# FERTILIZER OPTIMIZATION THROUGH MACHINE LEARNING-DRIVEN MODELS: AN EMPIRICAL INVESTIGATION ON SMART FARMING OF AMARANTH

**Abstract**

Amaranth is a highly nutritious leafy vegetable cum pseudo-cereal crop known for its adaptability to various climatic conditions, making it a promising crop for addressing the food security and nutritional needs of a growing population. To enhance its quality and boost yields, farmers mainly depend on synthetic fertilizers. However, the excessive use of inorganic fertilizers to maximize crop yields poses significant ecological risks. This study aimed to investigate the impact of excessive inorganic fertilizer on the growth, yield, and physiological attributes of Amaranthus with the aid of advanced machine learning paradigm. An experimental pot trial was conducted using different NPK fertilizer dosage regimes, and agronomic parameters such as moisture level, crop yield, plant height, leaf length, leaf width etc. were measured and analyzed using statistical methods. The results demonstrated that the application of excessive inorganic fertilizer initially promoted plant growth but surpassed optimal levels resulting in negative effects, including stunted growth and reduced vigor. By identifying the Amaranthus's productivity and adaptability in different chemically treated soil conditions and automatically phenotyping its traits using image-based machine learning models, this study aims to determine the overuse of synthetic fertilizers. A comparative evaluation of different learning algorithms was carried out and the experimental result proves that SVM classifier could be a more appropriate learning algorithm for the proposed system with 80% accuracy. These findings highlight the importance of adopting sustainable fertilizer practices for the cultivation of Amaranthus and emphasize the need for ecological balance in crop production systems.

**Keywords:** Amaranth, unfair use of inorganic fertilizers, ecosystem pollution, smart farming, fertilizer management, machine learning.

## 1. Introduction

Vegetable production in India plays a crucial role in ensuring food security for its population (Din et al. 2022). Vegetables are integral to a well-balanced diet as they supply vital nutrients, vitamins, and minerals necessary for optimal health and nutrition. They are essential for overall health, helping individuals meet their dietary requirements and combat malnutrition. India has a diverse agro-ecological environment, allowing for the cultivation of a wide range of vegetables, from root vegetables to leafy greens etc. (Arora 2023). The significance of leafy vegetables in promoting a balanced diet is becoming increasingly apparent, particularly in regions with a significant vegan population. Amaranth species, a tropical leafy vegetable, plays a significant role in the daily consumption of leafy greens (Sarkar et al. 2022). Notably, *Amaranthus tricolor*, known for its lush leaves, is one of

India's most widely consumed leaf vegetables owing to its great nutritional value and commercial importance. To effectively cultivate Amaranth, it is essential to comprehend the influence of various nutrient sources on its yield and to identify key factors that may limit its production.

In recent years, the deterioration of soil quality has emerged as a major concern, with serious consequences for agricultural productivity and environmental sustainability (Saidmamatov et al. 2023). Several factors have contributed to this decline, including intensive agricultural practices, land degradation, soil erosion, pollution, and climate change. Intensive farming practices, characterized by excessive fertilizer application have taken a toll on soil health (Prashar and Shah 2016). Repeated chemical inputs without proper nutrient management can disrupt the natural balance of soil nutrients, leading to nutrient imbalances, reduced soil fertility, and decreased organic matter content.

In the present era, the soils in India mostly exhibit inherent infertility and low organic matter content due to the repeated usage of chemicals over time, making them less suitable for intensive cultivation (Das et al. 2022). In this regard, several studies have been carried out on the effects of different fertilizers on plant growth (Grzyb et al. 2012; Senjobi et al. 2012). Additionally, excessive reliance on inorganic fertilizers can have negative long-term effects on plant growth (Oyedeji et al. 2014). Furthermore, the overuse of chemical fertilizers can affect the plant quality and make it more susceptible to diseases and pests, as it disrupts the ecosystem's natural balance. This can result in reduced crop yields and increased reliance on pesticides, further escalating environmental concerns. Therefore, exploring alternative approaches that promote plant health and productivity is essential while minimizing the potential risks associated with excessive chemical fertilizer usage.

Several studies have investigated the impact of fertilizers on plant growth and yield (Merghany et al. 2019; Gao et al. 2020; Dhakshayani and Surendiran 2023). In a two-year field experiment, (Sabourifard et al. 2023) examined the effects of sowing date and various fertilizer treatments (combination of farmyard manure, urea and vermicompost) on maize yield and oil quality. The findings revealed that timely sowing and a combination of urea and vermicompost resulted in the highest seed yield. A recent research study conducted by (Ramteke and Shirgave 2012) examined the influence of commonly used fertilizers, namely Biozyme, Diammonium phosphate, and urea, on the growth of three different vegetable plant species. The study specifically focused on important growth parameters, including germination rate, seedling survival, seedling height, and root-to-shoot ratio. The researchers used 0.01 M (v/v) fertilizer solutions to study the impact of various fertilizers on the development of these key vegetable plants. There have been several studies comparing the use of organic and inorganic fertilizers. (Alzamel et al. 2022; Wu et al. 2022). One such research (Masnang and Wibaningwati 2023) attempted to assess the effectiveness of several techniques of organic fertilizer application on the development and production of taro plants. The research examined six classes involving diverse placements and types of organic fertilizers. The influence of these treatments was specifically examined in relation to the growth and development of the Amaranthus crop. A field experiment was conducted with the same crop to assess the impact of various organic and inorganic fertilizers (Olowoake 2014). The findings revealed that organomineral fertilizer led to a significantly higher yield than NPK fertilizer. Moreover, the residual effect of the organomineral fertilizer positively influenced plant height, leaf count, and yield. As an extended work, the same author conducted a subsequent study investigating the influence of NPK fertilizers on crop development (Olowoake and Adebayo 2014). The results indicated that the application of organomineral fertilizers resulted in notably higher dry shoot weight when compared to the NPK treatment.

In recent years, there has been a surge of interest in a modern approach to agriculture known as "Smart Agriculture," which holds the potential to assist farmers in making informed decisions to maximize yields across diverse field conditions. Central to the concept of "Smart Agriculture" is the integration of artificial intelligence (AI) techniques such as machine learning (ML) and deep learning (DL). In ML, the process involves constructing a model from a finite training set capable of generalizing the characteristics observed in the training examples to novel instances (Prato & Zanni, 2008). The fundamental objective of ML is to address "Inverse Problems," which entails deducing the causal factors responsible for observed phenomena from a set of observations (Wikipedia, 2022). These causal factors represent the underlying patterns within the dataset, which ML algorithms strive to identify based on the provided data points, or observations. Given this definition of ML, it becomes evident that its functioning closely aligns with our objective of predicting fertilizer overuse through image-based automated phenotyping. As previously mentioned, capturing images of the observable green parts of plants can potentially unveil the soil conditions (causal factors) influencing their growth.

The task at hand is distinctly a classification problem, with predefined classes outlined in advance. Machine learning offers a range of robust algorithms tailored for classification tasks. As per recent research findings, the efficacy of different classifiers can fluctuate depending on the dataset and features involved (Kwon & Sim, 2013). Hence, for a thorough assessment, we have selected four standard machine learning classifiers: Support Vector Machine (SVM), Decision Tree (DT), Random Forest (RF), and Logistic Regression (LR). In this section, we meticulously compare the performance of these classifiers to provide a comprehensive analysis.

The images of the datasets were downscaled into 1600 x 1200 pixels. The experiments were conducted with the training-test ratio fixed as 8:2. All the experiments were conducted on python 3 over the HP Pavilion notebook laptop with Intel (R) Core (TM) i5-7200U CPU @ 2.50GHz with 8GB of RAM running windows 10 operating system. All the models were trained using the Sklearn python package and OpenCV.

Numerous studies have investigated the effects of various fertilizers, but there is a lack of research specifically examining the impact of excessive usage of inorganic fertilizers with varying dosages on growth and yield. Our underlying ideology for this study is based on the belief that one effective approach to preserving or enhancing soil fertility is utilizing fertilizers judiciously based on actual requirements and limiting to what is necessary. Much like other crops, Amaranthus grows best on soil with a high proportion of organic matter and sufficient nutrient sources. However, it has been observed that farmers often use excessive amounts of fertilizer, surpassing the actual requirements of the crop, which negatively impacts the plant growth (Merghany et al. 2019). Hence, the aim of this study is to examine the effects of excessive application of inorganic fertilizers on the development and production of Amaranthus, through machine learning approach. By understanding the consequences of this practice, we aim to provide valuable insights for promoting sustainable farming practices and optimizing fertilizer management in Amaranthus cultivation.

## 2. MATERIALS AND METHODS

### 2.1. Plant experiment

The experiment involved Amaranthus seeds procured from the local market in Karaikal village. To prepare for sowing, the seeds were carefully washed with distilled water. The trial was conducted during the summer season of the year 2022, spanning a period of 45 days. The seeds were sown in plastic planters measuring 12 inches, with dimensions of 35.56 x 15.5 x 28 cm, and a soil capacity of 13 kg per pot. The native soil of the Karaikal village region, the coastal alluvial soil known for its suitability for paddy and pulse production, was used as the growing medium of the Amaranth plants.

The soil utilized in the experiment had not been subjected to any fertilizer application and had been previously farmed several years ago. The soil had a gentle slope and exhibited medium drainage properties. The major micronutrients, namely the Nitrogen (N), Phosphorous (P) and Potassium (K) contents of the soil used as growing medium in this experiment was analyzed using the recommended standard analytical procedures by the Department of Agriculture, Government of Puducherry. The physicochemical properties of the experimental soil as per the soil test report are furnished in Table 1.

Upon conducting the soil test, it was found that the available NPK levels of the experimental soil were significantly lower than the recommended NPK levels for Tamil Nadu soil as per the recommendation (TNAU, 2020). The inadequate levels of nutrients in the soil could be due to the low organic matter content in the soil, which can make it unsuitable for agricultural purposes. To attain the recommended NPK levels, it is necessary to supplement the soil with specific quantities of fertilizers. According to the guidelines, the Optimum Nutrient Treatment (ONT) involves adding urea, DAP, MOP with 1.5 gm, 1.95 gm and 0.69 gm, respectively. As previously discussed, it is optimal for farmers to use the required quantity of NPK fertilizer. However, small-scale farmers frequently overuse fertilizers due to economic constraints and a lack of access to expert knowledge.

In order to systematically examine the effects of fertilizer overuse, ten different nutrient treatment classes were created for the Amaranthus study. An optimal class (C1) was established with no fertilizer added, while the control class (C10) received the recommended standard amount of NPK fertilizer (ONT). Eight additional classes with different levels were established based on the ONT quantity as a baseline. Four of the classes (C2-C5) received a moderate excess of fertilizer, while the remaining classes (C6-C9) received a large excess of fertilizer. The experimental setup of all the classes is shown in Fig. 1. The measurements of the excess fertilizer added for each treatment can be found in Table 2. The fertilizers were mixed with the soil one week prior to the start of the experiment. Equal amounts of amaranth seeds, 20 grams each, were sown in every planter and covered with a thin layer ($<0.5$ mm) of soil using the hand-dibble method. Water was applied only when the top layer of soil appeared dry (once every two days). The experiment was conducted under open field conditions with an average of seven hours of daily sunlight exposure.

Phenotypical features of the Amaranthus were measured and recorded according to standard procedures. Three randomly chosen plants from each pot were tagged for measurement at the beginning of the experiment. Every 15 days, all the phenological traits namely the plant height, number of leaves per plant, leaf area, stem girth, and days to bud initiation were observed and recorded for the three random replicates of each class. After 45 days, the plants were harvested, and their fresh weight was measured to analyze yield potential. Fig. 2 depicts a graphical abstract of the experiment. Daily weather and soil-related data, including temperature, relative humidity, soil pH, soil moisture, and sunlight intensity, were also measured throughout the course of the experiment. HTC1 sensors were used to record temperature and relative humidity, and a 4-in-1 digital soil test meter was utilized to capture soil-related data. The sensors used were low-cost, portable, and readily available.

The experiment was conducted for Amaranthus and observed for various biometric traits namely plant height, leaf length, leaf width, leaf area ratio, number of leaves plant$^{-1}$, stem girth, days to flowering, plant fresh and dry weight, moisture content, dry matter content, leaf area duration and absolute growth (Ribeiro et al. 2017). The various levels of fertilizers are provided in Table 2. The experiment was laid on randomized block design (RBD), with three replications for each treatment. The validity of the experiment results were made through the analysis of variance (ANOVA) (Panse et al. 1967) and the statistical analysis of data was performed using RStudio Desktop Version 2022.07.1+554. The statistical analysis employed in this study involved the use of ANOVA to determine the significant differences, followed by Duncan's multiple range tests to establish the significance of the mean SE (standard error) values at a significance level of $p < 0.05$. The Pearson correlation analysis and principal component analysis were additionally carried out to obtain deep understanding on the effect of fertilizers doses on amaranth plants.

### 2.2. Machine learning model approach

At first, we trained the ML models with the original 740 samples from our dataset. The performance of the ML models in this dataset was borderline. It is well known that the quantity of data has a critical impact on the learning ability of the ML models. As per (Mahesh, 2019), the performance of supervised ML models is very data-dependent and largely relies on the amount of training data available. It is very challenging to produce training datasets that are appropriately large in many situations. In this regard, data augmentation is an appealing technique for dealing with small-sized datasets. Data augmentation is employed to increase the number of data points by modifying them slightly (Wikipedia, 2022). In general, simple transformations like mirroring and rotation are carried out to augment an image dataset. In this paper, we apply two data augmentation techniques: horizontal and vertical flips of the top view images.

Evaluation metrics play an important role in understanding the classification performance of different ML models. The following classical evaluation metrics are considered: Accuracy, precision, recall, and F1-Score. Accuracy is the most holistic metric, which gives the percentage of predictions done correctly. Precision measures total positive cases that are correctly predicted from the total predicted cases in a positive class. Precision helps quantify how good a model performs with respect to a given class. The recall measures the proportion of positive cases that are correctly predicted. F1- score is used to define the harmonic mean between precision score and recall. In addition, we also present the confusion matrix in for an easier visual evaluation.

## 3. Result and discussion

### 3.1. Findings from plant experiment

#### 3.1.1. Mean performance of amaranth plants under different fertilizer classes

The performance of morphological traits namely the plant height, leaf length, leaf width, number of leaves plant$^{-1}$, leaf area plant$^{-1}$, stem girth and day to first flowering are presented in Fig. 3. The means of physiological traits and fresh foliage yield are shown in Fig. 4. The maximum plant height was recorded under C10 (48.00 cm), followed by C3 (47.33 cm) and C1 (43.00 cm), whereas the minimum plant height was seen in C6 (26.33 cm). This shows that the P application in excess reduced the plant growth. In C10, the leaf length and width were found to be insignificant at 45 DAS. The number of leaves plant-1 was found to be maximum in C10 (11.67), followed by C3 (10.00) and C1 (9.67). From Fig. 3, it is apparent that the leaf area plant-1 is highest in C10 (349.24 cm$^2$), followed by C1 (296.61 cm$^2$) and C3 (219.98 cm$^2$). The leaf area index was the highest in C10 (174.62), followed by C1 (148.30) and C3 (109.99). The maximum stem girth was noticed in the plants under C10 (2.90 cm), followed by C1 (2.73 cm) and C3 (2.53 cm). Fig. 3 explains that the stem thickening was more in C10 and C1, which thereon reduced. However, in C3, the stem thickening was reduced. The leaf yield plant-1 was found to be maximum in C1 (16.01 g), followed by C10 (15.04 g) and C3 (13.91 g). However, the C10 showed superiority in growth parameters and the C1 showed superiority in fresh foliage yield. This proved that the optimal dosage of NPK fertilizers produces the highest fresh foliage yield in Amaranthus. This was in confirmation with the reports of (Ribeiro et al. 2017), whose report stated that the combination of fertilizers performs better than the sole application. The earliest flowering was seen in C9 (35.67 days), while the plants under C2 (44.67) were the last to flower. The highest moisture content was noted in C2 (92.65 per cent), followed by C4 (90.68 per cent), C9 (90.34 per cent), and C6 (90.17 per cent). Fig. 4 explains the effect of different fertilizer classes on dry matter content, leaf area duration, and absolute growth rate. The dry matter content was the highest in C1 (0.003). This might be the reason attributed to the highest foliage yield. The leaf area ratio was found insignificant. The leaf area duration was the maximum in C1 (17.64 cm$^2$/day), followed by C10 16.77 cm$^2$/day) and C3 (13.53 cm$^2$/day). The highest absolute growth rate was found in C10 (2.84), followed by C3 (2.75) and C1 (2.40). As the plant height increased, a noticeable increase in the leaf count was observed. As the plant serves as the photosynthetic source organ, the rise in the total amount of leaves plant$^{-1}$ affects the plant's overall performance. (Law-Ogbomo and Ajayi 2009).

#### 3.1.2. Correlation among the plant traits as influenced by the different fertilizer doses

The fig. 5 shows the correlation among the plant traits influenced by various fertilizer combinations. The fresh foliage yield showed the highest correlation with leaf width, dry weight (Pearson r = 0.92), followed by leaf area duration (r=0.90) and plant height (r=0.89) and absolute growth rate (r=0.87), indicating that these traits are the major attributes of foliage in amaranth plants. This fact holds true for the plants under C10 () and C3 (), as revealed by the PCA biplot. On the other hand, yield was negatively correlated with leaf area ratio (r=-0.23) and moisture content (r=-0.34). This is in line with the results of the PCA biplot, where the negative associations of these two traits against yield and its attributes are displayed. Therefore, the leaf width, dry weight, leaf area duration, plant height and absolute growth rate are the direct factors influencing yield in amaranth plants.

**3.1.3. Principal component analysis for dissecting relationship with and within plant traits and fertilizer treatments**

The variability induced by the effect of different fertilizer combinations were explored through PCA. The PCs that showed eigenvalues of >1 are considered for result interpretation. Fig. 6a shows the eigenvalue of first four PCs *viz.*, 10.6, 1.8, 1.3 and 0.4, respectively. Thus, only the first three PCs are considered for further evaluation of the effect of different doses of fertilizers on the amaranth plants. The fig. 6b reveals that the highest variance was held by the PC1, followed by PC2 and PC3, which altogether contributed for 92.7% of the total variability imparted by the fertilizers. The upcoming components reveal the plant traits that contributed to the variability. It also gives us a better understanding of how the fertilizers influence the morpho-physiological traits of amaranth plants. The fig. 6c presents the correlation among the PCs and plant traits. The plant traits namely leaf area plant$^{-1}$, leaf area index, stem girth, dry weight and leaf area duration showed higher positive correlation with PC1 while moisture content and leaf area ratio showed negative correlation with foliage yield. In PC2, the higher positive correlation was found with days to 50% flowering, moisture content, leaf length and dry matter content showed negative correlation. The fig. 6d shows the factor loadings of each plant traits captured by first 3 PCs. The highest factor loadings was found with moisture content (0.18), followed by leaf area ratio (0.02). Notably, only these traits showed positive factor loadings in PC1, while all the other traits showed negative factor loadings. This indicates that moisture content and leaf area ratio are the primary contributors to the variability, indicating that these are the traits that most influenced by the different fertilizer doses. In PC2, the highest factor loadings was observed in days to 50% flowering (0.65), followed by moisture content (0.49), manifesting them to be the secondary contributors to the total variability. Notably, the moisture content which showed higher factor loadings in both PC1 and PC2, is the most influenced trait, providing the most to the variability. The fig. 6e shows the contribution of each plant trait to the PCs. In PC1, the highest contribution was made by the leaf area plant$^{-1}$ (8.96), leaf area index (8.96), stem girth (8.84), dry weight (8.74) and leaf area duration (9.17), aligning with the pattern of correlation between the PCs and plant traits. For the same PC, days to 50% flowering and leaf area ratio showed the lowest contribution. In PC2, the highest contribution was made by days to 50% flowering (42.77), followed by moisture content (24.26). Therefore, fig. 6 explains the variability imparted by the effect of different fertilizer doses. It also give insights into the traits that are most influenced by the effect of different fertilizer doses.

Fig. 7 shows the biplot presenting the relationship within plant traits and the association between variables and treatment classes. This biplot also shows which treatment influenced which plant trait ultimately enabling us to the find the treatments (fertilizer doses) favouring yield maximization in amaranth plants. The fresh foliage yield plant$^{-1}$ shows higher association with plant height, leaf width, absolute growth rate, number of leaves plant$^{-1}$ and leaf area index. The positive associations were seen with other traits namely number of leaves plant$^{-1}$, leaf area index, leaf area plant$^{-1}$, stem girth, leaf area duration, dry weight, dry matter content and leaf length. On contrast, the negative association with yield were found with moisture content and leaf area ratio which are in turn negatively associated with each other. The highest yield was seen with C1, followed by C10 and C3. The superiority of C1 on yield was attributed to the maximum leaf length, dry matter content, dry weight, leaf area duration, stem girth, indicating that these traits favour the higher foliage yield. The C10 was superior in yield, despite being control, due to higher leaf area index, leaf area plant$^{-1}$, number of leaves plant$^{-1}$ and leaf width. The C3 was superior in terms of plant height and absolute growth rate. Thereby, the biplot provides on understanding on the facts that directly influence maximization and the fertilizers/ their combinations for the same. On the other hand, fertilizer combinations such as C8, C6, C9 and C7 are not recommended for amaranth production, as they didn't yield a good performance and yield. Furthermore, C2 and C4 can be classified as moderate-impact combinations yet inferior to C1 , C10 and C3 .

### 3.1.4. Analysis on Benefit-Cost Ratio

The benefit-to-cost ratio (BCR) of our experiment is analyzed to assess its effect on financial benefits (Table 3). The calculation of BCR is performed per hectare (equation (1)), according to which the highest BCR is noted under control. However, C2 showed higher BCR among the fertilizer classes, followed by C4 and C5. Thus, fertilizers are not mandatory for an economically higher yield for a crop like Amaranthus. However, the supply of NPK fertilizers would boost the plants' physiology and thereby increase the yield, as proved through this investigation.

$$Benefit - \text{cost ratio} = \frac{\text{Present value of benefit expected from the experiment}}{\text{Present value of the cost of the experiment}}$$

The results showed that the plants under C1 showed superior performance when compared to the others. The BCR analysis showed that the C2 is highly economical with a higher BCR among the fertilizer treatment, though the control (C10) showed the highest BCR. The correlation analysis indicated that the high fresh foliage yield is attributed to the hike in plant dry weight, leaf width, and leaf area duration. A positive correlation between the fresh foliage yield and other leaf-related biometric traits was registered.

The present investigation on growth analysis of Amaranth reveals that the Amaranth plants could produce sustained performance even without the fertilizer supply, provided the available soil nutrient status is optimally rich. This is evident as the superior growth performance is evidenced under the control pots, where no fertilizers were added (C10). However, the optimal dosage of fertilizers (C1) resulted in the yield maximization of the green foliage of Amaranth. Therefore, we recommend that the optimum dosage of fertilizers is required to maximize the yield potential of the commercially grown Amaranth for local markets. The correlation analysis showed that the green foliage yield is positively correlated with the dry weight and leaf area duration. It becomes evident that the maximized yield produced under the optimal dosage of nutrients (C1) is attributed to the enhanced dry matter production and prolonged longevity of the plants. The BCR analysis showed that the highest economy of the fertilizers was met with the control, followed by the single fertilizer applications such as C2, C4, and C5. However, yield maximization can be attained with an optimal dose of fertilizers combined. Sustained production or home garden production can be achieved without the need for fertilizer application, provided that the native soil possesses adequate nutrient content, as demonstrated in the current experiment.

### 3.2. Findings from machine learning models

This section discusses the results obtained from the four ML models considered. Two experiments were carried out with four different ML models: LR, DT, RF, and SVM, with and without data augmentation. It is noted that in all the cases, the model performed better when it was implemented with the augmented dataset.
We have observed from Table 4 that among the four different classifiers investigated in this paper, SVM achieves the highest classification accuracy. The hyperparameter tuning for our SVM model was done using the Gridsearch technique. The parameter combination we considered for Gridsearch is given in Table 5. We have also manually experimented with two kernel functions, Linear and RBF (Gaussian), to find our model's optimal kernel function. The classification accuracy of SVM- linear and SVM- RBF obtained are 78% and 80%, respectively. RBF kernel function has produced the best classification accuracy of 80% compared to the linear kernel.

Fig. 8 presents a comparative study based on the performance of four different classifiers on Amaranthus crop images with and without data augmentation. The figure clearly shows the advantage of data augmentation in terms of improved accuracy rate. For a visual summary of the model's performance, confusion matrix is plotted where the values are represented with colour density. This heatmap helps us quickly visualize each class's distribution accuracy (Classwise accuracy). Fig. 9 shows the confusion matrix of our SVM model with 80% classification accuracy. Here, the row represents the predicted outcome, and the column represents the ground truth class labels of the different chemically treated Amaranthus images (C1-C10).

## 4. CONCLUSIONS

The decline in soil quality is primarily attributed to the adoption of inadequate soil and crop monitoring strategies employed in the growing stage. The overapplication of chemical fertilizers, due to the lack of knowledge regarding crop nutrient requirements has led to diminishing soil health and subsequent yield losses. To address this issue, it is essential to adopt proper fertilizer management techniques that minimize the adverse impact. This study analyzes the excessive use of inorganic fertilizers (NPK) in Amaranthus cultivation. Experiments were carried out with ten different levels of NPK fertilizers, including control and optimal level. The analysis indicated a positive correlation between green foliage yield, dry weight, and leaf area duration. This indicates that as the dry weight and leaf area duration increase, the yield of green foliage also tends to increase. Furthermore, the plants subjected to the optimal nutrient dosage (C1) exhibited greater accumulation of biomass, resulting in higher dry weight. Thus, the findings emphasize the need to limit the usage of inorganic fertilizers to the actual requirements of the crop, avoiding excessive doses. Additionally, the experimental results conducted have clearly demonstrated the capability of classifying the chemically treated plants and the effectiveness of the different ML classifiers in terms of the overall performance metrics (Accuracy, Precision, Recall, F1 Score). Among the four models, SVM classifier outperformed with 80% accuracy, notably for the augmented data. Thus, using plant image data, the proposed system enables end users and farmers to assess plant productivity and soil nutritional requirements effectively. By promoting judicious fertilizer management, farmers can achieve optimal growth and yield of Amaranthus while minimizing environmental degradation.

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**Table 1. Physicochemical properties of the experimental soil**

| Parameters | Soil test value |
|---|---|
| Quality of soil | Silt |
| Ph | 7.85 |
| Salinity level | 0.47 |
| Total Nitrogen (g $kg^{-1}$) | 52.640 |
| Total Phosphorous (g $kg^{-1}$) | 21.312 |
| Exchangeable base Potassium (g $kg^{-1}$) | 365.760 |

**Table 2. Treatment details**

| Class ID | Class Name /Treatments involved | Amount of fertilizers added (in grams) | | |
|---|---|---|---|---|
| | | N | P | K |
| C1 | Optimal | 1.5 | 1.95 | 0.69 |
| C2 | $N_{150}$ | 2.25 | - | - |
| C3 | $P_{150}$ | - | 2.92 | - |
| C4 | $K_{150}$ | - | - | 1.03 |
| C5 | $N_{200}$ | 3.0 | - | - |
| C6 | $P_{200}$ | - | 3.9 | - |
| C7 | $K_{200}$ | - | - | 1.38 |
| C8 | N-P-$K_{150}$ | 2.25 | 2.92 | 1.03 |
| C9 | N-P-$K_{200}$ | 3.0 | 3.9 | 1.38 |
| C10 | Control | - | - | - |

**Table 3. Benefit-cost ratio under different fertilizer doses**

| Treatments | Cost (Rs) | Benefit (Rs) | B:C |
|---|---|---|---|
| C1 | 116670.18 | 19212000 | 164.67 |
| C2 | 22327.27 | 12756000 | 571.32 |
| C3 | 119854.54 | 16692000 | 139.27 |
| C4 | 33060.36 | 14688000 | 444.28 |
| C5 | 29636.36 | 10944000 | 369.28 |
| C6 | 159945.45 | 6228000 | 38.94 |
| C7 | 44158.54 | 6948000 | 157.34 |
| C8 | 174442.18 | 7848000 | 44.99 |
| C9 | 232940.36 | 10176000 | 43.69 |
| C10 | 400.00 | 18048000 | 45120.00 |

**Table 4. Performance evaluation of different classifiers**

| S. No | ML models | Without data augmentation | | | | With data augmentation | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Accuracy | Precision | Recall | F1-Score | Accuracy | Precision | Recall | F1-score |
| 1 | LR | 64 | 65 | 64 | 63 | 75 | 76 | 76 | 75 |
| 2 | DT | 62 | 70 | 65 | 64 | 71 | 70 | 72 | 70 |
| 3 | RF | 62 | 69 | 62 | 62 | 78 | 79 | 78 | 78 |
| 4 | SVM | 74 | 77 | 74 | 76 | 80 | 81 | 80 | 79 |

**Table 5. Parameters considered for Gridsearch in the SVM classifier**

| C | Gamma | Kernel |
|---|---|---|
| [1, 100, 1000] | - | Linear |
| | [0.00001, 0.0001, 0.001] | Rbf |


Fig 1. Experimental setup with different NPK classes of treatments

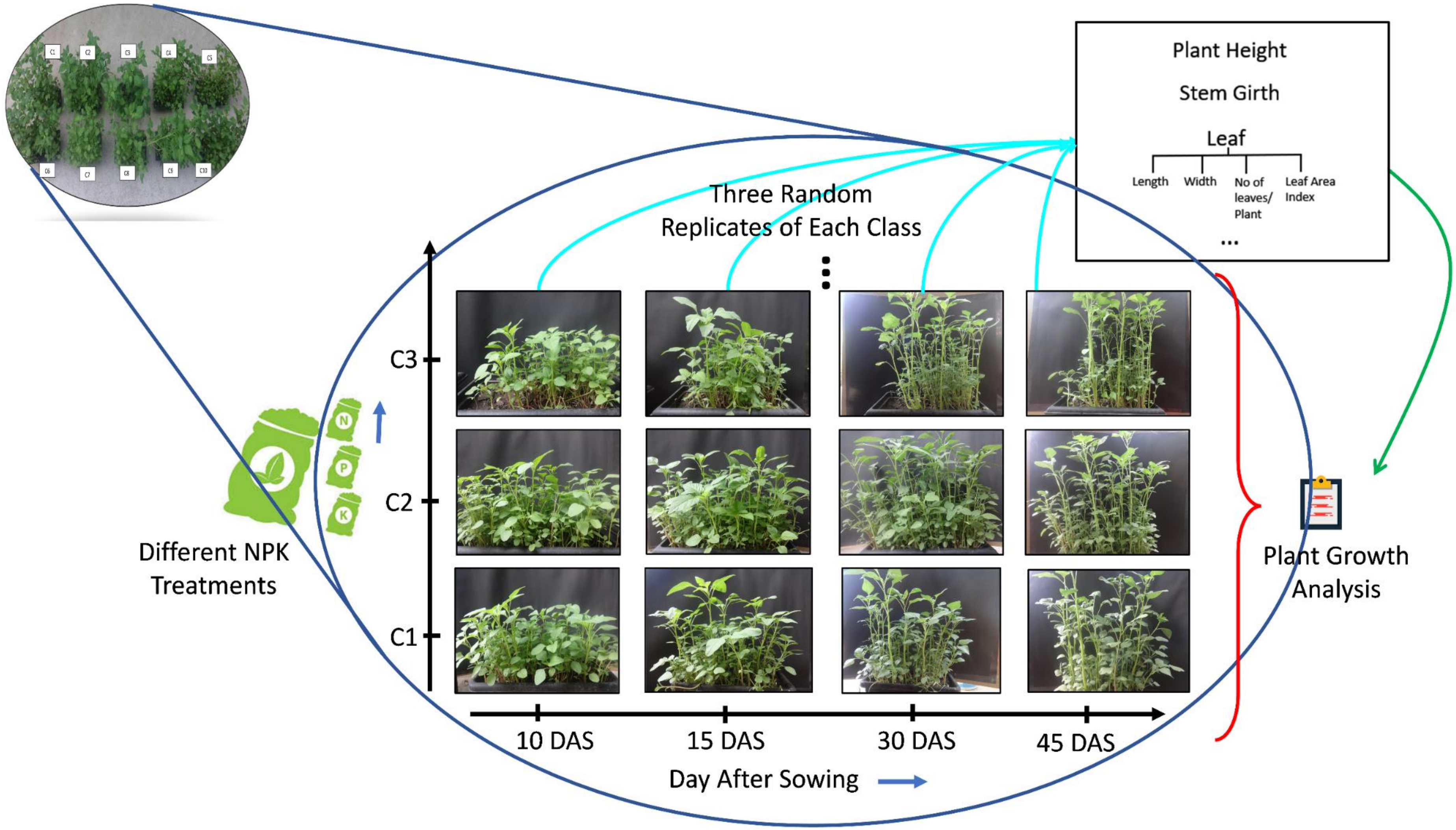


**Fig. 2. Graphical abstract of the experiment**

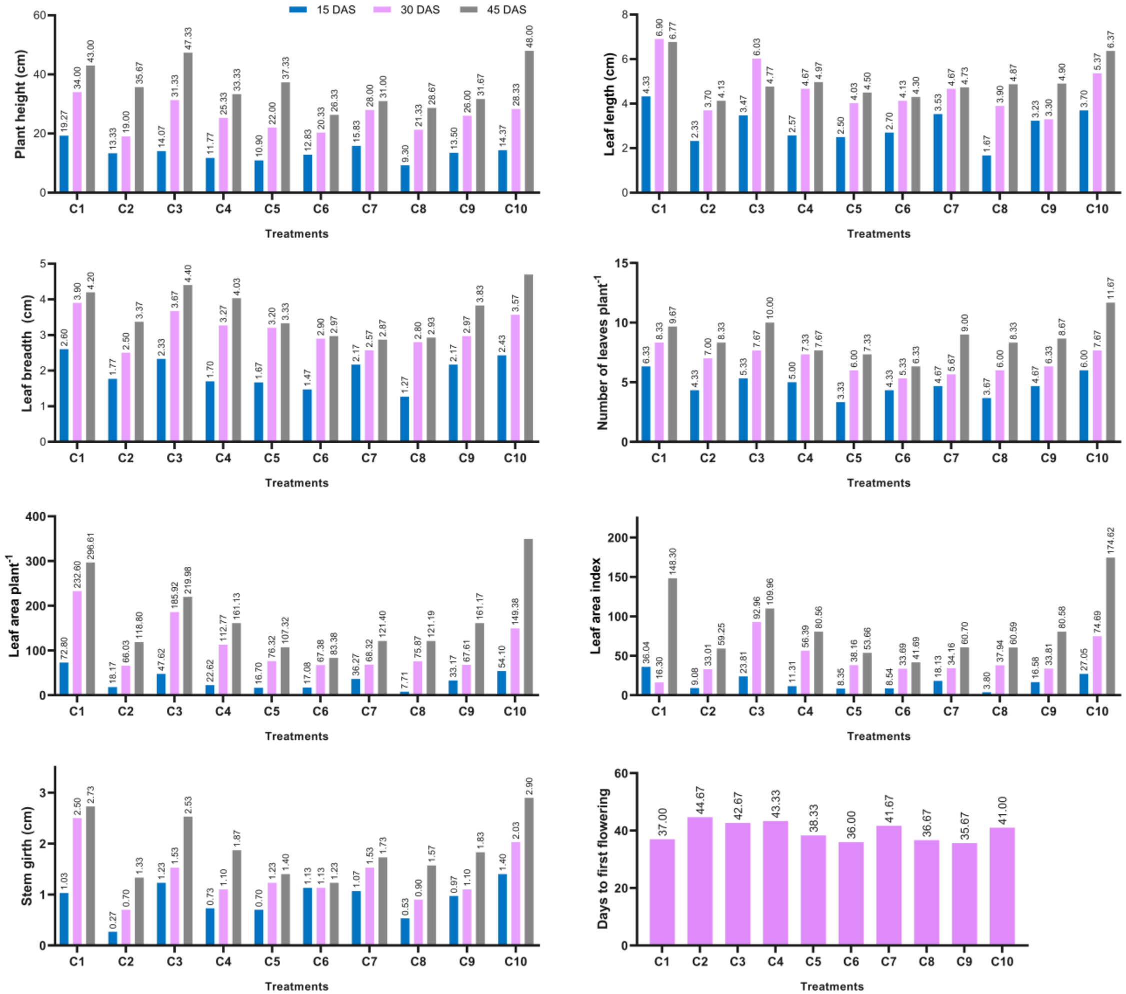


**Fig. 3. Mean performance of morphological traits of amaranth plants under different fertilizer doses**

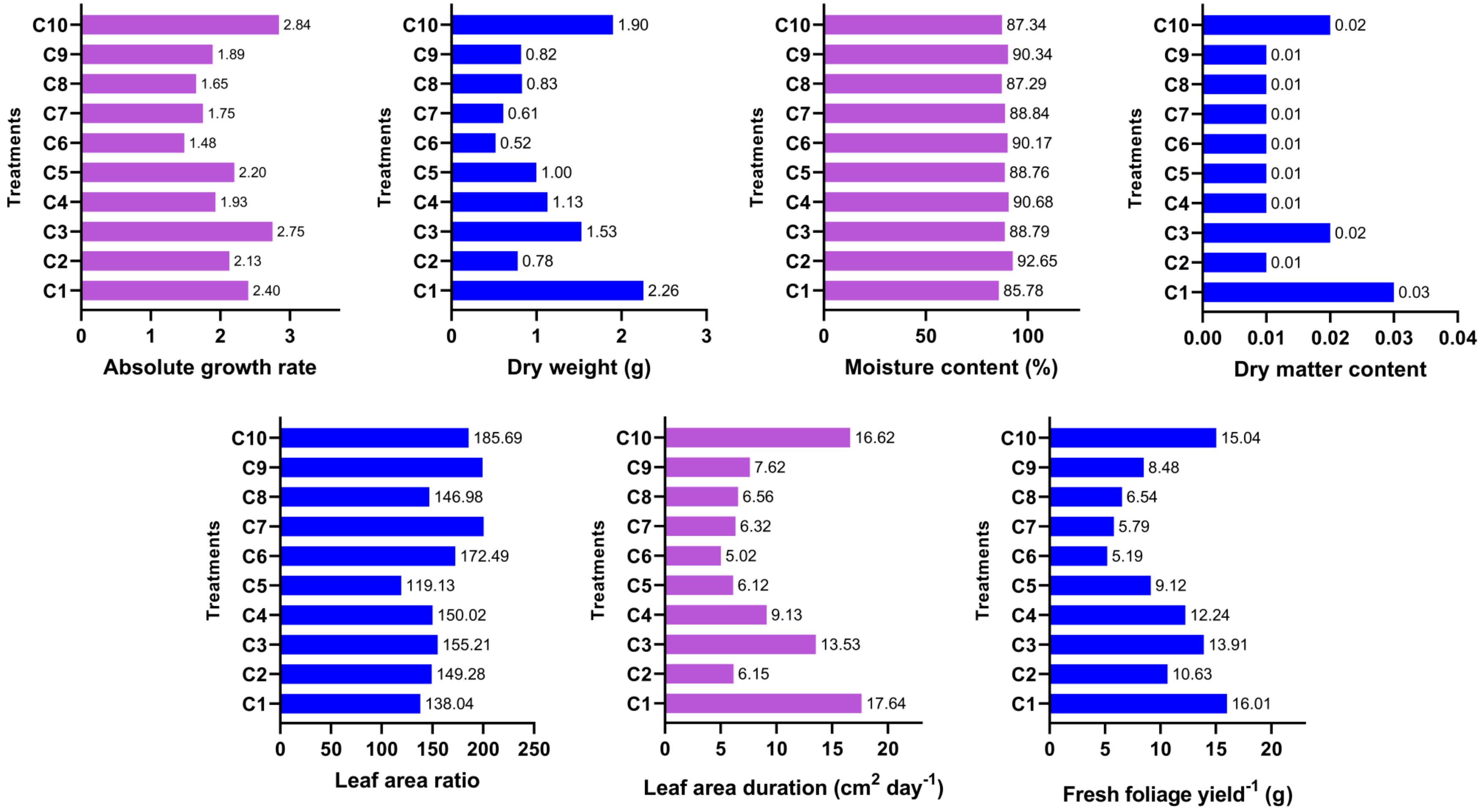


**Fig. 4. Mean performance of physiological traits and fresh foliage yield of amaranth plants under different fertilizer doses**

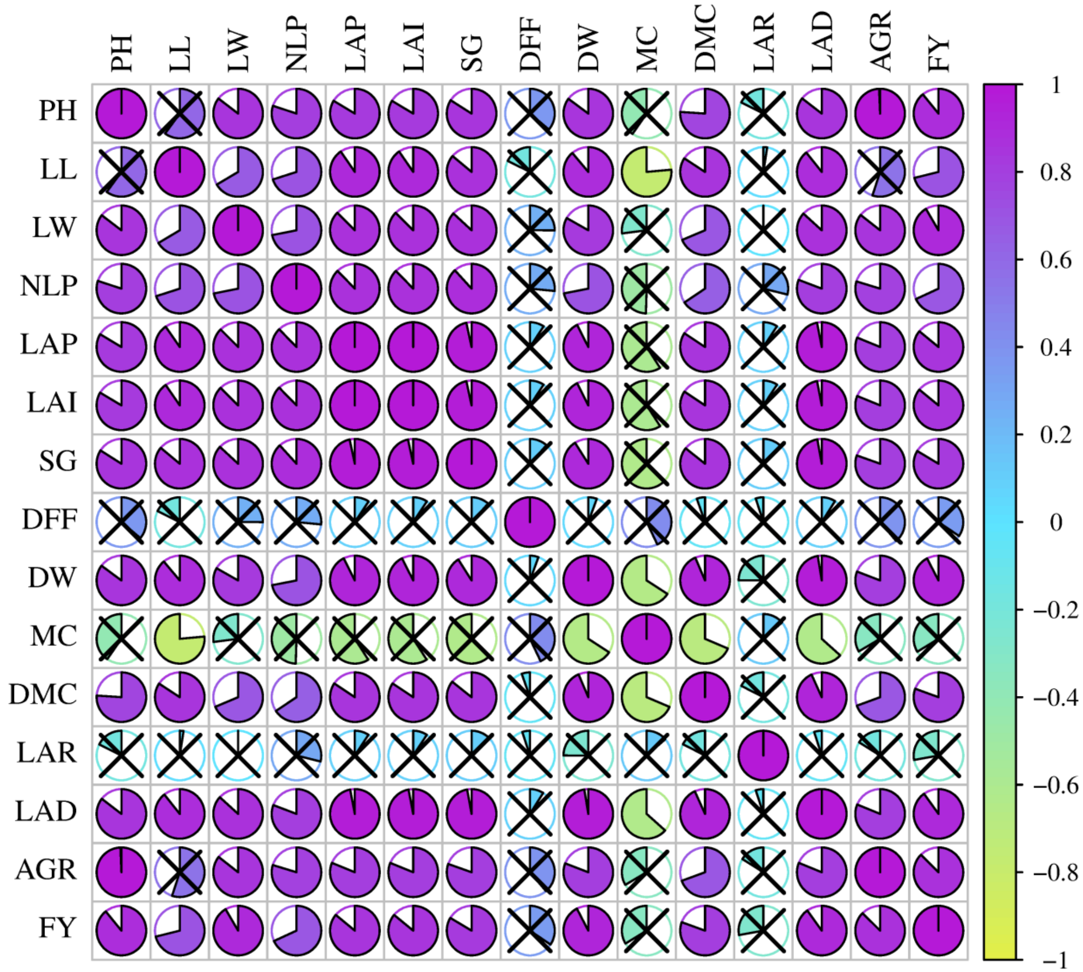


**Fig. 5. Pearson correlation coefficients showing relationship among the plant traits**

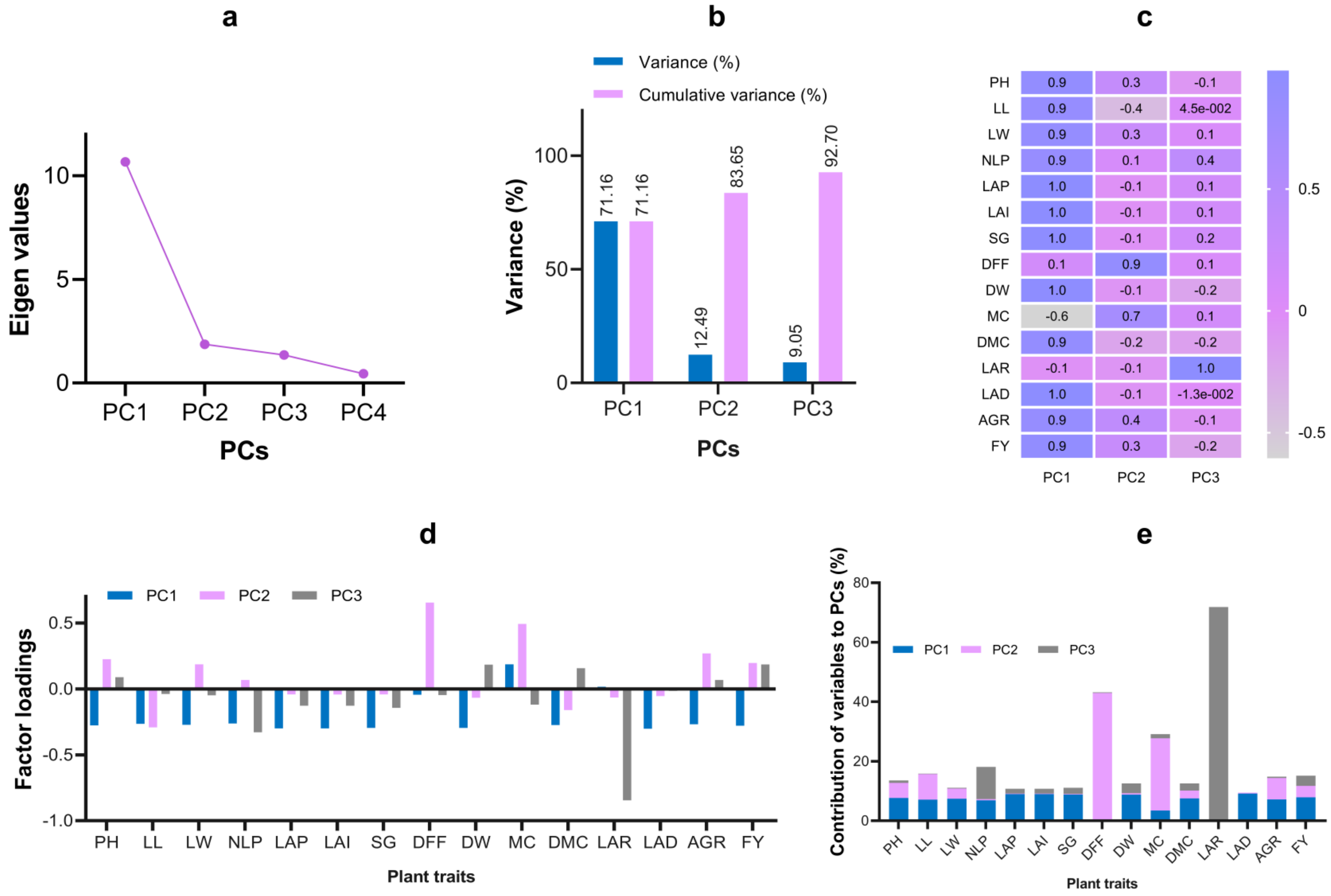


**Fig. 6. Results from PCA explaining a) eigenvalues; b) individual and cumulative variances of PCs; c) Correlation among the plant traits and PCs; e) Factor loading for plant traits captured by PC1, PC2 and PC3; e) Contribution of variables to the variability captured in PC1, PC2 and PC3**

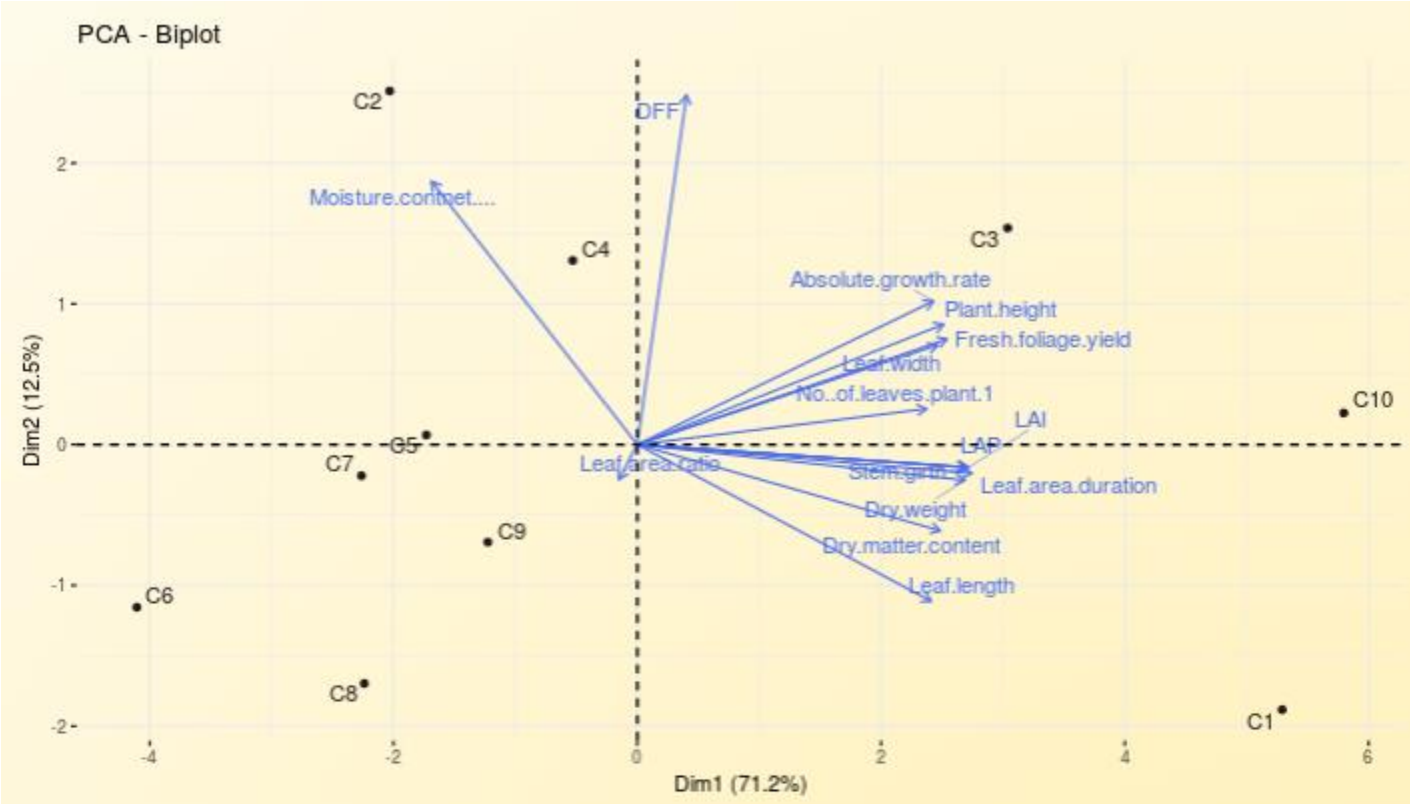


**Fig. 7. PCA biplot showing the association between and among the plant traits and treatment classes**

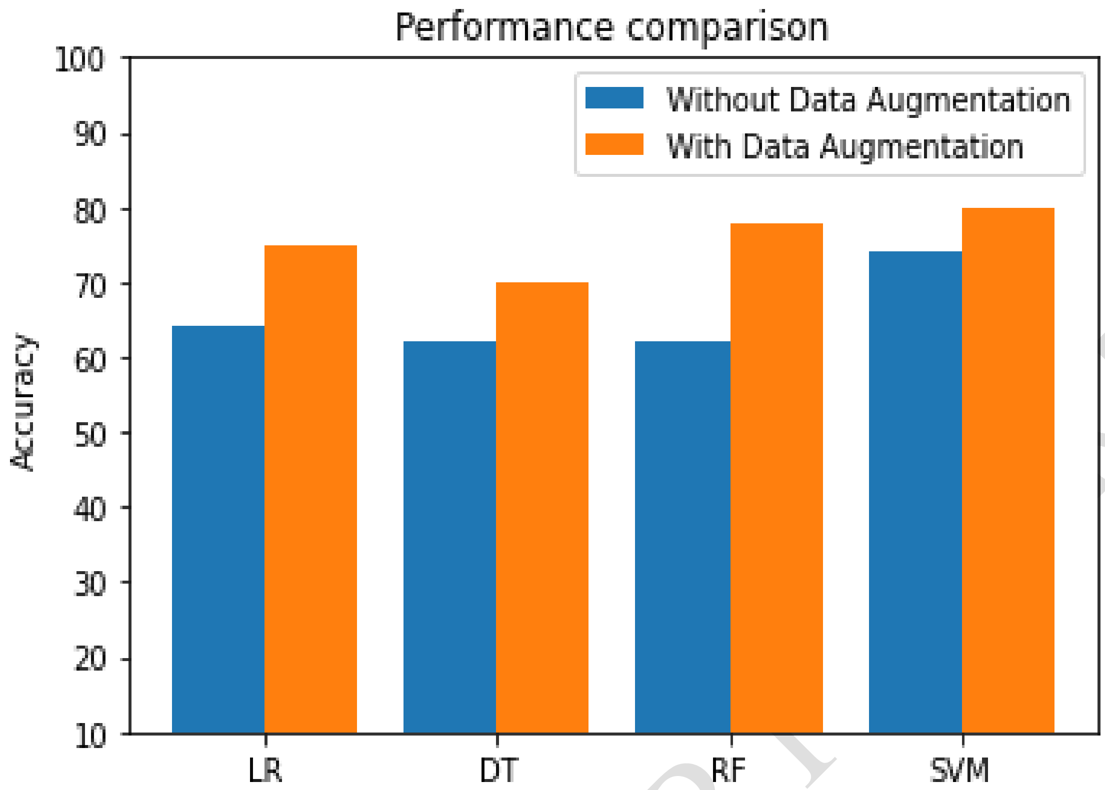


**Fig. 8. Performance comparison of different ML classifiers**

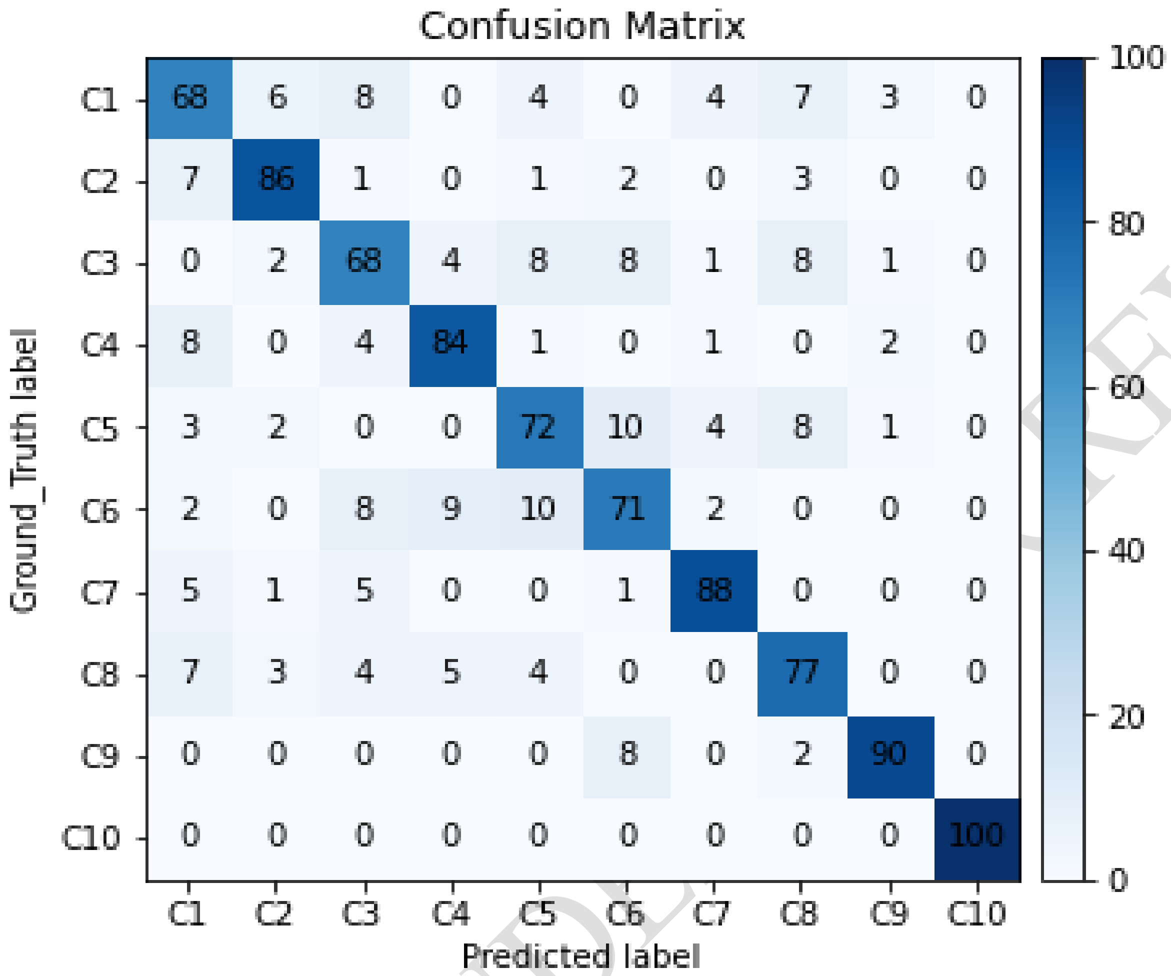


**Fig. 9. Performance comparison of different ML classifiers under different fertilizer doses**