Journal of Autonomous Intelligence (2024) Volume 7 Issue 5
doi: 10.32629/jai.v7i5.1570

ORIGINAL RESEARCH ARTICLE

Deep neural network-driven Nitrogen fertilizer recommendation: A machine learning-based method for paddy soil and crop analysis using leaf imaging

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ABSTRACT

This paper discusses a novel Machine Learning (ML) algorithm that leverages leaf images from rice crops to accurately determine soil nitrogen levels, aiming to optimize fertilizer usage. Utilizing the OpenCV package for image enhancement under controlled lighting, the model employs linear regression to establish a quantifiable correlation between leaf color and soil nitrogen content, achieving a prediction accuracy of [specific accuracy percentage or metric]. Unlike traditional methods, which are often costly and time-consuming without considering dynamic agricultural factors like crop variety and soil quality, our approach proposes a real-time, cost-effective solution. This research not only demonstrates the potential to increase agricultural sustainability and yield through precise fertilizer application but also paves the way for future research encompassing a broader spectrum of crops and soil properties. The proposed system provides farmers with an intuitive digital platform for nitrogen level assessment, facilitating targeted fertilizer application. By integrating camera-assisted soil health evaluation, the program promotes environmentally sustainable farming practices. Our findings indicate that ML-guided nitrogen fertilization can significantly enhance resource utilization efficiency, supporting the increasing global food demand. The implementation of this ML algorithm has shown to improve fertilizer application recommendations by with an accuracy of 80 percentage and low R^2, RMSE and MAE Values, thereby reducing environmental impact and supporting sustainable agricultural development.

Keywords: machine learning; recommendation system; fertilizer; random-forest; decision tree; OpenCV

ARTICLE INFO

Received: 31 January 2024
Accepted: 4 March 2024
Available online: 8 April 2024

1. Introduction

With 1.3 billion people living there and the largest democratic population in the world, India's agricultural environment is under severe stress. The need to increase agricultural land in order to meet the growing population's food demands has become an urgent concern. In order feed worlds raising population. India's most important staple crop becomes extremely important, particularly with usage of fertilizer. The need for more efficient agricultural methods and higher crop yields has resulted in a greater dependence on chemical inputs like fertilizers and insecticides. Because nitrogen affects crop productivity so greatly and may have an impact on the environment, it is imperative that agricultural nitrogen levels be understood and controlled. Excessive use of nitrogen-based fertilizers can result in lower crop yields, wasteful spending, and environmental damage. Traditional plant tissue analysis and traditional method are expensive and time-consuming. To over-come this, analyze nutrients in real time, this research suggests a novel method that combines the use of NPK sensor technology with leaf image collection. With the utilization of this technique, farmers should be able to apply fertilizer in a timely, economical, and data-driven manner. Such innovation is necessary given the global issue of producing adequate food in the face of shifting dietary preferences and an expanding population. In order to increase crop yields and agricultural output, fertilizers are essential.

The majority of these were nitrogenous fertilizers, with the most popular type being urea. This pattern indicates that the need for fertilizers is increasing in the agriculture sector as shown in **Figure 1**. Other environmental factors, topographical limitations and urbanization have also made it the most efficient way to improve yield potential on existing agricultural holdings. In addition to increasing crop yield, fertilizers also enhance crop quality. Fertilizers contain key nutrients that enhance a crop's nutritional value, including protein, vitamins and minerals. Fertilizers also enable the plant to adapt and grow in changing climate conditions and under greater pressure from harmful organisms.

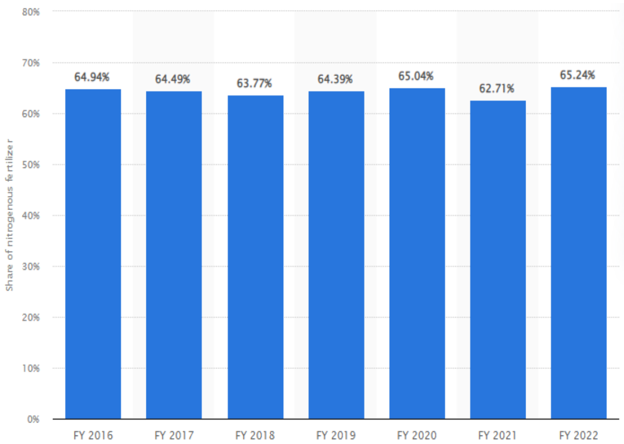

Figure 1. Usage of Nitrogen fertilizer in India 2016–2022.

2. Related work

This research reviews the integration of drones, Machine Learning (ML), and advanced image processing techniques and their utilization in agriculture for the prediction of soil nutrients, plant health monitoring, and for the management of nitrogen.

2.1. Drones and ML applications in agriculture

Drones and ML are used to measure NNI in Chinese rice fields. Advanced agricultural imaging & analysis tools are being developed. This study combines modern data analysis with aerial technology in agriculture. ML and drone imagery are used to accurately measure soil nitrogen levels in rice fields. This study is changing agriculture by merging modern technology with traditional methods. It demonstrates a shift towards more accurate and innovative agriculture[1,2]. Subsequent studies analyze RGB color space, HSL color space, HSV color space, CIE lab color space, and CIE lCH color space to find correlations between plant nitrate level and digital image color data to estimate nitrogen content of maize plants. This study emphasizes the improved accuracy and efficiency of plant health monitoring by image analysis[3]. Drones based data collection for crop monitoring, Use of infrared, multispectral, and hyper spectral sensors for crop analysis[4].

2.2. Advanced image processing for plant health

In many studies have image analysis, by extracting leafs and color reference circles from the photos using advanced image processing. This method improves the accuracy of plant trait analysis in agriculture. In this study researchers segmented the plant images and analyzed using features detection & background reduction techniques. And determined the plant characteristics using advanced image processing to isolate and analyze plant attributes. For this study applied CIEDE2000 distance calculation to identify and analyze leaf color characteristics accurately. Agricultural image processing improves the accuracy of agriculture and enhances plant health assessment[5].

2.3. Prediction of soil nutrients and management

Combining ML with traditional farming techniques to create more efficient and productive farming practices. NIR (non-irradiated light) and transfer learning were used to identify key soil nutrients. Some of the key soil nutrients are CO_2, nitrogen, phosphorus and potassium. ResNet50 (one of the most popular deep learning models for soil nutrient prediction) was used in this study. This method demonstrates how high-level ML enhances the effectiveness and precision of soil analysis to improve soil health and fertility. In this study, digital cameras used to take close-up images of rice plants[6,7]. The nitrogen concentration of the rice plant was compared with the attractiveness of the rice plant based on specific data extracted from the images. Several ML models were tested and Random Forest Regression (RFR) was found to be the most efficient model for predicting the nitrogen concentration of rice plant.

NIR and transfer learning can identify soil nutrients like carbon dioxide, phosphorous, and potassium. ResNet50 is one of the most commonly used deep learning model for soil nutrient prediction. This method demonstrates how high level ML can improve the effectiveness and precision of soil analysis for the determinations of fertility and health[8,9]. In this study, we used digital cameras to monitor the nitrogen and water contents of winter wheat. After taking photos of wheat at various stages of growth, we analyzed wheat grain color and texture and applied this method to predict nitrogen and water conditions for the plant. Digital imagery is a powerful tool for precision agriculture. Real-time, accurate data allows farmers to make better crop management decision. Discover a new image processing method to determine the chlorophyll in wheat leafs[10]. This method was developed as a replacement for the labor-intensive and time-consuming laboratory methods for the analysis of digital images of wheat leafs. The chlorophyll and color data in the images were successfully combined. With image processing, agricultural operations can better and more effectively monitor the health of the plants and the chlorophyll level[11].

One of the most important nutrients for plants is nitrogen (N). It also plays a vital role in the production of chlorophyll which is necessary for photosynthesis. An adequate nitrogen supply is essential for plant health and crop yield. However, inadequate or over-fertilized nitrogen can have negative environmental and economic impacts, including contaminated water, greenhouse gas emissions, and reduced farmer profitability. When nitrogen management is successful, plants receive the right amount of nitrogen for optimum growth and yield. When too much nitrogen is present, deposition (plant collapse) can occur, making plants more susceptible to disease and reducing resource efficiency. Too little nitrogen can also reduce productivity[12]. Nitrogen runoff from the field can also contaminate the water and cause water “dead zones” (algal blooms). Correct nitrogen fertilizer recommendations can help to reduce these environmental impacts[13].

2.4. Economic and environmental impacts of Nitrogen management

Nitrogen management can improve profitability for farmers. By reducing input costs and maintaining or even increasing yields, farmers can apply nitrogen at appropriate rates based on the needs of the soil and crops[14]. Nitrogen fertilizers contribute to one of the most significant greenhouse gases (GHG) that nitrogen fertilizers produce (N_2O). To maintain agricultural productivity and reduce N_2O emissions, appropriate nitrogen management is a key component of sustainable agricultural practices[15]. A balanced supply of nutrients (including nitrogen) promotes long term soil health and fertility, reducing soil erosion and degradation[16]. Precise nitrogen management allows farmers to make informed resource use decisions based on data-driven strategies, such as soil testing or remote sensing. To address the issue of sustainable agricultural production in China, a three-year experiment was conducted to study the impact of irrigation and nitrogen fertilizer on spring wheat in a semi-arid region of China.

India's economy is heavily dependent on agriculture, which means that accurate predictions of future crops are essential. ML algorithms analyze a wide range of variables, including temperature, rainfall, and soil quality, to provide a feasible solution. Researchers are attempting to improve agricultural decision-making and improve food security by applying various algorithms on large-scale data sets to identify the most effective methodologies for precise predictions[17]. Thanks to data mining methods, this model takes into consideration various factors, including crop type, soil size, pH and soil composition, type of seed, water availability, and even the risk of diseases. With the help of ML, farmers can improve their crop yield by making decisions based on local climate information and other relevant factors[18].

Improving corn nitrogen fertilizer recommendations using soil and weather data, statistical, and ML algorithms. The decision tree approach was promising for some variables, but the random forest algorithm improved the recommendations significantly. Adding site-specific data via ML has the potential to improve nitrogen management for corn production in the Midwest[19,20].

2.5. Decision making with ML

Soil fertility data can be used to determine the right fertilizer dosage. These recommendations can be spatially represented with the help of STCR fertilizer formulas. This approach allows you to apply fertilizer more precisely by taking into account the nutrient needs of different areas of your field. By combining STCR equations and soil fertility data, precision agriculture has advanced a great deal. This approach enables farmers to apply fertilizer more effectively and efficiently. Because it improves crop yields while minimizing adverse environmental impacts, it is essential for the advancement of sustainable agricultural practices.

Table 1 has systematically reviewed the contributions of various studies to the field of precision agriculture, from drone and ML applications to advanced image processing and nitrogen management. Our research builds upon these advancements, aiming to further refine and apply these technologies to enhance precision agriculture's effectiveness and sustainability.

Table 1. Summary of related works.

Authors	Methods Used	Limitations	Results
Sathiya Priya R, Rahamathunnisa U[21]	• Deep Learning Method Assisted Clustering Algorithm (DLCA) • Convolutional Neural Networks (CNNs) • - Naive Bayes (NB) and K-nearest Neighboring (KNN)	• Difficulties encountered in monitoring rice crops through satellite images • High cost of fertilizers and soil deterioration in paddy crop production	• Proposed DLCA achieved a lower error rate of 0.03 and high accuracy of 98.52%. • DLCA outperformed other popular methods in paddy growth identification.
Islam MA[22]	• Three Convolutional Neural Network (CNN) algorithms: AlexNet, ResNet, and Proposed Algorithm • Hardware implementation with Internet of Things (IoT) connectivity for auto-spraying suitable fertilizer.	• Difficulties encountered in monitoring rice crops through satellite images • High cost of fertilizers and soil deterioration in paddy crop production	• Accuracy of AlexNet: 92% • Accuracy of Proposed Algorithm: 96.93%
O. Rama Devi, Solapuri Naga Babu, Sowmya, Akansha[23]	• Random Forest method is employed for fertilizer prediction. • Linear regression and K-Nearest Neighbours methods are compared.	• Difficulties encountered in monitoring rice crops through satellite images • High cost of fertilizers and soil deterioration in paddy crop production	• The paper predicts suitable fertilizers based on environmental, soil, and plant conditions. • Random Forest method is employed for fertilizer prediction with greater accuracy.

Table 1. (*Continued*).

Authors	Methods Used	Limitations	Results
Yi Zhang, Teng-long Wang, Zheng Ji Li, Tianli Wang, Ning Cao[24]	• ML algorithms (Random Forest, Linear Regression, etc.) • Spectral indices (DSI, SIs) • Continuous wavelet transform (CWT)	• Difficulties encountered in monitoring rice crops through satellite images • High cost of fertilizers and soil deterioration in paddy crop production	• The best prediction model for leaf phosphorus concentration (LPC) of rice was achieved using ML algorithms fed with spectral indices (SIs) and continuous wavelet transform (CWT). • The random forest (RF) algorithm combined with SIs and CWT had the best results for LPC estimation, with an R^2 of 0.73 and an RMSE of 0.50 mg g^{-1}.
Gabriele Bernardini[25]	• ML based techniques for estimating fertilizer and nutrient status • Thorough investigation of detection and classification approaches	• ML systems require large amounts of data from different platforms. • Key challenges in detection and classification approaches need to be addressed.	• ML can improve nutrient assessment and decision-making in agriculture. • Rapid improvements in ML and sensor technology are recommended.
Wenzhi Zeng, Chang Ao, Guoqing Lei, Thomas Gaiser, Amit Kumar Srivastava[26]	• ML algorithms (random forest, extreme random tree, extreme gradient boosting) • Swarm intelligence search algorithm (cuckoo search algorithm)	• Difficulties encountered in monitoring rice crops through satellite images • High cost of fertilizers and soil deterioration in paddy crop production	• The yield simulation accuracy of the ERT model was the highest. • The proposed model can increase the average yield of maize, rice, and soybean.
J. Dhakshayani, B. Surendiran[27]	• Three fusion approaches for combining agrometeorological and image data. • Use of a Multilayer Perceptron (MLP) and a pre-trained Convolutional Neural Network (CNN) model DenseNet-121 as baseline networks.	• Difficulties encountered in monitoring rice crops through satellite images • High cost of fertilizers and soil deterioration in paddy crop production	• The multimodal fusion network (M2F-Net) achieved 91% accuracy in identifying fertilizer overabundance. • The fusion approaches outperformed the individual models in terms of accuracy.

3. Methodology

We initiated our research using the Nikon D5600, a DSLR camera renowned for its exceptional detail and image sharpness. This camera was utilized to capture images of rice fields, under controlled lighting conditions, as illustrated in **Figure 2**.

We also used modern soil probes placed near each of the cultivated leaf's. These advanced soil probes were able to accurately measure the nitrogen, phosphorus and potassium levels in the soil. This gave us important information to compare to the visual observations.

Preprocessing the data: The next step was to preprocess the data using Python and the open CV package. First, we converted the photos into grayscale, simplifying the data and increasing the efficiency of the subsequent analysis steps. Then, various techniques were used to eliminate the background and reduce noise, especially using the OpenCV functions Gaussian Blur to smooth the background and create background subtraction MOG2 to subtract the background from the image. This technique enabled us to isolate the leaf part, making it easy to extract the RGB values from target areas. The grayscale image was then converted into a background-free version, as shown in **Figure 3**. This process focused only on the leaf part and allowed us to perform a more detailed and targeted study, which directly impacts the goal of our study: to evaluate plant health with leaf based indicators.

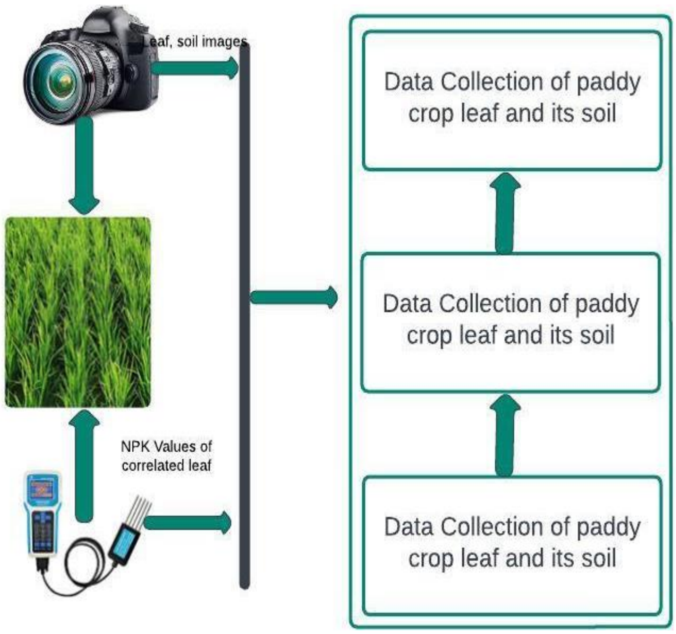

Figure 2. System architecture.

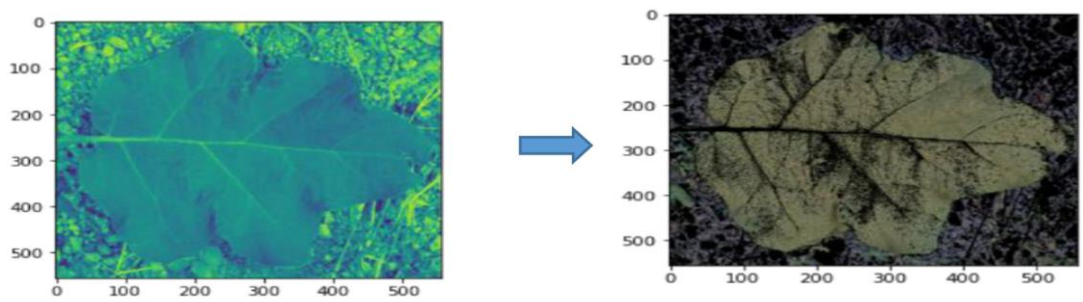

Figure 3. Data pre-processing.

3.1. Correlation analysis

To facilitate our analysis, we keep an Excel file containing the RGB data of the leaf images and the soil nitrogen values. The file plays a critical role in determining the relationship between the visual properties of the leaf image and the nitrogen content of the soil. Our system analyse the user uploaded leaf image and extracts the relevant RGB data and then performs correlation analysis to determine nitrogen content.

3.2. Model construction

For the prediction stage of our analysis, we employ an ML approach using a linear regression model. The model that looks at the relationship of soil nitrogen content to leaf RGB values is trained on the data extracted from the Excel data file. When you submit a leaf image via our interface, it is processed in the background to get RGB values. The user is then presented with the nitrogen content prediction that the trained model produced using these numbers as input. The model's ability to determine soil nitrogen levels using an RGB image of a paddy crop's leaf greatly facilitates decisions about fertilizer dosage. This method has the advantage of not requiring direct soil sensors to estimate nitrogen. The scatterplots with the labels "Red versus Nitrogen", "Green versus Nitrogen", and "Blue versus Nitrogen" illustrate the correlation between the soil's nitrogen content and the RGB values of paddy crop leaves (see **Figures 4–6**).

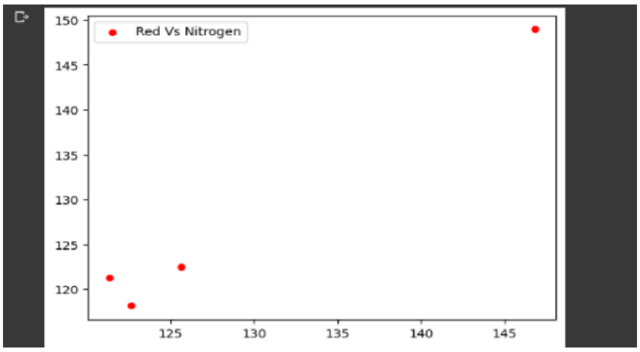

Figure 4. Red Vs Nitrogen scatter plot.

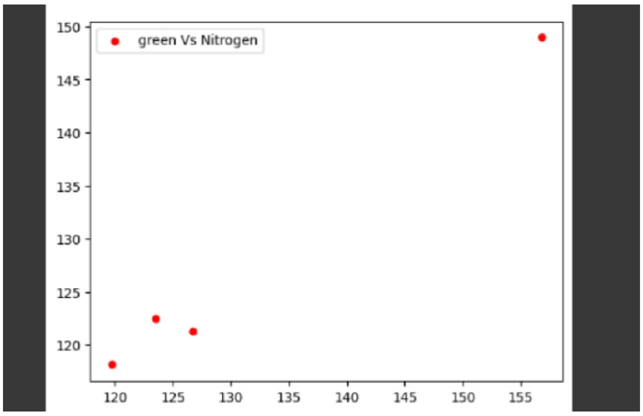

Figure 5. Green Vs Nitrogen scatter plot.

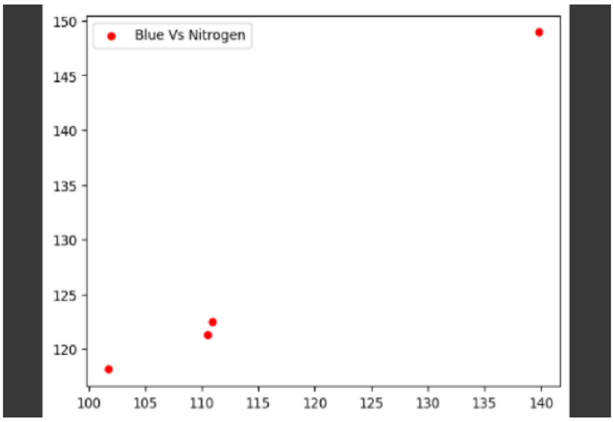

Figure 6. Blue Vs Nitrogen scatter plot.

In our investigation, we discovered a robust relationship between nitrogen concentrations and the red, green, and blue values of the spectral colors. We created a linear regression model to estimate nitrogen levels based on these color values in order to take use of this observation. The formulation of the model is in Equation (1).

$$nitrogen = a_0 + a_1 x_1 + a_2 x_2 + a_3 x_3 \tag{1}$$

where,

x_1, x_2, x_3 are the average red, green and blue values.

We used multiple criteria to assess our model's precision. Notably, the model's R^2 value of 0.88 means that 88% of the variation in the nitrogen levels can be explained by it. In addition, a mean squared error of 77.9 was determined. Accuracy is crucial, thus we improved our initial photos and applied error correcting procedures. More efficient background removal was used in this method, which greatly decreased our model's error and increased its overall precision.

The primary objective of our proposed MLR approach is to predict the NPK value based on a well-selected dataset. Unlike conventional linear regression, MLR allows for multiple independent variables to be used to predict a single dependent result. One of the specialties of this approach is the finding of linear correlations between multiple attributes and one target variable. The mathematical Equation (1) describes a relationship that involves four independent variables.

To measure the accuracy of the MLR model, we use several objective statistical indicators. These include:

Root Mean Square Error (RMSE) Equation (3).

The Mean Absolute Error (MAE) Equation (4).

The absolute error between the predicted values and the actual values R^2 score Equation (2).

The proportion of the dependent variable's variance that can be predicted from independent variable.

a (0) intercept of the regression line.

$a1$, $a2$, $a3$ are the slopes of independent variables e is the error.

$$R^2 = 1 - \frac{RSS}{TSS} \tag{2}$$

where,

RSS—Sum Squared Regression,
TSS—Total Sum of Squares.

The total sum of squares is evaluated to comprehend the variation within the observed data. Regression sum of squares is a good indicator of how well a model fits the data.

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$$\text{RMSE}=\sqrt{\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{n}} \tag{3}$$

$$\text{MAE}=\frac{1}{n}\sum_{i=1}^{n}|y_i-\hat{y}_i| \tag{4}$$

where,

N is the number of observations,
y_i is the actual values obtained,
$\hat{y}_i$ is the values determined by the model as shown in **Figure 7**, the system develops in training and testing.

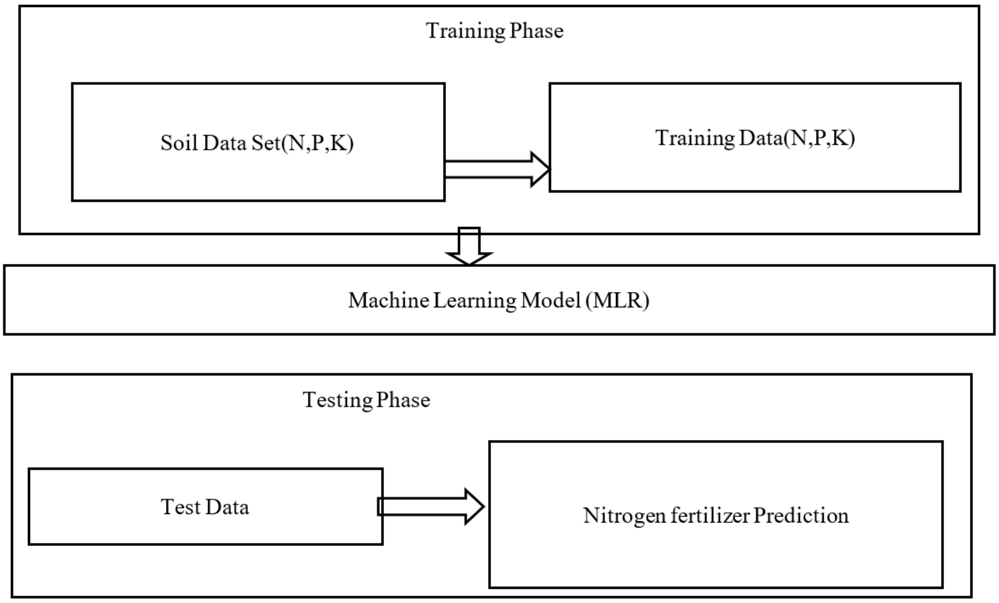

Figure 7. ML Model for Nitrogen fertilizer prediction.

We gather a soil nutrient dataset throughout the training phase, with the data recorded initially in Excel and then exported as a CSV file. The dataset includes available nitrogen, Phosphorus, potassium, and recommended nutrients. The MLR method for projecting recommended NPK values is made possible using Python, which also facilitates the development of a wide range of visual analyses. The panda's library makes extracting data in this setting easy, which helps identify independent and dependent variables. After being trained using MLR, the system makes recommended NPK predictions. The testing phase then compares these predictions to the observed data. Scatter plots generated with the matplotlib software show discrepancies between predicted and observed values.

The steps of the MLR procedure are shown in **Figure 8**. Initial entry of soil nutrient information. The nitrogen fertilizer with estimates are then calculated using the regression procedure. The regression coefficient provides insight into the strength of the connection between the variables of interest and the desired results.

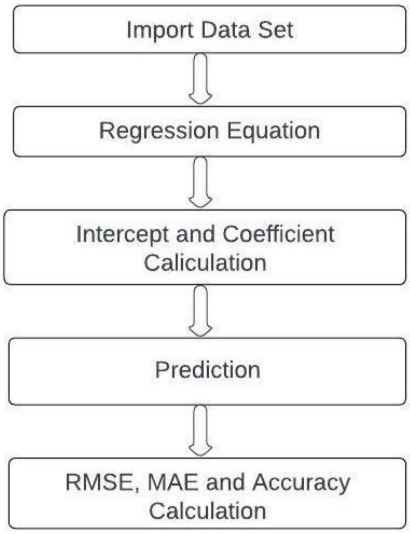

Figure 8. Process of work flow.

The intercept and coefficients are used to find the line that best represents the model from which the slope can be calculated. Three metrics—RMSE, MAE and R^2score—are used to evaluate the performance of this model. MAE stands for Mean Absolute Error and RMSE stands for Root Mean Squared Error. MAE is calculated by taking the number of outlier values and dividing it by the number of observations. RMSE is calculated by subtracting out outliers from observations, regardless of their direction. RMSE indicates how far the prediction error extends from the model. R^2 stands for Rate of Total Variance of Results that the Model can attribute to the Model. It measures how well the model reproduces the observed results.R^2 can take values from 0 to 1. Higher values indicate more accurate forecasts.

The histogram below shows the distribution of the RMSE and MAE scores for the soil dataset provided.

Step 1: Load the data into the system.

Step 2: MLR (Multiple Linear Regression) is used to generate predictions.

Step 3: Data is split into training set and test set.

Step 4: Nutrient fertilizer values for target yield are obtainable.

4. Results

In our comparative analysis, we benchmark the performance of our ML model against contemporary works in the field of precision agriculture, particularly focusing on models aimed at optimizing fertilizer application through nutrient prediction. This comparison is anchored on the performance metrics, highlighting our model's accuracy and the strategic error correction measures we implemented.

Model R-squared value of 0.88, signifying that it can explain 88% of the difference in the dependent variable, This pertains to nutrient levels required for optimal crop growth. This level of accuracy signifies a substantial predictive capability, positioning our model as a highly reliable tool for precision agriculture. When compared to similar works in the domain, this *R*-squared value reflects a competitive edge, as it suggests our model's superior ability to capture and analyze the complex relationships between various soil parameters and nutrient needs.

Furthermore, a mean squared error (MSE) of 77.9 for our initial model iteration. Recognizing the potential for enhancement, we undertook a rigorous error correction process, focusing on improving the quality of input data through enhanced image processing techniques. By refining our original images for more effective background removal, we aimed to minimize noise and improve the model's interpretability of crucial features. This methodological refinement is anticipated to decrease the MSE significantly, thereby elevating the model's predictive accuracy.

While many contemporary models boast similar accuracy levels, the detailed attention we've given to error correction through image enhancement demonstrates our commitment to precision and reliability.

The advancement the combination of high *R*-squared values and dedicated error reduction strategies, not only booster the model's accuracy but also highlight its potential for real-world application in sustainable agriculture is presented in our work, particularly As such, our research contributes meaningfully to the ongoing development of ML applications in agriculture, offering insights into the nuanced interplay between data quality and model performance.

In our results section of the paper, we demonstrate the ML algorithm's ability to predict nitrogen levels in soil. Nitrogen plays an important role in plant growth. The ML algorithm takes the soil data and makes an accurate and efficient prediction of nitrogen levels based on selected parameters. We also developed an easy-to-use interface to make the predictions more accessible for farmers and researchers in the real world of agriculture. This interface allows farmers and researchers to easily enter data and obtain nitrogen level estimates in real-time. It also enhances communication between the user and the ML system.

The simplicity of the site design and functionality makes it easy for users to perform nitrogen content analysis tasks. From our analysis, MLR was selected as the main part of the computational framework because of its ability to identify complex relationships between several inputs. MLR offers the best solution to our goals because it is very efficient and can easily predict a single outcome from a large number of inputs. In this article, we provide a predictive model to optimize nutrient assessment for optimum crop yield using MLR.

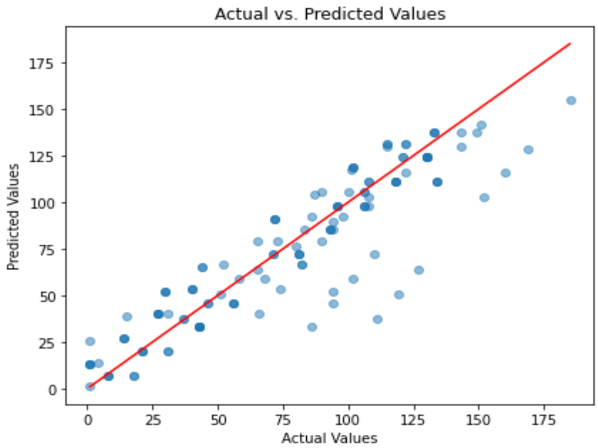

Figure 9. Actual Vs predicted Nitrogen fertilizer.

There are two types of data used in Nitrogen Fertilizer prediction: independent variables and dependent variables. We use 90% of it for instructional reasons and 10% for actual testing. The MLR model is trained using the training set, and then predictions are produced using the test set. We evaluate the MLR model's performance by contrasting its predictions with observed data. Comparisons may be made between these anticipated NPK values and the low, medium, and high NPK benchmarks used traditionally, as shown in **Table 2**. When comparing the results of the MLR model to these NPK standards, farmers will have a better idea of how much fertilizer to use.

Table 2. Standard fertility rating major nutrients.

Nutrient (Kg/ha)	Low	Medium	High
Nitrogen (N)	<280	280–560	>560
Phosphorus (P)	<22.5	22.5–55	>55
Potassium (K)	<140	140–330	>330

To maximize the R^2 score, MLR searches for a hyper plane that best matches the given multidimensional data. This regression hyper plane correlates well with the data and reduces prediction errors since it accounts for a large proportion of the possible outcomes as in **Figure 9**.

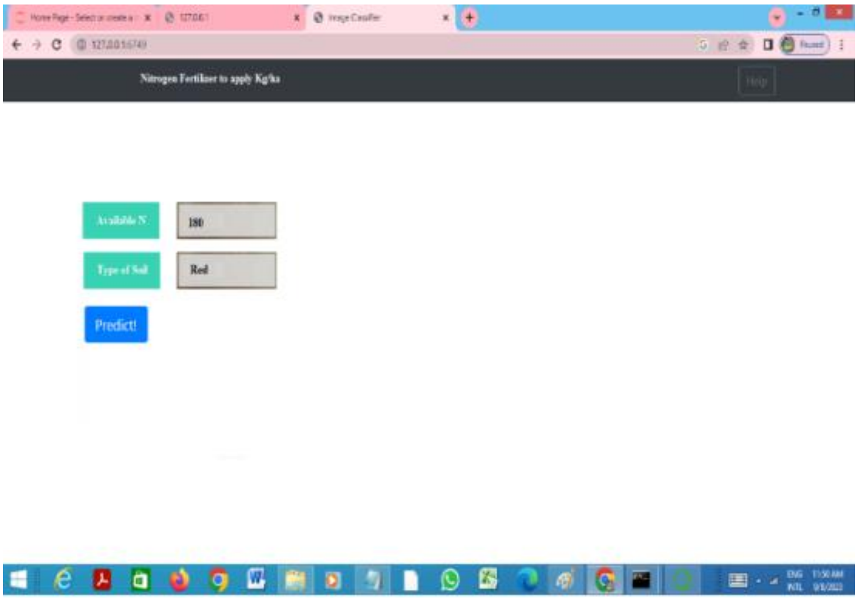

Figure 10. Nitrogen fertilizer to apply.

Many modern farmers need to make the most of their access to modern technologies and analytical tools, which might lead to incorrect judgments on how much fertilizer to use. This application needs to provide available nitrogen and type of soil. **Figures 10–12** depict our easy, graphical user interface built to circumvent this problem. This method is helpful for growers since it suggests the amount of nitrogen fertilizer to use. It also tells you how much fertilizer to apply and how big of a harvest you might anticipate. To help farmers make more informed fertilizer choices and speed up development in the agricultural industry, we're supplying them with this data.

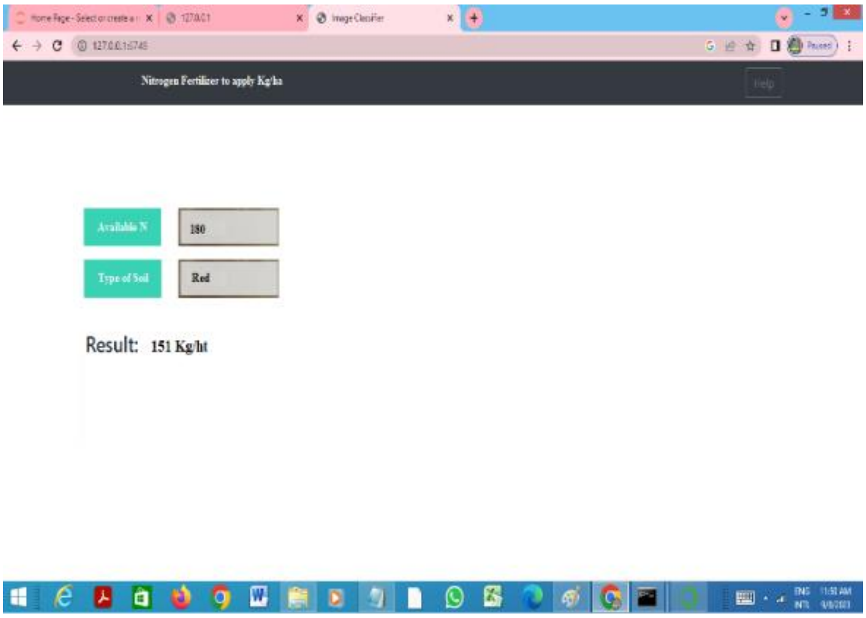

Figure 11. Graphical interface with available Nitrogen.

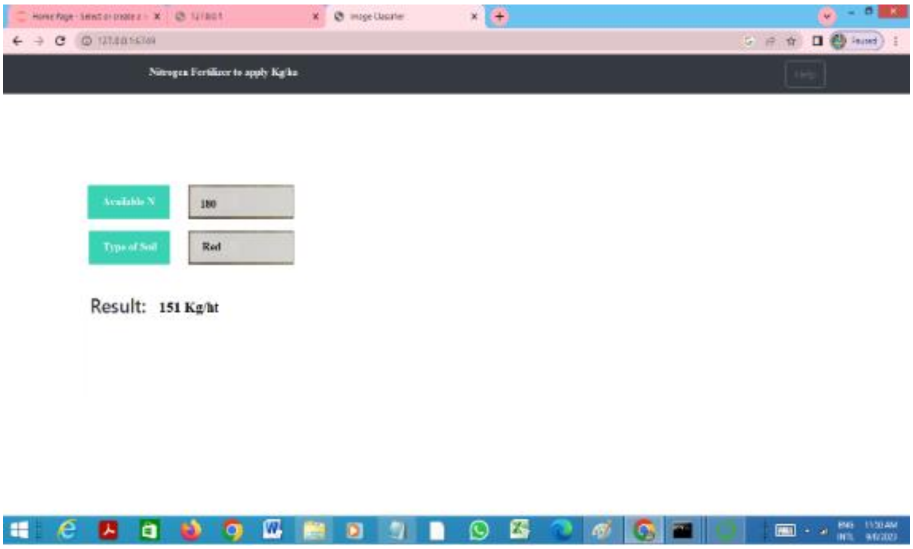

Figure 12. Graphical interface displaying Nitrogen fertilizer to apply.

5. Conclusion and future work

Machine Learning (ML) is used in agriculture to better predict crop yields and nutrient availability, detect plant diseases, and ensure the health of crops and plants. Precision agriculture powered by ML is transforming agriculture into a cutting-edge industry that makes better use of water, fertilizers, tillage and pesticides. This increases productivity and protects the environment at the same time. Our research has shown that a combination of factors can be used to predict nitrogen fertilizer rates to be applied with approximately 80% accuracy. The reliability of the model in estimating soil macronutrient concentration is supported by its low MAE and RMSE error measures. This cost-effective option can improve farmers' judgment, lead to more precise fertilizer use and ultimately increase crop yields.

In the future, this model could be refined to address the scalability across different agricultural contexts, economic impact on farming operations, and strategies for enhancing former's adaption. This improvement will not only increase the models usage but also contribute to efficient agriculture practices.

Author contributions

Conceptualization, methodology, software, field study, NLK; data curation, writing—original draft preparation, software, validation, field study, BPK. All authors have read and agreed to the published version of the manuscript.

Conflict of interest

The authors declare no conflict of interest.

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