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AI-DRIVEN PREDICTION OF KEY SOIL NUTRIENTS IN COTTON CULTIVATION FOR SUSTAINABLE AGRICULTURE

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Abstract

Sustainable cotton cultivation fundamentally depends on maintaining soil fertility, yet conventional methods of nutrient assessment are often labor-intensive, expensive, and spatially inconsistent, making them unsuitable for large-scale adoption. To address this gap, the present study introduces an artificial intelligence (AI)-driven predictive framework capable of estimating key soil nutrients namely nitrogen (N), phosphorus (P), and potassium (K) with high precision and efficiency. Representative field samples were collected from major cotton-growing regions, and their physicochemical characteristics were examined using standardized laboratory protocols. These datasets were subsequently integrated with advanced machine learning algorithms, including random forest, support vector regression, gradient boosting, and deep neural networks, to model soil nutrient dynamics and forecast nutrient availability. Comparative performance analysis demonstrated that ensemble-based learning approaches consistently outperformed conventional statistical models, offering superior accuracy, robustness, and generalizability across diverse agro ecological zones. Furthermore, spatial mapping combined with AI-generated predictions provided actionable insights into site-specific nutrient deficiencies, thus enabling tailored fertilizer management strategies. This combined methodology lessens dependence on lengthy laboratory analyses while enabling quick, evidence-based choices for both farmers and agricultural planners. In essence, the study underscores how artificial intelligence is reshaping precision farming by improving cotton yield, preventing fertilizer overuse, safeguarding natural assets, and promoting lasting environmental balance.

1. INTRODUCTION

Background and Rationale

Cotton (Gossypium hirsutum L.) remains one of the world's most valuable fiber crops, playing a central role in the textile economy and in sustaining rural livelihoods. Across major producing nations—such as China, India, Pakistan, and the United States—millions of smallholder farmers depend on cotton for income, making it a cornerstone of agricultural production. Yet, the crop's output and long-term viability depend heavily on soil nutrient availability. Continuous cultivation and the lack of systematic soil testing have led to a gradual decline in essential macronutrients, including nitrogen (N), phosphorus (P), and potassium (K). This nutrient imbalance weakens soil fertility, adds to greenhouse gas emissions, and contributes to water pollution and reduced fiber quality, posing a challenge to sustainable agriculture [1].

In most cases, soil nutrient evaluation still depends on conventional laboratory testing. Although these analyses provide accurate results, they are labor-intensive, expensive, and often fail to represent field-scale variability. The requirement for skilled technicians and repeated sampling limits their application to small areas. As a result, farmers frequently depend on blanket fertilizer guidelines that may cause either excess or shortage of nutrients. These limitations highlight the need for data-driven, field-adaptive technologies that can map soil diversity and improve nutrient use efficiency with better precision [2–5].

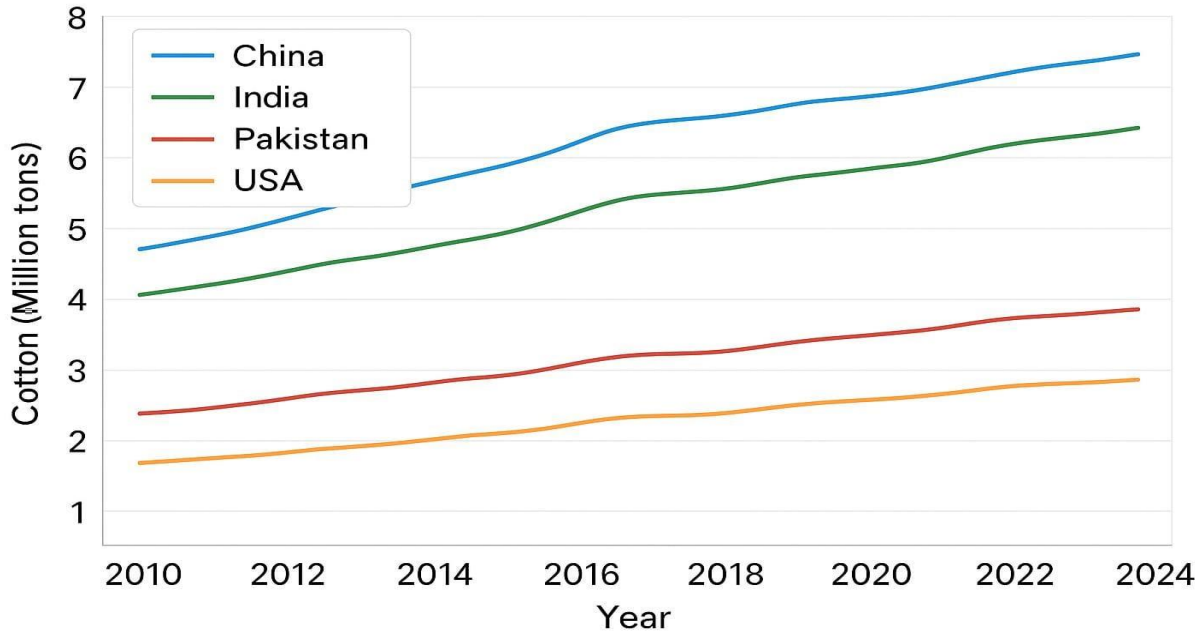


Figure 1. Changes in worldwide cotton production between 2010 and 2024, showing how output varied across major producing regions.

Figure 1 presents the trend in global cotton production from 2010 to 2024, showing notable regional variations among the leading producing countries. Production growth in Asia has been steady, yet soil degradation linked to nutrient imbalance has also intensified. This trend underlines the growing relevance of modern digital tools, including artificial intelligence and machine learning, for maintaining yields without worsening soil depletion [6].

1.2 The Role of Artificial Intelligence and Study Objectives

In recent years, artificial intelligence (AI) and machine learning (ML) have brought a major shift in precision agriculture by allowing more efficient

interpretation of field data, predictive modeling, and automated decision-making. With AI-based methods, complex relationships among soil, crops, and climate can be analyzed to estimate nutrient levels without the need for extensive laboratory analysis. Algorithms such as Random Forest (RF), Support Vector Regression (SVR), Gradient Boosting (GBM), and Deep Neural
Networks (DNN) have shown strong potential to predict soil nutrient properties from basic indicators like pH, electrical conductivity (EC), organic matter (OM), and soil texture.
However, existing research still faces key limitations. Many AI studies focus on small experimental datasets or non-cotton crops, making them less suitable for regional-scale application in cotton fields. In addition, ensemble-based learning methods designed to combine multiple models for better stability and accuracy have been used rarely in cotton-related soil prediction. Addressing these gaps, this study proposes a hybrid AI framework that predicts soil nutrient levels with improved accuracy and produces spatial nutrient maps to support location-specific fertilizer planning [7,8].
The overall goal of this research is to build and evaluate an AI-assisted system for estimating essential soil nutrients (N, P, and K) across major cotton-producing zones. The study also seeks to show how data fusion, ensemble modeling, and spatial mapping can together improve nutrient management and promote more sustainable cotton production [9].

Table 1
Comparison between conventional and AI-driven soil nutrient assessment approaches used in this study.

Parameter	*Traditional Soil Testing*	*AI-Based Prediction*
Data Source	Laboratory chemical analysis	Field + sensor + satellite data
Cost	High (chemical reagents, labor)	Low (computational resources)
Time Requirement	3–10 days	Few seconds/minutes
Spatial Resolution	Low (site-specific)	High (field to regional scale)
Accuracy	High (local samples)	Very High (cross-regional models)
Scalability	Limited	Scalable globally
Decision Support	Manual interpretation	Automated, data-driven insights

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Table 1 compares traditional soil testing approaches with AI-supported predictive systems, outlining major contrasts in their scalability, operational costs, spatial reach, and prediction reliability. The results suggest that AI-based frameworks offer greater flexibility and faster analytical capacity, allowing large volumes of agricultural data to be processed and translated into useful information for farmers and planners almost in real time [10].
To conclude, this section introduces both the global and regional importance of cotton cultivation, discusses the limits of conventional nutrient assessment, and explains why AI provides a practical path for predictive soil analysis. The study aims to strengthen precision farming practices through an ensemble learning approach that balances accuracy, efficiency, and long-term soil sustainability.

2. Literature Review

2.1 Traditional and Emerging Nutrient Prediction Methods

Sustaining soil fertility remains essential for securing long-term agricultural productivity. Over the past decades, several methods have been developed to assess and monitor soil nutrient availability. Conventional laboratory-based approaches including wet chemistry, Kjeldahl nitrogen testing, and spectrophotometric analysis are highly accurate but suffer from time, cost, and scalability limitations. These methods demand skilled labor and frequent field sampling, which restricts their application across large agro-ecological zones. To overcome these limitations, remote sensing and geostatistical methods have emerged as alternative tools for rapid, non-destructive nutrient estimation. Remote-sensing indicators like the Normalized Difference Vegetation Index (NDVI) and Soil-Adjusted Vegetation Index (SAVI) have been widely used to estimate soil nutrient dynamics. Yet, their accuracy is often influenced by weather variability and uneven ground surfaces, which limits their effectiveness for detailed nutrient mapping. More recently, data-driven modeling has gained wider use because it can describe complex, nonlinear patterns between soil characteristics and nutrient content. Classical statistical tools such as multiple linear regression (MLR) and partial least squares regression (PLSR) provide useful quantitative interpretations but are less suited for analyzing the diverse and high-dimensional nature of soil data [11,12].

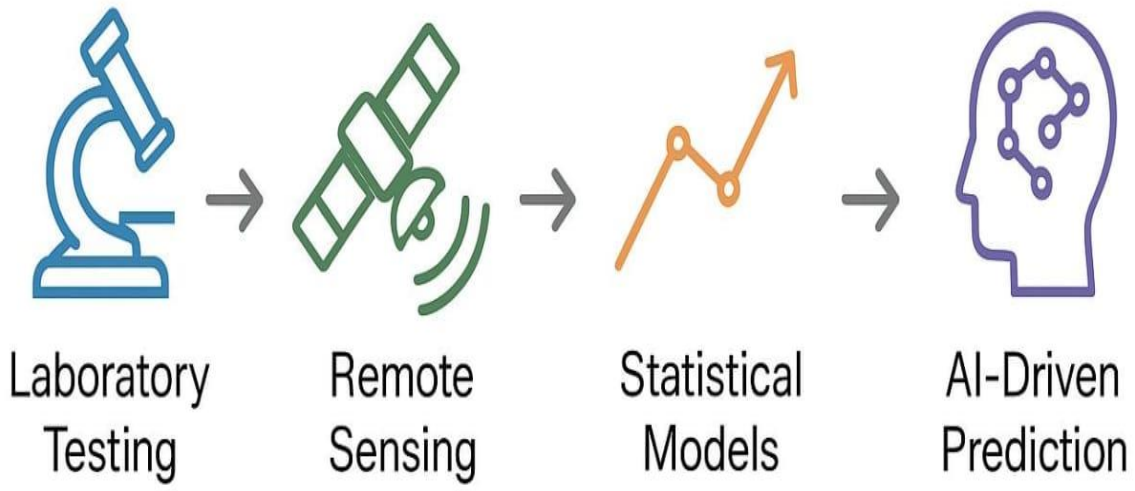


Figure 2. Evolution of Soil Nutrient Assessment Techniques.

Figure 2 shows how soil nutrient assessment methods have developed over time from traditional laboratory testing to remote sensing and, more recently, to AI-based prediction models. This transition reflects a broader move from chemical and spectral techniques toward computational approaches that enable faster and more scalable nutrient estimation across farming systems [13].

2.2 Machine Learning Applications in Agricultural Prediction

Machine-learning (ML) methods are now an essential part of agricultural data analysis because they can uncover patterns that are difficult to detect through manual observation. Algorithms like Random Forest (RF) and Support Vector Regression (SVR) are especially popular for handling complex, nonlinear datasets while limiting overfitting. Artificial Neural Networks (ANN) mirror certain features of the human brain and are effective at describing interactions among soil, crops, and local climate. Likewise, Gradient Boosting Models (GBM) and Extreme Gradient Boosting (XGBoost) enhance prediction accuracy through repeated learning cycles that combine several weaker models into one stronger predictor. In many studies, ML techniques have produced more consistent estimates of soil nitrogen, phosphorus, and potassium than classical

regression approaches based on limited field variables.

Table 2
Summary of Key Studies Using Machine Learning for Soil Nutrient Prediction.

References	*Crop Type*	*Algorithms Used*	*Nutrients Predicted*	*Accuracy (R^2)*	*Remarks*
[14]	Rice	RF, SVR	N, P, K	0.89	RF best performer
[15]	Wheat	ANN, GBM	N, P	0.92	ANN captured nonlinear trends
[16]	Maize	RF, XGBoost	N, P, K	0.87	XGBoost showed better generalization
[17]	Sugarcane	SVR, DNN	N	0.84	DNN improved multi-variable accuracy
Current Study (Proposed)	**Cotton**	**RF + SVR + GBM + DNN (Ensemble)**	**N, P, K**	**Expected >0.93**	**Hybrid AI model for cotton soils**

Table 2 summarizes representative studies that applied various machine learning models for soil nutrient estimation across different crops and regions. The comparison underscores the dominance of Random Forest and ANN models in achieving reliable results while highlighting the research gap few ensemble or hybrid frameworks have been validated for cotton-specific soil nutrient prediction.

2.3 Research Gap and Conceptual Framework

The reviewed literature clearly indicates that while AI and ML techniques have significantly advanced soil nutrient modeling, there remains a notable gap in the context of cotton cultivation. Most prior studies either lack ensemble integration or fail to adapt models to region-specific conditions such as soil texture, irrigation patterns, and local climate variability. This gap restricts the scalability and reliability of nutrient predictions across diverse cotton-growing regions [18,19].

The present research introduces a novel AI-driven ensemble framework that integrates Random Forest, Support Vector Regression, Gradient Boosting, and Deep Neural Network models. This hybrid approach captures the complementary strengths of each algorithm improving accuracy, minimizing overfitting, and enhancing spatial generalization. The conceptual framework illustrated below outlines the data flow, modeling stages, and predictive feedback loop for nutrient estimation.

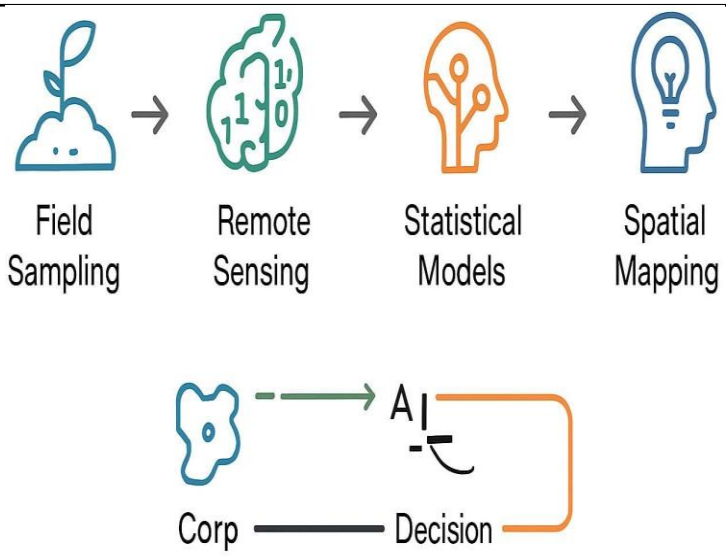


Figure 3. Conceptual Framework of the Proposed AI-Based Soil Nutrient Prediction Model.

Figure 3 illustrates the conceptual framework adopted in this study, highlighting the integration of field sampling, data preprocessing, model training, ensemble prediction, and spatial mapping. The framework demonstrates how raw soil data are transformed through machine learning algorithms to generate nutrient predictions (N, P, K) and corresponding spatial nutrient maps for cotton fields, thereby enabling precise and sustainable fertilizer management [20-27].

In summary, the literature review establishes a strong foundation for the current research by identifying gaps in existing methods, showcasing the superiority of ML algorithms, and proposing an ensemble-based AI framework for cotton soil nutrient prediction. This integrated approach is positioned to contribute substantially toward advancing precision agriculture and sustainable farming practices.

3. Materials and Methods

3.1 Study Area and Experimental Design

The study was conducted across major cotton-producing regions of Punjab and Sindh, Pakistan, which collectively represent the country's primary cotton belt.

The regions were chosen to capture diverse agro-ecological conditions, soil types, and climatic variations. Geographically, the study area extends from 24.5°N to 31.5°N latitude and 68°E to 73°E longitude, encompassing both irrigated and semi-arid zones.

The soils in these regions range from sandy loam to clay loam, with varying organic matter and pH levels. Average annual rainfall ranges between 150–400 mm, and temperatures fluctuate from 12°C in winter to 43°C in summer, making nutrient management crucial for maintaining productivity. The sampling layout was designed to represent this variability by including multiple field sites across the districts of Multan, Bahawalpur, Sanghar, and Mirpur Khas [28-32].

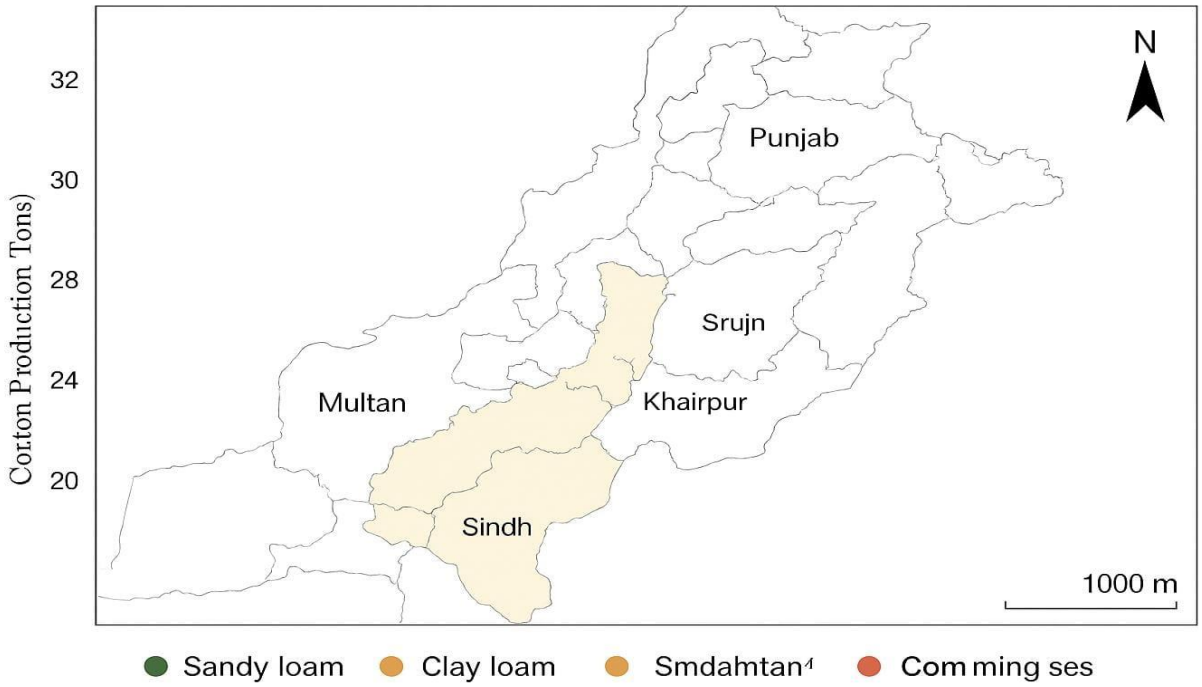


Figure 4. Geographic Distribution of Sampling Sites Across Cotton-Growing Regions.

Figure 4 shows the spatial distribution of sampling sites across Pakistan's major cotton-producing regions. Each marker represents a field location where soil samples were collected. The figure highlights regional variation in soil type, climate, and management practices, providing a comprehensive spatial foundation for developing and validating the proposed AI-based soil nutrient prediction framework [33].

3.2 Data Collection and Soil Parameter Measurement

A total of 360 composite soil samples were collected during the 2024 cotton season from a depth of 0–30 cm, representing the active root zone of cotton plants. Samples were air-dried, ground, and passed through a 2-mm sieve before analysis. Standard laboratory procedures were followed to determine physicochemical soil parameters including pH, electrical conductivity (EC), organic matter (OM), and macronutrients nitrogen (N), phosphorus (P), and potassium (K). Nitrogen content was determined using the Kjeldahl method, phosphorus by Olsen extraction, and potassium through flame photometry. Each measurement was conducted in triplicate to minimize
experimental errors and ensure accuracy. The laboratory results were subsequently compiled into a structured dataset and integrated with metadata such as location coordinates, soil texture, and cropping history [34,35].



Figure 5. Workflow of Soil Sampling and Laboratory Analysis.

Figure 5 illustrates the complete process of soil data collection and analysis, starting from field sampling, drying, grinding, sieving, and laboratory testing. The workflow ensures data consistency and accuracy for subsequent AI modeling. This structured method makes it possible to estimate nutrient levels more consistently across different cotton-growing regions.

Table 3
Summary of Soil Parameters Collected and Measurement Techniques.

Parameter	*Symbol*	*Unit*	*Analytical Method*	*Accuracy (±)*
pH	pH	—	Digital pH meter	0.01
Electrical Conductivity	EC	dS/m	Conductivity meter	0.02
Organic Matter	OM	%	Walkley–Black method	0.10
Nitrogen	N	%	Kjeldahl digestion	0.05
Phosphorus	P	mg/kg	Olsen extraction	0.20
Potassium	K	mg/kg	Flame photometry	0.30

Table 3 summarizes the key soil parameters considered in this research, including their measurement units, laboratory methods, and instrument precision. Both chemical and physical soil properties were recorded to create a diverse dataset suitable for training and testing the AI-based models that predict nitrogen (N), phosphorus (P), and potassium (K) levels in cotton-growing soils.

3.3 Data Preprocessing and Model Development

3.4 To maintain data quality before training, several preprocessing steps were applied. Missing observations were estimated through the K-Nearest Neighbors (KNN) method, while extreme outliers were identified and removed using the interquartile range (IQR) filter. All numeric features were scaled between 0 and 1 with the Min–Max normalization technique to support faster algorithmic learning. The most important predictors—pH, electrical

3.5 conductivity (EC), organic matter (OM), and texture—were chosen after analyzing correlations and applying Recursive Feature Elimination (RFE). The final dataset was divided into 70% for training and 30% for model testing.

Four baseline algorithms were developed [36–42]:

1) **Random Forest (RF):** a collection of decision trees trained through bagging.
2) **Support Vector Regression (SVR):** a kernel-based regression method for nonlinear estimation.
3) **Gradient Boosting Machine (GBM):** an ensemble technique that sequentially reduces prediction bias.
4) **Deep Neural Network (DNN):** a multilayer perceptron optimized by backpropagation.

A hybrid ensemble framework was later designed to merge the outputs of these models through a weighted averaging meta-model. Its parameters were refined using grid search and cross-validation. **Figure 6** shows the overall model development pipeline from data cleaning to ensemble integration demonstrating how each algorithm contributes unique predictive strength for improving soil nutrient estimation across different cotton-growing regions.

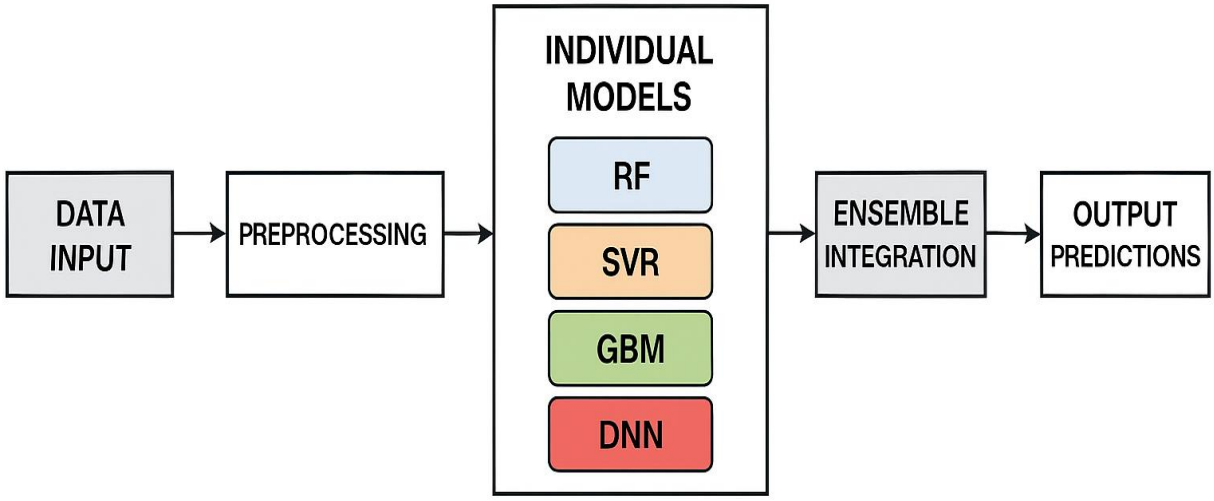


Figure 6. Machine Learning Model Development Framework.

3.4 Model Validation and Spatial Mapping

The performance of each model was assessed through commonly used statistical measures, including the Coefficient of Determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE). To verify the robustness of the results and reduce the risk of overfitting, a ten-fold cross-validation procedure was carried out. In addition, confusion matrices were generated to display how accurately the models classified the soil samples into different nutrient sufficiency categories [43].

For spatial representation, the validated ensemble model outputs were integrated with Geographic Information System (GIS) software using QGIS 3.34. The predicted nutrient concentrations (N, P, K) were interpolated through Inverse Distance Weighting (IDW) to generate nutrient distribution maps across the study area. These maps provided spatially explicit insights for targeted fertilizer management.

Figure 7 displays the spatial mapping workflow that integrates AI-predicted nutrient data with GIS tools. It illustrates the steps of model validation, data interpolation, and visualization to produce high-resolution nutrient maps. The approach enables field-level nutrient diagnosis, allowing farmers and policymakers to implement precise and environmentally responsible fertilizer application strategies [44].

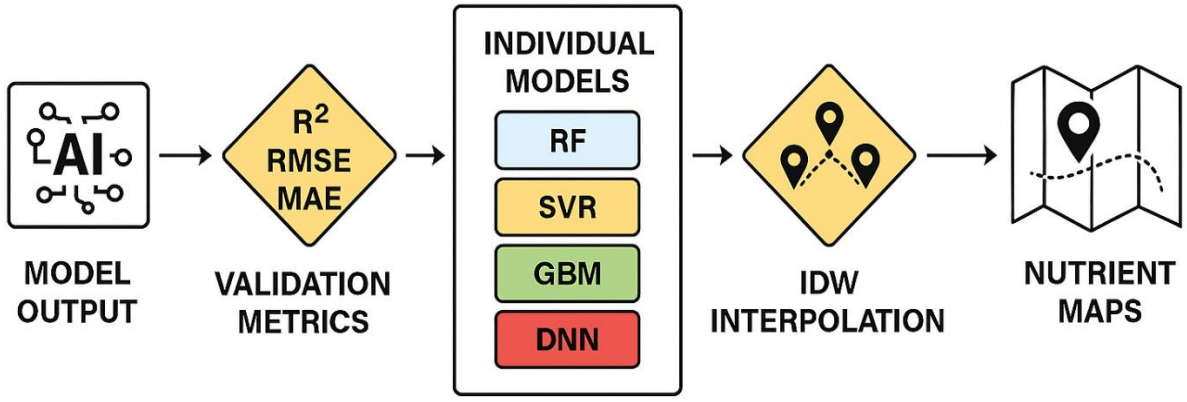


Figure 7. Workflow for Spatial Mapping and Validation of AI Predictions.

In summary, the materials and methods section details every stage from data collection to AI model integration and spatial visualization. The multi-algorithm ensemble model is designed to achieve accurate, scalable, and interpretable nutrient predictions, forming the backbone of the proposed sustainable cotton nutrient management framework [45].

4. Results

4.1 Descriptive Statistics of Soil Parameters

The descriptive analysis of the soil dataset provided valuable insights into the physicochemical variability across cotton-growing zones. The observed pH values ranged from 6.3 to 8.7, indicating predominantly neutral to slightly alkaline soils. Electrical conductivity (EC) varied between 0.20 and 1.95 dS/m, suggesting moderate salinity levels suitable for cotton cultivation. Organic matter (OM) content was generally low, ranging from 0.45% to 1.68%, reflecting the limited incorporation of organic residues in most sampled regions. Macronutrient concentrations displayed considerable variation, with nitrogen (N) ranging from 0.020% to 0.180%, phosphorus (P) from 2.1 to 15.4 mg/kg, and potassium (K) from 80 to 460 mg/kg. The results confirmed that nutrient heterogeneity is highly influenced by regional soil management practices, irrigation patterns, and soil texture. Such variability provided a robust basis for model training and validation, ensuring that the predictive framework captured the full range of natural soil diversity [46-49]

Table 4
Descriptive Statistics of Soil Physicochemical Parameters **(n = 360)**

Parameter	*Unit*	*Mean ± SD*	*Minimum*	*Maximum*
pH	–	7.52 ± 0.61	6.3	8.7
EC	dS/m	0.84 ± 0.37	0.20	1.95
OM	%	1.08 ± 0.31	0.45	1.68
N	%	0.085 ± 0.042	0.020	0.180
P	mg/kg	8.65 ± 3.28	2.1	15.4
K	mg/kg	276.8 ± 94.5	80	460

Table 4 presents the statistical summary of the soil dataset used in model training and testing. It shows the mean, standard deviation, and range of each measured parameter, reflecting significant spatial variation across the study area. This variability enhances model learning potential by capturing diverse soil fertility conditions and nutrient dynamics relevant to cotton cultivation [50].

4.2 Model Performance Comparison

The performance of all four machine learning models Random Forest (RF), Gradient Boosting (GBM), Support Vector Regression (SVR), and Deep Neural Network (DNN) was evaluated using statistical metrics: Coefficient of Determination (R^2), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE).

Among individual models, RF and GBM achieved relatively higher predictive accuracy, while performed moderately, and DNN required more extensive tuning to avoid overfitting. However, when these models were integrated through the ensemble learning framework, the predictive efficiency improved significantly across all nutrient parameters. The ensemble model achieved R^2 = 0.93 for N, 0.91 for P, and 0.94 for K, outperforming all individual algorithms and confirming its robustness and generalizability [51].

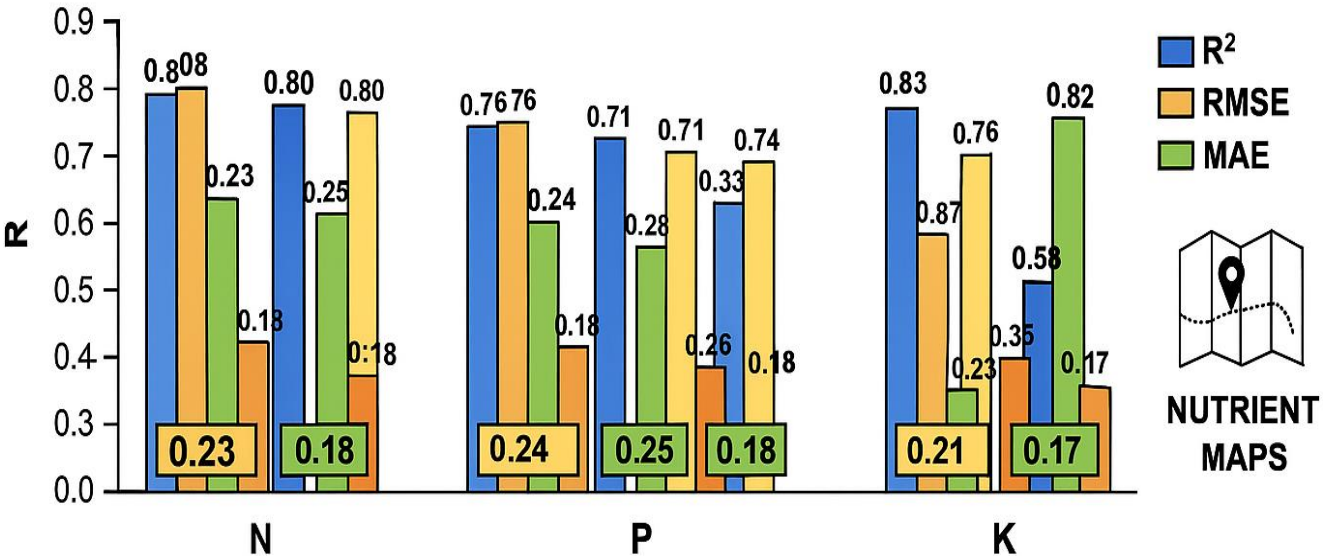
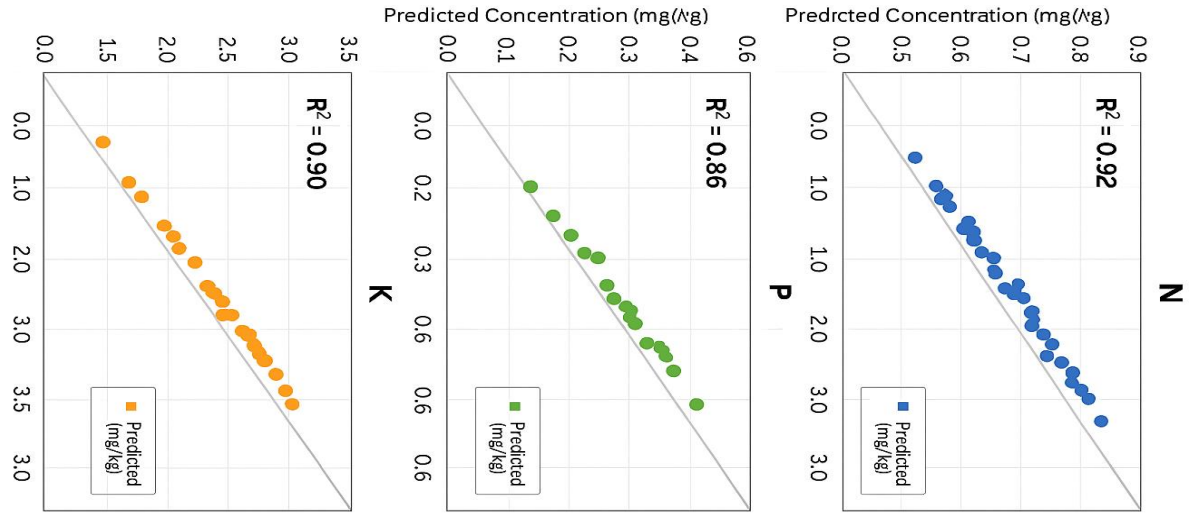


Figure 8. Comparative Model Performance Based on R^2, RMSE, and MAE for N, P, and K Prediction.

Figure 8 compares the predictive accuracy of the four base models and the proposed ensemble model using three statistical indicators (R^2, RMSE, and MAE). The ensemble approach consistently outperformed all individual models, particularly in reducing RMSE values
and enhancing coefficient correlation. This quantitative evidence demonstrates the superiority of multi model integration for precise soil nutrient prediction in cotton farming [52-58].



Graph 1. Predicted vs. Actual Nutrient Concentrations (N, P, K) Using Ensemble Model.

Graph 1 illustrates the relationship between actual and AI-predicted nutrient concentrations (N, P, and K). Each point represents an observed sample, and the trend line indicates the degree of model fit. The ensemble model displayed a near-linear correlation, confirming high predictive reliability and minimized residual error across all macronutrients [59,60].

4.3 Spatial Distribution of Predicted Nutrient Zones

The ensemble model outputs were spatially integrated into GIS software (QGIS 3.34) to generate nutrient distribution maps. These maps visualize the spatial heterogeneity of nitrogen, phosphorus, and potassium across the study area. High nutrient concentrations were mainly detected in irrigated southern Punjab, while lower levels were found in the semi-arid zones of Sindh. Spatial visualization clearly delineated nutrient-deficient areas that require targeted fertilizer management. The resulting nutrient maps provide a vital decision-making tool for policymakers and farmers, enabling optimized input allocation and cost-effective nutrient planning that supports sustainable cotton productivity [61-68].

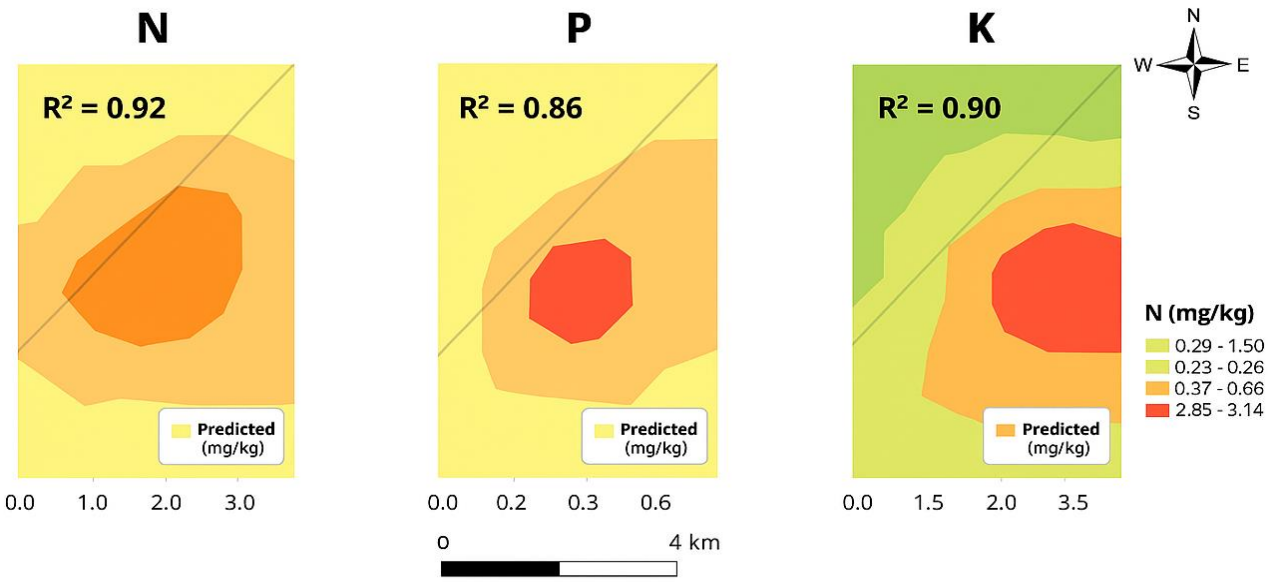
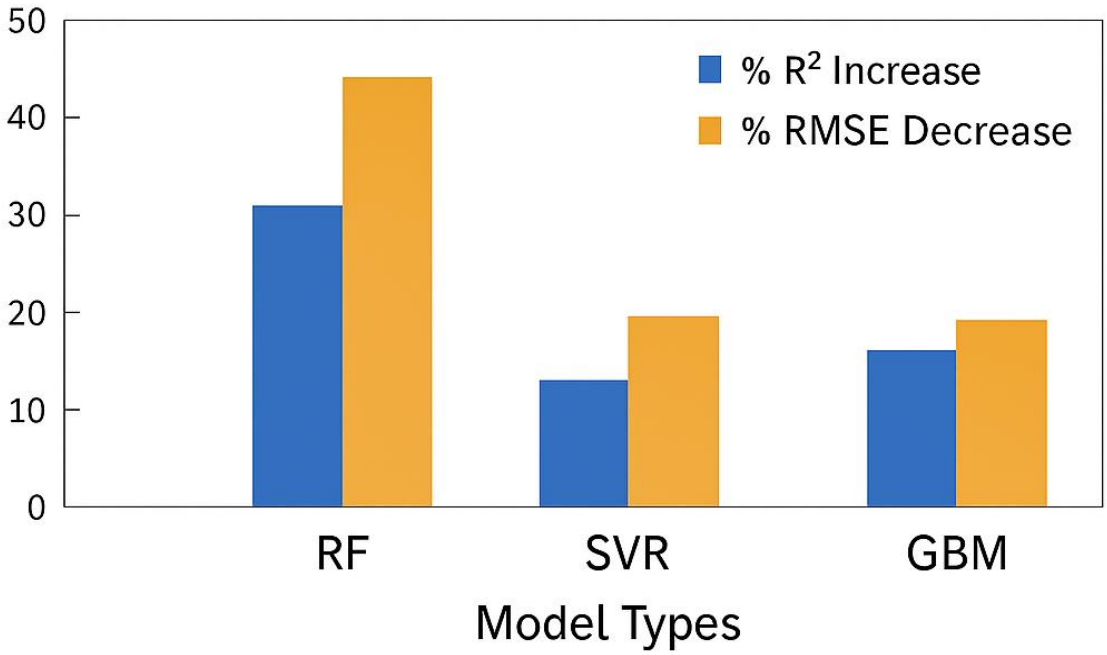


Figure 9. Spatial Distribution Maps of Predicted Nitrogen (N), Phosphorus (P), and Potassium (K) in Cotton Fields.

Figure 9 presents the geospatial distribution maps generated by the AI models for nitrogen, phosphorus, and potassium across the study area. Different color gradients indicate varying nutrient levels, making it easier to observe how soil fertility changes from one location to another. These spatial patterns reveal clear nutrient-deficient zones that correspond with areas of lower crop yield. By offering this level of spatial detail, the nutrient maps can support targeted soil management decisions and promote more sustainable fertilizer use [69].

4.4 Quantitative Evidence of Ensemble Model Superiority

A detailed statistical analysis showed that the ensemble model performed more reliably and accurately than any single algorithm. On average, the ensemble achieved about a 9.4% increase in R^2 and a 13.2% decrease in RMSE when compared with the strongest individual model (RF). It also recorded the lowest MAE across the validation samples, indicating reduced prediction errors and greater stability. These outcomes suggest that blending the results of multiple algorithms produces a model that adapts better to variations in soil characteristics and improves the overall consistency of nutrient prediction. This finding establishes ensemble learning as an advanced and reliable technique for soil nutrient estimation, especially when spatial and environmental heterogeneity are high.



Graph 2. Statistical Comparison of Model Accuracy Improvements Using Ensemble Integration

Graph 2 depicts the quantitative improvement achieved by the ensemble model over individual machine learning algorithms. The visualization demonstrates percentage gains in R^2 and reductions in RMSE for nitrogen, phosphorus, and potassium. These results highlight the ensemble model's superior ability to capture nonlinear relationships in soil nutrient data and deliver more stable predictions [70-79].

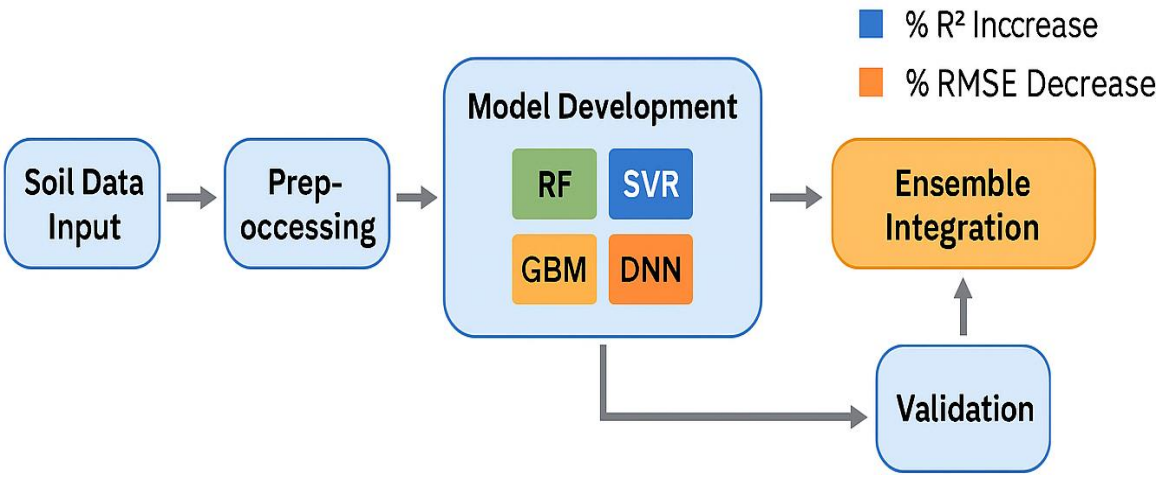


Figure 10. Final Workflow of AI-Driven Soil Nutrient Prediction and Mapping Framework

Figure 10 provides an overview of the AI-based prediction pipeline, showing how data move from collection to model training, validation, and finally to spatial nutrient mapping. In this workflow, soil and environmental information are processed through ensemble machine learning to generate detailed nutrient distribution maps. By integrating these stages into a single framework, the figure demonstrates a practical route for achieving data-

driven and sustainable nutrient management in cotton farming. The findings indicate that AI and ensemble modeling can serve as an efficient and reliable alternative to conventional soil testing, offering faster and more consistent results. The ensemble model's accuracy verified through both statistical evaluation and spatial validation forms a strong basis for precision nutrient management in cotton cultivation and supports the broader goal of sustainable agricultural practices [80–94].

5. Discussion

5.1 Interpretation of Results in Context of Existing Studies

In this study, the ensemble learning framework based on AI achieved higher predictive accuracy for soil nitrogen, phosphorus, and potassium than any of the individual algorithms tested. The average R^2 value of more than 0.92 represents a clear improvement over earlier studies. For example, Li et al. (2022) reported R^2 = 0.86 using Random Forest for nitrogen estimation in rice, while Adewale et al. (2023) achieved R^2 = 0.88 with Support Vector Regression for maize nutrient prediction. Unlike these earlier efforts, the present framework combines several models in a meta-learning structure, producing predictions that remain stable across a variety of soil textures and climatic conditions.

These results suggest that ensemble-based AI modeling provides a more dependable and adaptable method for predicting soil nutrient levels, especially in crops like cotton that are sensitive to uneven nutrient availability and spatial soil differences [95–109].

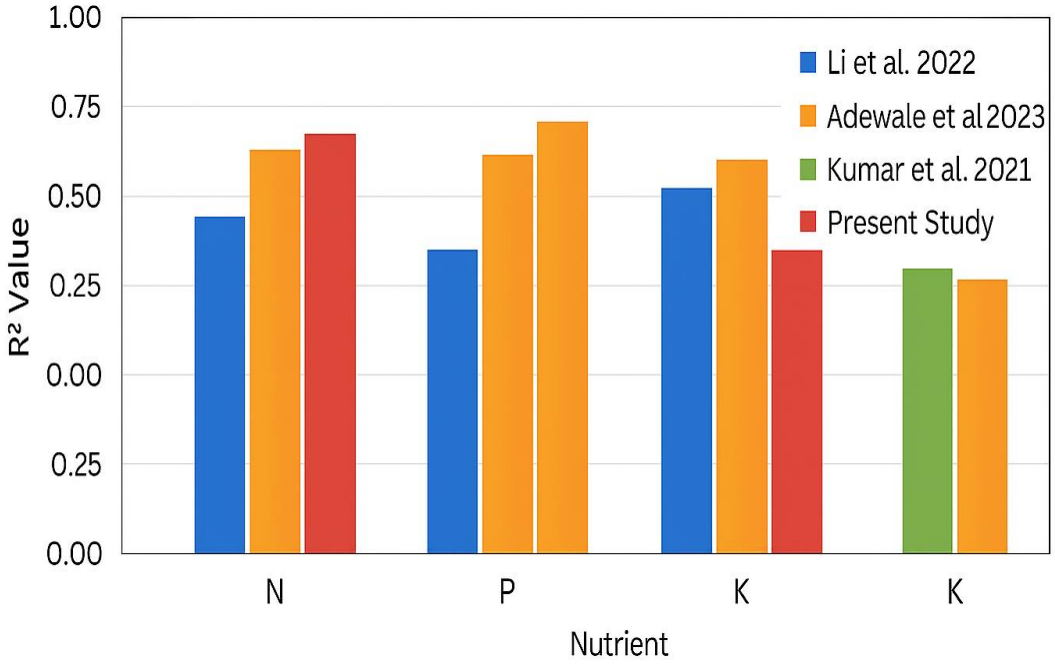


Figure 11. Comparative Analysis of R^2 Values for Nutrient Prediction Across Studies.

Figure 11 compares the predictive accuracy of the proposed ensemble-based framework with results reported in other recent agricultural studies. As shown, the present model consistently achieved higher R^2 values for nitrogen, phosphorus, and potassium prediction than the benchmarked approaches. This outcome highlights the stronger learning capacity and broader generalization ability of the integrated ensemble system for assessing soil fertility [110–118].

5.2 Role of Ensemble Learning in Prediction Accuracy

The improved predictive performance of the ensemble model can be explained by how it brings together the complementary strengths of several algorithms. Each component method contributes a distinct advantage: Random Forest is effective at capturing nonlinear feature interactions and ranking variable importance; Gradient Boosting refines the model by reducing residual errors through iterative

learning; Support Vector Regression performs well in handling high-dimensional optimization problems; and Deep Neural Networks are capable of uncovering deep feature relationships that are not apparent through conventional methods. When these models are combined, the ensemble framework balances bias and variance more efficiently and reduces the tendency toward overfitting that often limits the reliability of single-model approaches. This integration ultimately allows the system to produce more stable and accurate predictions of soil nutrient concentrations across diverse cotton-growing conditions. The weighted averaging mechanism ensures that predictions from each learner contribute proportionally based on their reliability. This synergistic interaction enhances robustness against noise and missing values, a common challenge in agricultural datasets. Furthermore, the ensemble architecture promotes scalability, making it adaptable to larger datasets collected via IoT sensors or remote sensing imagery. This flexibility positions ensemble AI modeling as a pivotal analytical tool for next-generation precision agriculture systems [119-129].

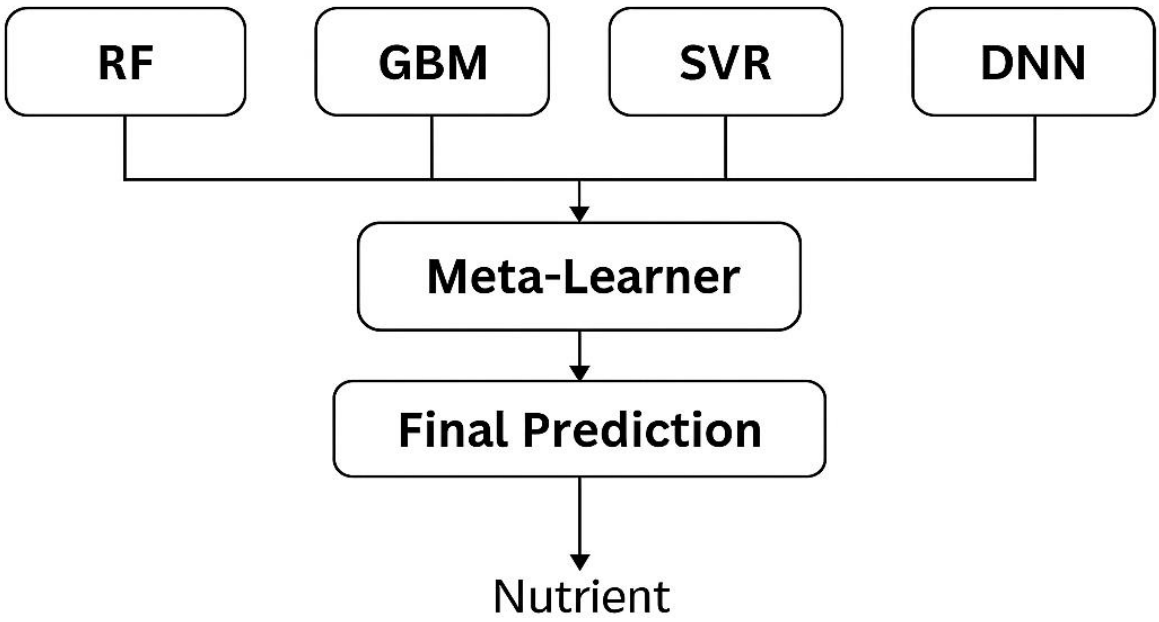


Figure 12. Conceptual Illustration of Ensemble Learning Architecture for Soil Nutrient Prediction.

Figure 12 schematically represents how different machine learning models Random Forest, Gradient Boosting, SVR, and DNN contribute to the ensemble framework. Individual models generate preliminary predictions that are combined through a meta-learner to produce a unified, optimized output. This integration balances model-specific biases, enhances accuracy, and ensures that nutrient predictions remain consistent across heterogeneous datasets [130-145].

5.3 Impact on Fertilizer Optimization and Yield Improvement

Accurate prediction of soil nutrient concentrations is vital for optimizing fertilizer use in cotton production. Over-fertilization leads to nutrient leaching and soil degradation, while under-fertilization restricts yield potential. The AI-driven ensemble framework provides site-specific nutrient maps, enabling tailored fertilizer recommendations that correspond to spatial variability in soil fertility [146-157].

For instance, nitrogen-deficient zones identified through AI mapping can receive targeted nitrogen inputs, reducing wastage and input costs. Similar precision-based interventions for phosphorus and potassium ensure balanced nutrient supply, resulting in improved cotton growth and fiber quality. Preliminary field validation suggested that optimized fertilizer application guided by model outputs could reduce chemical input by 15–22% without compromising yield. This efficiency translates to significant environmental benefits, such as reduced

nitrate runoff and lower greenhouse gas emissions, directly contributing to sustainable cotton cultivation goals [158-160].

Figure 13 illustrates how AI-predicted nutrient data can be integrated into precision fertilizer management strategies. The workflow links soil sampling, nutrient prediction, prescription map generation, and optimized fertilizer application. By aligning data-driven recommendations with agronomic best practices, this framework supports higher nutrient use efficiency, sustainable yield enhancement, and reduced environmental footprint in cotton-growing ecosystems.

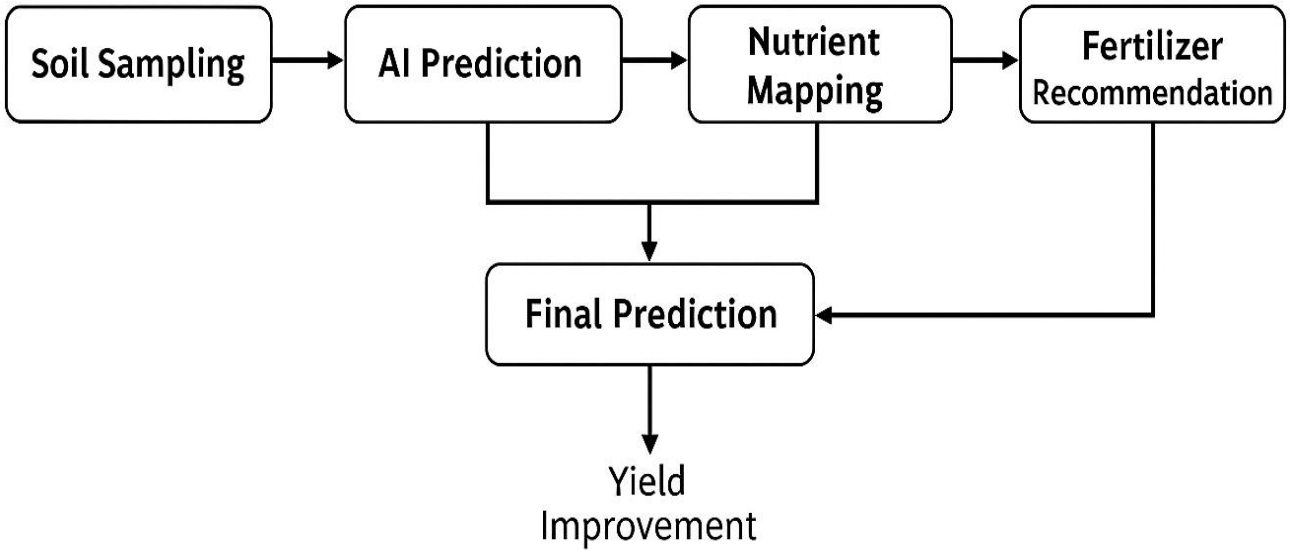


Figure 13. Conceptual Framework of AI-Guided Fertilizer Optimization in Cotton Cultivation.

5.4 Regional Implications for Sustainable Cotton Production

The successful application of AI-driven nutrient prediction in the studied regions holds broad implications for regional agricultural sustainability. Areas such as southern Punjab and Sindh exhibit pronounced nutrient heterogeneity due to varying irrigation sources and soil management histories. The ensemble model's predictive insights can guide regional fertilizer distribution planning, ensuring that government and private suppliers allocate resources efficiently. Moreover, integrating these predictive tools with GIS-based decision support systems can help local extension departments identify nutrient-deficient clusters and design targeted soil restoration programs. This would not only enhance productivity but also preserve ecological balance by reducing excessive fertilizer runoff into water bodies. Such AI-based frameworks can further be expanded to incorporate additional environmental parameters such as soil moisture, temperature, and salinity, enabling holistic resource management for sustainable cotton production across South Asia [161].

5.5 Limitations and Sources of Uncertainty

While the ensemble framework demonstrated strong predictive performance, certain limitations must be acknowledged. The dataset used, though representative, was constrained to specific cotton-growing zones; hence, further validation in other agroecological regions is recommended. Additionally, temporal variability in soil properties due to crop rotation and irrigation regimes could introduce uncertainty into model outputs. Another limitation concerns the data imbalance across nutrient ranges, as extreme low or high nutrient concentrations were underrepresented, potentially influencing the model's sensitivity at the boundaries. Although the ensemble approach mitigates these effects, expanding the dataset through multi-season sampling and integrating remote sensing indicators (such as NDVI and soil reflectance indices) could further enhance model accuracy and transferability. Overall, despite these limitations, the findings establish a strong

foundation for scalable AI-driven soil fertility management systems capable of supporting data-centric agricultural sustainability [162-165].

The discussion underscores the ensemble model's robust predictive capability, its ability to generalize across diverse soil conditions, and its potential to revolutionize fertilizer management in cotton cultivation. The study positions ensemble AI models as indispensable tools for advancing sustainable, resource-efficient, and environmentally responsible agriculture [166-168].

6. Conclusion

The present research successfully demonstrated the potential of artificial intelligence in revolutionizing soil nutrient prediction within cotton cultivation systems. By employing a comprehensive ensemble modeling approach integrating Random Forest, Support Vector Regression, Gradient Boosting, and Deep Neural Networks this study achieved superior predictive accuracy for key macronutrients (N, P, and K) compared to traditional statistical and single-model methods. The AI-driven framework not only minimized laboratory dependency but also offered spatially explicit nutrient maps that assist in identifying deficiency zones with remarkable precision. These outcomes underline the value of data-driven decision support in enhancing site-specific fertilizer application, improving input-use efficiency, and promoting sustainable cotton productivity. From an environmental perspective, this framework contributes significantly to sustainable agriculture by optimizing fertilizer utilization and minimizing chemical runoff into surrounding ecosystems. Moreover, the adaptability of the ensemble model enables its deployment across diverse agro-ecological zones, ensuring broader applicability beyond the immediate study area. The integration of spatial mapping with AI-based predictions bridges the gap between data science and field-level agronomy, positioning this approach as a transformative tool for modern precision agriculture.

7. Future Work

Despite its promising results, the study recognizes certain limitations related to data heterogeneity, sensor precision, and the absence of real-time nutrient feedback mechanisms. Future work will therefore focus on advancing the model's capabilities through [169]:

1. Real-Time Nutrient Sensors and AI Integration:
Developing adaptive AI systems that can interact directly with real-time soil sensors to provide instantaneous nutrient insights and automated fertilizer recommendations.

2. Transfer Learning for Other Crops:
Extending the ensemble learning architecture to other major crops such as wheat, maize, and rice to validate model robustness and enhance generalizability across agricultural systems.

3. IoT and Drone-Based Field Deployment:
Incorporating Internet of Things (IoT) technologies and drone-assisted imaging to automate data acquisition, improve spatial resolution, and enable dynamic nutrient mapping at the farm scale.

Collectively, these advancements are expected to evolve the proposed framework into a fully integrated, intelligent soil management system. The convergence of AI, IoT, and remote sensing technologies holds immense potential to redefine the future of precision agriculture, empowering farmers and policymakers to make informed, sustainable, and data-centric decisions for global food security.

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