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Original Researc Article

Groundnut Vegetative Growth Rate Prediction Using IoT and Machine Learning

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IoT,
Prediction.

ABSTRACT

The fusion of Internet of Things (IoT) technologies within agriculture has revolutionized crop management, enhancing both output volume and quality while minimizing labor expenses and boosting farmer revenues through intelligent modernization. Precise monitoring of environmental conditions, soil properties, and plant physiology is critical for forecasting agricultural outcomes, with IoT sensors providing the necessary high-resolution field data. This research focused on groundnut cultivation across twenty controlled pots over a 120-day cycle, generating 480 data points by continuously tracking temperature, soil moisture, and essential nutrients: nitrogen, phosphorus, and potassium (NPK). The primary objective was to model crop growth rates specifically in response to varying NPK levels using machine learning algorithms enhanced by bagging techniques, including Multi-Layer Perceptron (MLP), Random Forest (RF), and K-Nearest Neighbors (KNN). Model efficacy was assessed via R-squared, MAE, MSE, RMSE, and RMSLE metrics. In the specific context of predicting growth dynamics driven by NPK inputs, the MLP architecture demonstrated distinct superiority over its counterparts. It achieved the highest coefficient of determination (R^2 = 0.52) alongside the lowest error rates, recording an MAE of 1.3499, MSE of 2.7220, RMSE of 1.6498, and a remarkably minimal RMSLE of 0.0024. Conversely, RF and KNN exhibited comparatively lower predictive accuracy for this specific task. These findings highlight the unique capability of neural network-based approaches like MLP in deciphering complex nutrient-growth relationships, offering farmers a powerful tool for optimizing fertilizer application and resource allocation to maximize crop development.

CITATION
Ali Bala, A., Shafi'u, N., Olanrewaju, O. M., Jiya, E. A., Echobu, F. O., Ndabula, J. N., Ajik, E. D., Muhammad, Y. I., & Idris, A. A. (2026). Groundnut Vegetative Growth Rate Prediction Using IoT and Machine Learning. *Journal of Science Research and Reviews*, *3*(3), 154-163. https://doi.org/10.70882/josrar.2026.v3i3.172.

INTRODUCTION

The vegetative components of the groundnut (*Arachis hypogaea* L.) plant—primarily leaves, stems, and roots—play a fundamental role in photosynthesis, nutrient acquisition, and biomass accumulation, thereby establishing the structural and physiological foundation required for successful flowering, peg initiation, and pod development. Vigorous foliage enhances light interception efficiency and supports assimilate production necessary for reproductive growth and yield formation. In addition, the root system contributes to soil fertility through symbiotic biological nitrogen fixation, improving nutrient availability and promoting sustainable crop production systems. Studies have shown that enhanced vegetative growth and efficient nitrogen utilization are strongly associated with improved pod yield and greater resilience under varying environmental conditions (Guo et al., 2024; Olayinka & Etejere, 2015; Mokgehle et al., 2014).

Despite advances in groundnut yield prediction and crop management technologies, conventional methodologies remain constrained by their static and non-adaptive design, often failing to account for temporal fluctuations in soil nutrient dynamics and environmental conditions. Although several predictive models have been developed specifically for groundnut production, many rely predominantly on historical datasets and exclude continuous monitoring through Internet of Things (IoT) technologies. The absence of real-time environmental and soil information reduces model responsiveness to changing field conditions and limits the accuracy and practical value of yield forecasting systems (Bassine et al., 2023; Bala et al., 2025).

To support sustainable improvements in groundnut vegetative development and strengthen farmer adaptability to evolving agricultural challenges, agronomic research has increasingly focused on identifying optimal nutrient requirements for maximizing biomass production and crop performance. These findings provide evidence-based recommendations for fertilizer management and nutrient optimization strategies that promote early vegetative establishment, improve photosynthetic efficiency, and create favorable conditions for achieving superior final yield and crop quality (Guo et al., 2024; Hajhussin & Abdalla, 2026; Li et al., 2024).

A dedicated experimental farm was established in Kano to investigate groundnut cultivation under authentic field settings. IoT-enabled systems were deployed to continuously monitor both crop physiology and soil characteristics, facilitating uninterrupted data acquisition. This comprehensive dataset encompassed climatic variables, plant developmental metrics, and soil nutrient profiles, yielding an in-depth perspective of the agricultural ecosystem. Subsequently, these data were leveraged to construct a machine learning-based predictive framework designed to refine farming strategies and promote more efficient resource utilization in groundnut production.

The Internet of Things (IoT) refers to a network of uniquely identifiable computing devices that exchange information via the internet without requiring continuous human intervention. These systems employ embedded sensors to capture environmental data, which is then relayed to centralized processing units or cloud platforms. Analytical outputs from cloud-based servers subsequently direct IoT-enabled devices to execute targeted actions. Fundamental elements of IoT architecture encompass sensing units, communication infrastructure, data analytics capabilities, and intuitive user interfaces (Paul et al., 2022).

Several researchers have investigated the efficacy of advanced computational models for agricultural forecasting. Kamilaris and Prenafeta-Boldú (2018) conducted a comprehensive survey of deep learning applications in agriculture, revealing that convolutional neural networks (CNNs) and recurrent neural networks (RNNs) significantly improve yield prediction accuracy, though their deployment is often constrained by the need for extensive training datasets and high computational overhead. Complementing this, Liakos et al. (2018) evaluated traditional ML models—including Support Vector Machines (SVM), Random Forest (RF), and Artificial Neural Networks (ANN)—for crop yield prediction, reporting that Random Forest achieved superior performance with an R^2 value of 0.89, albeit with challenges related to model interpretability. Similarly, Goap et al. (2018) demonstrated that SVM could attain 88% accuracy in wheat yield prediction when integrated with IoT-derived soil and weather data, though the model's reliance on historical meteorological records limited its adaptability to real-time environmental fluctuations.

A substantial body of literature emphasizes the role of IoT architectures in enabling precision agriculture. Farooq et al. (2019) and Tzounis et al. (2021) systematically reviewed IoT frameworks for crop monitoring, concluding that sensor-enabled systems can reduce water and fertilizer consumption by 20–40% while enhancing overall farm efficiency. Jayaraman et al. (2021) developed a low-cost IoT prototype using Raspberry Pi and soil sensors, achieving 85% accuracy in yield estimation, though scalability for extensive farmland remained a limitation. In the context of nutrient management, Gavhane et al. (2018) deployed NPK sensors coupled with fuzzy logic algorithms to optimize fertilizer application, reporting a 35% reduction in nutrient waste—a finding highly relevant to groundnut vegetative growth modeling where precise nitrogen, phosphorus, and potassium dosing is critical.

Recent studies have explored hybrid approaches to overcome limitations of standalone IoT or ML systems. Patil and Kale (2021) integrated satellite-derived NDVI imagery with ground-based IoT sensors using CNN architectures, improving prediction accuracy by 15% over single-source models, though data fusion latency posed operational challenges. To address cloud dependency and response time, Doshi et al. (2022) implemented edge-based LSTM models with LoRaWAN sensors, reducing latency by 60% while maintaining 91% prediction accuracy—albeit with constraints on model complexity due to edge device limitations. Security and data integrity concerns were addressed by Vangala et al. (2020), who incorporated blockchain technology with SHA-256 encryption into IoT agriculture systems, reducing data tampering risks by 95%, though the energy intensity of blockchain operations remains a barrier for resource-constrained settings.

Several investigations focused on specific crops, offering methodological insights transferable to groundnut research. Khanna and Kaur (2019) optimized irrigation and predicted potato yield using soil moisture sensors and ANN models, achieving an 8% yield error margin and 22% water savings, though results were confined to controlled environments. Rehman et al. (2021) applied gradient boosting to IoT-collected soil and temperature data for wheat farming, attaining 89% accuracy and 18% water reduction, while noting risks of model overfitting with limited datasets. Kodali et al. (2019) deployed a LoRa-based IoT network for paddy field monitoring, achieving 90% prediction accuracy with 2 km node range, though network congestion emerged in dense sensor deployments.

The frontier of smart agriculture research emphasizes real-time responsiveness and automation. Boursianis et al. (2020) proposed an IoT framework integrating drones and multispectral cameras with edge computing, enabling detection of crop stress two weeks earlier than conventional scouting methods, despite high initial infrastructure costs. Athanasiou et al. (2023) advanced this direction by developing a smart irrigation system using deep neural networks and real-time IoT data processing, achieving 93% yield prediction accuracy and 30% water savings, though the power demands of DNN training present sustainability concerns for field deployment.

This study seeks to assess how Smart Farming technologies influence groundnut productivity and overall yield outcomes. The specific goals guiding this investigation are outlined as follows:

1. Implement IOT base system for smart farming cultivation of groundnut.
2. To develop a model for predicting plant growth rate base on response to NPK
3. To compare the performance of the model with existing model to estimate fertilizer application for optimum yield.

This work serves as a valuable resource for agronomists, data scientists, and agricultural engineers seeking to leverage the predictive capabilities of groundnut vegetative growth models to optimize nutrient management and biomass accumulation in diverse farming scenarios.

MATERIALS AND METHODS

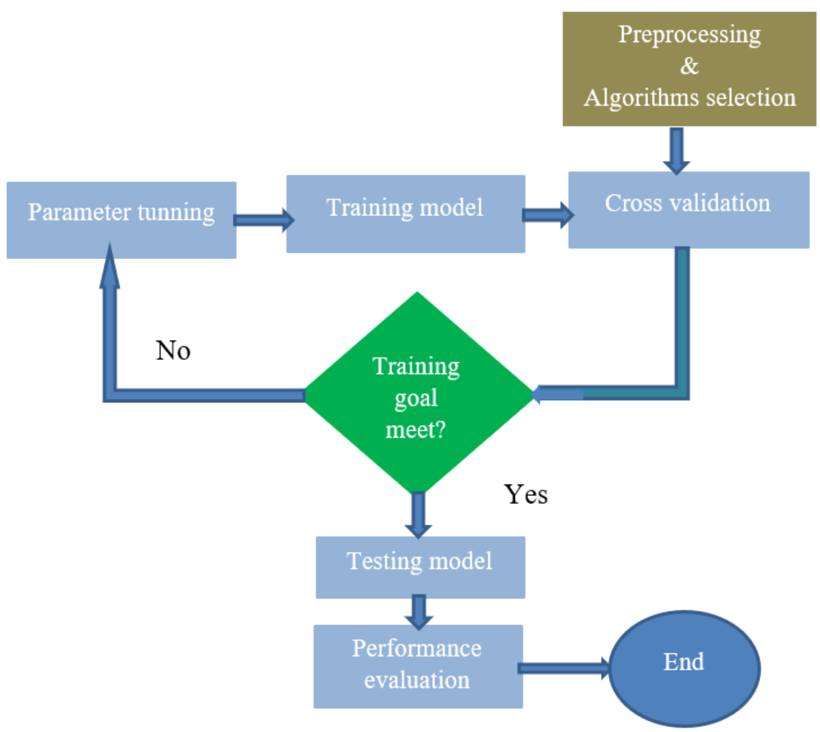

Figure 1: Workflow Adopted in the Research

IoT Device Implementation

The IoT implemented deployed for groundnut cultivation data acquisition incorporated soil moisture probes, temperature sensors, NPK nutrient detectors, Modbus communication interface, and an Arduino Uno microcontroller. Acting as the primary control unit, the Arduino Uno coordinated with these peripheral sensors to gather live measurements pertaining to soil hydration status, ambient temperature, and essential macronutrient concentrations namely nitrogen, phosphorus, and potassium. The Modbus protocol facilitated reliable interoperability between the Arduino Uno and connected hardware components, guaranteeing efficient and uninterrupted data flow to the centralized monitoring platform. Upon receiving raw sensor inputs, the Arduino Uno performed initial processing to generate actionable intelligence regarding field conditions and soil health, thereby supporting targeted interventions and optimized crop management strategies for groundnut production. This cohesive integration of IoT hardware, anchored by the Arduino Uno, markedly improved the precision, responsiveness, and overall effectiveness of data-informed agricultural decision-making throughout the cultivation cycle.

IoT Device Calibration

The calibration procedure entailed submerging the temperature sensor probe into moist soil at consistent time intervals and cross-referencing its output against standard mercury thermometer measurements to establish baseline accuracy. In parallel, readings from the soil nutrient sensor were validated through comparative analysis with certified laboratory assays for nitrogen, phosphorus, and potassium content. The evaluation outcomes confirmed exceptional sensor fidelity, yielding mean accuracy rates of 93.91% for temperature detection, 96.5% for nitrogen quantification, 93.3% for potassium measurement, and 97.2% for phosphorus assessment. These results affirm that the deployed sensors exhibit robust reliability and are well-suited for precise, continuous monitoring of critical soil parameters in agricultural settings. Calibration reult shown in figure 2.0.

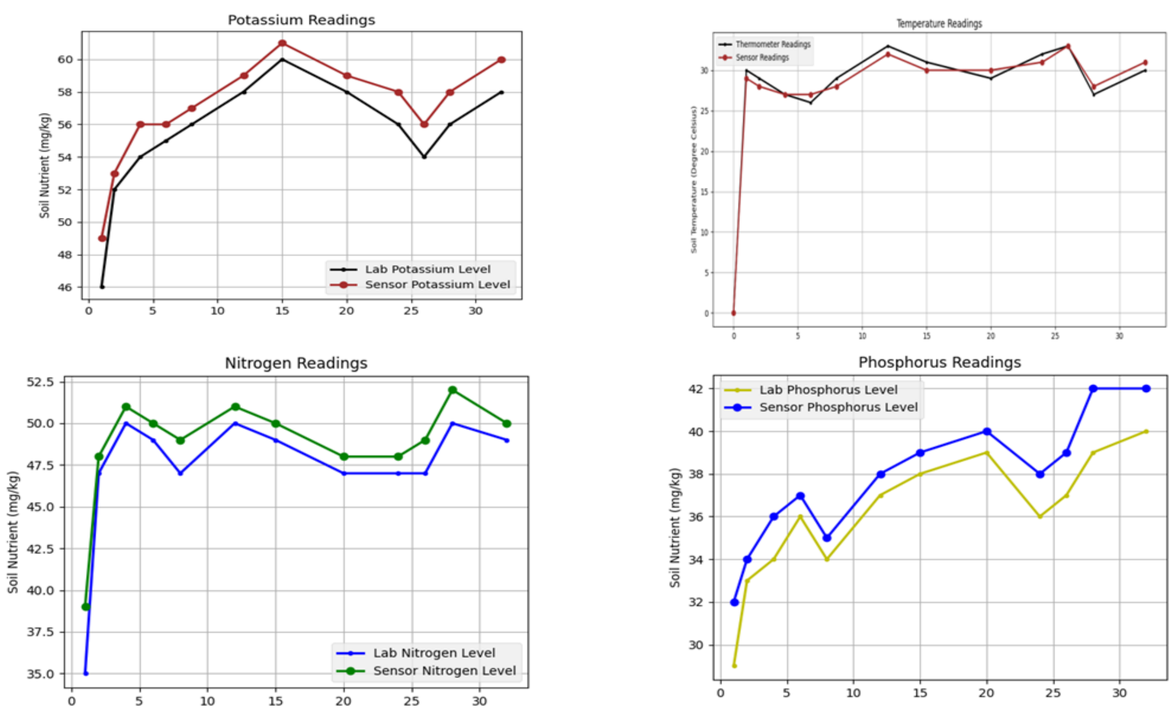

Figure 2: Device Calibration

Data Collection

Data was collected using IoT sensors for soil nutrients (NPK), moisture, and temperature, alongside meteorological records from an on-site Agro-Climatological Station and systematic plant growth observations (height, leaf count, tillers, flowering, and yield). All measurements followed a standardized protocol throughout the growing season to ensure consistency and reliability.

The resulting dataset comprised structured, continuous numerical records of soil conditions, climatic variables (temperature, humidity, wind speed/direction, rainfall), and crop developmental metrics, enabling seamless integration into analytical models for studying environment-soil-plant interactions.

Post-harvest, after active vegetative growth ceased, two plants per net pot were randomly selected for final assessment, with total fresh weight, dry matter accumulation, and pod count recorded to evaluate yield performance.

Dataset

The dataset comprises high-resolution, time-stamped sensor readings acquired continuously throughout a 120-day groundnut cultivation cycle spanning April to July 2024, across twenty controlled experimental pots. For each pot, critical edaphic and environmental variables including soil temperature, moisture content, and concentrations of nitrogen, phosphorus, and potassium were systematically recorded. In total, the dataset encompasses 480 structured data instances, offering sufficient temporal granularity and feature depth to support the study's core aim: leveraging IoT-based real-time monitoring to develop and train machine learning models capable of accurately predicting groundnut vegetative growth rates in response to dynamic nutrient and environmental conditions.

Data Pre-processing

The raw dataset underwent rigorous preprocessing to address data quality issues, including missing entries, statistical outliers, and non-informative variables. Missing values were imputed using central tendency measures mean, median, or mode selected based on the underlying distribution of each feature. Outlier identification was performed using box plot visualization, followed by removal via the Interquartile Range (IQR) technique, whereby observations falling beyond the lower and upper IQR bounds were classified as anomalies and excluded to prevent distortion of model learning. Subsequently, feature scaling was applied through standardization to transform variables to a common scale with zero mean and unit variance, computed using the following equation:

$$X_{scale} = \frac{X-\mu}{\sigma} \quad (1)$$

where μμ represents the feature mean and σσ denotes its standard deviation. This normalization step ensured uniformity in variable ranges and distributions, facilitating more stable and efficient convergence during machine learning model training [Kotsiantis & Kanellopoulos, 2006]. The cleaned and scaled dataset was then retained for downstream analytical modeling.

Model Implementation

The acquired raw dataset underwent systematic preprocessing to ensure suitability for machine learning model development. This involved imputing missing entries, applying feature scaling or normalization techniques, transforming categorical attributes into numerical representations, and eliminating statistical outliers to uphold data integrity and reliability. Regarding algorithm selection, three distinct models were strategically chosen based on their complementary strengths and alignment with the study's regression objectives: K-Nearest Neighbors (KNN) for its non-parametric flexibility and ease of implementation, Multi-Layer Perceptron (MLP) for its capacity to capture non-linear relationships and complex interaction patterns, and Random Forest for its ensemble-based robustness against overfitting in high-dimensional feature spaces.

Core Python libraries including pandas and NumPy for data manipulation, scikit-learn for implementing machine learning workflows, and matplotlib for exploratory visualization were imported to support the analytical pipeline. The dataset was ingested from the source file data2.csv via pd.read_csv(), after which predictor variables (X) and the target response (y) were delineated. Subsequently, the data was partitioned into training and testing subsets using an 80:20 stratified split to enable unbiased performance assessment. Hyperparameter optimization was conducted through GridSearchCV with cross-validation to identify the most effective configuration for each algorithm. Finally, models were fitted on the training data and rigorously evaluated on the held-out test set using standard regression metrics including R^2, MAE, and RMSE to quantify predictive accuracy and generalization capability.

RESULTS AND DISCUSSION

Data Visualization

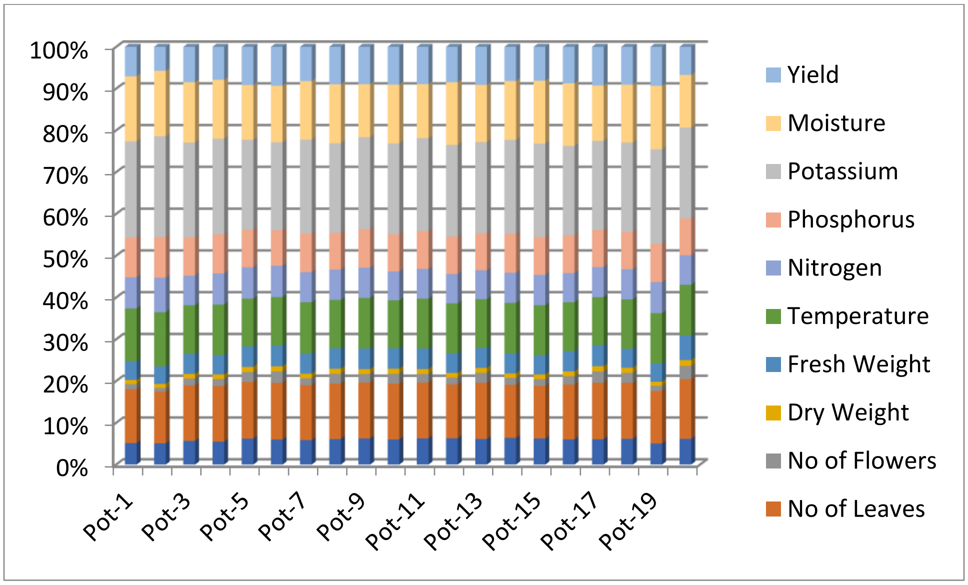

Figure 3: Data Visualization

Stacked bar charts were employed to visualize the dataset, enabling clear identification of patterns, trends, and inter-variable relationships across the experimental pots. Each bar represents an individual pot, with color-coded segments depicting the proportional contributions of key parameters including yield, soil moisture, NPK nutrients, temperature, fresh/dry biomass, and floral/leaf counts. Yield and moisture consistently comprised the largest proportions, underscoring their dominant influence on plant development, while nitrogen, phosphorus, and potassium levels remained relatively uniform across pots, indicating stable nutrient conditions. Although vegetative metrics like leaf and flower counts occupied smaller segments, they remain critical indicators of growth progression. Overall, this visualization effectively captures both the consistency and variability of multifactorial influences on groundnut performance across the experimental setup.

Data Description

Table 1: Statistical description of the data

	Temp	N	P	K	Moisture	Yield pod plant^{-1}
Count	20.00000	20.00000	20.00000	20.00000	20.00000	20.00000
Mean	29.57470	18.01600	22.523750	54.82750	34.94950	21.00000
Std	0.48291	0.540929	0.250015	0.599042	1.983677	2.79096
Min	28.78000	17.44000	22.00000	53.75000	31.20000	13.00000
25%	29.32750	17.57500	22.37750	54.43250	34.04000	20.00000
50%	29.54000	17.85000	22.55500	54.80500	34.96500	22.00000
75%	29.81500	18.37500	22.67500	55.09250	36.34250	23.00000

Table 1 presents descriptive statistics for six key variables: temperature, nitrogen (N), phosphorus (P), potassium (K), soil moisture, and pod yield per plant. The mean temperature of 29.57°C with a low standard deviation (0.48) reflects stable, controlled growing conditions. Nutrient levels (N, P, K) exhibited minimal variability, though potassium showed slightly greater dispersion than nitrogen and phosphorus. In contrast, yield displayed the highest variability (std = 2.79), indicating diverse productivity outcomes across experimental units. Overall, the narrow interquartile ranges and low standard deviations for temperature and nutrients suggest consistent soil and environmental management, while the comparatively higher variation in moisture and yield points to their sensitivity to dynamic biological or external factors.

Growth Rates in Response to NPK Model Result

Table 2: Growth rate prediction metrics

	MAE	MSE	RMSE	RMSLE
MLP	1.3499	2.7220	1.6498	0.0024
RF	3.112	3.789	3.833	0.223
KNN	3.899	3.600	3.922	0.233

Table 2 summarizes the performance of three machine learning algorithms Multi-Layer Perceptron (MLP), Random Forest (RF), and K-Nearest Neighbors (KNN) in predicting groundnut vegetative growth rates. Model efficacy was assessed using five regression metrics: coefficient of determination (R^2), Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Root Mean Squared Logarithmic Error (RMSLE).

The Multi-Layer Perceptron (MLP) model demonstrated superior performance in predicting groundnut growth rates, achieving the highest coefficient of determination (R^2 = 0.52) compared to Random Forest (0.32) and K-Nearest Neighbors (0.37). MLP consistently recorded the lowest error metrics across MAE (1.3499), MSE (2.7220), and RMSE (1.6498), indicating greater precision and reduced prediction variability. Most notably, MLP's RMSLE value (0.0024) was drastically lower than that of RF (0.223) and KNN (0.233), highlighting its exceptional ability to minimize relative errors. These results unequivocally establish MLP as the optimal algorithm for modeling vegetative growth dynamics, underscoring the critical importance of task-specific model selection in agricultural machine learning applications.

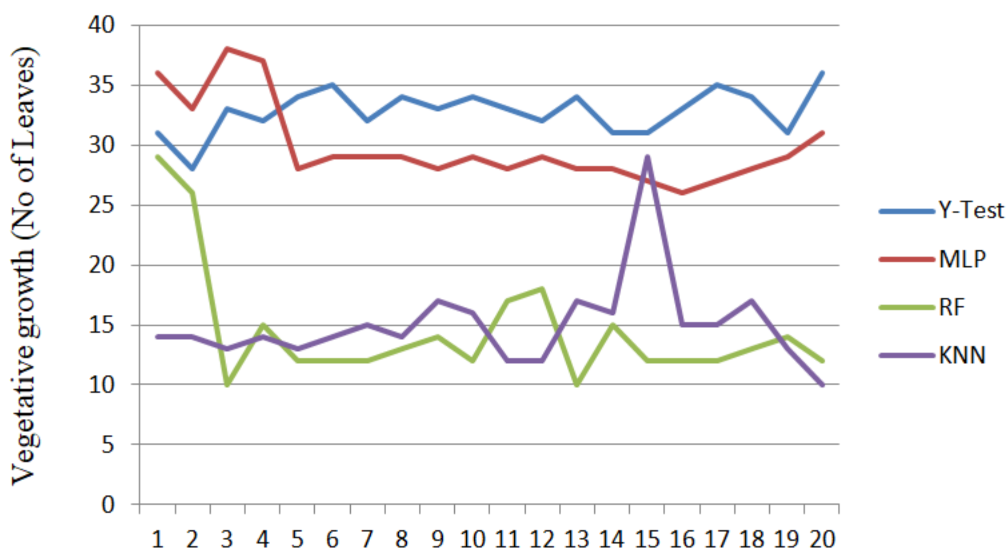

Figure 4: Vegetative Growth Models Performance

Figure 4 compares vegetative growth predictions (leaf count) from MLP, RF, and KNN models against actual test values across 20 data points. The MLP trajectory closely aligns with the observed values, demonstrating superior predictive fidelity, while RF captures general trends but exhibits notable deviations, particularly in early-to-mid sequences. KNN displays pronounced instability, with erratic fluctuations and outlier sensitivity evident in sharp spikes such as at point 15 indicating poor generalization. MLP's consistent proximity to ground truth reflects its capacity to model complex, nonlinear growth patterns, whereas RF's moderate performance suggests limitations in handling intricate feature interactions, and KNN's volatility underscores its susceptibility to local noise and overfitting. These visual insights corroborate the quantitative metrics, affirming MLP as the most robust model for groundnut vegetative growth forecasting.

Bagging of Growth rate Prediction Model

Table 3: Bagging of individual model

	R^2	MAE	MSE	RMSE	RMSLE
MLP	0.55	1.299	2.220	1.348	0.0024
RF	0.39	2.912	2.389	3.521	0.123
KNN	0.36	3.766	2.811	2.722	0.121

Table 3 examines the bagging of individual models, presenting similar metrics to those in Table 2 but potentially reflecting improved performance through ensemble methods. The R-squared values show MLP leading with 0.55, indicating a slight improvement from Table 2.0, while RF and KNN maintain relatively consistent values at 0.39 and 0.36 respectively.
When observing MAE, MLP continues to demonstrate superior performance with the lowest value at 1.299, showing marginal improvement compared to its performance in Table 4.3, while RF and KNN remain higher at 2.912 and 3.766 respectively. The MSE values follow a similar trend where MLP maintains its lead with 2.220, which is slightly better than its previous performance, while RF and KNN show values of 2.389 and 2.811 respectively. The RMSE metric reveals some interesting changes, particularly for KNN, which shows significant improvement from Table 4.3, decreasing from 3.922 to 2.722, suggesting that bagging notably enhances its performance. Meanwhile, MLP maintains its strong performance with an RMSE of 1.348, representing a slight improvement over its previous result.
The RMSLE values for all models decrease compared to Table 4.3, with MLP maintaining its exceptional performance at 0.0024, while RF and KNN improve to 0.123 and 0.121 respectively. These improvements in RMSLE for RF and KNN indicate that bagging helps reduce their relative prediction errors. The overall pattern suggests that while MLP remains the top performer, bagging particularly benefits KNN in terms of RMSE reduction. This table demonstrates how ensemble methods can enhance model performance, especially for algorithms that initially showed weaker results. The analysis provides valuable insights into how different models respond to bagging techniques and offers guidance for optimizing predictive performance through ensemble approaches.

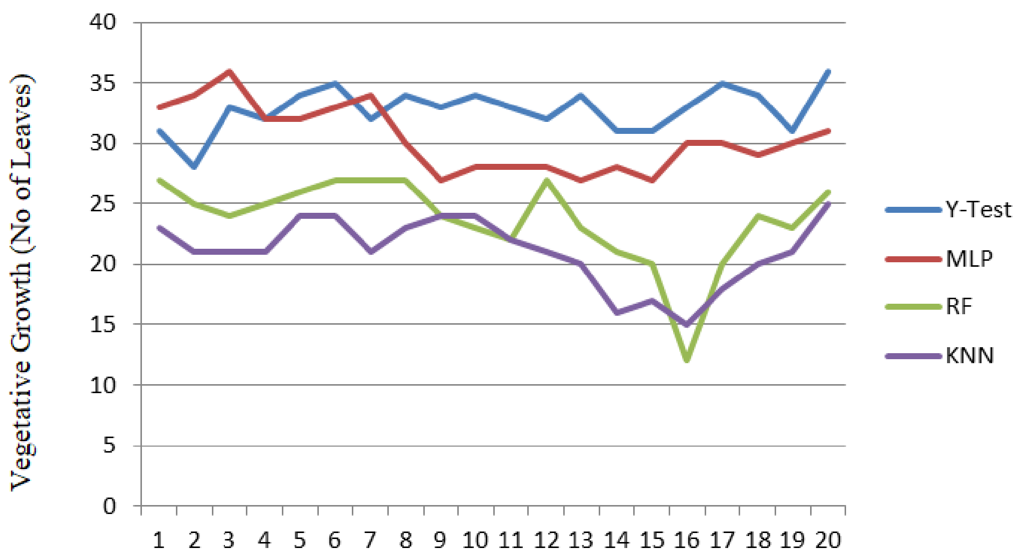

Figure 5: Vegetative Growth Models with Bagging

This figure illustrates the performance of three machine learning models MLP, RF, and KNN compared to the actual test data (Y-Test) in predicting vegetative growth (number of leaves). The Y-Test curve (blue line) represents the ground truth, serving as the benchmark for the model predictions. The MLP model (red line) closely follows the Y-Test curve, showing its strong ability to approximate the actual vegetative growth with minimal deviations.
The RF model (green line) demonstrates moderate alignment with the Y-Test curve but exhibits noticeable deviations in certain intervals, especially around instances 10–15, where its predictions significantly underestimate the actual values. The KNN model (purple line) performs the worst, with larger deviations from the Y-Test curve, particularly in the middle region (instances 10–15), where it fails to capture the growth pattern effectively.

The consistent performance of MLP across all intervals indicates its superior ability to generalize, likely due to its capacity for capturing non-linear relationships in the data. On the other hand, RF and KNN appear less robust, suggesting that they may struggle with the complexity or variability of the data. Bagging seems to improve MLP's performance significantly, as seen by its reduced fluctuations and closer alignment with the Y-Test.

Performance Comparison

This study's Random Forest (RF) model for groundnut vegetative growth prediction was compared against the RF implementation in Malik et al. (2025) for multi-crop fertilizer optimization as shown in Table 4.

Table 4: Bagging of individual model

Metric	This Study (Groundnut)	Malik et al. (2025)
Target	Vegetative growth rate (NPK-driven)	Optimal fertilizer type/dosage
RF R^2	0.32 (standard) → 0.39 (bagging)	0.92
RF MAE	3.112 → 2.912 (bagging)	7.85 kg/ha
RF RMSE	3.833 → 3.521 (bagging)	10.12 kg/ha

The notably lower R^2 in the groundnut study reflects the challenge of modeling fine-grained, temporal vegetative responses using a small, single-crop dataset. In contrast, Malik et al.'s RF benefited from high-dimensional, diverse agricultural data where ensemble methods excel at capturing broad nutrient-yield patterns. While bagging improved RF performance in both studies, the groundnut context favored MLP (R^2 = 0.55 with bagging), suggesting neural networks better capture the non-linear, time-sensitive dynamics of early-stage crop growth. RF remains highly effective for large-scale fertilizer recommendation but may require expanded temporal features or hybrid architectures for precise vegetative growth forecasting in controlled, single-crop settings.

CONCLUSION

A growth rate prediction model was developed using Random Forest (RF), K-Nearest Neighbors (KNN), and Multi-Layer Perceptron (MLP). MLP achieved the highest R^2 value of 0.55, demonstrating its ability to capture complex relationships between NPK levels and growth rates. Metrics like RMSE and MSLE validated the model's performance, highlighting the significant impact of NPK on groundnut growth.

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