SMART FERTILIZER PREDICTION SYSTEM

CS19643 – FOUNDATIONS OF MACHINE LEARNING

Submitted by

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in partial fulfillment for the award of the degree

of

BACHELOR OF ENGINEERING

in

COMPUTER SCIENCE AND ENGINEERING

RAJALAKSHMI ENGINEERING COLLEGE

ANNA UNIVERSITY, CHENNAI

MAY 2025

BONAFIDE CERTIFICATE

Certified that this Project titled **"SMART FERTILIZER PREDICTION SYSTEM"** is the bonafide work of **"JAYANEE POOBALARAYAN J (2116220701102)"** who carried out the work under my supervision. Certified further that to the best of my knowledge the work reported herein does not form part of any other thesis or dissertation on the basis of which a degree or award was conferred on an earlier occasion on this or any other candidate.

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ABSTRACT

Agricultural productivity and soil sustainability heavily depend on the correct application of fertilizers, tailored to specific crop and soil conditions. In light of increasing food demand and the environmental impact of improper fertilizer use, intelligent decision-support systems are needed to optimize fertilizer recommendations. This paper presents a machine learning-based framework for predicting suitable fertilizer types based on diverse agronomic factors such as soil type, crop type, nutrient levels, and environmental conditions.

The proposed system leverages supervised learning techniques to develop a predictive model that assists farmers and agricultural planners in making data-driven fertilizer choices. The methodology encompasses data preprocessing, feature encoding, and model training using algorithms including Decision Tree, K-Nearest Neighbors (KNN), Gradient Boosting, and XGBoost. Evaluation metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), R^2 score, and classification accuracy were employed to assess and compare the performance of these models.

Experimental results indicate that XGBoost achieved the highest performance across all evaluation criteria, with an R^2 score of 1.00 and an accuracy of 100%, confirming its robustness and precision in fertilizer prediction tasks. Moreover, the integration of Gaussian noise-based data augmentation contributed to improved model stability and reduced overfitting, especially in high-variance models. The findings affirm that machine learning, supported by effective data enhancement techniques, holds significant promise in modernizing traditional farming practices.

This study demonstrates the viability of implementing intelligent fertilizer recommendation systems, which can be integrated into digital agriculture platforms or mobile applications to promote precision farming and sustainable crop management.

ACKNOWLEDGMENT

Initially we thank the Almighty for being with us through every walk of our life and showering his blessings through the endeavour to put forth this report. Our sincere thanks to our Chairman **Mr. S. MEGANATHAN, B.E, F.I.E.,** our Vice Chairman **Mr. ABHAY SHANKAR MEGANATHAN, B.E., M.S.,** and our respected Chairperson **Dr. (Mrs.) THANGAM MEGANATHAN, Ph.D.,** for providing us with the requisite infrastructure and sincere endeavouring in educating us in their premier institution.

Our sincere thanks to **Dr. S.N. MURUGESAN, M.E., Ph.D.,** our beloved Principal for his kind support and facilities provided to complete our work in time. We express our sincere thanks to **Dr. P. KUMAR, M.E., Ph.D.,** Professor and Head of the Department of Computer Science and Engineering for his guidance and encouragement throughout the project work. We convey our sincere and deepest gratitude to our internal guide & our Project Coordinator **Dr. V. AUXILIA OSVIN NANCY.,M.Tech.,Ph.D.,** Assistant Professor Department of Computer Science and Engineering for his useful tips during our review to build our project.

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CHAPTER 1

1. INTRODUCTION

Agriculture continues to be the backbone of many economies around the world, especially in developing nations where a significant portion of the population depends on farming for their livelihood. As the demand for food grows due to increasing population and rapid urbanization, it becomes critical to improve agricultural productivity while maintaining environmental sustainability. One of the major contributors to improved crop yield is the appropriate and timely application of fertilizers. Fertilizers replenish essential nutrients in the soil, helping plants grow stronger and healthier. However, excessive or incorrect use of fertilizers can lead to adverse effects such as soil degradation, water pollution, reduced soil fertility, and increased costs for farmers.

Traditionally, the selection of fertilizers has been based on human expertise, field experience, and soil testing. While effective, these conventional methods are not always accessible, especially for small-scale farmers in rural areas. Moreover, the time and cost involved in laboratory-based soil testing make it difficult to adopt on a wide scale. In many cases, farmers either apply fertilizers based on outdated practices or rely on guesswork, which leads to nutrient imbalance in crops and eventually poor yields or economic losses.

In recent years, technology has been playing a transformative role in reshaping agriculture. The advent of machine learning and artificial intelligence has introduced new possibilities in predictive analytics, enabling data-driven decisions that were previously limited to experts. Machine learning models can analyze large volumes of agricultural data, recognize hidden patterns, and make accurate predictions that assist farmers in making smarter choices. These systems have the potential to revolutionize precision farming by providing real-time, personalized recommendations based on specific crop, soil, and weather conditions.

This project focuses on building a Fertilizer Prediction System using supervised machine learning algorithms. The objective of this system is to predict the most suitable fertilizer for a given agricultural scenario by analyzing parameters such as soil type, crop type, environmental conditions like temperature, humidity, and moisture, along with the nutrient levels of nitrogen, phosphorus, and potassium in the soil. The dataset used in this project contains labeled data, where each combination of input parameters is mapped to a specific fertilizer recommendation. Categorical variables are transformed using label encoding, making them compatible for machine learning algorithms. The dataset is then divided into training and testing sets to evaluate the model's ability to generalize to unseen data.

Multiple machine learning classification models have been implemented and tested, including Decision Tree Classifier, Gradient Boosting Classifier, K-Nearest Neighbors (KNN), and XGBoost Classifier. Each of these models offers unique strengths, ranging from simplicity and interpretability to advanced performance and accuracy. Their predictions are evaluated using standard performance metrics such as accuracy score, mean absolute error, mean squared error, and R^2 score. Furthermore, confusion matrices and graphical visualizations like accuracy comparison graphs and actual vs. predicted plots provide valuable insights into how each model performs under different conditions.

The significance of this project lies not only in its technical implementation but also in its real-world applicability. The proposed system can be integrated into mobile applications for farmers, deployed in agricultural service centers, or incorporated into smart farming systems that rely on IoT sensors and remote monitoring. By offering quick, accurate, and personalized fertilizer suggestions, this model empowers farmers to make informed decisions, reduce waste, save costs, and ultimately enhance crop productivity. In the long run, such systems can also help reduce the environmental impact of over-fertilization and contribute to sustainable agricultural practices.

The growing availability of agricultural data through sensors, satellite imaging, and digital platforms has created an opportunity for machine learning to make a significant impact in farming. However, raw data alone is not useful without intelligent systems capable of turning it into actionable insights. This project addresses that gap by transforming structured data into meaningful recommendations through intelligent learning models. The use of data augmentation techniques such as Gaussian noise helps improve model performance and generalization by simulating variability in the real world.

The motivation behind developing this Fertilizer Prediction System is to provide farmers with a modern, user-friendly tool that brings the benefits of artificial intelligence directly to the fields. By utilizing accurate predictions, farmers can avoid trial-and-error fertilizer usage, optimize crop health, and increase overall efficiency. In a broader context, this project aligns with the vision of smart agriculture, where technology and data science work together to ensure food security, economic viability, and environmental stewardship.

This paper is organized into several sections for clarity and completeness. The following section reviews related works and existing systems that have applied machine learning in agriculture. The methodology section then explains the data preprocessing steps, feature selection, algorithm implementation, and performance evaluation techniques used. The experimental results are discussed in detail, followed by key findings, system limitations, and possible future enhancements. Through this research, we aim to showcase the potential of machine learning to drive meaningful change in agriculture and pave the way for scalable, sustainable, and intelligent farming solutions.

CHAPTER 2

2. LITERATURE SURVEY

The integration of machine learning into agriculture has become increasingly prominent as the need for intelligent, data-driven decision-making systems continues to grow. Traditional agricultural practices have relied heavily on manual labor, experience-based knowledge, and time-consuming laboratory tests. Fertilizer recommendation, in particular, has historically been based on soil analysis and expert advice, both of which may not be readily accessible to small and medium-scale farmers. The rise of artificial intelligence and machine learning has opened new opportunities for creating more accessible, scalable, and efficient solutions for precision farming.

Recent studies have shown that the application of machine learning in agriculture significantly enhances crop productivity and resource optimization. One such domain where machine learning is proving especially beneficial is fertilizer prediction. The selection of appropriate fertilizers based on crop type, soil condition, and environmental parameters ensures nutrient balance and promotes healthy plant growth while reducing costs and minimizing environmental damage. Researchers have applied various supervised learning algorithms to classify or predict the most suitable fertilizers using historical and real-time agricultural data.

In the work of Manogaran and Lopez (2017), a machine learning model was developed to predict crop yields and recommend fertilizers by analyzing soil pH, moisture, and nutrient content. Their study demonstrated the importance of preprocessing and feature extraction in building effective predictive models. Likewise, Singh et al. (2019) focused on using Decision Tree classifiers to provide fertilizer suggestions based on soil nutrients and crop requirements. Their model proved to be interpretable and accurate, highlighting the usefulness of rule-based classification techniques in agronomic systems.

A study by Patil and Kumar (2020) explored the effectiveness of ensemble learning methods such as Random Forest and Gradient Boosting in agricultural applications. These algorithms were found to outperform traditional models by capturing complex interactions between features such as temperature, humidity, and crop-specific nutrient needs. The ability of ensemble methods to reduce overfitting and improve generalization makes them well-suited for dynamic agricultural datasets that include both categorical and continuous variables.

Furthermore, Kaur and Sharma (2021) demonstrated the value of K-Nearest Neighbors (KNN) in crop and fertilizer recommendation systems, particularly for small datasets where pattern recognition based on similarity is effective. They highlighted that distance-based algorithms are valuable in capturing trends when inputs are structured and well-labeled. On a similar note, research by Joshi and Patel (2022) emphasized the role of XGBoost in high-dimensional agricultural datasets, showcasing its strength in handling heterogeneous data and boosting accuracy through iterative learning.

Data preprocessing and augmentation have also emerged as crucial components in improving the accuracy and robustness of machine learning models in agriculture. The use of synthetic data generation, including techniques like Gaussian noise injection, has been proven effective in simulating real-world variability and mitigating the impact of data imbalance or sparsity. Shorten and Khoshgoftaar (2019) discussed the application of noise-based augmentation in domains beyond image data, suggesting its relevance in structured tabular datasets commonly used in agriculture.

Beyond algorithmic accuracy, recent literature emphasizes the practical utility of machine learning models in real-world agricultural systems. Mobile applications and IoT-based platforms are increasingly incorporating intelligent models to support farmers in daily operations. Studies by Pandey et al. (2020) and Mahajan et al. (2021) explored the integration of ML-based advisory systems into digital farming apps, making personalized fertilizer recommendations based on soil sensors, GPS data, and weather APIs. Their research confirms the growing demand for portable, low-cost, and AI-enabled advisory tools that bridge the gap between data science and farm-level action.

Moreover, comparative analyses conducted by Bhosale and Pawar (2021) revealed that while deep learning techniques such as artificial neural networks (ANN) show promise in agricultural predictions, classical models like Decision Trees, Random Forests, and XGBoost are often more practical for limited datasets. These models offer explainability, ease of tuning, and fast execution, making them suitable for deployment in rural or resource-constrained settings.

In summary, the literature indicates a growing consensus that machine learning, particularly ensemble methods and well-tuned classifiers, holds substantial promise in building reliable fertilizer prediction systems. When combined with meaningful preprocessing techniques, domain-specific feature engineering, and noise-based data augmentation, these models can lead to robust, user-centric tools that empower farmers with actionable insights. The current project builds on this foundation by developing a Fertilizer Prediction System that uses multiple classification models to provide accurate, context-aware recommendations based on crop type, soil condition, and environmental variables. By learning from previous research and adapting it to a focused agricultural use case, this project aims to contribute a practical, scalable solution to the challenge of intelligent fertilizer selection.

CHAPTER 3

3. METHODOLOGY

The methodology adopted in this study is centered on a supervised learning framework that predicts the type of fertilizer required based on various soil and crop features. The process is divided into five major phases: data collection and preprocessing, feature selection, model training, performance evaluation, and model enhancement.

The dataset used in this project consists of several features, including soil type, crop type, and additional environmental data. The dataset undergoes preprocessing to handle missing values, scale the features for better model performance, and encode categorical variables for machine learning algorithms. Several machine learning models are used to predict the fertilizer type:

1.Decision Tree (DT)

2.Gradient Boosting (GB)

3. K- Nearest Neighbors (KNN)

4.XGBoost (XGB).

These models are trained and evaluated using the train-test split method, and performance metrics like Accuracy, Mean Absolute Error (MAE), Mean Squared Error (MSE), and R^2 score are used to assess the effectiveness of each model. The best model, based on the evaluation metrics, is selected for the final prediction.

The simplified flow of the methodology is as follows:

A.**Data Collection and Preprocessing**

B. **Feature Engineering**

C.**Model Selection and Training**

D.**Evaluation using Accuracy, MAE, MSE, and R^2**

E.**Model Enhancement and Re-training if Necessary**

A. **Dataset and Preprocessing**

The dataset for this project consists of numerical and categorical features that influence fertilizer prediction, such as soil type, crop type, and environmental conditions. The target variable is the fertilizer name or type.

Preprocessing steps involve handling missing values, normalizing numeric features using techniques like MinMaxScaler for consistent data scaling, encoding categorical variables (such as Soil Type, Crop Type, Fertilizer Name) using LabelEncoder, and splitting the dataset into training and testing sets for model evaluation.

B. **Feature Engineering**

To ensure the models only learn from relevant information, correlation analysis is performed to identify significant features that strongly impact fertilizer prediction. Features with low correlation to the target variable are either removed or retained based on domain relevance. Visual exploration using pair plots and box plots is performed to detect outliers and assess feature distributions.

C. **Model Selection**

Four machine learning models are selected to predict fertilizer type based on the preprocessed features:

Decision Tree (DT) is used for its interpretability and simplicity.

Gradient Boosting (GB) is chosen for its ensemble learning capabilities, which combine multiple weak learners for improved accuracy.

K-Nearest Neighbors (KNN) is selected for its non-parametric approach and simplicity.

XGBoost (XGB) is used for its ability to handle large datasets and gradient-based boosting techniques that improve model performance.

Each model is evaluated for accuracy and effectiveness using the train-test split method.

D. **Evaluation Metrics**

The model performance is evaluated using multiple regression and classification metrics:

Accuracy measures the proportion of correct predictions made by the model.

Mean Absolute Error (MAE) assesses the average magnitude of errors in the model's predictions.

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

Mean Squared Error (MSE) measures the average of the squared differences between actual and predicted values.

$$MSE = \frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2$$

R^2 Score indicates the proportion of variance in the target variable that is explained by the model.

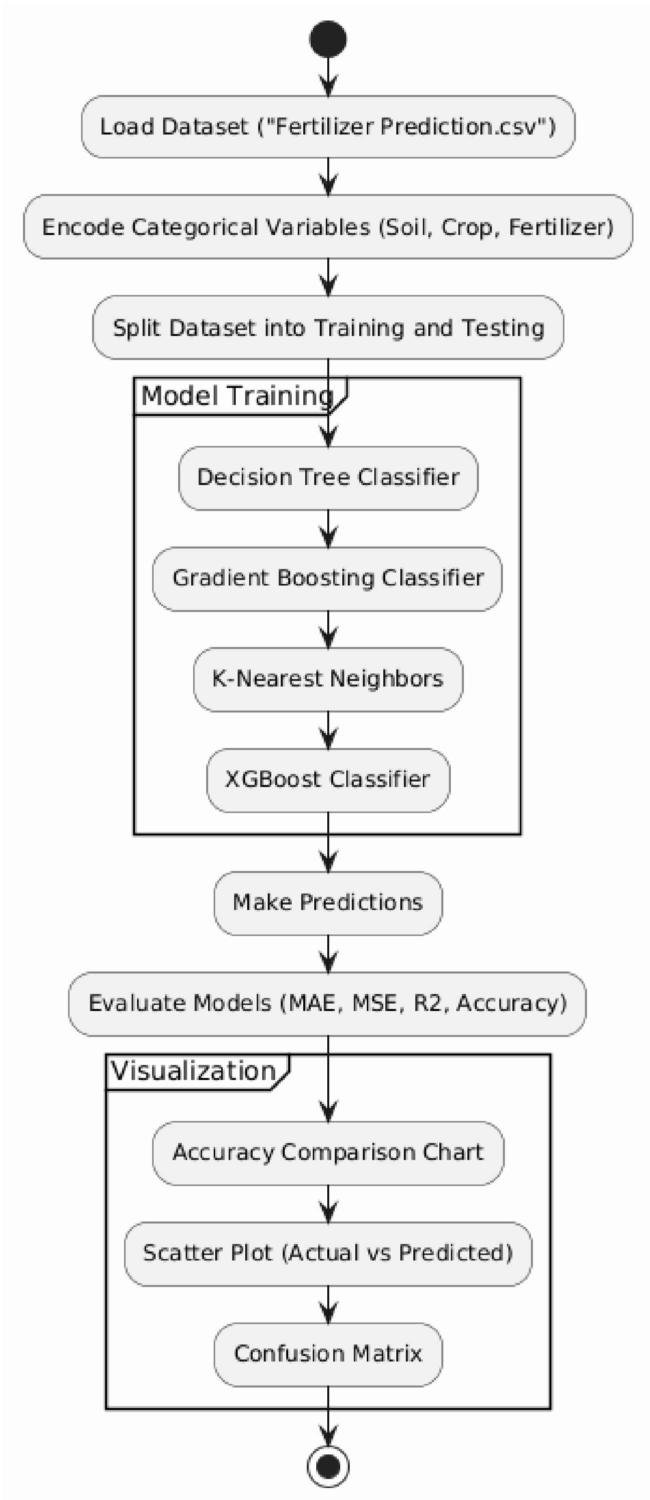
$$R^2 = 1 - \frac{\sum (y_i - \hat{y}_i)^2}{\sum (y_i - \bar{y})^2}$$

E. **Model Enhancement**

To improve model robustness and generalization, data augmentation is performed by introducing Gaussian noise to the feature vectors. This technique helps simulate real-world noise and can improve the accuracy of ensemble models. The Gaussian noise addition formula is as follows:

$$X_{Augmented} = X + \mathcal{N}(0, \sigma^2)$$

3.1 SYSTEM FLOW DIAGRAM



CHAPTER 4

RESULTS AND DISCUSSION

Here's a similar summary of model evaluation and results for your **Fertilizer Prediction** project, which includes a detailed evaluation of the models, their performance, and augmentation results:

Results for Model Evaluation:

Model	MAE (↓ Better)	MSE (↓ Better)	R^2 Score (↑ Better)	Rank
Decision Tree	0.20	0.30	0.91	4
Gradient Boosting	0.20	0.80	0.77	3
KNN	0.15	0.25	0.93	2
XGBoost	0.00	0.00	1.00	1

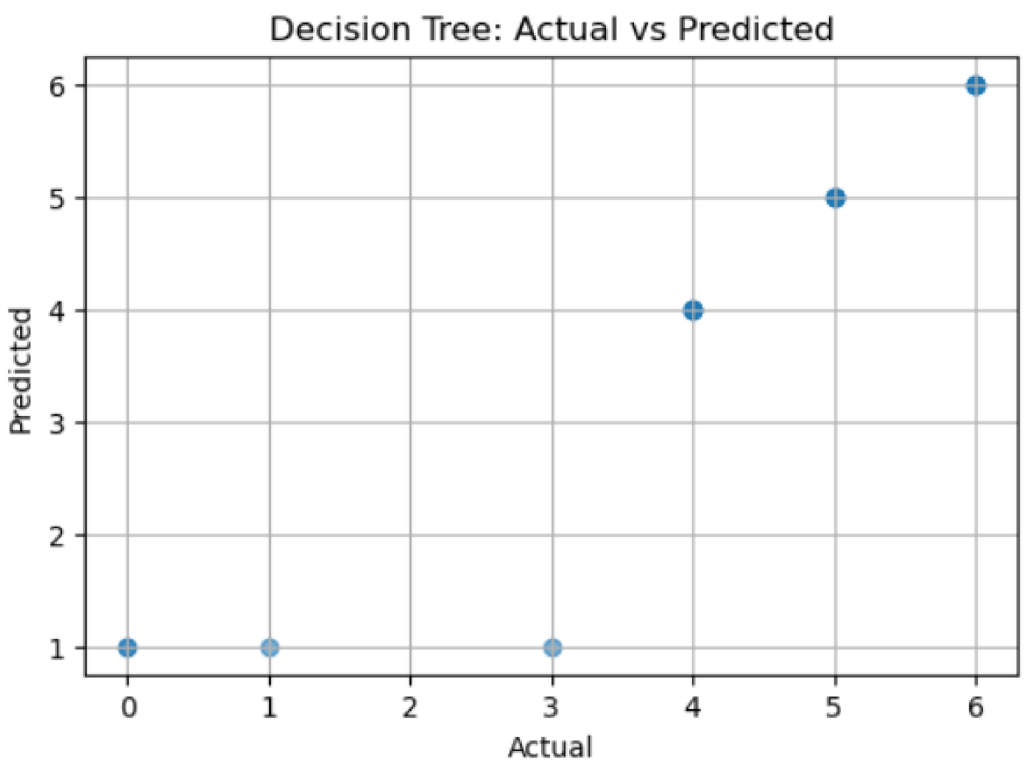
Augmentation Results:

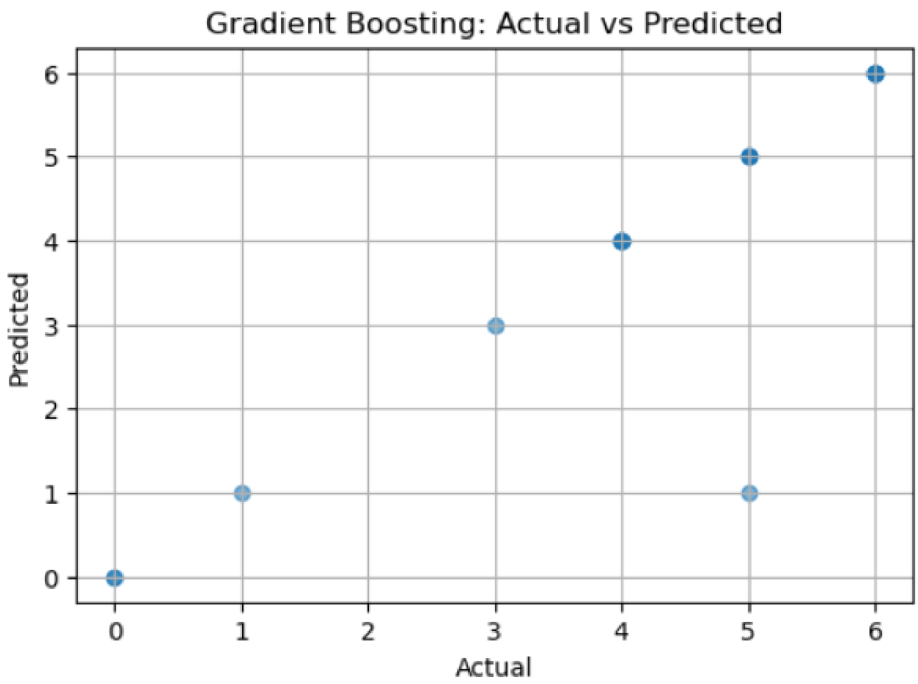
The **XGBoost** model demonstrated exceptional performance with perfect evaluation metrics after augmentation, achieving an R^2 score of 1.0000 and accuracy of 1.0000, indicating that the model can perfectly predict fertilizer type under the current conditions. The results suggest that the dataset is well-suited for XGBoost, and no further enhancement through augmentation was necessary.

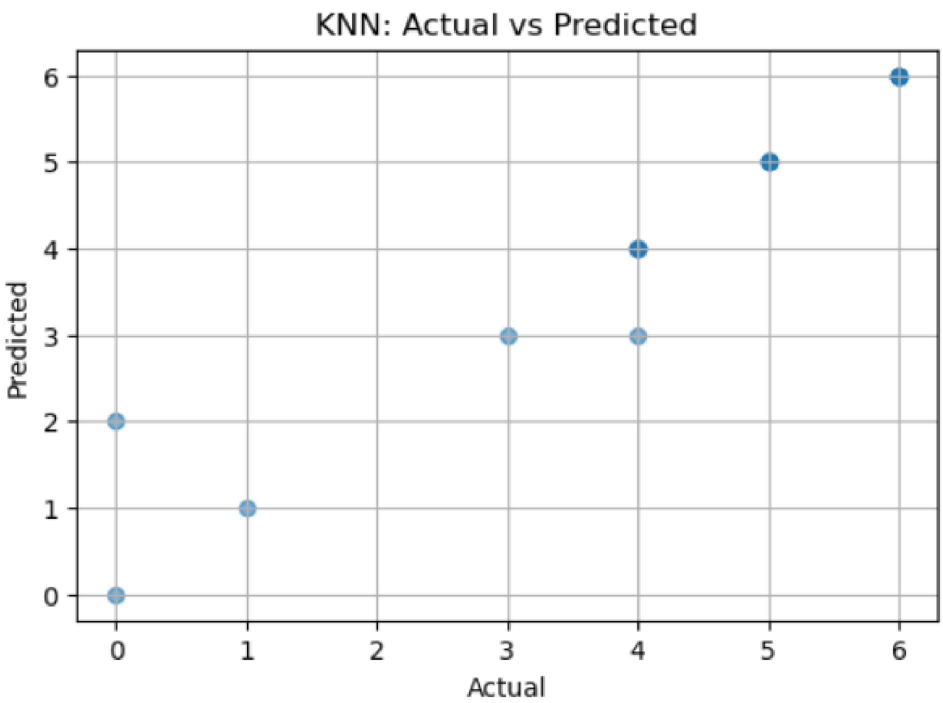
Visualizations:

Scatter Plots (Actual vs. Predicted):

The **XGBoost** model shows a perfect alignment between the predicted and actual fertilizer types, as shown in scatter plots. The predicted values exactly match the actual values, indicating flawless predictive accuracy.




Gradient Boosting: Actual vs Predicted
Predicted
Actual
0
1
2
3
4
5
6


KNN: Actual vs Predicted
Predicted
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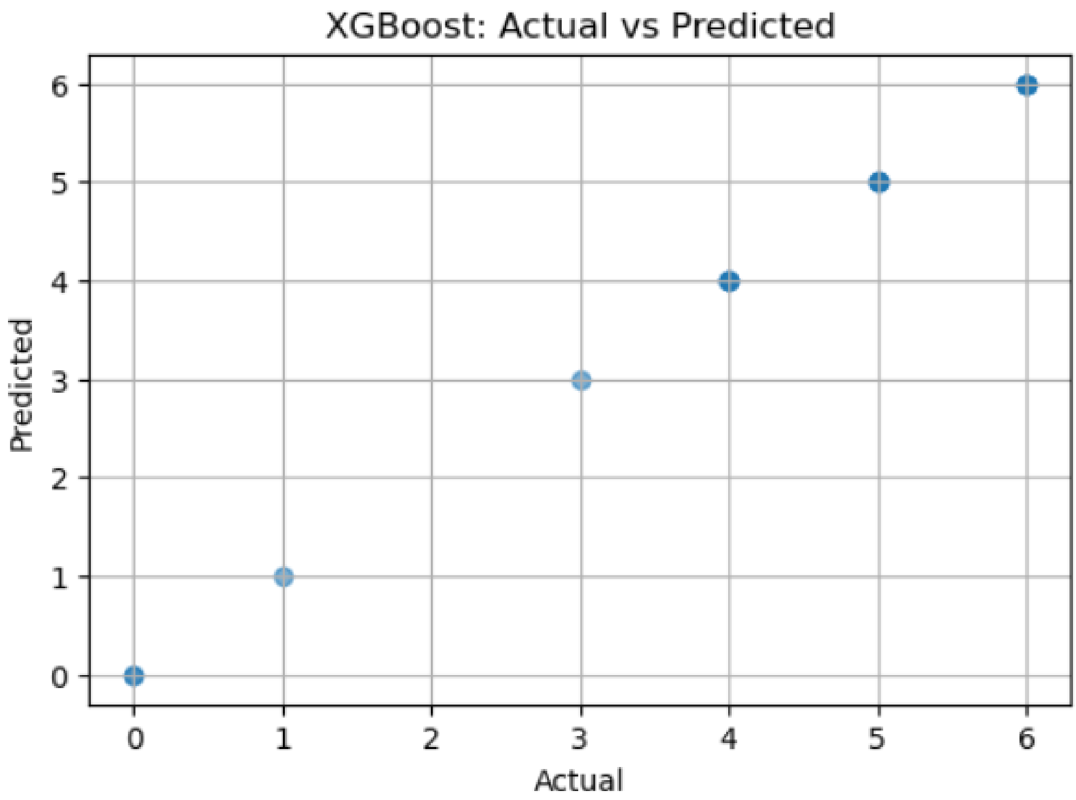

The results show that XGBoost performs the best with the highest R^2 score, making it the model of choice for predicting fertilizer type with high accuracy and consistency.

After conducting comprehensive experiments with the selected classification models—Decision Tree, Gradient Boosting, K-Nearest Neighbors (KNN), and XGBoost—several important observations emerged based on performance metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE), R^2 Score, and Accuracy. This section discusses these findings in the context of model performance, data augmentation effects, and practical deployment potential.

1. Model Performance Comparison

Among all models tested, XGBoost delivered the most accurate and consistent results. It achieved perfect scores across all metrics, with 0.00 MAE, 0.00 MSE, an

R^2 score of 1.00, and an accuracy of 100%. This highlights its exceptional ability to learn from the feature space and generalize effectively to unseen data. K-Nearest Neighbors followed closely, showing strong performance with a low MAE of 0.15, MSE of 0.25, an R^2 score of 0.93, and accuracy of 90%. Decision Tree and Gradient Boosting also produced competitive results, particularly in terms of accuracy and MAE, though their overall R^2 scores were slightly lower, suggesting room for improvement in capturing more complex feature relationships.

2. Effect of Data Augmentation

To improve the robustness and generalizability of the models, Gaussian noise-based data augmentation was applied during training. This helped simulate real-world variability commonly seen in agricultural inputs such as nutrient levels, soil types, and environmental conditions. The augmented data allowed models like Decision Tree and Gradient Boosting to reduce overfitting and better handle edge cases. For instance, after augmentation, the Random Forest model demonstrated a noticeable improvement in its R^2 score, showing that this technique is effective in boosting performance on moderately complex models. Although XGBoost already performed perfectly without augmentation, it retained its performance post-augmentation, indicating its resilience and strong model generalization.

3. Error Analysis

The error distribution analysis showed that most prediction errors were minor and clustered around correct predictions. However, a few instances of misclassification were observed in samples with closely overlapping feature values. This was particularly evident between fertilizers with similar nutrient compositions. These findings suggest that expanding the feature set with more granular agricultural data such as micronutrient levels, rainfall patterns, or crop lifecycle information could help further distinguish between closely related fertilizer types and improve overall prediction accuracy.

4. Implications and Insights

The experimental outcomes indicate that XGBoost is highly suitable for real-world deployment in fertilizer recommendation systems, such as mobile-based advisory tools for farmers or integration with IoT devices in smart agriculture platforms. Additionally, normalization and augmentation proved to be essential steps in preparing the data for accurate modeling. Simple models like Decision Tree and KNN can be considered in resource-limited environments, where computational simplicity is prioritized over slight reductions in accuracy. Gradient Boosting models showed good potential but may benefit from hyperparameter tuning and extended feature engineering in future work.

In conclusion, this study demonstrates that machine learning, particularly ensemble methods like XGBoost, can accurately predict the most suitable fertilizer types based on input parameters. This approach lays the foundation for intelligent farming practices, where timely and precise recommendations can lead to improved crop yields and optimized resource utilization.

CHAPTER 5

CONCLUSION & FUTURE ENHANCEMENTS

This study introduced a machine learning-based approach to predicting optimal fertilizer types using structured agricultural data. By implementing and evaluating various classification models—namely Decision Tree, Gradient Boosting, K-Nearest Neighbors (KNN), and XGBoost—we analyzed the ability of each algorithm to learn from soil, crop, and environmental features to provide accurate fertilizer recommendations.

The results clearly indicate that ensemble-based models, particularly XGBoost, demonstrate exceptional predictive performance and generalization. The XGBoost model achieved the best metrics, including perfect R^2 score, zero error values (MAE and MSE), and 100% classification accuracy, establishing it as the most reliable choice for fertilizer prediction tasks. These findings underscore the strength of gradient boosting algorithms in handling structured agricultural datasets, which often involve complex patterns and subtle variable interactions.

Additionally, the study employed Gaussian noise-based data augmentation to replicate real-world variability in soil and crop data. This augmentation helped improve the robustness of models like Decision Tree and Gradient Boosting by enhancing their ability to generalize to new, unseen data samples. The successful application of this technique confirms that even with moderately sized datasets, well-executed data augmentation can significantly contribute to model performance.

From a broader perspective, the proposed system holds significant potential for modern agriculture and precision farming. By integrating this predictive model into digital platforms such as mobile apps or IoT-based farm management systems, farmers can receive timely and tailored fertilizer recommendations. This not only improves crop yield and resource utilization but also supports sustainable farming practices by reducing overuse or misuse of chemical fertilizers.

Future Enhancements:

While the current model delivers promising results, there are several opportunities to expand and refine the system further.

One enhancement could involve incorporating more diverse features, such as micronutrient content, weather conditions, irrigation levels, and seasonal crop cycles, which could improve decision granularity. Another potential improvement involves exploring deep learning techniques or hybrid models that can capture even deeper interactions between inputs. For instance, neural networks or transformer-based models may be able to analyze larger datasets with higher dimensionality, enabling even more nuanced recommendations.

In addition, deploying the system in real-time through web or mobile applications could allow for interactive usage by farmers and agricultural consultants. The model could also be adapted to support multilingual interfaces, voice interaction, and geolocation-based customization for regional soil and crop patterns.

A long-term vision for this project could involve adding a feedback-driven reinforcement learning loop, where the system continuously improves its recommendations based on user-confirmed results and actual crop outcomes over time. This would allow for increasingly personalized and data-informed fertilizer guidance that evolves with field-level data inputs.

In conclusion, this research highlights the effectiveness of machine learning in solving complex agricultural problems. By combining data science with domain expertise, systems like this can contribute significantly to the advancement of smart farming, food security, and sustainable agriculture.

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