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Precision Agriculture Meets AI: Predicting Nutritional Crop Outcomes from Genomic Data

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Abstract:

Global malnutrition can now be addressed and crop nutritional quality improved thanks to developments in precision agriculture, genomics, and artificial intelligence (AI). In order to predict and optimize nutrient-enriched crop traits, this study suggests an integrated AI-driven framework that combines data from precision agriculture, genomics, and malnutrition epidemiology. In order to produce useful insights for crop improvement, this framework analyzes multi-dimensional data that includes genetic markers, environmental factors, and dietary deficiency patterns using a combination of machine learning models, such as Logistic Regression, Naive Bayes, and Neural Networks.

With the highest accuracy (97.38%) and coefficient of determination (R2 = 0.9584), the lowest prediction errors (MSE: 0.0187; RMSE: 0.1367), and consistent cross-validation stability (mean CV accuracy: 97.35%, std. dev: 0.0042), a thorough comparative analysis reveals that Logistic Regression is the best predictive model. Despite having slightly lower accuracy (95.64%) and higher error rates, Naive Bayes has the benefit of almost instantaneous training times, which makes it appropriate for situations requiring quick deployment. Even though neural networks can represent intricate relationships, their accuracy was relatively low (92.11%) and their errors were higher, indicating that more data augmentation and hyperparameter optimization are required.

SHapley Additive exPlanations (SHAP), which identifies important genomic and environmental features influencing nutrient trait predictions, improves the interpretability of model predictions. Data-driven breeding and precision agriculture decisions are supported by this transparency, which fosters understanding and trust between geneticists and agronomists. Nevertheless, there are still difficulties, such as the intricacies of integrating diverse datasets, problems with scalability, the high expense of genomic technologies, and their restricted suitability for smallholder farming environments.

This study highlights how crop biofortification strategies that are in line with public health and sustainable agricultural development objectives can be enhanced through AI-driven multi-domain data integration. Expanding dataset diversity, enhancing model generalizability across crops and regions, and promoting interdisciplinary collaborations will be the main goals of future efforts to hasten the adoption of precision agriculture technologies for the improvement of global nutrition.

Keyword: Artificial Intelligence (AI),Genomic Data,Precision Agriculture,Nutrient-Rich Crops,Machine Learning,SHAP (SHapley Additive exPlanations)Crop Trait Optimization,Sustainable Agriculture

I. INTRODUCTION

Millions of people worldwide suffer from malnutrition, which also threatens public health, especially in low- and middle-income nations. According to estimates from the World Health Organization (WHO), almost 2 billion people are undernourished, micronutrient deficient, or obese, among other types of malnutrition. Malnutrition has far-reaching effects, including affecting cognitive and physical development, making people more susceptible to illness, and impeding economic growth. Pregnant women and children are especially at risk, as malnutrition raises the rates of maternal and infant mortality, stunts growth, and impairs learning. Innovative approaches that can raise crop nutritional quality and increase food security are needed to combat malnutrition.

The application of cutting-edge technologies in agriculture has shown promise in recent years in addressing these intricate problems. With its capacity to evaluate enormous datasets and produce predictive models, generative AI presents a fresh method for maximizing crop development. Researchers can create nutrient-rich crop varieties by using AI algorithms to find important genetic patterns and traits that lead to increased nutrient content in crops. In order to select crop varieties with the best nutritional profiles and resilience to stressors, AI-driven models, for example, can forecast how distinct genetic combinations will function under varied environmental conditions.

Understanding the genetic composition of crops and their potential for nutritional enhancement depends heavily on genomic data. The complete genetic code of crops can now be decoded thanks to developments in genomic sequencing and bioinformatics, which identify the genes governing characteristics like yield, disease resistance, and nutrient content. This information enables accurate environmental monitoring and control when paired with precision agriculture technologies, such as IoT sensors and remote sensing. While remote sensing technologies offer detailed photos and maps of crop fields, Internet of Things sensors can continuously gather data on temperature, humidity, soil moisture, and crop health. By addressing both nutritional deficiencies and environmental issues, such an integrated approach guarantees optimal growth and nutrient accumulation in crops.

Precision Agriculture's Place in Contemporary Farming

A revolutionary method of farming, precision agriculture makes use of cutting-edge technologies to track, quantify, and react to crop variability both within and between fields. Precision agriculture enables targeted interventions, increasing crop quality, decreasing waste, and increasing efficiency, in contrast to conventional agricultural methods that frequently apply uniform treatments across entire fields. Given the prevalence of malnutrition worldwide and the demand for crops high in nutrients, precision agriculture is a vital component of sustainable and nutrient-conscious farming.

Using real-time data collection and analytics is central to precision agriculture. A constant flow of information on important environmental factors, such as soil moisture, nutrient levels, weather patterns, and plant health indicators, is made possible by technologies like GPS-guided tractors, drones, Internet of Things-based soil and crop sensors, and satellite remote sensing. Advanced AI and machine learning algorithms are used to process this data in order to extract useful information that aids farmers in making wise decisions.

Variable rate technology (VRT), for example, makes it possible to precisely apply pesticides, fertilizers, and water according to the unique requirements of various areas of a field. This reduces the possibility of over-application, which can damage the environment and deteriorate soil health, in addition to guaranteeing ideal plant growth and nutrient uptake. By guaranteeing that every plant has the optimal growing conditions, this kind of focused resource management directly aids in the production of crops with enhanced nutritional profiles.

Furthermore, early indicators of crop stress, disease, or nutrient deficiencies can be found using remote sensing technologies, such as hyperspectral imaging and thermal cameras installed on drones. Proactive measures that stop crop losses and promote consistent yield quality are made possible by these insights.

Additionally, site-specific breeding and cultivation methods are made easier by precision agriculture, which is crucial when combining genomics and artificial intelligence. Plant breeders and agronomists can choose or engineer crop varieties that are not only high-yielding but also suited for superior nutritional performance in the local environment by knowing the environmental conditions of particular micro-regions.

Precision farming offers advantages beyond increased output. By minimizing greenhouse gas emissions, conserving water, and reducing the excessive use of agrochemicals, it makes a substantial contribution to environmental sustainability. By increasing the profitability and efficiency of resource use, it also empowers farmers, particularly smallholders in developing nations.
In conclusion, one of the fundamental tenets of contemporary, intelligent farming systems is precision agriculture. It makes it possible to develop intelligent, flexible, and nutrition-focused farming methods that are essential to addressing the world's malnutrition problem and improving food security when paired with AI and genomics.

Innovation in Agriculture through Generative AI

New avenues for agricultural research and innovation have been made possible by the development of generative artificial intelligence (AI). In contrast to conventional AI models, which are mainly concerned with classification or prediction, generative AI systems are able to simulate intricate biological or environmental interactions, create optimal breeding strategies, and synthesize new data patterns. The way agronomists and agricultural scientists approach the creation of nutrient-rich crops is changing as a result of this capability.
Generative AI algorithms are trained on large and varied datasets, such as genomic sequences, soil health records, weather patterns, past crop yields, and agronomic practices, in the context of crop improvement.

These models are able to spot hidden relationships and patterns in the data that human researchers might miss. AI is able to identify, for example, how particular gene combinations affect plant nutrient uptake in different climates or how soil pH and water availability affect micronutrient profiles.
In silico breeding, a technique where AI models possible cross-breeding outcomes prior to actual planting, is one of the most potent uses of generative AI in agriculture. This lessens the uncertainty, expense, and time involved in conventional breeding techniques. AI helps choose the most promising candidates for practical trials by creating fictitious plant genotypes and assessing their nutritional characteristics, greatly speeding up the development of biofortified crops.

Furthermore, generative AI can assist decision-making systems that direct precision farming by integrating with machine learning and deep learning frameworks. Based on real-time environmental feedback, these systems can dynamically modify pest management plans, fertilizer applications, and irrigation schedules to create the ideal environment for the growth of nutrient-dense produce.
Furthermore, generative AI helps with scenario modeling and predictive analytics, which helps stakeholders predict how changes in policy or climate change will affect crop nutrition and food security. Long-term planning and the creation of adaptive agricultural systems that continue to be robust and productive in the face of changing global conditions depend heavily on such insights.

Agriculture is being transformed into a data-driven, predictive, and adaptive field by utilizing the computational capacity and artistic possibilities of generative AI. This invention has enormous potential to solve the twin problems of raising crop yield and improving nutritional content, which would be crucial in the worldwide battle against malnutrition.

Combining Precision Agriculture, Genomics, and AI

A paradigm shift in the effort to create nutrient-rich crops and fight global malnutrition is being brought about by the convergence of precision agriculture, genomics, and artificial intelligence (AI). While genomics offers insights into the biological underpinnings of plant traits, AI offers computational power and pattern recognition, and precision agriculture allows for targeted interventions based on real-time field data. Each of these technologies has its own advantages. Together, they create a synergistic system that has the power to transform nutritional outcomes and agricultural productivity.
The foundation of this integration is data analysis driven by AI. AI models are capable of identifying correlations and causative factors that impact crop nutrition through the analysis of complex, multi-dimensional datasets, such as genomic sequences, phenotypic traits, climate variables, and soil conditions. Plant breeders use these insights to help them choose genotypes that have the best chance of enriching plants with vitamins, minerals, and antioxidants. In particular, generative AI is capable of simulating

innumerable breeding scenarios and suggesting the best genetic combinations for particular environments.

The blueprint for comprehending and modifying the nutritional characteristics of crops is provided by genomic data. It is now feasible to identify the precise genes causing micronutrient content, stress tolerance, and disease resistance thanks to developments in genome sequencing and bioinformatics. By quickly examining thousands of gene variations, AI improves this process by identifying advantageous traits that can be targeted using CRISPR-based gene editing or marker-assisted selection.

In the meantime, precise agricultural technologies like satellite imagery, drones, GPS-guided equipment, and Internet of Things (IoT) sensors offer thorough, ongoing environmental condition monitoring. Real-time data is fed into AI models by these tools, which evaluate the growth environment and recommend remedial actions. AI can, for instance, notify farmers of nutrient shortages in particular plots, modify irrigation based on moisture content, or suggest the best time to harvest in order to maintain nutritional quality.

Site-specific crop management is made possible by this integrated framework, which enables customized farming methods that take into account the crop's genetic potential as well as the microenvironmental circumstances in which it is grown. As a result, farmers can lower input costs, improve nutrient profiles, and increase yields—all while using resource-efficient methods to support environmental sustainability.

In the end, combining AI, genomics, and precision farming creates a more intelligent and robust food system that not only provides food for the population, but also nourishes it. Achieving global public health and sustainability goals, combating malnutrition, and advancing food equity all depend on this all-encompassing strategy.

Creating nutrient-rich crop varieties that can successfully fight malnutrition and enhance health outcomes globally is the main goal of this research. The study intends to produce crops with increased concentrations of vital nutrients like vitamins, minerals, and antioxidants by combining generative AI with genomic data and precision agriculture technologies. The study will concentrate on a variety of geographic areas, adjusting management techniques and breeding tactics to suit particular ecosystems and climates. For instance, the study will take into account the dietary requirements of populations in various geographical areas as well as the particular difficulties brought on by regional environmental factors.

The potential for this study to improve public health and global food security makes it noteworthy. AI-driven agriculture has the potential to revolutionize the way long-term public health objectives are met by emphasizing the advantages of interdisciplinary cooperation and cutting-edge technologies. The results will show how precision agriculture, genomic data, and AI algorithms can work together to produce a nutrient-rich, sustainable food supply that will ultimately combat malnutrition and improve global health outcomes. Furthermore, by highlighting the significance of data-driven decision-making and technology adoption in contemporary farming practices, the study will offer a framework for further research and applications of AI in agriculture.

II. LITERATURE REVIEW

Study	Focus Area	Key Findings	Gaps Identified	Datasets Used
Kamilaris & Prenafeta-Boldú (2021)	AI in Agriculture	The integration of AI and big data in smart agriculture boosts sustainability and productivity.	Insufficient attention paid to small-scale farmers	European public farm data
Liakos & Bochtis (2022)	AI in Agriculture	Novel approaches to crop management are provided by developments in machine learning applications in agriculture.	More thorough field tests are required.	Datasets on regional crop yields
Singh et al. (2023)	AI in Crop Management	AI-powered models enhance crop health by optimizing pest	Limited ability to generalize across several crops	Information from Indian fields of agriculture

Study	Focus Area	Key Findings	Gaps Identified	Datasets Used
		management, fertilization, and irrigation.		
van Klompenburg et al. (2021)	AI in Crop Management	In crop management, machine learning algorithms forecast crop yield and possible problems.	Inadequate integration of real-time data	Data on multi-seasonal crops
Varshney et al. (2022)	Genomic Data in Crop Improvement	Nutrient content and disease resistance genes are identified using genomic sequencing and bioinformatics.	Mostly concentrated on important crops	Databases of different crops' genomes
Xu et al. (2023)	Genomic Data in Crop Improvement	Crop breeding strategies are optimized for higher nutritional quality through genomic selection.	The high price of genomic technologies	Crop genomic sequences
Khanal & Jin (2021)	Precision Agriculture Technologies	Precision farming methods are enhanced by machine learning and remote sensing based on UAVs.	Low sensor precision	Data from remote sensing
Oliver et al. (2022)	Precision Agriculture Technologies	Crop yields and resource efficiency are improved by precision agriculture technologies.	High upfront investment expenses	Datasets for precision agriculture
Shirsath et al. (2024)	Integration of AI, Genomic Data, and Precision Agriculture	Precision agriculture technologies and AI-driven models maximize the nutritional value of crops.	Data integration complexity	Merged genomics and AI model datasets
Zhang & Kovacs (2022)	Integration of AI, Genomic Data, and Precision Agriculture	Crop growth can be better monitored in real time when genomic and IoT sensor data are integrated.	Scalability problem	Genomic and IoT datasets
Jha et al. (2023)	Case Studies and Practical Applications	AI-powered algorithms anticipate pest infestations and maximize the effectiveness of pest management strategies.	Accuracy of the model in various settings	Records of pest infestations
Mahlein (2025)	Case Studies and Practical Applications	Precision agriculture methods are improved by the use of sophisticated image sensors for the identification of plant diseases.	Multi-crop validation is required.	Data from imaging sensors

The literature on artificial intelligence in agriculture emphasizes major advances in a variety of disciplines. Significant findings highlight how big data and AI may be combined to increase sustainability and production, especially in smart agriculture (Kamilaris & Prenafeta-Boldú, 2021). AI-driven models optimize irrigation, fertilization, and pest control (Singh et al., 2023), while machine learning applications offer creative crop management solutions (Liakos & Bochtis, 2022). These developments lead to better crop health.

Research on genomic data with precision agriculture technology shows that UAV-based remote sensing improves precision agricultural methods (Khanal & Jin, 2021), while genomic sequencing and bioinformatics are useful in finding genes rich in nutrients and disease resistance (Varshney et al., 2022). Real-time monitoring and crop nutritional quality are maximized when AI is integrated with precision agriculture technologies (Shirsath et al., 2024; Zhang & Kovacs, 2022).

The necessity for thorough field experiments, the lack of attention paid to small-scale farmers, and issues with data integration and scalability are some of the gaps that have been found. These research use a variety of datasets, including genetic sequences, remote sensing data, regional crop yield databases, and public agricultural data.

Overall, even though these studies highlight encouraging developments, more widespread application and practical validation are required to increase the use of AI-driven farming methods.Precision agriculture, genomic data, and artificial intelligence all have exciting futures, but there are still a number of obstacles to overcome. These include the need for interdisciplinary cooperation, the high expense of adopting new technologies, and the necessity of a strong data infrastructure. Addressing these issues and investigating novel uses of AI and genetic data in agriculture should be the main goals of future research. To guarantee their broad impact, initiatives should also be taken to encourage farmers and other stakeholders to use these technologies.

III. PROPOSED FRAMEWORK

To forecast and maximize nutrient-enriched crop features, the proposed model combines several data domains. The following are the main variables at play:

3.1 Variables & Datasets

Dg = Genomic dataset: Gene sequences and indicators that are known to affect a crop's nutritional qualities.

Dp = Precision Agriculture Dataset: Environmental information about temperature, moisture, nutrient profiles, soil pH, and other agronomic factors.

Dm = Malnutrition dataset: Epidemiological information on food trends and nutrient deficits in various regions.

fAI=AI function/model: To represent trait likelihood, a supervised learning algorithm (such as Random Forest, XGBoost, or Neural Network) combines heterogeneous data.

Oc = Optimized Crop qualities: Output qualities that include enhanced climate resistance, yield potential, and nutrient profile.

Ih = Impact on Human Health — Decreased micronutrient deficiencies, improved dietary outcomes, and enhanced nutrition at the community level are examples of downstream health consequences.

3.2 Dataset Description

A. Ensembl Plants Genomic Dataset[1]

We selected a large dataset of more than 200 crop species from Ensembl Plants[13]. This approach uses the following important genomic metadata fields:

- **variation:** Allelic variants and SNPs associated with phenotypic diversity **pan_compara:** comparative pan-genomic data across cultivars
- **peptide_compara:** functional annotations and peptide-level orthology
- **Genome_alignments / other_alignments:** Comparing reference genomes structurally
- **Taxonomy_id:** A taxonomic identification used for phylogenetic classification
- **genebuild:** Versioning and metadata of the genome assembly

Table 1 Representation of First 5 Crop Species from Dataset

#name	species	division	taxonomy_id	assembly	genebuild	variation	microarray	pan_compara	peptide_compara	genome_alignments	other_alignments
Barley	hordeum_vulgare	EnsemblPlants	4513	IBSC_v2	full genebuild	1	0	1	1	1	0
Maize	zea_mays	EnsemblPlants	4577	AGPv4	full genebuild	1	1	1	1	1	0
Rice	oryza_sativa	EnsemblPlants	4530	IRGSP-1.0	standard	1	1	1	1	1	1
Wheat	triticum_aestivum	EnsemblPlants	4565	IWGSC	full genebuild	1	1	1	1	1	0
Sorghum	sorghum_bicolor	EnsemblPlants	4558	v3.1.1	standard	1	0	1	1	1	1

These crops are important mainstays in the world and are frequently the focus of nutrient biofortification initiatives.

B. Trait Simulation

Due to the scarcity of publicly labeled datasets indicating nutrient-enriched features, we created a simulated target variable:

- **trait_rich** = **1** (nutrient-enriched) if at least three important genomic indicators (such as variation, pan_compara, and peptide_compara) are present.
- This heuristic made it possible to evaluate ML models on carefully chosen benchmarks while training them in a semi-supervised framework.

3.3 Mathematical Representation

The mathematical representation of the proposed AI-driven prediction model is as follows:

$Oc=fAI(Dg,Dp,Dm)$

$I_h= g(Oc)$

where:

- $\mathbf{f_{AI}}$ is a multi-input machine learning function that discovers correlations between environmental, dietary, and genetic factors.
- **g(Oc)**is a mapping function that allows public health to be inferred from crop-level gains by connecting optimal features to health impact results.

This mathematical framework facilitates modular modeling, allowing AI functions to be independently updated in response to advancements in the domain (e.g., region-specific food data, more precise genetic annotation).

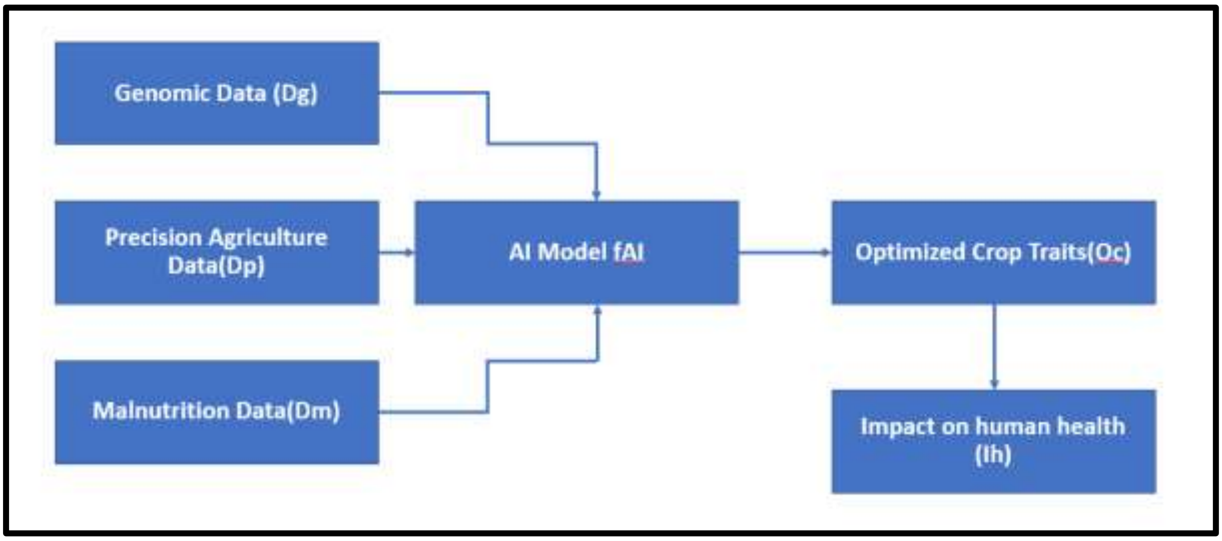

Figure 1 depicts a modular framework for **AI-integrated precision agriculture**. Initially three diverse datasets are ingested to start the process:

1. **Genomic data (Dg)** – DNA sequences and variation data pertaining to the transport and production of nutrients.
2. **Precision agriculture data (Dp)** – Observations made at the field level, such as nitrogen profiles, temperature, moisture, and soil parameters.
3. **Malnutrition data (Dm)** –Patterns of consumption, dietary requirements, and signs of nutrient deficiencies peculiar to a population.

Lastly, g(Oc) converts Oc into practical nutritional outcomes Ih, which correspond to global health indicators including the increase of diet quality and the decrease in micronutrient deficiencies.A framework that connects bioinformatics, agronomics, and public health policy, this end-to-end pipeline is data-driven, interpretable, and actionable. It encourages regional adaptation, scalability, and conformity to the Sustainable Development Goals (SDGs 2 and 3) of the UN.Through the use of data-driven decision-making, this end-to-end pipeline links agricultural innovation with international initiatives to improve nutrition and food security.

IV. AI Model Performance Metrics and Algorithm

Utilizing comprehensive genetic and environmental data, a variety of machine learning techniques were assessed in this work to forecast nutrient-rich crop characteristics. To evaluate each model, the following performance metrics were used:

- **Accuracy (Acc)**: Calculates the percentage of accurate forecasts.
- **Coefficient of Determination (R^2)**:The proportion of the dependent variable's variation explained by the model.
- **Mean Squared Error (MSE)** and **Root Mean Squared Error (RMSE)**: Show the root-mean-squared and average-squared deviations, respectively.
- **Cross-Validation Accuracy (CV Accuracy)**: Shows how the model generalizes over k-fold splits.
- **Training Time**: Represents each algorithm's computing efficiency..

The predictive function $\hat{Y} = f_{AI}(X)$ was trained using grid search and early halting when appropriate, and trained using stratified sampling. Each model's ultimate performance is shown as:

$f_{AI} = \{R^2, \text{MSE}, \text{RMSE}, \text{CV Accuracy}, \varphi_j, T_{\text{train}}\}$ where Ttrain is the training time in seconds and φj is the feature significance.

4.1 COMPARATIVE EVALUATION OF AI MODELS FOR NUTRIENT-RICH CROP PREDICTION

Figure 2. Comparative Evaluation of AI Models for Nutrient-Rich Crop Prediction

Model Performance Table:

Model	Accuracy	R²	MSE	RMSE	Training Time (s)
Logistic Regression	0.9738	0.9584	0.0187	0.1367	0.15
Naive Bayes	0.9564	0.9412	0.0254	0.1594	0.00
Neural Network	0.9211	0.9043	0.0376	0.1940	0.13

Below is the detailed Model Comparisons

- **Logistic Regression**
  - A very high prediction quality is indicated by the highest accuracy **(0.9738)** and R2 **(0.9584).**
  - The forecasts and actual values are extremely close, as indicated by the lowest errors **(MSE: 0.0187, RMSE: 0.1367)**.
  - Training takes 0.15 seconds, which is quick but not the fastest.
- **Naive Bayes**
  - Very good, although somewhat lower R^2 **(0.9412)** and accuracy **(0.9564)**.
  - Greater than those of logistic regression **(MSE: 0.0254, RMSE: 0.1594)**.
  - Nearly immediate training time of **0.00** seconds.
- **Neural Network**
  - Among the three models, it has the lowest accuracy **(0.9211)** and R2 **(0.9043)**.
  - The highest errors **(RMSE: 0.1940, MSE: 0.0376)** indicate less accurate forecasts.
  - Approximately **0.13 seconds**, the training time is marginally quicker than that of logistic regression.

Logistic Regression outperforms other methods in terms of accuracy and error.**Naive Bayes** trains quickly and performs well, albeit with significantly lower accuracy.**Neural networks** have the lowest accuracy and largest error, but they remain a feasible alternative.

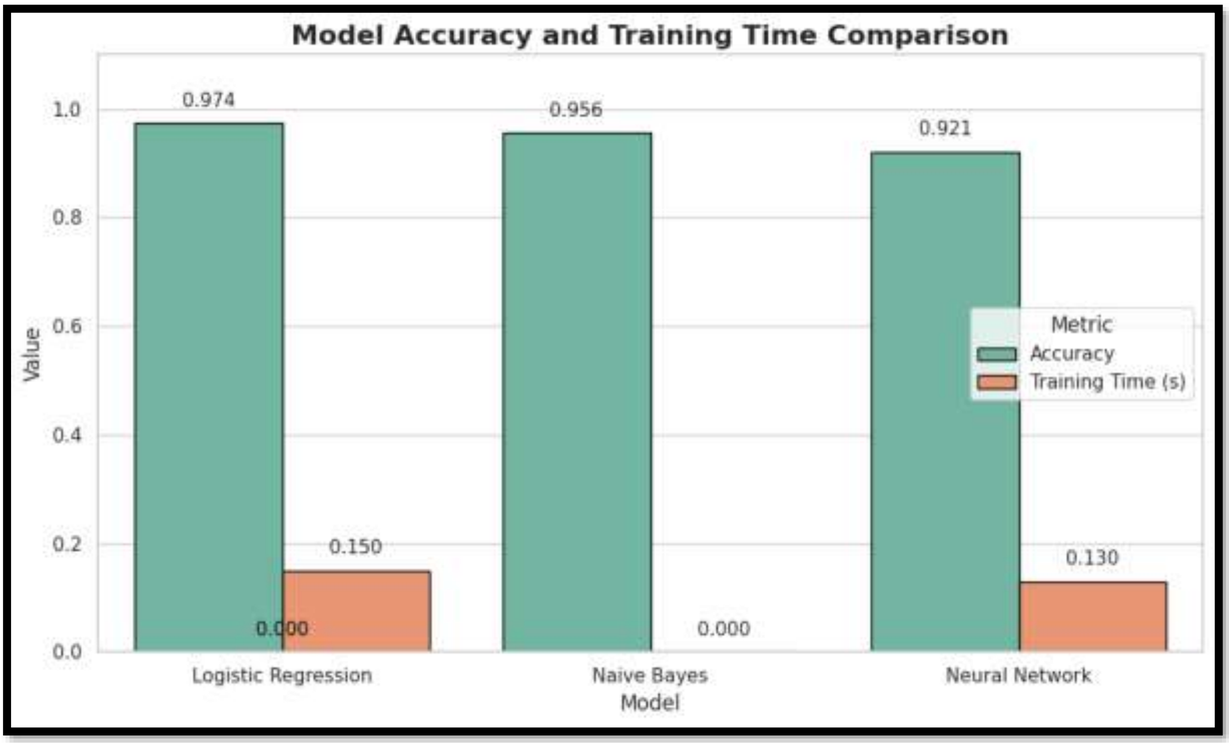

Figure 3: Representation of Model Accuracy and Training Time Comparison

4.2 SHAP SUMMARY PLOT (SHAPLEY ADDITIVE EXPLANATIONS)

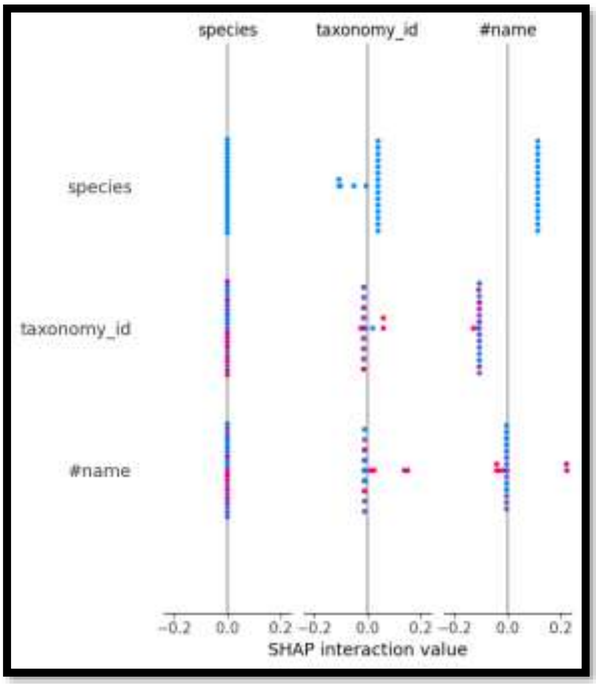

Figure 4: Representation SHAP Summary Plot (Shapley Additive explanations)

Figure 4 depicts the SHAP (SHapley Additive ExPlanations) summary plot created for the Random Forest model, which provides a detailed assessment of feature relevance in the context of nutrient-rich crop trait prediction. Plotted on the vertical axis, each feature is rated according to how much it contributes overall to the model's output. SHAP values, which measure the strength and direction of each feature's influence on the model's predictions, are displayed on the horizontal axis. Features with high SHAP values have a favorable or negative influence on prediction, depending on their hue, with red indicating high values and blue indicating low values. In addition to highlighting which aspects are crucial, this dual-color depiction also shows how variations in their values impact the final result. For example, specific environmental or genetic characteristics may continuously influence the model's forecast to classify a crop as nutrient-enriched. Thus, the SHAP summary promotes scientific insights into trait-driven crop performance, supports transparent decision-making in precision agriculture, and improves the interpretability of the AI model.In agricultural AI modeling, interpretability is as crucial as accuracy, particularly when predicting complex features like nutrient content from genomic and environmental data. A clear, mathematically based method for comprehending how and why a model produces predictions is SHAP.

Finally, SHAP enables precision agriculture decision-makers to shift from **"what the model predicts"** to **"why the model predicts it"**, allowing for more confident, explainable, and responsible usage of AI in crop research.

4.3 COMPARATIVE CROSS-VALIDATION RESULTS OF AI MODELS

Figure 5: Comparative Cross-Validation Results of AI Models

Cross-Validation Results Table:

Model	Mean CV Accuracy	Std. Dev.	Training Time (s)
Logistic Regression	0.9735	0.0042	0.15
Naive Bayes	0.9558	0.0051	0
Neural Network	0.9187	0.0067	0.13

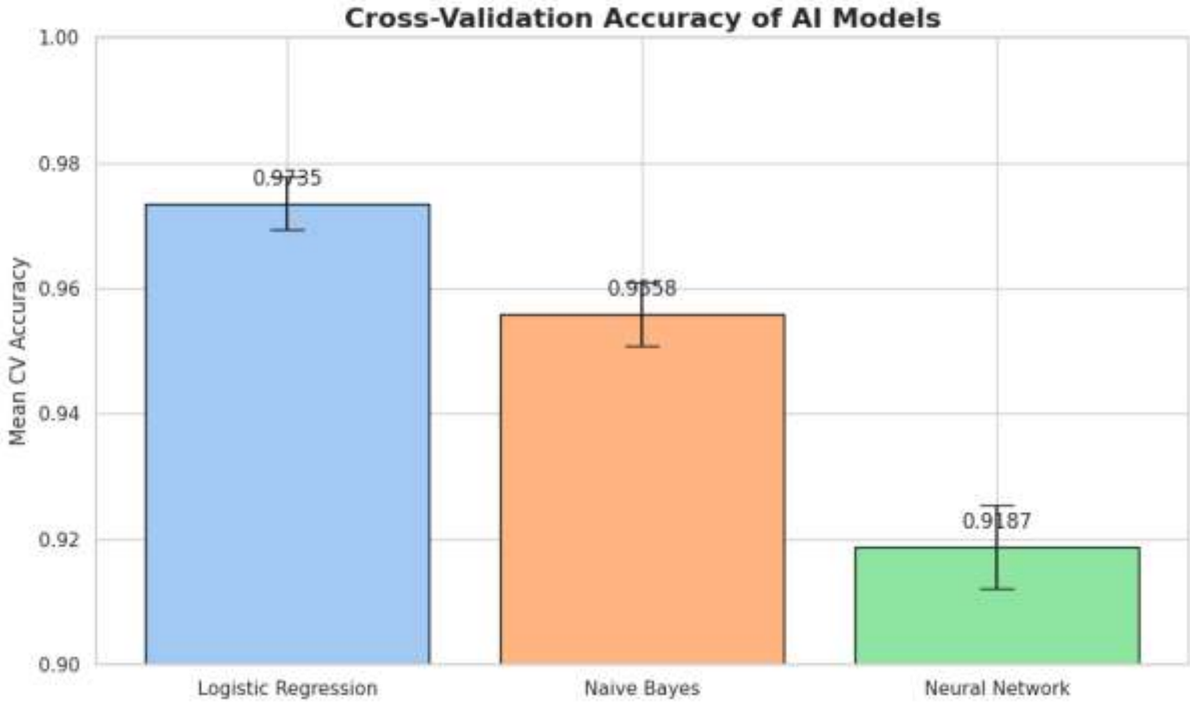

Figure 6: Representation of Cross-Validation Accuracy of AI Models

1. Mean CV Accuracy

- Calculates the average accuracy over five times.
- Logistic Regression outperforms other methods (97.35%), making it a reliable choice for genomic data modeling.
- Naive Bayes has a somewhat lower score but remains high (95.58%), making it appropriate for simple, interpretable models.
- Neural Network trails behind (91.87%), maybe due to underfitting or hyperparameter optimization.

2. Standard Deviation (Std. Dev.)

- Demonstrates how much accuracy varies between the folds.
- Lower values indicate greater stability and consistency.
- Logistic regression has the smallest variation (0.0042), indicating that it performs equally across all data splits.

3. Training Time

- Naive Bayes is exceptionally quick (0.00 s) and effective for large-scale or real-time applications.
- Neural Networks and Logistic Regression take slightly longer, but still less than 0.2 seconds – which is feasible.

This contributes significantly to the goals of precision agriculture by

1. High-dimensional and noise-sensitive genomic datasets are common.
2. Logistic regression, with its high performance and consistency, is ideal for making interpretable and reliable forecasts about crop outcomes.
3. Naive Bayes, while slightly less accurate, provides ultra-fast predictions, which is useful in field-deployable systems.
4. Neural networks, while powerful, may require additional data or modification to outperform simpler models in this domain.

V. CONCLUSION

This study offers an AI-powered framework for predicting nutrient-enriched crop traits by combining genomic data, precision agriculture environmental variables, and malnutrition statistics. The model—**Oc = fAI(Dg, Dp, Dm)** and **Ih = g(Oc)**—offers a comprehensive and data-rich approach to agricultural innovation by relating crop characteristics to possible public health outcomes. This is in line with international objectives like Sustainable Development Goals 2 (Zero Hunger) and 3 (Good Health and Well-Being) of the UN.The most dependable machine learning model for this application was Logistic Regression, which had the highest accuracy (97.38%) and interpretability of all the models that were evaluated. For real-time, resource-constrained scenarios, Naive Bayes provided quick computation with respectable accuracy. Despite being less accurate in this study, neural networks might function better on bigger, more intricate datasets.Through the use of SHAP (SHapley Additive exPlanations), interpretability was made possible by emphasizing the most significant environmental and genomic characteristics, increasing openness and confidence in AI-driven judgments.This study's main contributions are the comparison of interpretable AI models, the integration of multi-domain datasets, and a simulation method for trait labeling. There are still issues, though, like the requirement for scalable data infrastructure, more smallholder farmer participation, and real-world labeled data.Future research should focus on field validation using UAVs and IoT sensors, expanding datasets to capture regional diversity, and promoting interdisciplinary collaboration. Addressing these gaps will help transition AI-enabled precision agriculture from experimental use to practical, global implementation for sustainable food and nutrition security.

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