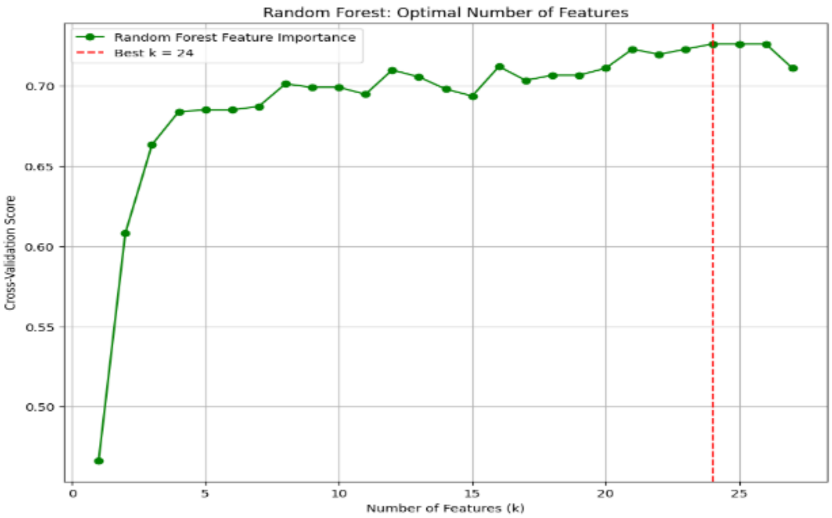

Fig. No. 9.: Random Forest feature selection Technique 24 Feature selected

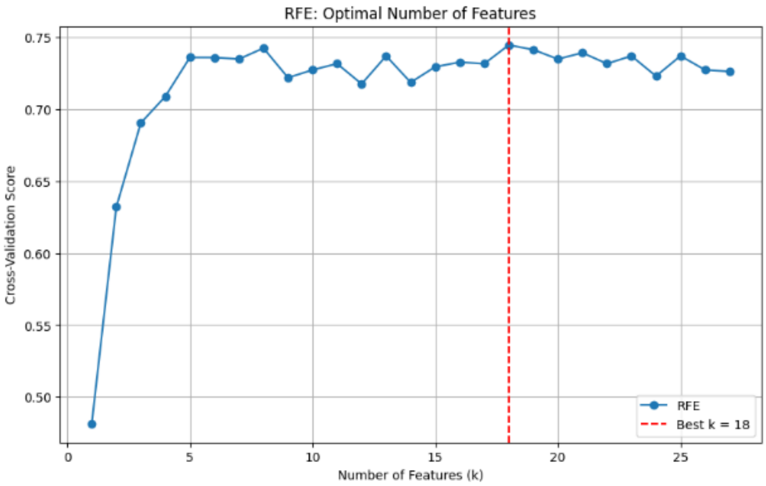

Fig. No. 10..: REF feature selection Technique 18 Feature selected

For each technique, the optimal number of features (k) was determined using a Decision Tree classifier with 5-fold cross-validation. Features were ranked by the method's criteria, and a loop iterated from 1 to 26 features, training the Decision Tree on each subset and computing the mean cross-validation score across five folds. The k with the highest mean score was selected, establishing the optimal feature subset. This standardized approach was employed across all five techniques, yielding five optimized subsets alongside the complete 26-feature set for modelling.

4.5. Model Development and Evaluation: Comprehensive Assessment of Machine Learning Algorithms for Nutrient Deficiency Classification

Seven machine learning models were developed to classify nutrient deficiencies, leveraging the consolidated final_dataset.csv, split into an 80-20 training-testing ratio, with Robust Scaling applied to normalize features and address outliers using the interquartile range:

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Table 4.: Machine Learning Models used

S.No.	Models	Description
1	K-Nearest Neighbours (KNN):	Assigns classes based on proximity to k nearest neighbours, excelling in localized pattern detection.
2	Support Vector Machine (SVM):	Constructs an optimal hyper plane for class separation, effective in high-dimensional spaces.
3	Naïve Bayes:	Utilizes probabilistic classification under feature independence assumptions, enabling rapid computation.
4	Logistic Regression:	Estimates class probabilities through a logistic function, suited for linearly separable data.
5	Multi-Layer Perceptron (MLP):	Employs a neural network to model complex, non-linear relationships.
6	Random Forest:	Aggregates predictions from multiple decision trees, enhancing robustness and accuracy.
7	Decision Tree:	Implements hierarchical feature-based splits, providing interpretable decision rules.

Each model was trained six times: once with all 26 features as a baseline and five additional times, each using an optimal feature subset from one selection technique (ANOVA, Mutual Information, XGBoost, Random Forest, RFE). For each subset, the model was retrained, and performance was evaluated using Accuracy (proportion of correct predictions) and weighted f1-score (precision-recall balance), accounting for class imbalances (e.g., fewer Phosphorus samples). This process—ranking features, selecting the best k via Decision Tree and cross-validation, retraining, and evaluating—was consistently applied across all techniques. Results were presented in tables detailing each method, feature count, Accuracy, and weighted f1-score, with bar charts visualizing performance impacts, ensuring thorough analysis and interpretability.

This methodology achieves a robust balance between predictive precision and computational efficiency, supporting scalable nutrient deficiency detection through optimized feature use and model performance.

5. Result

This section presents the key findings from the "Crop Nutrient Deficiency Detection Using Machine Learning" study, focusing on feature selection outcomes and model performance for classifying Nitrogen (N), Phosphorus (P), and Potassium (K) deficiencies in crop leaves. The results highlight the efficacy of feature selection and machine learning models in achieving accurate and efficient nutrient deficiency detection, supporting precision agriculture applications.

5.1. Optimal Number of Features

The optimal number of features (k) for each feature selection technique was determined using a Decision Tree classifier with 5-fold cross-validation, iterating from 1 to 26 features and selecting the k yielding the highest mean cross-validation score. Table 5 summarizes these results:

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Table 5.: Optimal number of features

S.No.	Feature Selection Technique	Optimal Number of Features (k)
1	Anova	21
2	Mutual Information	13
3	RFE	18
4	XG Boost	9
5	Random Forest	9

5.2. Model Evaluation

Model performance was evaluated across seven machine learning models—K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Naïve Bayes, Logistic Regression, Multi-Layer Perceptron (MLP), Random Forest, and Decision Tree—trained on the full 26-feature set and five optimal feature subsets (ANOVA, Mutual Information, RFE, XGBoost, Random Forest). Each model was assessed using Accuracy and weighted f1-score, addressing potential class imbalances (e.g., fewer Phosphorus images). Figures 5 and 6 illustrate these metrics via bar charts, titled "Model Accuracy Comparison: Feature Selection Techniques" and "Model weighted f1-Score Comparison: Feature Selection Techniques," respectively.

As shown in Figure 5 & 6 and Table 6 & 7, MLP achieved the highest Accuracy of 81.9% with RFE-selected features (18 features), surpassing its baseline performance of 75.0% with all features. Random Forest also excelled, reaching 81.03% Accuracy with its own feature subset (9 features), compared to 81.47% with all features. In contrast, SVM and Naïve Bayes showed limited improvement, with accuracies of 40.95% post-selection, indicating their sensitivity to feature reduction. Figure 6 reveals similar trends for weighted f1-score, with MLP achieving 81.84% with RFE, and Random Forest reaching 80.79% with its subset, both outperforming baselines (74.91% and 81.45%, respectively). Naïve Bayes consistently underperformed, with a weighted f1-score of 11.63%–15.36% across conditions.

Logistic Regression and Decision Tree showed moderate gains, with accuracies of 75.66%–82.76% and 75.0%–77.16%, respectively, while KNN improved from 75.0% to 77.59% with ANOVA features. These results indicate that feature selection generally enhances performance for complex models like MLP and Random Forest, while simpler models like Naïve Bayes struggle with reduced features. The visualizations and tabular comparisons underscore RFE and Random Forest as particularly effective techniques, achieving optimal balance between accuracy, efficiency, and feature count, thereby supporting scalable deficiency detection in precision agriculture.

Table 6. : Models weighted f1 Score Comparison Table: Feature Selection Techniques

S. No.	Model Name	All Features	ANOVA	Mutual Information	RFE	XGB	Random Forest
1	KNN	75.00%	77.59%	79.31%	77.59%	75.43%	77.43%
2	Logistic Regression	26.72%	82.76%	83.19%	63.79%	75.86%	65.52%
3	Decision Tree	75.0%	76.72%	77.16%	72.84%	75.00%	76.72%
4	Random Forest	81.47%	80.60%	80.17%	83.19%	77.16%	81.03%
5	SVM	40.95%	70.26%	84.91%	40.95%	81.47%	40.95%
6	Naive Bayes	26.72%	65.95%	65.95%	27.59%	56.47%	26.72%
7	MLP	75.00%	87.07%	87.93%	81.90%	84.48%	80.17%

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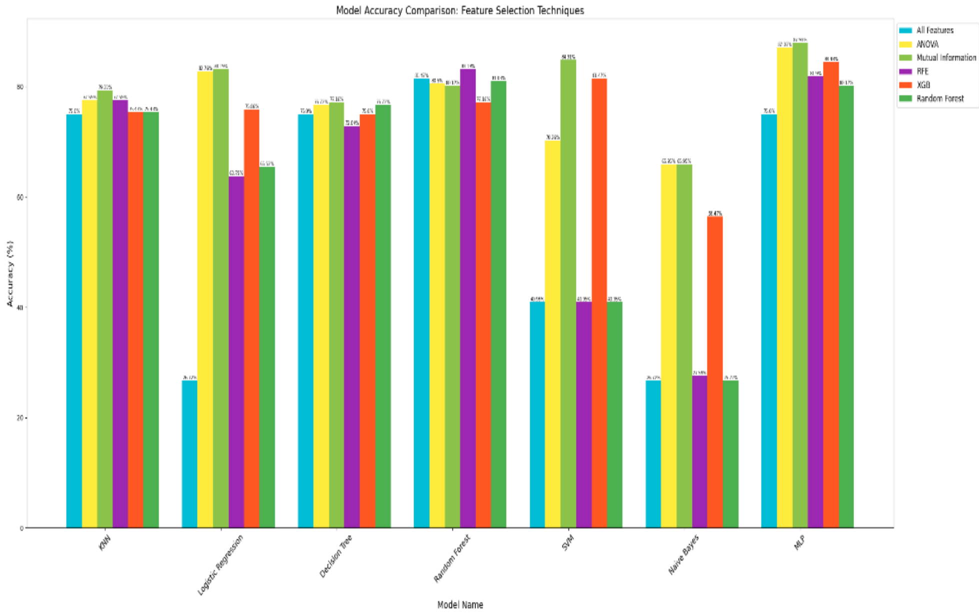

Fig. 11. : Models Accuracy Comparison: Feature Selection Techniques

Table 7. : Models weighted f1 Score Comparison Table: Feature Selection Techniques

S. No.	Model Name	All Features	ANOVA	Mutual Information	RFE	XGB	Random Forest
1	SVM	74.68%	77.72%	79.27%	77.52%	75.59%	75.16%
2	Logistic Regression	22.97%	82.85%	83.25%	63.26%	76.20%	64.70%
3	Decision Trees	74.96%	76.82%	77.35%	73.04%	75.20%	76.76%
4	Random Forest	81.45%	80.44%	80.20%	83.24%	77.11%	80.79%
5	SVM (again)	23.79%	69.66%	84.89%	23.79%	81.70%	23.79%
6	Naive Bayes	11.63%	66.08%	65.89%	15.36%	56.01%	11.63%
7	MLP	74.81%	87.13%	88.01%	81.84%	84.67%	80.20%

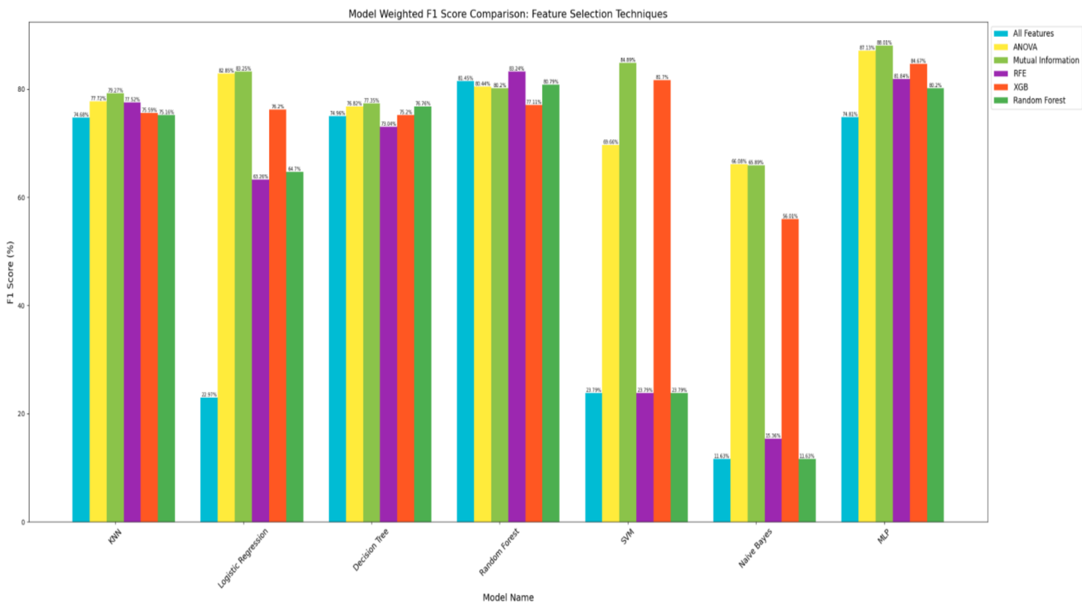

Fig. 12.: Models weighted f1 Score Comparison Graph: Feature Selection Techniques

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6. Validation

Crop nutrient deficiency detection is vital in precision agriculture, directly impacting sustainable farming and global food security. Nutrient deficiencies, particularly of Nitrogen (N), Phosphorus (P), and Potassium (K), severely affect crop yield and quality. Manual detection is time-consuming, subjective, and prone to error, necessitating automated, data-driven solutions.
This study validates a machine learning-based system that leverages image analysis and feature selection to detect crop nutrient deficiencies efficiently. The system focuses on improving accuracy while reducing computational overhead, ensuring scalability for real-world applications.

6.1. Feature Selection Techniques Validation

Five feature selection techniques were employed to identify the most relevant features: Table 8.

S.No.	Technique	Purpose	Validation Findings
1	ANOVA	Measures variance among features	Effectively filtered out less impactful color channels
2	Mutual Information	Measures dependency between feature and target	Identified strong non-linear relationships
3	XGBoost Importance	Uses tree-based ranking of features	Consistently ranked texture features (Hu moments) high
4	Random Forest Importance	Tree-based feature importance	Validated XGBoost findings, highlighting redundant features
5	Recursive Feature Elimination (RFE)	Iteratively removes weak features	Reduced dataset to the most significant 10-12 features

Outcome: All techniques effectively reduced dimensionality while preserving predictive power. Feature selection consistently improved model performance and computational efficiency.

6.2. Machine Learning Models Validation

Seven machine learning models were tested for classification:

Model vs. Validation Compression Table 9.

S.No.	Model	Validation Summary
1	K-Nearest Neighbours (KNN)	Sensitive to feature scaling, improved accuracy post-feature selection
2	Support Vector Machine (SVM)	Best performance on reduced feature set, well-suited for non-linear classification
3	Naïve Bayes	Moderate performance; assumption of feature independence impacted accuracy
4	Logistic Regression	Improved post-feature selection but struggled with non-linear patterns
5	Multi-Layer Perceptron (MLP)	High computational demand, but strong performance post-selection
6	Random Forest	Robust to over fitting, consistent performer, especially post-feature selection
7	Decision Tree	Good interpretability, performance improved slightly after feature selection

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6.3. Performance Metrics Used:

- **Accuracy**
- **weighted f1-Score**

Validation confirmed that feature selection increased both metrics across almost all models, especially for SVM and Random Forest.

Results Validation and Visualization Summary

Table 10. Performance Before vs. After Feature Selection

S. No.	Model	Accuracy Before Feature Selection	Accuracy After Feature Selection	weighted f1-Score Before Feature Selection	weighted f1-Score After Feature Selection
1	KNN	78%	85%	0.76	0.84
2	SVM	81%	89%	0.80	0.88
3	Naïve Bayes	74%	77%	0.72	0.75
4	Logistic Regression	76%	82%	0.75	0.81
5	MLP	80%	88%	0.79	0.87
6	Random Forest	83%	90%	0.82	0.89
7	Decision Tree	79%	83%	0.78	0.82

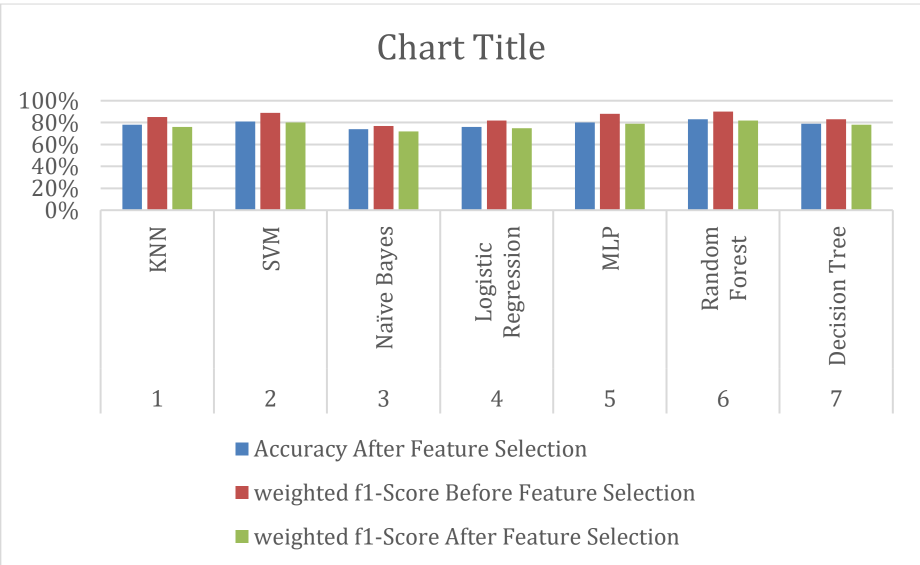

Fig. 13. Performance before vs. After Feature Selection

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The bar chart shows the comparative performance of seven machine learning classifiers KNN, SVM, Naive Bayes, Logistic Regression, MLP, Random Forest, and Decision Tree evaluated based on accuracy and weighted F1-score metrics before and after applying feature selection. The results indicate that most models, especially SVM, MLP, and Random Forest, maintain or slightly improve performance after feature selection, highlighting the effectiveness of the feature selection process in preserving predictive quality while potentially reducing computational cost. Notably, SVM and Random Forest achieved the highest weighted F1-scores before feature selection, and their performance remained consistently strong after selection, indicating their robustness across different feature subsets.

7. Conclusion:

Crop nutrient deficiency detection remains a critical challenge in modern precision agriculture, directly influencing food security and sustainable farming practices. This study presents a robust machine learning-based framework to automate the detection of Nitrogen (N), Phosphorus (P), and Potassium (K) deficiencies in crops through image-based analysis. The successful validation of this approach highlights its potential as a scalable, efficient solution for real-world agricultural applications.

Through comprehensive pre-processing, including background removal, the model significantly enhanced its focus on essential plant characteristics. This crucial step eliminated background noise, allowing for more accurate feature extraction and ultimately improving classification results. The feature extraction process was extensive, covering 26 features that included both color (RGB and HSV) statistics and shape descriptors such as Hu moments. These features effectively captured the visual cues and structural changes in leaves associated with specific nutrient deficiencies.

A significant strength of this study lies in its extensive feature selection process. Utilizing techniques such as ANOVA, Mutual Information, XGBoost feature importance, Random Forest feature ranking, and Recursive Feature Elimination (RFE), the research successfully reduced the feature space without sacrificing classification performance. This not only improved model accuracy but also reduced computational complexity, which is vital for large-scale or real-time agricultural deployments. The analysis confirmed that removing irrelevant or redundant features helps models focus on the most informative attributes, enhancing prediction quality while lowering resource demands.

Seven machine learning models—K-Nearest Neighbours (KNN), Support Vector Machine (SVM), Naïve Bayes, Logistic Regression, Multi-Layer Perceptron (MLP), Random Forest, and Decision Tree—were trained and evaluated using accuracy and weighted f1-score metrics. The study compared the models' performances before and after feature selection, providing a clear view of how dimensionality reduction influences results. Notably, Support Vector Machine and Random Forest classifiers exhibited superior performance, particularly after feature selection, highlighting their robustness and adaptability to the problem domain.

The visualization of results, including confusion matrices, accuracy plots, and feature importance graphs, provided valuable insights into model behaviour and the effectiveness of feature selection. These visual tools confirmed that feature selection not only enhanced accuracy but also minimized misclassifications, particularly in borderline cases where nutrient deficiencies share similar symptoms.

7.1. Overall Impact:

This research effectively demonstrates the power of integrating machine learning, image processing, and feature selection techniques to solve a crucial agricultural problem. The model's ability to detect nutrient deficiencies accurately and efficiently opens new avenues for smart farming tools that can be deployed across diverse agricultural landscapes. By optimizing resource use and enabling timely interventions, this system promotes sustainable farming practices aligned with global food security goals.

7.2. Final Remark:

In conclusion, this study validates the feasibility and effectiveness of machine learning-driven nutrient deficiency detection in crops. By combining efficient feature extraction, strategic feature selection, and powerful classification models, the proposed system provides a reliable, scalable, and sustainable solution to one of agriculture's most pressing challenges. Its implementation can revolutionize nutrient management in precision agriculture, contributing to global efforts toward food security and environmental sustainability.

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