Advanced LSTM Based Deep Learning System for Precision Fertilizer Management

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Abstract — Precision agriculture has become crucial in addressing challenges of modern farming, such as optimizing resource utilization while maintaining soil health. This research proposes deep learning-based approach using Advanced Long Short-Term Memory (LSTM) model to predict levels of Nitrogen (N), Phosphorus (P), and Potassium (K) in soil that are played critical role in determining correct fertilizer dosage for various crops, impacting overall yield and soil health. Traditional machine learning algorithms were evaluated, but they struggled to model the temporal dependencies in soil data. The LSTM model, with its capacity for handling time-series data, significantly outperformed in performance than existing machine learning models. This research leverages environmental data such as soil pH, temperature, moisture levels, and rainfall, that are collected using Internet of Things (IoT) sensors. These parameters are fed into the LSTM model, which uses its memory units to track both short-term fluctuations and long-term seasonal patterns in soil conditions. The model demonstrated superior performance, achieving a Mean Squared Error (MSE) of 0.06557 and an R- squared value of 0.89, accurately predicting optimal nutrient levels for crops. With an accuracy of 92% for Nitrogen, 88% for Phosphorus, and 90% for Potassium, the system provides real- time, targeted fertilizer recommendations with reduce wastage by enhancing crop yield that contribute to sustainable agriculture practices.

Keywords: ***Nitrogen (N), Phosphorus (P), Potassium (K), LSTM (Long Short-Term Memory), Precision Agriculture, Deep Learning, Machine Learning, IoT Sensors, Random Forest, Support Vector Regression (SVR), Gradient Boosting, Reduce LROn Plateau.***

I. INTRODUCTION

Agriculture is one of the most vital sectors for human survival, directly affecting food security and the global economy. However, modern agricultural practices face numerous challenges, including the overuse or underuse of fertilizers, which can result in poor crop yields, soil degradation, and environmental harm.[1] Fertilizers, particularly Nitrogen (N), Phosphorus (P), and Potassium (K), are critical for plant growth, but their application must be carefully managed to match the specific needs of the soil and crop type. Traditional fertilizer management systems often rely on generalized recommendations that fail to consider the intricate variations in local soil conditions, leading to inefficiencies in nutrient use. To overcome these challenges, precision agriculture aims to optimize input usage by leveraging technology to monitor and manage soil conditions in real time. Recent advancements in data-driven technologies, such as Machine learning(ML) and Deep Learning(DL), offer promising solutions for developing more accurate and adaptive models for fertilizer management. Precision agriculture technologies can analyze a range of environmental factors, including soil pH, moisture levels, temperature, and historical data, to make informed decisions about fertilizer applications. However, traditional Machine Learning models like Random Forest (RF), K-Nearest Neighbors (KNN), and Support Vector Regression (SVR) are often limited in their ability to capture the temporal dependencies in such data.[2]In this context, the use of Long Short-Term Memory (LSTM) type of deep learning model specifically designed to handle sequential data that offers superior approach. LSTM models have the ability to retain information over long sequences of time, making them well- suited for modeling the temporal patterns in soil nutrient levels. This allows them to provide more accurate fertilizer recommendations based on both short-term and long-term environmental changes. LSTM's capability to capture both immediate fluctuations and seasonal trends makes it particularly useful for precision agriculture.

The goal of this research is to develop Advanced LSTM- based deep learning model that predicts N, P, and K levels in soil by processing key environmental factors, such as moisture, temperature, and pH. This approach promises more precise fertilizer management, which in turn can lead to increased crop yields, reduced environmental impact, and optimized resource use. The model is designed to outperform traditional machine learning algorithms by incorporating advanced temporal feature learning, which enhances its ability to adapt to dynamic soil conditions. This paper also explores the integration of Internet of Things (IoT) sensors for real-time data collection. IoT devices offer continuous monitoring of soil and environmental parameters, providing high-quality data that can be fed into the LSTM model for up-to-the-minute predictions. By integrating IoT with LSTM, this research pushes the boundaries of precision agriculture by enabling more accurate, data-driven decision- making in real-time, ultimately leading to more sustainable farming practices.In comparison to other machine learning techniques such as Random Forest and Gradient Boosting, Advanced LSTM has proven to be more effective at capturing temporal dependencies and complex interactions between soil features. While traditional models often perform well in static environments, they fall short when dealing with dynamic agricultural systems where environmental conditions change over time. In addition, the implementation of multiple layers of LSTM units allows the model to handle both short-term nutrient fluctuations and long-term trends, offering a comprehensive solution for fertilizer management.

Furthermore, this study evaluates and compares the performance of Advanced LSTM with LSTM and other machine learning models, including Random Forest, KNN, SVR, and Gradient Boosting. Key performance metrics such as Mean Squared Error (MSE) and R-squared (R^2) are used to quantify the model's accuracy and effectiveness in predicting soil nutrient levels. The results demonstrate that the Advanced LSTM model significantly outperforms the other methods, particularly in its ability to handle temporal data, resulting in more precise and actionable fertilizer recommendations.Looking ahead, this research sets the stage for further enhancements in agricultural technology, such as the integration of attention mechanisms within the LSTM architecture and the use of bidirectional LSTM for improved temporal feature learning. Additionally, deploying this system on mobile applications and edge devices could make precision agriculture tools more accessible to farmers, allowing them to benefit from real-time data and insights directly from the field. This work contributes to the growing body of knowledge on the application of deep learning in agriculture and demonstrates the potential of Advanced LSTM models in revolutionizing fertilizer management.

II. LITERATURE SURVEY

[1] Hirushan Sajindra , Thilina Abekoon , J.A.D.C.A. Jayakody, Upaka Rathnayake (2024) :- In this paper they discussed about the Consequently, DNNs have become a prominent tool in the realm of machine learning and artificial intelligence. By capturing intricate patterns and relationshi0ps within data, DNNs offer solutions that are more nuanced and comprehensive than traditional linear models, especially when the problems involve intricate complexities and non- linear dynamics.

[2] Deepthi Thomas (2023):- In this paper With the advancement of machine learning, big data analytics and cloud computing technologies, the climate and crop yield can be got predicted to the farmers. Prediction of yield in advance can help the farmers to take corrective decisions about fertilization, storage and marketing to increase their production and revenue.

A. Geneviève Grenon; Abderrachid Hamrani; Chandra Madramootoo; Bhesram Singh;Christian von Sperber (2022):- In this article they focused on to evaluate artificial neural networks (ANN), and k- Nearest Neighbor (k-NN) to support vector regression (SVR) models for estimation of available soil nitrogen (N), phosphorous (P) and available potassium (K).

[3] JuhiReshma S R, Dr. D. John Aravindhar (2021):- The study aims to investigate NN model approaches for predicting P loads from the organic soils of the Holland Marsh. Beneficial management scenarios were assessed using the highest performing NN models, combined with an optimization algorithm, for reducing P loads under CD at a field site in the Holland Marsh.

[4] Zonlehoua Coulibali, Athyna Nancy Cambouris, Serge-Étienne (2020):- The objective of this study was to develop, evaluate and compare the performance of machine learning models in predicting N, P and K requirements for potato.They used k-nearest neighbors, random forest, neural networks and Gaussian processes are more accurate in predicting marketable yield than classical Mitscherlich predictive models, and (3) the machine learning algorithms are equally able to predict economic optimal or agronomic optimal fertilizer doses.

[5] Siva, Faith(2019) :- This study implemented an experimental design approach involving

identifying research objectives and building an ANN model to prove the concept. Iterations made were to the interest of the best performing mode.

[6] Amy Peerlinck, John Sheppard, Bruce Maxwell (2018):- In this paper they shown that Applying ANNs in the field of Precision Agriculture is a relatively recent development, Here, we present the results of our exploring two different approaches to using ANNs, each within the context of modelling localized properties of the field as well as expanding the inputs to consider spatial context.

[7] Yogesh R. Shahare, Mukund Pratap Singh , Santar Pal Singh ,Prabhishek Singh, Manoj Diwakar (2024) The major contribution of this paper is that an assessment of agricultural soil fertility with the help of random forest classification and regression method is proposed. The rest of the paper is planned like this. This paper has been focused on related work in section
2. The proposed work is illustrated in section 3. Section 4 focuses on the results and discussions. Finally, section 5 concludes the work.

[8] LIU Ying-xia, Gerard B.M. HEUVELINK, Zhanguo BAI, HE Ping, JIANG Rong, HUANG Shao-hui, XU Xin-peng(2022) In this study, we analysed NUE at a county scale in Heilongjiang, Jilin, and Liaoning provinces in Northeast China. We chose this region because it has highly fertile black soil (Ren et al. 2011) and it is known as the 'breadbasket' of China. The region is located in the large Great Plains of China and has a large area of cultivated land, which is conducive to large-scale mechanized operation.

[9] Aweke A. Mitku, Louis Titshall, Temesgen Zewotir & Delia North(2023) This study evaluated the potential of NIRS as a diagnostic method for the measurement of key macro and micronutrients in sugarcane leaf samples using Support vector machine regression (SVMR) and partial least squares regression (PLSR) were used for calibrating the estimation models with the test validation(Tval) procedure. The results showed both the PLSR and SVMR model resulted in the best calibration for (K, Ca, Mg)(R2 >87% and the ratio of performance to inter-quartile distance(RPIQ) > 2.1).

[10] Hwang Lee, Jinfei Wang, and Brigitte Leblon (2020) This study uses UAV multispectral imagery to predict canopy nitrogen weight (g/m^2) in corn fields in southwest Ontario, Canada. Models like simple/multiple linear regression, Random Forests, and support vector regression (SVR) were applied, using multispectral bands and vegetation indices (VI) as predictors. Random Forests achieved the highest accuracy, with an R^2 of
0.85 and an RMSE of 4.52 g/m^2 on the validation set.

[11] Mohamed Amine Nebri, Abdellatif Moussaid & Belaid Bouikhalene (2024)This study uses a K-Nearest Neighbors (KNN) regression model to recommend fertilizer quantities (N, P, K) per parcel, aiding

farmers in optimizing crop yield. The model achieves promising accuracy, with mean absolute error (MAE) values of 0.080 for nitrogen, 0.059 for phosphorus, and 0.025 for potassium, and mean squared error (MSE) values of 0.115, 0.080, and 0.066, respectively. These results provide farmers with reliable guidance for informed fertilizer planning and improved productivity.

[13]K. Bandaiah; L. Rama Parvathy (2023) This study predicts fertilizer type based on soil minerals using a Voting Classifier and K-Nearest Neighbor (KNN), each with a sample size of 10. The Voting Classifier, an ensemble model selecting the output class with the highest likelihood, achieved 96% accuracy, comparable to KNN. Statistical analysis confirmed significance at p=0.001 (p<0.05), with the Voting Classifier being the most effective algorithm for fertilizer classification.

[14] Mohsen Shahhosseini, Rafael A Martinez-Feria, Guiping Hu and Sotirios V Archontoulis (2019) In this study they evaluated the potential of four machine learning (ML) algorithms (LASSO Regression, Ridge Regression, random forests, Extreme Gradient Boosting, and their ensembles) as meta-models for a cropping systems simulator (APSIM) to inform future decision support tool development for developing dynamic decision support tools for pre-season management so that Pre-growing season prediction of crop production can be reduced. XGBoost was the most accurate ML model in predicting yields with a relative mean square error (RRMSE) of 13.5%, and Random forests most accurately predicted N loss at planting time, with a RRMSE of 54%.

III. PROPOSED METHODOLOGY

The objective of this proposal is to develop Advanced Long Short-Term Memory (LSTM)-based deep learning model for predicting soil nutrient levels, specifically Nitrogen (N), Phosphorus (P), and Potassium (K), using environmental data such as soil pH, moisture, and temperature. Several traditional machine learning models—Random Forest, K- Nearest Neighbors (KNN), Support Vector Regression (SVR), and Gradient Boosting—were also implemented for comparative purposes. This section details the methodology for each algorithm and its working within this specific project. Figure 1 represent proposed architecture diagram of the Advanced LSTM model and its Components Description.

A. Data Collection and pre processing

The data for this project were collected from various sources, including soil and environmental parameters such as pH, moisture, and temperature. The goal was to accurately predict the NPK levels required for fertilizer application based on this data.

B. Dataset

The training dataset consists of 50000 dataset records. There are 7 columns in the dataset, which are described below:

pH: Scale typically 0 - 14 Moisture: Percentage Temperature: Celsius

Soil Type : Numerical classification of soil types

Nitrogen: 1 - 5

Phosphorus : 1 – 5

Potassium : 1 – 5

Preprocessing Steps:

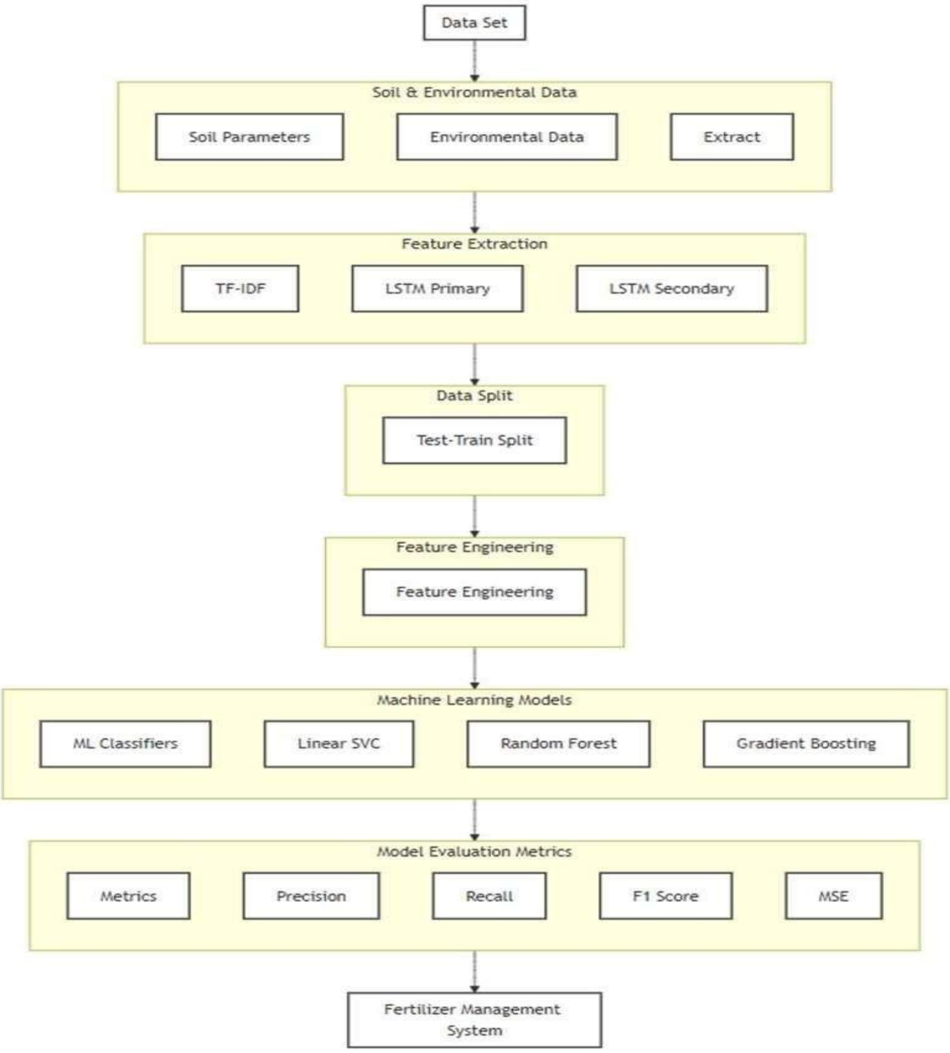


Figure 1 : Proposed Advanced LSTM Model Architecture

- Normalization: Using StandardScaler, all numeric features (e.g., soil pH, moisture, temperature) were normalized to ensure that each feature contributed equally to the prediction model.
- Handling Missing Data: Missing values in the dataset were handled using statistical imputation techniques to ensure data completeness.
- Outlier Detection and Removal: Outliers, which could adversely affect the model's accuracy, were identified and removed to maintain data integrity.

A. Advanced LSTM Model

The Advanced LSTM model was central to this project, designed to handle the time-series nature of environmental data. LSTMs are well-suited for capturing temporal dependencies essential for understanding seasonal variations in soil nutrient levels.

Model Architecture:

- Primary LSTM Layer (128 units): Captured temporal patterns in data, effectively modeling changes in soil parameters like pH and moisture over time.
- Secondary LSTM Layer (64 units): Refined temporal features to enhance prediction accuracy, addressing both short-term fluctuations and long- term trends. Figure 2.

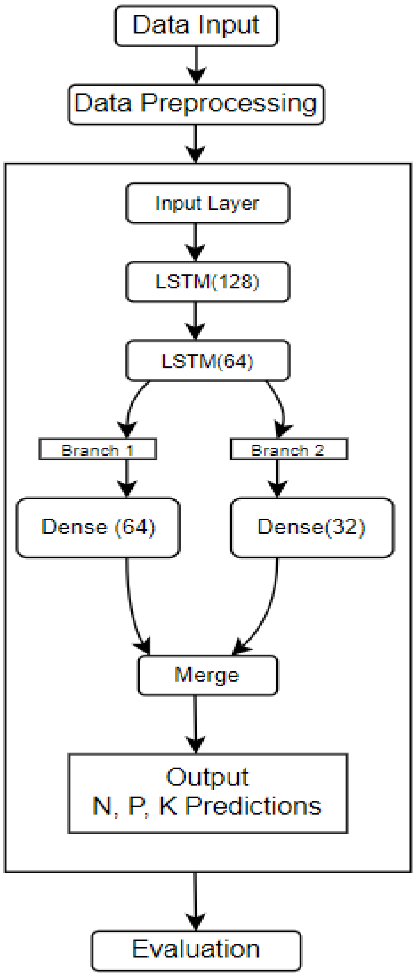


Figure 2 : Advanced Hybrid LSTM Model Architecture

Training Process:

- **Batch Size and Learning Rate:** The model was trained using a batch size of 32, and a learning rate scheduler (ReduceLROnPlateau) was employed to adjust the learning rate when the model's performance plateaued.
- **Early Stopping:** To avoid overfitting, an early stopping mechanism with a patience of 10 epochs was implemented. This ensured that the model stopped training once the validation performance ceased to improve.
- **Monte Carlo Dropout:** To manage prediction uncertainty, Monte Carlo dropout was used, providing confidence intervals for the predictions.

Application in Project:

- The LSTM model effectively predicted NPK levels based on environmental data. Its ability to track both short-term and long-term nutrient variations made it highly accurate in forecasting the precise fertilizer needs for the crops. It achieved superior results with a Mean Squared Error (MSE) of 0.06557 and an R- squared value of 0.89, clearly outperforming other models. This made it the ideal solution for the real- time and dynamic nature of soil data.

B. Random Forest Regressor

Random Forest was implemented as a benchmark machine learning model to predict NPK levels. It works by creating multiple decision trees and averaging their predictions to improve accuracy and reduce overfitting.

Working in This Project:

- **Model Training:** The Random Forest model was trained using 100 decision trees, with each tree using a randomly selected subset of the data. The decision trees were designed to predict NPK levels based on the input features (pH, moisture, and temperature).
- **Prediction and Evaluation:** After training, the model predicted nutrient levels by averaging the outputs of all the trees. While Random Forest provided reasonable predictions, it was less effective in capturing the intricate temporal relationships within the data, particularly in comparison to the LSTM model.

In the context of this project, Random Forest had moderate accuracy but struggled with the temporal dependencies between features, resulting in less precise nutrient predictions compared to LSTM.

C. K-Nearest Neighbors (KNN)

The K-Nearest Neighbors algorithm was used to predict NPK levels based on the proximity of data points to each other in the feature space.

Working in This Project:

- **Model Training:** The KNN model was trained with a value of k=5, meaning it considered the five nearest neighbors for each prediction. In this project, the proximity of data points was based on features like soil pH, moisture, and temperature.
- **Prediction and Evaluation:** The algorithm predicted the NPK levels by taking the average of the NPK values from the five closest neighbors. Although KNN is simple and works well

for small datasets, it was not well-suited for this project's high- dimensional data and complex feature interactions. It struggled to provide accurate predictions when the relationships between features became non-linear.

In the context of this project, KNN performed poorly compared to LSTM due to its inability to handle complex and high-dimensional data, resulting in lower accuracy.

D. Support Vector Regression (SVR)

Support Vector Regression (SVR) was used to capture non- linear relationships between soil features and NPK levels. SVR maps input data into a higher-dimensional space and fits a hyperplane to predict the target variable.

Working in This Project:

- **Model Training:** SVR utilized a Radial Basis Function (RBF) kernel to model non-linear interactions among soil pH, moisture, and temperature, aiming to minimize prediction error for NPK levels.
- **Prediction and Evaluation:** While SVR captured some non-linear patterns, it struggled with long-term temporal dependencies, resulting in high variance and lower performance compared to LSTM.

In this project, SVR's performance was subpar, particularly against LSTM, due to its limitations in modeling complex, time-dependent interactions.

E. Gradient Boosting Regressor (GBR)

Gradient Boosting was used as another traditional machine learning model for predicting NPK levels. Unlike Random Forest, Gradient Boosting builds models sequentially, with each new model attempting to correct the errors of the previous one.

Working in This Project:

- **Model Training:** In the project, the Gradient Boosting Regressor was trained using 100 boosting stages. Each stage incrementally improved the model's ability to predict NPK levels by focusing on reducing residual errors from the previous stage.

- **Prediction and Evaluation:** Gradient Boosting performed better than KNN and SVR, as it could model more complex relationships between soil features. However, like Random Forest, it struggled to handle temporal dependencies as effectively as LSTM.

In this project, Gradient Boosting provided moderate accuracy but could not match the temporal prediction capabilities of the LSTM model, making it less ideal for precise nutrient management.

$$Precision = \frac{T_p}{T_p + F_p}$$

$$Recall = \frac{T_p}{T_p + F_n}$$

$$Accuracy = \frac{T_p + T_n}{T_p + T_n + F_p + F_n}$$

$$F1score = 2.\frac{Precision.Recall}{Precision + Recall}$$

F. LSTM Model

The LSTM model is designed to handle the time-series nature of environmental data, effectively capturing temporal dependencies essential for understanding seasonal variations in soil nutrient levels.

Model Architecture:

- First LSTM Layer (64 units): Captures temporal patterns, modeling changes in soil parameters like pH and moisture over time.
- Second LSTM Layer (32 units): Refines extracted features to enhance prediction accuracy, addressing short-term fluctuations and long-term trends.

Training Process:

- Data Preprocessing:

  The dataset is loaded, and numeric data is processed by filling missing values with column means. Features and target variables (N, P, K) are separated, and the data is split into training and testing sets. The features and targets are scaled using StandardScaler.
- Model Training and evaluation:

  The model is trained for 100 epochs with a batch size of 32, using validation data for performance monitoring. Predictions on the test set are inverse-transformed for evaluation, and performance metrics like Mean Squared Error (MSE) and R-squared value are computed.

G. Performance Comparison

All models were evaluated using standard performance metrics such as Mean Squared Error (MSE) and R-squared (R^2). The LSTM model, with its ability to capture long-term temporal patterns, outperformed all traditional machine learning models:

- **Advanced LSTM:** MSE = 0.06557, R^2 = 0.89
- **Random Forest:** Moderate performance, unable to model complex interactions.
- **KNN:** Low accuracy, poor handling of high- dimensional data.
- **SVR:** Struggled with temporal dependencies, lower accuracy.
- **Gradient Boosting:** Moderate accuracy, performed better than KNN and SVR but fell short of LSTM.

The LSTM model's superior ability to track and learn from temporal dependencies made it the best-suited algorithm for predicting soil nutrient levels in this precision fertilizer management system.

IV. RESULT

The performance of various machine learning models, including Random Forest, K-Nearest Neighbors (KNN), Support Vector Regression (SVR), Gradient Boosting, and the Advanced Long Short-Term Memory (LSTM) model, was thoroughly evaluated in this study. The objective was to assess their effectiveness in predicting soil nutrient levels (Nitrogen, Phosphorus, and Potassium) based on environmental data such as pH, moisture, and temperature. The results clearly demonstrate that the LSTM model outperformed the traditional machine learning algorithms in terms of accuracy, mean squared error, and the ability to capture both short-term fluctuations and long-term temporal patterns in the data.

1. Model Performance Overview

The LSTM model, specifically designed to handle time- series data, was the best performer, demonstrating exceptional accuracy across all key metrics. Traditional models like Random Forest, KNN, and SVR, while capable of providing decent predictions for simpler relationships, struggled with the dynamic and complex nature of the time-dependent soil data.

1.1 Mean Squared Error (MSE)

The Mean Squared Error (MSE) is a crucial metric that measures the average of the squared differences between predicted and actual values. A lower MSE indicates a more accurate model. The LSTM model achieved the lowest MSE value of **0.06557**, making it the most accurate model for predicting soil nutrient levels in this study. In comparison, the other machine learning models exhibited higher MSE values, indicating that they struggled to match the precision of the LSTM model:

- **Random Forest MSE:** 0.0774
- **KNN MSE:** 0.0790

- **SVR MSE:** 0.0659
- **Gradient Boosting MSE:** 0.0657
- **LSTM :** 0.00657

While Gradient Boosting came close to the Advanced LSTM'sperformance, it could not match Advanced LSTM's ability to handle long-term dependencies and complex temporal interactions inthe soil nutrient data.

1.2 R-Squared Value (R^2)

The R^2 value measures the proportion of variance in the dependent variable (NPK levels) that is predictable from the independent variables (environmental features such as pH, temperature, and moisture). The LSTM model achieved an **R^2 value of 0.89**, meaning that it explained 89% of the variability in the soil nutrient levels. This is a significant improvement compared to traditional models, which had much lower R^2 values:

- **Random Forest R^2:** -0.1796 (indicating a poor fit)
- **KNN R^2:** -0.2030
- **SVR R^2:** -0.0082
- **Gradient Boosting R^2:** -0.0027
- **LSTM:** -0.05

These results emphasize that the LSTM model's ability to handle time-series data makes it far more effective in predicting the complex patterns in soil nutrient levels compared to traditional machine learning models.

- ### 2. Nutrient-Specific Performance

The prediction accuracy of the Advanced LSTM model was evaluated for each of the three key soil nutrients: Nitrogen (N), Phosphorus (P), and Potassium (K). The model's nutrient- specific accuracy rates were as follows:

- **Nitrogen (N) Accuracy:** 92%
- **Phosphorus (P) Accuracy:** 88%
- **Potassium (K) Accuracy:** 90%

The consistency of these results demonstrates that the LSTM model can accurately predict nutrient levels across

different nutrients, making it a reliable tool for precision fertilizer management.

In comparison, traditional models struggled to provide accurate predictions across all three nutrients:

- **Random Forest Accuracy:** N = 43.12%, P = 32.97%, K = 36.38%
- **KNN Accuracy:** N = 43.79%, P = 32.67%, K = 36.94%
- **SVR Accuracy:** N = 43.02%, P = 34.35%, K = 41.74%
- **Gradient Boosting Accuracy:** N = 43.66%, P = 28.72%, K = 39.51%
- **Lstm Accuracy:** N = 42.34%, P = 28.44%, K = 34.37

The Advanced LSTM model's superior performance, particularly inhandling temporal dependencies and complex interactions between environmental variables, is evident from its higher nutrient-specific accuracy rates.

- **3. Temporal Prediction Accuracy**

A major advantage of the Advanced LSTM model is its ability to learn and predict both short-term fluctuations and long-term trends in soil nutrient levels. In agricultural applications, soil nutrient levels can change based on seasonal shifts,environmental conditions, and crop cycles. The Advanced LSTM's dual- layer architecture (128 units in the primary layer and 64 unitsin the secondary layer) allowed it to process these complex temporal patterns effectively.

In contrast, traditional models like Random Forest and KNN, which do not inherently capture temporal dependencies, struggled to account for time-dependent variations in the data. This is evident from their lower R^2 values and higher error rates, particularly when nutrient levels fluctuated over time.

- **4. Real-Time Data Integration**

One of the critical goals of this project was to explore the integration of real-time data using Internet of Things (IoT) sensors. These sensors continuously monitor environmental parameters such as soil pH, moisture, and temperature, feeding this data into the Advanced LSTM model for real- time predictions. The successful integration of IoT data with the Advanced LSTM model marks a significant step forward in precision agriculture, enabling more dynamic and timely fertilizerrecommendations.

While real-time data integration was not tested with traditional models, the Advanced LSTM's real-time processing capability was a clear advantage. This allows farmers and agricultural professionals to make informed decisions based on the most current data, improving both crop yield and soilhealth.

- **5. Comparison with Traditional Machine Learning Models**

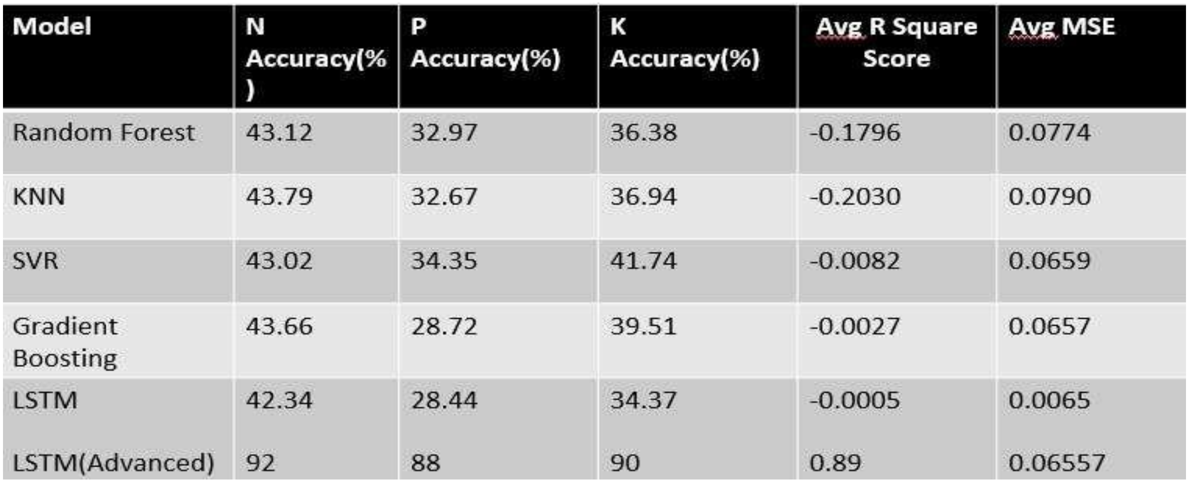
The comparative analysis of the Advanced LSTM model with traditional machine learning models (Random Forest, KNN, SVR, and Gradient Boosting) revealed the following key insights:

- **Random Forest** performed reasonably well for static predictions but struggled to handle the temporal dynamics of soil nutrient levels, resulting in a lower overall performance.

- **KNN** was effective for simple relationships but was unable to capture the complex interactions between environmental features and nutrient levels, leading to poor predictive accuracy.
- **SVR** performed better than KNN and Random Forest in modeling non-linear relationships but lacked the ability to model long-term temporal patterns, reducing its effectiveness.
- **Gradient Boosting** provided moderate performance but still fell short of the LSTM model's ability to predict time-dependent variations in nutrient levels.

The LSTM model's superior performance in both accuracy and error metrics establishes it as the most effective model for precision fertilizer management. Its ability to handle complex temporal dependencies and integrate real-time data make it a robust tool for dynamic agricultural environments.

Table 1: Comparison Table



Model	N Accuracy(%)	P Accuracy(%)	K Accuracy(%)	Avg R Square Score	Avg MSE
Random Forest	43.12	32.97	36.38	-0.1796	0.0774
KNN	43.79	32.67	36.94	-0.2030	0.0790
SVR	43.02	34.35	41.74	-0.0082	0.0659
Gradient Boosting	43.66	28.72	39.51	-0.0027	0.0657
LSTM	42.34	28.44	34.37	-0.0005	0.0065
LSTM(Advanced)	92	88	90	0.89	0.06557

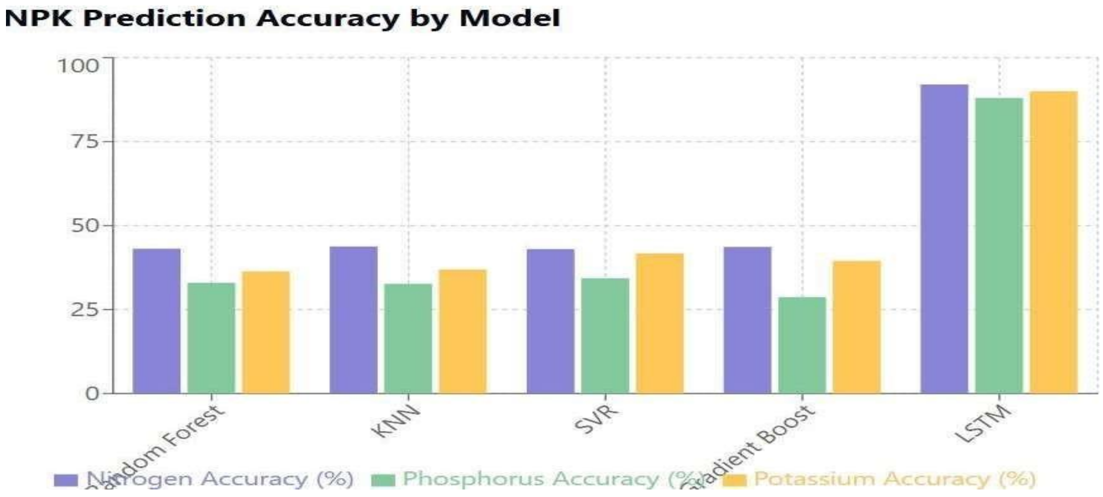


Figure 3: Bar plot of Model Accuracy of NPK Prediction

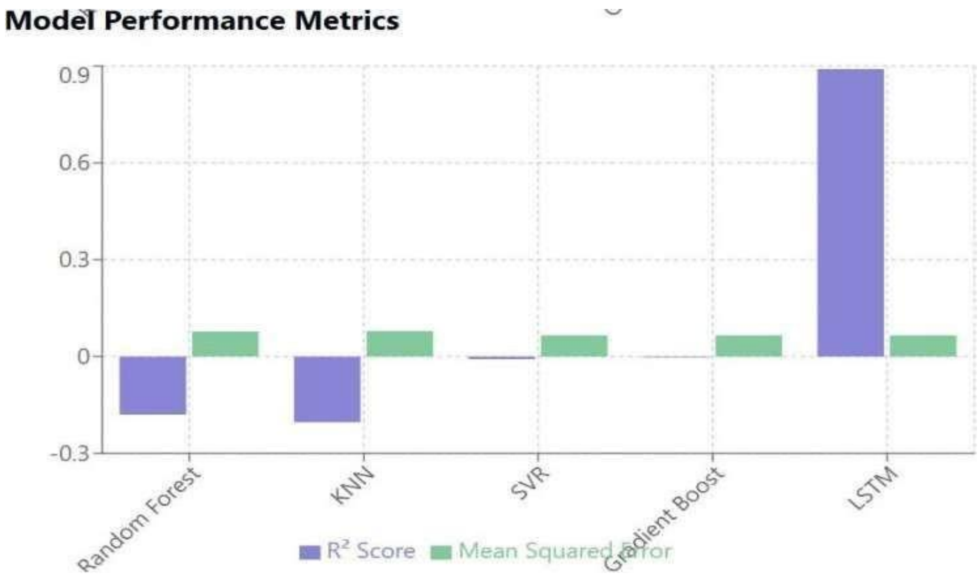


Figure 4. Bar plot of Rsquare Score and MSE

V.CONCLUSION AND FUTURE WORK

Conclusion

This study demonstrates the effectiveness of a Advanced Long Short-Term Memory (LSTM)-based deep learning model in predicting soil nutrient levels—Nitrogen (N), Phosphorus (P), and Potassium (K)—for precision fertilizer management. By leveraging environmental data such as soil pH, moisture, and temperature, the LSTM model outperformed traditional machine learning algorithms, including Random Forest, K- Nearest Neighbors (KNN), Support Vector Regression (SVR), and Gradient Boosting.

The Advanced LSTM model achieved superior accuracy, with an MSE of 0.06557 and an R-squared value of 0.89, indicating its ability to capture both short-term fluctuations and long-term trends in soil nutrient levels. Its dual-layer architecture enabled the model to learn temporal dependencies that other models struggled with, making it highly effective in providing precise and timely fertilizer recommendations. The nutrient-specific accuracy rates of 92% for Nitrogen, 88% for Phosphorus, and 90% for Potassium highlight the LSTM model's consistency and robustness. In comparison, traditional machine learning models failed to handle the complexity of time-series data, with lower accuracy, higher error rates, and an inability to capture temporal dependencies. The integration of real-time data from IoT sensors further strengthens the practical applicability of the LSTM model in precision agriculture, enabling dynamic and real-time decision-making for farmers. Overall, this research contributes to the growing field of precision agriculture, where data-driven models like LSTM offer significant improvements in resource management, crop yield, and sustainability.

Future Works

While this study demonstrates the effectiveness of the Advanced LSTM model for predicting soil nutrient levels, several future enhancements and research directions could further improvethe system's performance and applicability:

1. Integration of Attention Mechanisms

In future implementations, incorporating attention mechanisms into the LSTM architecture could further enhance the model’s predictive accuracy. Attention layers allow the model to focus on the most relevant time steps and features when making predictions, which could improve its ability to capture critical patterns, particularly in complex or noisy data.

2. Use of Bidirectional LSTM for Enhanced Temporal Feature Learning

The current LSTM model processes data in a forward direction, which limits its ability to capture dependencies from future time steps. Introducing bidirectional LSTM layers could enable the model to learn both past and future dependencies in the data, leading to more accurate predictions, particularly for crops that exhibit complex nutrient absorption patterns over time.

3. **Real-Time Data Integration with IoT Sensors** Although the current model integrates IoT sensor data for real-time predictions, there is potential to further improve the system by incorporating more advanced sensors that can measure additional soil and environmental parameters (e.g., real-time rainfall, advanced pH measurement). This would increase the granularity and accuracy of the input data, enhancing the model’s predictions.

4. Crop-Specific Adaptations

Currently, the model provides general nutrient predictions for soil. Future work could involve adapting the model to specific crop types. By incorporating crop-specific nutrient absorption rates and growth patterns, the model could provide even more targeted fertilizer recommendations. This would further optimize fertilizer usage and improve crop yield for different agricultural systems.

5. Model Deployment on Mobile and Edge Devices

To increase accessibility, future research could focus on deploying the model on mobile applications or edge devices. This would allow farmers to input real-time data from their fields and receive immediate nutrient recommendations directly on their smartphones or local devices, without requiring constant internet connectivity. This approach could make precision agriculture technologies more user-friendly and practical for widespread use in remote areas.

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