International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(3s) 2026 pp. 1041-1062
https://doi.org/10.70917/ijcisim-2026-2441
Article

ANDFO: Soil Nutrient Assessment and Fertilizer Dosage Recommendation for Efficient Crop Nutrient Management

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Abstract: Effective management of nutrients of soils is critical towards enhancing the productivity of agriculture and long-term sustainability of agriculture. Nevertheless, uncontrolled fertilizers application without regard to the soil-specific nutrient statuses usually results in an imbalance, low yield, and environmental influence. This research is an attempt to come up with an intelligent system that can accurately detect nutrient deficiency and recommend the optimal dosage of fertilizers. To achieve this, the proposed Adaptive Nutrient Deficiency Fertilizer Optimization (ANDFO) algorithm examines the following essential soil parameters Nitrogen (N), Phosphorus (P), Potassium (K), and pH and compares it to the ideal nutrient needs of crops. The approach unites the deficiency identification, the recommendation of the type of fertilizers, dosage estimation, and the analysis of estimation of growth into a single approach. The feasibility of the proposed model is proven in experimental results where the proposed model gets the accuracy of 0.99 % and this is better than the current methods. The system is useful in that, it helps to enhance nutrient balance, the health of soils, and performance of crops following application of fertilizers. To conclude, the ANDFO framework is a valid, economical, and feasible solution to implement precision agriculture through minimizing the unnecessary use of fertilizers, maximizing productivity, and sustaining productivity.
Keywords: Crop Nutrient Management, Fertilizer Optimization, Nutrient Deficiency, Soil Analysis, Soil Fertility and Sustainability.

1. Introduction

Agriculture is an extremely significant sector in terms of food security as well as sustainable growth in which the nutrient management of soils plays a major role in increasing crop yields and soil solvency. However, the improper application of fertilizers and faulty estimation of the nutrients are likely to lead to soil erosion, low yield and greater harm to the environment. Conventional methods of agriculture use recommendations that are generic, without taking into account the soil-specific situations, and hence lead to ineffective use of the nutrients. To tackle these issues, current developments have been based on merging Machine Learning (ML), Deep Learning (DL) and Internet of Things (IoT) technology to achieve accuracy in agriculture and smart decision-making.

Some research have discussed more sophisticated approaches to crop prediction and soil nutrient analysis, such as ML and DL models to predict nutrient management [1], IoT-based solutions to soil analysis and crop recommendation [2], and explainable AI to predict sustainable yield [3]. It has also been noted that frameworks of nutrient management are essential in research [4], ensemble DL to classify soils [5], and hybrid models, like Convolutional Neural Network – Long Short-Term Memory (CNN-LSTM) to predict yields [6]. Also, the IoT-based fertilizer recommendation systems [7], nutrient efficiency optimization [8], and large-scale ML-based yield prediction systems [9] are examined as well as the spatial variability modeling [10], soil carbon estimation with the help of ML models [11], and systems of crop prediction with the help of various algorithms [12]. Nevertheless, these techniques usually do not ensure optimization of the dosage of fertilizers, correction of deficiency in real time and actionable recommendations. To address these shortcomings, the research will present the Proposed Adaptive Nutrient Deficiency Fertilizer Optimization algorithm that will combine the nutrient deficiency detection, the fertilizer type recommendation, the dosage optimization, and the soil health evaluation into a single algorithm to offer an efficient and effective solution to sustainable precision agriculture.

The most important primary contribution and motivation are,

- The smart ANDFO algorithm in order to detect and analyse the accurate soil nutrient deficiency.
- To give the accurate type and dosage of fertilizers to give the best nutrient management.
- To decrease the high level of fertilizer application and propagate economical and sustainable agriculture.
- To enhance crop growth, prediction of yield and overall evaluation of soil health.
- To create a simple, understandable, and useful system in contrast to the existing sophisticated approaches.

Organization: The background research and the related work are provided in Section 2, whereas the description of the proposed ANDFO methodology, including its architecture, workflow, equations, and pseudocode are presented in Section 3. Section 4 is a discussion and analysis of the results and analysis and lastly, Section 5 is a conclusion of the research covering future scope.

2. Background Study

Moharana P.C. et al. (2020) [13] proposed the application of geostatistical analysis and fuzzy clustering to develop site-specific delineation of management zone to identify the limiting factors to yield in irrigated hot arid areas in India. The research involved spatial variability mapping and clustering techniques, however, there was a weakness in the ability to deal with the temporal variability and real-time prediction, and findings presented enhanced zone-based nutrient management with higher yield stability.

Barbosa A. et al. (2020) [14] built the model of crop yield response on the basis of Convolutional Neural Networks (CNN) to train on to learn intricate connections between the practice of crop management and yield outcomes. CNN-based DL enhanced prediction accuracy and limitation was noted because of the need to have large training datasets and its performance was shown to be better than the available regression models.

Dhal S.B. et al. (2022) [15] proposed the idea of ML-based nutrient optimization of aquaponic irrigation systems with small training datasets to help in plant growth prediction. Limited samples were used in the work to apply the models of supervised learning, however, scalability was limited to large-scale farming, and performance improved the efficacy of nutrient control and accuracy of plant growth.

Snapp S. et al. (2023) [16] examined spatially differentiated strategies of nitrogen supply strategies to resolve global food and fertilizer price crisis based on field-level nutrient management data. The research concentrated on agronomic optimization, as opposed to intelligent automation, which was incurred in the absence of AI-based prediction models, and the findings revealed that location-specific supply of nitrogen showed a great benefit in terms of productivity and fertilizer efficiency.

The research by Thapa S. et al. (2021) [17] applied experimental soil nutrient analysis and agronomic evaluation to investigate the micronutrient management to enhance soil fertility, soil health and soybean yield. They used existing soil testing and field experiments, but had the limitation of lack of predictive analytics and yield and soil quality improved through micronutrient balancing.

Peng X. et al. (2022) [18] estimated Nitrogen (N), Phosphorus (P), and Potassium (K) in grape leaves at various growth stages by applying the UAV multispectral remote sensors and ML models. Remote sensing and regression models enhanced nutrient estimation although, there was a constraint in environmental sensitivity and calibration of data and results showed to predict nutrient precisely in precision farming.

Dawar K. et al. (2021) [19] experimentally analyzed the impact of different levels of biochar on wheat yield, efficacy of N use, and Nitrous Oxide (N_2O) emissions through soil treatment analysis. The strategy was based on field experiments that were not intelligently optimised, constrained on unavailability of adaptive decision models, and demonstrated that utilised optimised biochar concentrations enhanced yield and minimised emissions.

Xiao Q. et al. (2021) [20] compared the effects of long-term manuring on the carbon use efficiency of the microorganisms and soil fertility through soil chemistry and a microbial examination. Existing soil fertility assessment techniques were employed, however, lack of foreseeable nutrient endorsement structures and results showed that long-term manure usage enhanced the health and efficiency of the soils.

Vemunuri J. et al. (2025) [21] proposed biochemical urease-sensitive precision agriculture crop yield prediction based on enhanced fuzzy logic models and deep learning models. Hybrid fuzzy-DL method enhanced predictive power, although it had a weakness of being limited by the complexity of computation and the dependency of datasets and the yield predictive accuracy was better when using the hybrid models as opposed to using conventional ML models.

In Sharafat M.S. et al. (2025) [22], precision agriculture has been developed by using the soil parameters and weather measurements in creating the IoT-enabled AI-based real-time crop prediction system. The system involved the use of IoT sensors featuring ML models, however, constraint was in the cost of hardware and complexity of deployment and found the results of the system predict the crops correctly in real-time with improved decision support.

Table 1: Background Study on Crop Recommendation, Soil Nutrient Analysis and Precision Agriculture Methods.

Author (Year)	Concept	Research Gap	Methods	Limitations	Key Results
Motamedi, B. & Villányi, B. (2024) [23]	Bayesian-optimized ensemble decision trees for crop recommendation	Limited integration of uncertainty-aware ensemble learning in agriculture	Ensemble decision trees with Bayesian optimization	High computational complexity and data dependency	Improved crop recommendation accuracy with optimized decision boundaries
Alam, M.S.B. et al. (2025) [24]	Crop recommendation with uncertainty quantification	Lack of uncertainty modeling in ML-based agricultural decisions	ML with probabilistic uncertainty modeling	Complexity in interpreting uncertainty outputs	Enhanced decision reliability and sustainable crop selection
Mohammed, G. et al. (2024) [25]	Soil phosphorus dynamics and crop yield simulation	Insufficient long-term comparative studies on fertilization impacts	Simulation modeling for organic and mineral fertilization	Site-specific dependency and long-term validation required	Better understanding of phosphorus behavior and yield response
Raju, R. & Thasleema, T.M. (2025) [26]	BO-CNN for nutrient stress classification	Limited hyperparameter optimization in crop stress detection	CNN with Bayesian hyperparameter tuning	Requires large labeled datasets	Improved classification accuracy for nutrient stress detection
Mishra, P. et al. (2025) [27]	Microfluidic colorimetry for soil nutrient detection	Lack of rapid, on-site nutrient detection systems	Microfluidic devices with colorimetric analysis	Device calibration and environmental sensitivity	Fast and accurate soil nutrient detection in field conditions
Ling, J. et al. (2025) [28]	Soil organic carbon thresholds and fertilizer impact	Limited global-scale threshold analysis for carbon-fertilizer interaction	Global data analysis and statistical modeling	Variability across regions and soil types	Identified SOC thresholds influencing carbon sequestration
Pantigoso, H.A. et al. (2023) [29]	Root exudates enhancing phosphorus solubilization	Limited understanding of microbial	Laboratory microbial and biochemical analysis	Controlled conditions may not reflect field reality	Improved phosphorus availability via

		interaction mechanisms			microbial stimulation
El-Akhdar, I. et al. (2024) [30]	Organic and biofertilizer effects on wheat cultivation	Limited sustainable solutions for sandy soils	Field experiments with organic and biofertilizers	Soil variability and scalability issues	Enhanced soil health and increased wheat yield

The table 1 above is a summary of the past research associated with crop recommendation, nutrient prediction, soil fertility analysis, and precision agriculture based on the use of ML, simulation, biofertilizer, and soil chemistry techniques. Concept, methods used, research gap, limitations and key results have been pointed out in the table to establish the necessity of better intelligent nutrient optimization and prediction models.

Research Gap

- Current practices do not have ways of detecting nutrient deficiencies when they occur and the recommended dose of fertilisers.
- Most of the methods only concentrate on prediction but do not give any actionable solution on how to improve the health of soil.
- Very high computational costs and usage of IoT or big data restrict practical applications in the real world.

3. Proposed Methodology

In this section, the proposed ANDFO algorithm is introduced its overall structure and workflows to analyze the nutrients in the soil and optimize the use of fertilizers are mentioned. It describes the mathematical equations applied in detection of nutrient deficiency, mapping of fertilizers and dose calculation. Further, the entire process is shown using step-by-step pseudo code to understand the system implementation in a better manner.

3.1 Dataset Description

Dataset Link: Crop Recommendation Dataset

The crop recommendation dataset consists of 2,200 samples, each representing a unique combination of soil nutrient properties and climatic conditions associated with a specific crop. The dataset integrates soil macronutrients (N, P, K) and soil pH with environmental parameters such as temperature, humidity, and rainfall to support data-driven agricultural decision-making. The target variable is the crop label, indicating the crop best suited to the given soil–climate conditions. All features are numerical and continuous, while the target is categorical, making the dataset suitable for multiclass classification, clustering, and decision-support analysis. The dataset is cleaning, well-structured, and contains no missing values, enabling straightforward pre-processing and reproducible experimentation.

3.2 Proposed Algorithm Novelty:

- Built-in Detection and Recommendation ANDFO is also designed to perform nutrient deficiencies detection and directly combine fertilizer recommendations and optimization in one workflow, which is not done in existing systems where detection and recommendation are considered separately.
- Optimization-based Soil Matching – The algorithm used an innovative distance-based soil selection and optimization mechanism (ANDFO Core) that is capable of identifying the optimal soil sample to use on a particular crop and regulate the level of nutrients efficiently to ensure any potential growth is maximized.
- Holistic Growth Evaluation - ANDFO is a combination of nutrient deficiency analysis and growth estimation prior to and after fertilizer application and is a holistic, data-driven crop recommendation and yield improvement approach

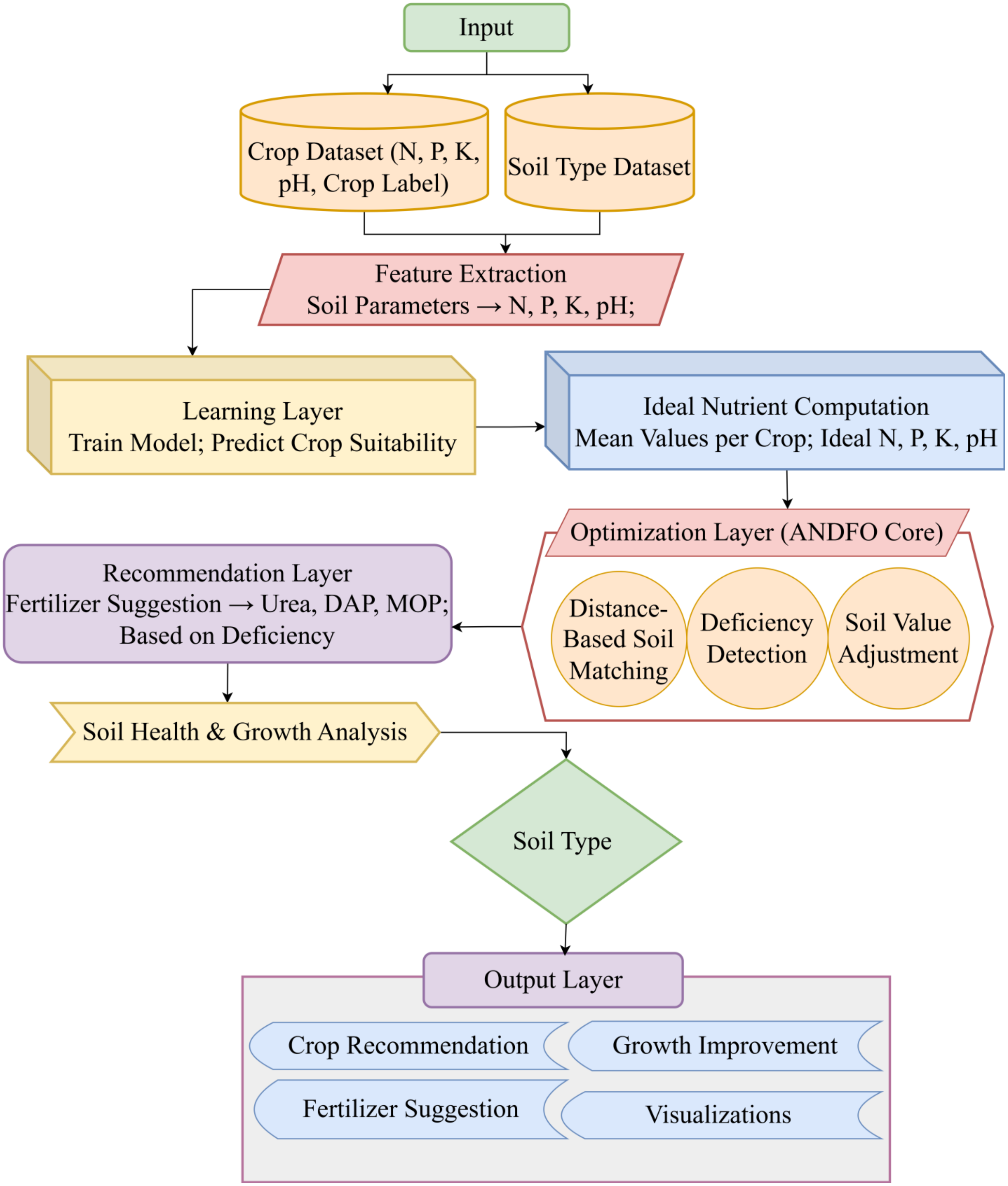


Figure 1: Workflow of proposed Algorithm

The above figure 1 shows the entire workflow of the proposed ANDFO system beginning with the input datasets with the extraction of features, learning, nutrient computation, optimization and recommendation. It also emphasizes the integration of soil nutrient analysis, optimization of different types of fertilizer, and soil health analysis to produce precise crop advice and better production results.

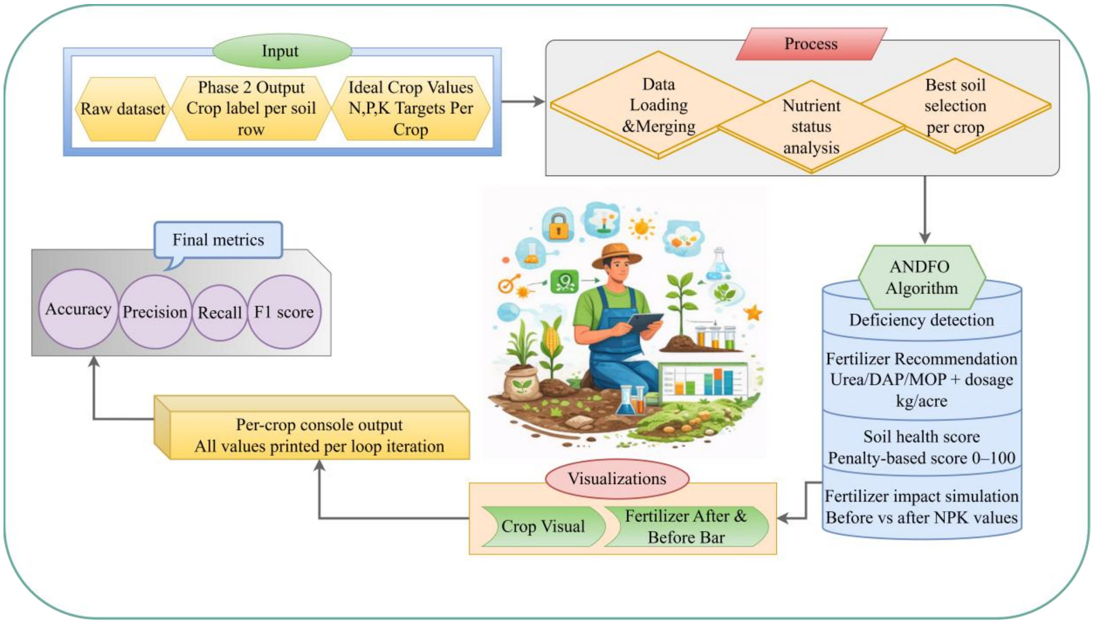


Figure 2: ANDFO Framework of soil nutrient analysis and fertilizer recommendation

In above figure 2, implicates raw soil and crop data. It is followed by the nutrient status appraisal and optimum soil selection by the system, and then the ANDFO algorithm of deficiency detection, fertilizer advice and scoring of crop improvement with before and after simulation. Lastly, the framework will produce per-crop outputs, visualization and performance metrics as a measure of model effectiveness.

3.3 ANDFO Algorithm for Soil Nutrient level detection

The proposed ANDFO algorithm will be intelligent to forecast nutrient deficiencies in the soil and to optimize the dosage of fertilisers applied to manage crop nutrient. The current ways of applying fertilizers have weaknesses in form of failure to analyze the soil correctly, excessive use of fertilizers, and unbalanced nutrients that result in low yields and erosion of soil. In order to tackle these issues, the ANDFO algorithm examines the soil parameters including Nitrogen, Phosphorus, Potassium and PH and contrasts the with the nutrient requirements of the crop to effectively identify deficiencies. An optimization strategy is then used to calculate the exact kind and amount of fertilizer needed, at the lowest cost and the maximum amount of nutrient efficiency. The strategy will allow real-time, data-driven decision-making in the agricultural sector, which will guarantee sustainable agriculture and enhanced productivity.

$$S = \{N, P, K, pH\} \quad (1)$$

In equation 1 means that S represents that complete soil nutrient set N, P, K represents a Nitrogen, Phosphorus, Potassium content in soil and pH represents a level of acidity or alkalinity of soil. By condensing all the required nutrients and PH level in a well-organized form, this equation determines the original state of soil. It functions as the starting point of determining the soil fertility and additional nutrient measurement.

$$R = \{N_r, P_r, K_r\} \quad (2)$$

In equation 2 means that, R is a required set of nutrients needed to grow a crop, N_r is a required level of nitrogen needed to grow a crop, P_r is a required level of phosphorus needed to grow a crop, and K_r is a required level of potassium needed to grow a crop. This equation defines the optimum nutrient concentrations required to have an optimum crop growth. It is used as a reference point to be compared to the existing soil nutrients.

$$D_i = R_i - S_i \quad (3)$$

In equation 3 is D_i is a deficiency of nutrient i, R_i is a required value of nutrient i, S_i is an available soil value of nutrient i. This equation calculates the difference between the requirements and availability of nutrients of each element. It assists in determining the deficiency of a nutrient in the soil or whether it is adequate.

$$D_i = \begin{cases} R_i - S_i, & if S_i < R_i \\ 0, & if S_i < R_i \end{cases} \quad (4)$$

Equation 4 depicts that R_i is a required level of nutrient, S_i is a level of nutrient in the soil. Such state guarantees that only deficient nutrients are taken into account by removing the surplus values. It eliminates the application of unneeded fertilizers when the nutrients are adequate.

$$F_i = f(D_i) \quad (5)$$

In equation 5 is the fact that F_i is a kind of fertilizer needed to supply nutrient i and f is a mapping procedure which transforms deficiency into the type of fertilizer. Such an equation is used to match every nutrient deficiency with an appropriate kind of fertilizer. It converts the value of analytical deficiency into actual agricultural suggestions.

$$Q_i = \frac{D_i}{E_i} \quad (6)$$

Equation 6 is the expression that Q_i is a quantity of fertilizer that is needed, and E_i is an efficacy factor of fertilizer. This equation is used in determining the required amount of fertilizer according to deficiency and efficiency. It corrects actual losses occurring in the world to make the desired level of nutrient attained.

$$C = \sum(Q_i \cdot cost_i) \quad (7)$$

In equation 7 is an indication that C indicates the total fertilizer cost, $cost_i$ is a cost of fertilizer. This equation calculates the sum of all the cost of the fertilizers needed to correct the soil. It assists in the assessment of the economic viability of nutrient management.

$$\min C \quad subject\ to\ Q_i \geq D_i \quad (8)$$

In equation 8 signifies that D_i is a nutrient deficiency. This equation reduces the total cost of fertilizers but at the same time makes sure that all the nutrient deficiencies are met. It is cost effective and also meets the agricultural productivity needs.

$$Y = f(N, P, K) \quad (9)$$

In equation 9 is where Y is crop yield, N, P, K is the levels of essential nutrients. In this equation, crop production is directly dependent on the proportions of important nutrients. It highlights the fact that the best way to handle nutrients is to achieve greater agricultural productivity.

3.3.1 Fertilizer Recommendation and Soil Health Assessment using ANDFO

The proposed ANDFO algorithm applied in the nutrient deficiency detection is also applied to the process of recommendations so that there is a single and uniform approach to the issue. It will start by loading the crop data and derive the essential soil variables including Nitrogen (N), Phosphorus (P), Potassium (K) and pH. It then adopted patterns based on the data and measures performance based on conventional metrics. In every crop, the algorithm will compute the optimum nutrient values with the help of the average statistics and choose the best fitting soil sample by computing the distance between the average optimum nutrient value and the actual value. The nutrient condition is termed as Low, Optimal, or High according to a predetermined threshold and the deficiency is established by comparing real soil values with the ideal ones. Depending on the deficiencies identified, appropriate fertilizers like Urea, DAP and MOP are encouraged. The overall health of soil is assessed and a score of soil health is computed and the growth is estimated prior to and after fertilizer application and growth measured. The last stage is when the system determines the type of soil and delivers the results and metrics of comparison.

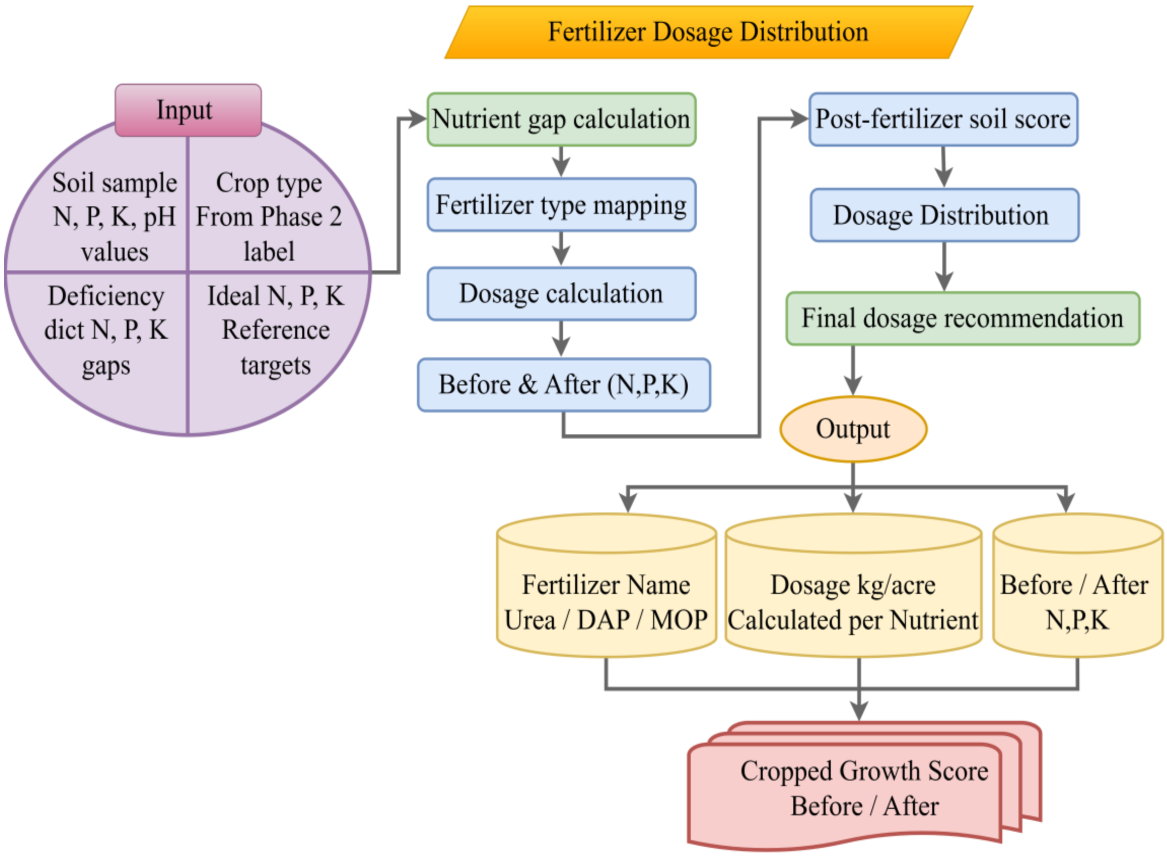


Figure 3: Workflow of Dosage Distribution and Recommendation of Fertilizers.

Figure 3 above provides a methodical process of fertilizer recommendation, involving input information like soil nutrient values (N, P, K, and pH), type of crop and types of nutrient deficiency. It works on these inputs by looking at the analysis of a nutrient gap, mapping of the fertilizer type, and calculation of a dosage and then comparing the soil conditions before and after fertilizing. Lastly, the system has the outputs of optimized fertilizer type, dosage per acre, and a relative NPK level which are used to estimate the crop growth score improvement.

$$D = \sqrt{(N - N_i)^2 + (P - P_i)^2 + (K - K_i)^2} \qquad (10)$$

In equation 10 symbolizes that D is the distance between the soil and the ideal condition, N, P, K is the real value of nutrient in the soil, $N_i, P_i K_i$ is the ideal nutrient values in the soil. Determines the distance of the specified soil to the desired crop (minimum distance = best fit).

$$Def_x = max(0, I_x - S_x) \qquad (11)$$

In equation 11 represents that Def_x represents that eficiency of nutrient x, I_x is an ideal value of nutrient x, S_x is a real soil value of nutrient x. This is the calculation of the deficiency of nutrient in the soil as compared to the ideal amount. The max function makes sure that deficiency is never in the negative (no surplus is taken into consideration).

$$SH = 100 - \sum(|S_x - R_x| \times w) \qquad (12)$$

In equation 12 expresses that SH is a score of soil health (0–100), S_x is an actual soil value, R_x is a recommended/ideal value and w is a penalty weight factor. Assesses the general quality of the soil using the reduction of the score on the deviation of the ideal values

$$U_x = S_x + (F_x \times \eta) \qquad (13)$$

In equation 13 means that U_x is a revised value of nutrient in soil following fertilizer, S_x is an initial nutrient value in soil, F_x is an amount of fertilizer, η is a fertilizer efficacy (e.g., 0.8). Refreshes soil nutrients following the application of fertilizer based on the efficiency in reality.

$$G = \left(\frac{1}{n}\sum min\left(\frac{U_x}{I_x}, 1\right)\right) \times SH \quad (14)$$

Equation 14 indicates that G is the growth score, I_x is ideal nutrient value, SH is soil health score n is a number of nutrients (3: N, P, K). This approximates crop growth in regard to the proximity of nutrients to ideal levels. It integrates nutrient balance and soil health to give the forecast of the end quality of yield.

Algorithm: ANDFO Crop & Soil Analysis System

```
BEGIN
INPUT:
Crop dataset (N, P, K, pH, Crop Label)
Soil type dataset
LOAD crop dataset and soil type dataset
// Step 1: Data Preparation
Extract features (N, P, K, pH) and crop labels
Split dataset into training and testing
// Step 2: Model Process
Train model using training data
Predict using test data
// Step 3: Evaluation
Compute Accuracy, Precision, Recall, F1 Score
// Step 4: Ideal Value Calculation
FOR each crop
   Calculate mean values of N, P, K, pH
END FOR
// Step 5: Main Analysis
FOR each crop DO
   Find best soil sample (minimum distance)
   Determine nutrient status:
      N, P, K → Low / Optimal / High
      pH → Acidic / Neutral / Alkaline
   Compute deficiency:
      deficiency = max(0, ideal - soil)
   Recommend fertilizer:
      Urea, DAP, MOP based on deficiency
   Calculate soil health score (0–100)
   Apply fertilizer:
```

```
    AFTER = soil + deficiency
  Estimate growth:
    Calculate BEFORE & AFTER scores
    Classify → Poor / Moderate / Good / Excellent
  soil type:
    Nearest match from dataset
    Also based on pH rule
  Display results and plots
END FOR
// Step 6: Final Output
Display comparison table (Growth BEFORE vs AFTER)
END
OUTPUT:
Crop analysis
Fertilizer recommendation
Soil health score
Growth comparison (Before & After)
Soil type
Performance metrics
```

To analyze the suitability of crops, the ANDFO algorithm loads crop and soil samples, isolates soil characteristics (N, P, K, pH) and pre-treats the data to be trained and assessed. It subsequently calculates the optimal nutrient value of each crop, identifies the closest soil sample, calculates the nutrient status, identifies the nutrient deficiencies and the recommended nutrient balance of the soil using the right type of fertilizer and the soil health is calculated. Lastly, it approximates crop growth prior to and post application of fertilizer, determines the type of soil, and provides crop analysis, fertilizer recommendation, soil health evaluation and comparison growth results.

4. Result and Discussion

The findings of the proposed ANDFO algorithm are carried out and tested in Python to achieve the rightful and effective analysis of soil and crops data. The evaluation of the performance is done by detecting nutrient deficiency, recommended fertilizers and soil health of various crops. The relative comparison shows that it is more accurate, precise, and recalls a larger number of correct ones and less false ones. The results prove the efficiency of the technique in increasing crop growth and improving sustainable agriculture.

4.1 Detection of the Nutrient Deficiency and Soil Analysis

This section contains the discussion of the nutrient level of soils and determines the lack of certain nutrients in relation to the recommended nutrient content of crops.

Table 2: Analysis of Crop-Wise Nutrient Status and Soil pH condition

No	Crop	N Status	P Status	K Status	pH Status
1.	Rice	Optimal	Optimal	Optimal	Neutral

2.	Maize	Optimal	Optimal	Low	Acidic
3.	Chickpea	Low	Optimal	High	Neutral
4.	Kidneybeans	Low	Optimal	Low	Acidic
5.	Pigeonpeas	Low	Optimal	Low	Acidic
6.	Mothbeans	Low	Optimal	Low	Acidic
7.	Mungbean	Low	Optimal	Low	Acidic
8.	Blackgram	Low	Optimal	Low	Alkaline
9.	Lentil	Low	Optimal	Low	Acidic
10.	Pomegranate	Low	Low	Low	Neutral
11.	Banana	Optimal	Optimal	Optimal	Neutral
12.	Mango	Low	Low	Low	Acidic
13.	Grapes	Low	High	High	Neutral
14.	Watermelon	Optimal	Low	Optimal	Neutral
15.	Muskmelon	Optimal	Low	Optimal	Neutral
16.	Apple	Low	High	High	Neutral
17.	Orange	Low	Low	Low	Neutral
18.	Papaya	Optimal	Optimal	Optimal	Neutral
19.	Coconut	Low	Low	Low	Acidic
20.	Cotton	High	Optimal	Low	Alkaline
21.	Jute	Optimal	Optimal	Optimal	Neutral
22.	Coffee	High	Low	Low	Neutral

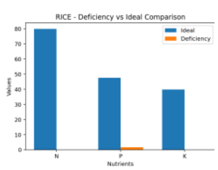
The above table 2 shows of important soil nutrients (Nitrogen, Phosphorus and Potassium) and pH conditions of various crops. It determines the nutrient as low, optimal or high as well as the level of acidity or alkalinity of the soil. The analysis assists in the knowledge of the soil fertility status and assist in accurate nutrient management and fertilizer advice to enhance crop production.

Table 3: Analysis of Soil Nutrient status and deficiency of crops

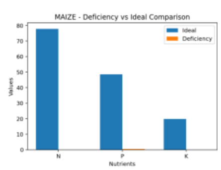
Crop	pH Value	Soil Nature	Soil Type	Ideal N	Ideal P	Ideal K	Ideal pH	Def N	Def P	Def K
RICE	6.58	Neutral	Loamy Soil	79.89	47.58	39.87	6.43	0	1.58	0
MAIZE	5.59	Acidic	Laterite / Peaty	77.76	48.44	19.79	6.25	0	0.44	0
CHICKPEA	6.72	Neutral	Loamy Soil	40.09	67.79	79.92	7.34	0	0	0
KIDNEYBEANS	5.67	Acidic	Laterite / Peaty	20.75	67.54	20.05	5.75	0.75	0.54	1.05
PIGEONPEAS	5.67	Acidic	Laterite / Peaty	20.73	67.73	20.29	5.79	0.73	0.73	1.29
MOTHBEANS	3.71	Acidic	Laterite / Peaty	21.44	48.01	20.23	6.83	0	0	0
MUNGBEAN	3.71	Acidic	Laterite /	20.99	47.28	19.87	6.72	0	0	0

			Peaty							
BLACKGRAM	7.73	Alkaline	Saline / Clay	40.02	67.47	19.24	7.13	0.02	0	2.24
LENTIL	5.67	Acidic	Laterite / Peaty	18.77	68.36	19.41	6.93	0	1.36	0.41
POMEGRANATE	6.73	Neutral	Loamy Soil	18.87	18.75	40.21	6.43	0	1.75	1.21
BANANA	6.05	Acidic	Laterite / Peaty	100.23	82.01	50.05	5.98	0.23	2.01	0
MANGO	5.67	Acidic	Laterite / Peaty	20.07	27.18	29.92	5.77	1.07	1.18	0.92
GRAPES	6.00	Acidic	Laterite/Peaty	23.18	132.53	200.11	6.03	1.18	0	0
WATERMELON	6.88	Neutral	Loamy Soil	99.42	17.00	50.22	6.50	0	0	0
MUSKMELON	6.88	Neutral	Loamy Soil	100.32	17.72	50.08	6.36	0.32	0	0
APPLE	6.00	Acidic	Laterite / Peaty	20.80	134.22	199.89	5.93	0	1.22	0
ORANGE	6.55	Neutral	Loamy Soil	19.58	16.55	10.01	7.02	1.58	2.55	0
PAPAYA	6.75	Neutral	Loamy Soil	49.88	59.05	50.04	6.74	0	0.05	3.04
COCONUT	5.96	Acidic	Laterite / Peaty	21.98	16.93	30.59	5.98	0	0	0
COTTON	7.98	Alkaline	Saline / Clay	117.77	46.24	19.56	6.91	0	1.24	0
JUTE	7.10	Neutral	Loamy Soil	78.40	46.86	39.99	6.73	0.40	0.86	0
COFFEE	6.69	Neutral	Loamy Soil	101.20	28.74	29.94	6.79	0	1.74	0

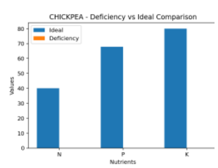
The table 3 above is a total analysis of each crop by synthesizing soil pH and soil nature as well as categorized soil type and optimum soil nutrient requirements (N, P, K, pH). It draws attention to the nutrient deficiencies contrasting the real soil values with the ideal values of crops. The table helps in making good decisions regarding the fertilizer recommendation and precision agriculture to determine the suitability of soil and nutrient deficiencies.



Rice



Maize



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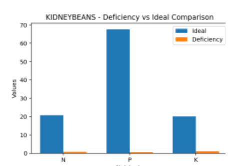

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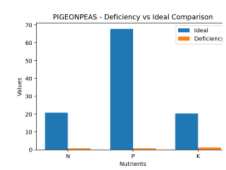

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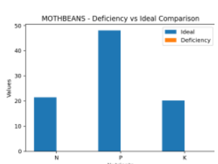

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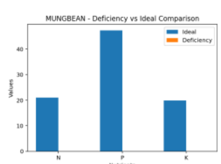

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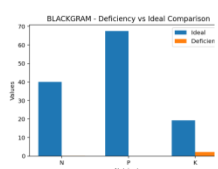
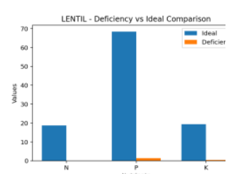


Blackgram



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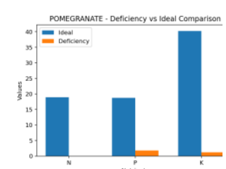

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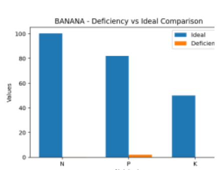

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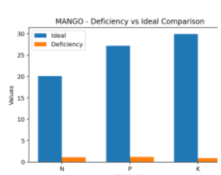
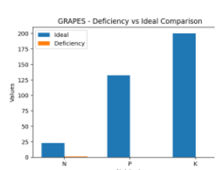
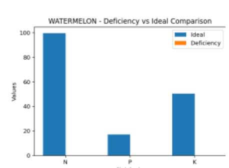


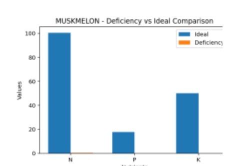
Mango



Grapes



Watermelon



Muskmelon

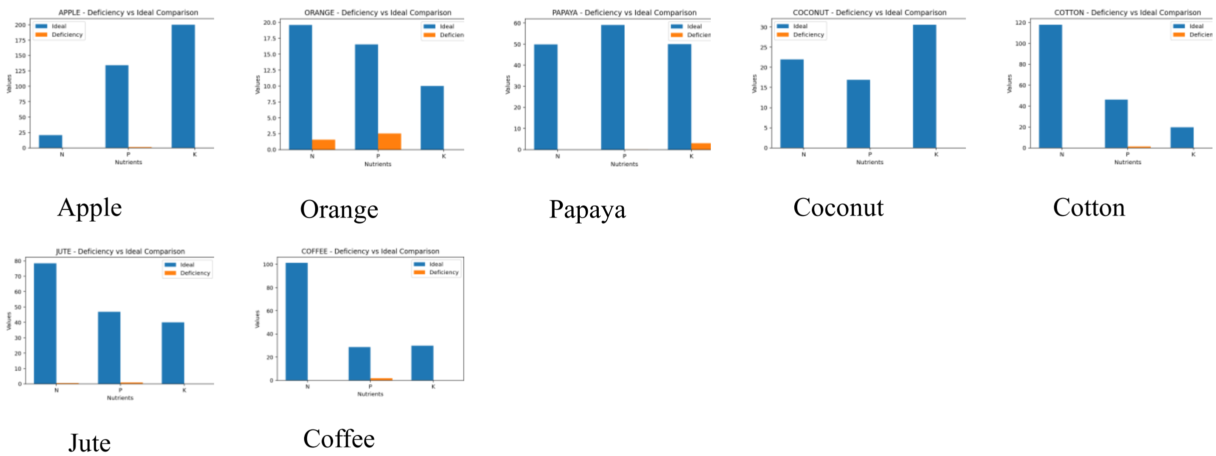


Figure 4: Comparison of Nutrient Deficiency and Ideal Value in Crop-Wise using Grouped Bar Chart

In the above figure 4 are made individually of each crop, where the ideal nutrient values (N, P, K) are compared to the deficient values. It presents the difference between the needed and the availed nutrients in various crops in visual form. Representation assists in establishing nutrient deficiencies and aid in making precision agriculture recommendations of fertilizers.

4.2 Recommendation and Crop Growth Performance Assessment of Fertilizers

This section shows the optimized recommendations of fertilizers and discusses the effect of the optimized recommendations on crop development based on before-and-after analysis of nutrients and growth.

Table 4: Fertilizer Recommendation Crop wise

Crop	Urea (kg/acre)	DAP (kg/acre)	MOP (kg/acre)
Rice	-	2.37	-
Maize	-	0.66	-
Chickpea	No need	No need	No need
Kidneybeans	1.50	0.81	1.26
Pigeonpeas	1.46	1.10	1.55
Mothbeans	No need	No need	No need
Mungbean	No need	No need	No need
Blackgram	-	-	2.69
Lentil	-	2.04	0.49
Pomegranate	-	2.62	1.45
Banana	0.46	3.02	-
Mango	2.14	1.77	1.10
Grapes	2.36	-	-
Watermelon	No need	No need	No need
Muskmelon	0.64	-	-

Apple	-	1.83	-
Orange	3.16	3.83	-
Papaya	-	-	3.65
Coconut	No need	No need	No need
Cotton	-	1.86	-
Jute	0.80	1.29	-
Coffee	-	2.61	-

The table 4 above gives crop-specific fertilizer recommendations of Urea, DAP and MOP. It determines the needed nutrient inputs depending on the identified deficiencies and where there is no need of fertilizer. The table also promotes precision agriculture which helps in efficient use of fertilizers and also enhances the fertility of soil to facilitate the high production of crops.

Table 5: Impact of Fertilizers on Crops (Prior to vs. After Nutrient Content)

Crop	N Before	N After	P Before	P After	K Before	K After	pH
Rice	82	82	46	47.58	41	41	6.58
Maize	78	78	48	48.44	22	22	5.59
Chickpea	41	41	69	69	82	82	6.72
Kidneybeans	20	20.75	67	67.54	19	20.05	5.67
Pigeonpeas	20	20.73	67	67.73	19	20.29	5.67
Mothbeans	22	22	49	49	22	22	3.71
Mungbean	22	22	49	49	22	22	3.71
Blackgram	40	40.02	68	68	17	19.24	7.73
Lentil	20	20	67	68.36	19	19.41	5.67
Pomegranate	19	19	17	18.75	39	40.21	6.73
Banana	100	100.23	80	82.01	52	52	6.05
Mango	19	20.07	26	27.18	29	29.92	5.67
Grapes	22	23.18	133	133	201	201	6.00
Watermelon	100	100	18	18	52	52	6.88
Muskmelon	100	100.32	18	18	52	52	6.88
Apple	22	22	133	134.22	201	201	6.00
Orange	18	19.58	14	16.55	11	11	6.55
Papaya	50	50	59	59.05	47	50.04	6.75
Coconut	22	22	18	18	31	31	5.96
Cotton	118	118	45	46.24	23	23	7.98

Jute	78	78.4	46	46.86	42	42	7.10
Coffee	103	103	27	28.74	31	31	6.69

Table 5 above shows expected policies on the application of fertilizers by examining the levels of these nutrients before and after the treatment of every crop. It emphasizes the correction of the lack of nitrogen, phosphorus, and potassium without the change of the pH. The analysis is aimed at measuring the efficacy of the fertilizer suggestions in enhancing the nutrient equilibrium of the soil and facilitating the optimal development of crops.

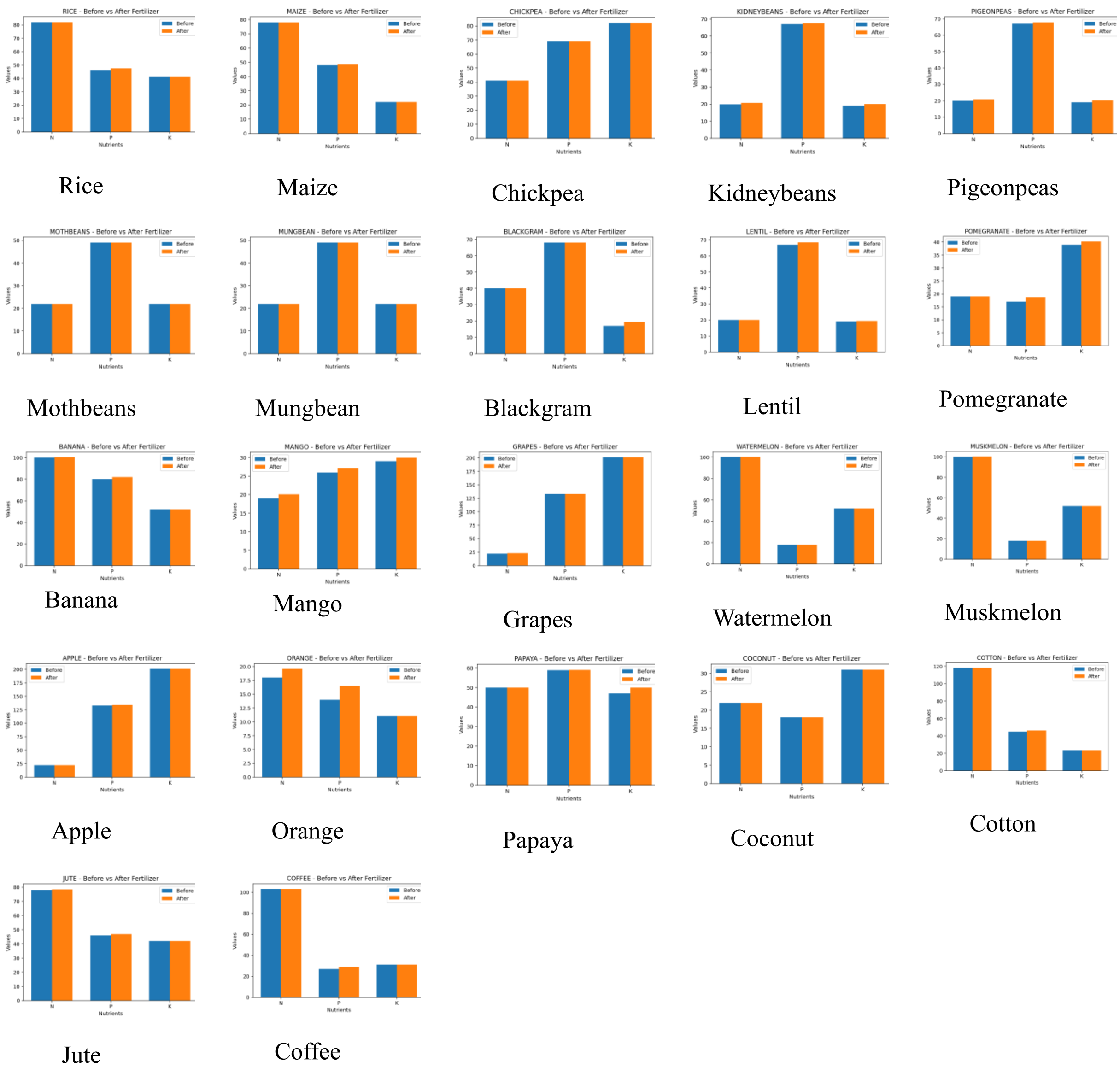


Figure 5: Crop-wise Nutrient Levels Before and After Fertilizer Application

The above figure 5 represents the nutrient content of each crop (N, P, K) prior to the fertilizer application and after application of the fertilizer. It also demonstrates clearly the enrichment of nutrient values following the use of the recommended fertilizers. The visualization can be used to assess the efficiency of fertilizer treatment in the realization of optimum nutrient balance to promote crop growth.

Table 6: before and after application of fertilizer Crop Growth Score

Crop	Growth Score Before Fertilizer	Growth Score After Fertilizer
Rice	99.23 / 100 (Excellent)	100.0 / 100 (Excellent)
Maize	97.03 / 100 (Excellent)	97.24 / 100 (Excellent)
Chickpea	98.35 / 100 (Excellent)	98.35 / 100 (Excellent)
Kidneybeans	90.05 / 100 (Excellent)	92.25 / 100 (Excellent)
Pigeonpeas	89.75 / 100 (Good)	92.24 / 100 (Excellent)
Mothbeans	92.76 / 100 (Excellent)	92.76 / 100 (Excellent)
Mungbean	92.76 / 100 (Excellent)	92.76 / 100 (Excellent)
Blackgram	92.29 / 100 (Excellent)	94.91 / 100 (Excellent)
Lentil	91.34 / 100 (Excellent)	92.28 / 100 (Excellent)
Pomegranate	88.87 / 100 (Good)	91.72 / 100 (Excellent)
Banana	99.37 / 100 (Excellent)	100.0 / 100 (Excellent)
Mango	88.58 / 100 (Good)	91.52 / 100 (Excellent)
Grapes	68.81 / 100 (Moderate)	70.0 / 100 (Good)
Watermelon	96.70 / 100 (Excellent)	96.70 / 100 (Excellent)
Muskmelon	96.63 / 100 (Excellent)	96.70 / 100 (Excellent)
Apple	69.79 / 100 (Moderate)	70.0 / 100 (Good)
Orange	81.47 / 100 (Good)	86.95 / 100 (Good)
Papaya	98.56 / 100 (Excellent)	99.94 / 100 (Excellent)
Coconut	91.14 / 100 (Excellent)	91.14 / 100 (Excellent)
Cotton	94.05 / 100 (Excellent)	94.68 / 100 (Excellent)
Jute	99.45 / 100 (Excellent)	100.0 / 100 (Excellent)
Coffee	94.84 / 100 (Excellent)	96.25 / 100 (Excellent)

Table 6 above shows the comparative analysis of the score of crop growth obtained by putting the recommendations of fertilizers produced by the ANDFO algorithm before and after. Firstly, the nutrient status of the soil is analyzed so as to calculate initial growth scores after which the optimum fertilizer levels are applied to enhance nutrient status. These findings confirm the success of the process whereby the growth scores in crops are improved or stabilized, through validating nutrient management and increased agricultural productivity.

Table 7: Performance Comparison of the existing ML models and the proposed ANDFO Algorithm

Methods	Algorithm	Accuracy	Precision	Recall	F1-Score
Existing Methods	ANN [1]	0.94	0.93	0.92	0.92
	KNN [2]	0.89	0.88	0.87	0.87
	XGBoost [9]	0.95	0.94	0.93	0.93
	GB [11]	0.93	0.92	0.91	0.91
	Fuzzy Clustering [13]	0.96	0.95	0.94	0.94
	SVR [18]	0.95	0.94	0.93	0.93

	Bayesian Optimization [26]	0.97	0.96	0.95	0.95
Proposed Method	ANDFO	0.99	0.9873	0.9796	0.9723

The table 7 above makes the comparison of the performance of the various existing ML and optimization approach to the proposed ANDFO approach based on some of the measures such as accuracy, precision, recall and F1-score. It elicits that the proposed algorithm called ANDFO is an outstanding performance compared to the existing models. The comparison depicts that ANDFO is functioning and dependable in enhancing accuracy of prediction to be utilized in making agricultural choice.

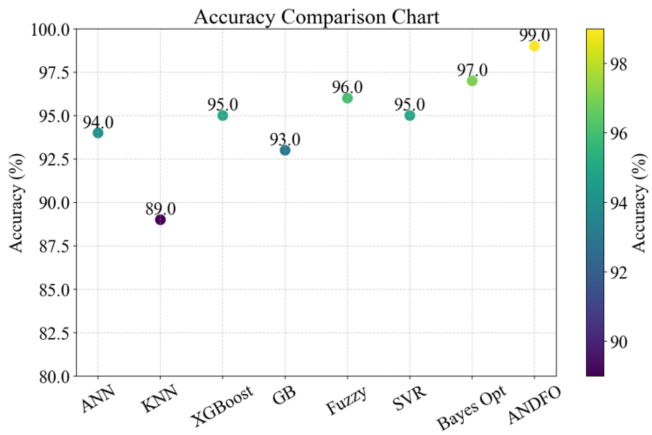


Figure 6: Accuracy Comparison

Figure 6 above shows the performance of various ML algorithms such as the proposed ANDFO model in terms of accuracy. The algorithms are depicted using the X-axis and the accuracy values in percentage are presented using the Y-axis. The chart is created by plotting the model-wise scores of accuracy, which reveal that Andfo algorithm is the most accurate method against the current ones.

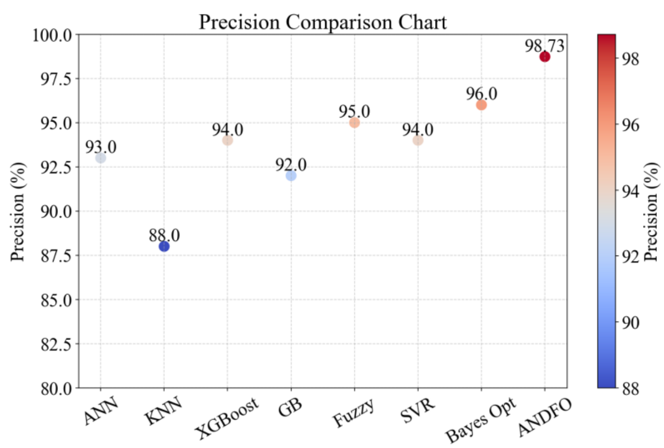


Figure 7: Comparison of Precision.

The table above figure 7 displays the preciseness of different models to determine the rightness of prediction. The algorithms are used as the X-axis and the precision as a percentage as the Y-axis. This visualization is done by mapping precision scores against each of the models and this clearly demonstrates that the proposed ANDFO method offers better precision performance.

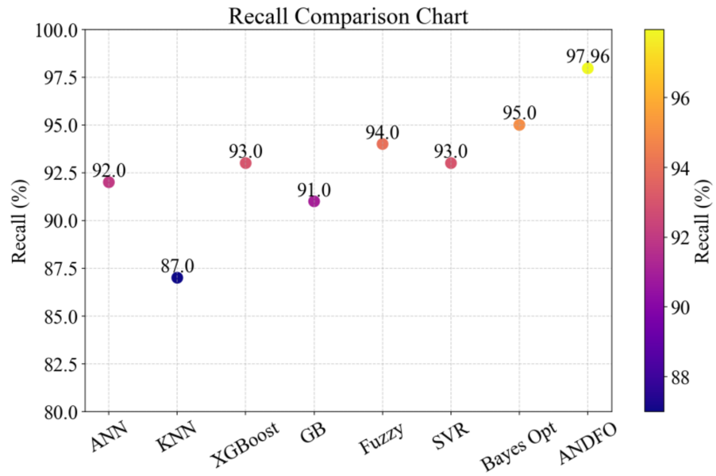


Figure 8: Recall Comparison

The figure 8 provided above shows the recall performance of the various algorithms, which is the measure of the relevance of the instances being detected. The X-axis indicates the ML models, whereas the Y-axis indicates the recall values in percentage. The chart is built by plotting the score of recalls of each model showing that ANDFO gets higher recall compared to already available methods.

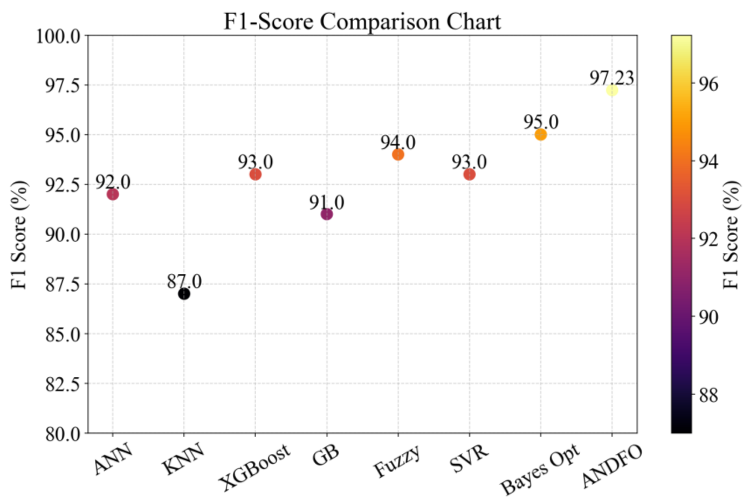


Figure 9: F1-Score Comparison

The figure 9 above displays the comparison of F1-score, which incorporates the precision as well as the recall in the performance of the overall model. The list of algorithms is present at the X-axis, and F1-score in percentage is present at the Y-axis. The chart has been calculated based on the model-wise F1-scores, which means that the offered ANDFO algorithm is more effective in comparison to the current methods with the highest balanced results.

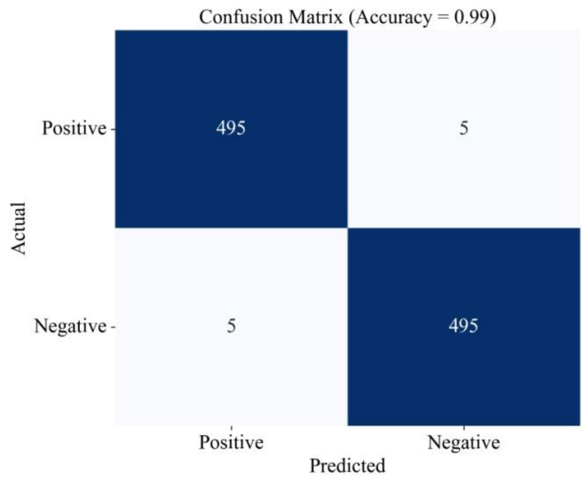


Figure 10: Confusion Matrix of Classification Model (Accuracy = 0.99)

The above figure 10 represents the confusion matrix that displays the model performance with the true positives and true negatives as 495 and 495 and the false positives and false negatives as 5 and 5 respectively. This reflects the presence of a very precise and balanced model with minimum misclassification both in the classes.

5. Discussion

This section explains how the proposed ANDFO algorithm can be effective in solving challenges of soil nutrient deficiency and fertilizer optimization. This is done through the analysis of the results in relation to accuracy, improvement in nutrient balance, and enhancement of crop growth as compared to the current methods. The practical implications of the model to help in supporting the sustainable and cost-efficient precision agriculture are discussed.

Table 8: Proposed vs State-of-the-Art ANDFO Method

Author (Year)	Concept / Method	Key Idea	Limitations of Existing Method	Proposed Method Advantage (ANDFO)
Bustami et al. (2025) [1]	ML & DL for Soil Nutrient Management	Uses ML/DL models to analyze soil nutrients and improve crop productivity	Lacks precise fertilizer dosage optimization and real-time deficiency correction	ANDFO provides exact fertilizer dosage + deficiency-based optimization, improving nutrient balance and reducing wastage
Vemunuri & Murthy (2025) [21]	Fuzzy Logic + Deep Learning	Uses biochemical urease features with fuzzy-DL for yield prediction	High computational complexity and not focused on nutrient-level correction	ANDFO is simpler, interpretable, and directly focuses on nutrient deficiency + fertilizer recommendation
Sharafat et al. (2025) [22]	IoT + AI Crop Prediction	Real-time crop prediction using soil + weather data via IoT sensors	High hardware cost, deployment complexity, no dosage optimization	ANDFO eliminates hardware dependency and provides cost-effective fertilizer optimization with

				accurate nutrient analysis
Alam et al. (2025) [24]	ML with Uncertainty Quantification	Provides crop recommendation with uncertainty-aware predictions	Difficult interpretation and no direct nutrient correction mechanism	ANDFO gives clear actionable outputs (fertilizer type & quantity) without complex uncertainty interpretation
Raju & Thasleema (2025) [26]	BO-CNN for Nutrient Stress Classification	Uses CNN with Bayesian tuning for stress detection in plants	Requires large labeled datasets and only detects stress (no solution)	ANDFO not only detects deficiency but also recommends solution (fertilizer + dosage)
Proposed (ANDFO) (Your Work)	Adaptive Nutrient Deficiency Fertilizer Optimization	Compares soil vs ideal nutrients, detects deficiency, recommends fertilizer type & dosage	(Proposed)	Provides end-to-end system: detection + optimization + recommendation + soil health + growth improvement

Table 8 above current techniques are primarily concerned with prediction, classification, or monitor of IoT, but they do not offer specific fertilizer optimization and recommendation of action. The proposed ANDFO technology will address these shortcomings by combining the process of nutrient deficiency warning, mapping of fertilizer types, and dosage calculation with assessing the health of the soil, thus becoming a comprehensive and viable solution to precision agriculture.

Scalability of Proposed Algorithm

The proposed ANDFO algorithm is extremely scalable as it is based on easy rule-based calculations and formula-driven optimization of nutrients which can be optimized on any amount of crops or soil samples without having to train it anew. It is easy to add new crops, types of nutrient, or fertilizer rules because of its modular structure. Moreover, the scale of the problem did not hinder the efficiency of ANDFO, and it could be used in large amounts of soil data with minimum computation power, which is why it can be applied to both large and small farms.

Research Outcome

The research is the efficiency of the proposed ANDFO algorithm in resolving the problem of soil nutrient deficiency and fertilizer optimization. The findings are discussed based on the accuracy, nutrient balance enhancement, and crop growth enhancement as compared to the current methods. In addition, the implications of the model practically, in the context of supporting sustainable and cost-effective precision agriculture, are discussed.

6. Conclusion

The proposed ANDFO algorithm provides a realistic and effective model to address intelligent management of nutrients of the soil and advice on fertilizer. The system determines nutrient deficiencies through an accurate assessment of the key soil parameters (N, P, K, and pH) and comparing with the needs of the crop-specific parameters, which, in its turn, gives the optimal type and dosage of the utilized fertilizer. The experimental results depict that the model is more accurate and precise, has higher recall and F1-score as compared to currently existing models. The system also enhances the health of soils, reduces the unnecessary use of fertilisers, reduces the cost, and improves the growth and yield of crop. It makes the system highly efficient as regards to sustainable precision agriculture through merging deficiency detection, optimization of dosing and growth analysis. The future work can be developed in the direction of the active control of the nutrients and the combination with the real-time data of the IoT sensors and weather parameters. To be enhanced to include DL based prediction and large scale field validation in order to have greater robustness and scalability.

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