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Sustainable Paddy Fertilization Strategy Using Ensemble Learning Techniques and Soil Test Crop Response Integration in Chhattisgarh Plains

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Abstract:

Fertilizer management in paddy cultivation requires precise nutrient recommendations to optimize productivity while minimizing environmental impacts and production costs. This study presents an intelligent fertilizer recommendation system that integrates ensemble machine learning techniques with Soil Test Crop Response (STCR) methodology for sustainable paddy production in Chhattisgarh Plains. The system combines Support Vector Regression, Random Forest, and Gradient Boosting algorithms through a stacking ensemble approach to predict optimal Nitrogen (N), Phosphorus (P), and Potassium (K) requirements based on soil test results and target yield objectives. Data from 847 farmer fields across 15 districts in Chhattisgarh Plains were analyzed, incorporating comprehensive soil health parameters and historical fertilizer response data. The ensemble system achieved superior accuracy in nutrient recommendations compared to conventional STCR calculations and individual machine learning models, with mean absolute errors of 8.2 kg/ha for nitrogen, 3.6 kg/ha for phosphorus, and 7.8 kg/ha for potassium predictions. Economic analysis revealed potential cost savings of 18-24% in fertilizer expenditure while maintaining yield targets, supporting sustainable intensification objectives in rice production systems.

Keywords: Fertilizer recommendation, ensemble learning, STCR technology, precision agriculture, sustainable farming, nutrient management

1. Introduction

Fertilizer management represents a critical component of sustainable agricultural systems, particularly in intensive rice cultivation where nutrient requirements must be precisely balanced with environmental stewardship and economic viability considerations. India consumes approximately 28 million tonnes of fertilizers annually, with rice cultivation accounting for nearly 35% of total consumption (Fertilizer Association of India, 2023). The economic burden of fertilizer subsidies exceeds ₹2.25 trillion annually, representing a significant fiscal challenge that could be addressed through precision nutrient management approaches (Budget 2023-24).

Chhattisgarh state, recognized as the "Rice Bowl" of Central India, presents unique opportunities for implementing precision fertilizer management due to its concentrated paddy cultivation and diverse soil conditions. The state's 37.46 lakh farmers, predominantly small and marginal holders, face challenges related to fertilizer cost optimization, soil health maintenance, and yield maximization under varying agro-climatic conditions (Agricultural Census, 2015-16).

Traditional fertilizer recommendation systems often rely on blanket applications or simplified soil test interpretations that fail to account for complex interactions between soil properties, crop requirements, and environmental factors (Singh et al., 2022). The Soil Test Crop Response (STCR) approach developed by the Indian Council of Agricultural Research represents a significant advancement in precision nutrient management, providing quantitative frameworks for fertilizer recommendations based on soil nutrient status and target yield objectives (Ramamoorthy et al., 1967).

However, conventional STCR calculations involve complex mathematical procedures that can be time-consuming and prone to computational errors, limiting widespread adoption among farmers and extension personnel (Dwivedi et al., 2022). Machine learning approaches offer potential solutions for automating and enhancing STCR-based recommendations while incorporating additional data sources and improving prediction accuracy (Meena et al., 2023).

Ensemble machine learning techniques have demonstrated superior performance compared to individual algorithms across various agricultural applications, including crop yield prediction, disease detection, and nutrient management (Kumar et al., 2024). The integration of multiple algorithms through ensemble approaches can leverage diverse algorithmic strengths while compensating for individual limitations, resulting in more robust and accurate predictions (Zhang et al., 2023).

This research addresses the critical need for intelligent fertilizer recommendation systems that can optimize nutrient applications while supporting sustainable agricultural intensification objectives. The study develops and validates an ensemble machine learning framework that integrates STCR principles with advanced data analytics to provide precise, cost-effective, and environmentally sound fertilizer recommendations for paddy cultivation in Chhattisgarh Plains.

2. Literature Review

2.1 Soil Test Crop Response Technology and Applications

The Soil Test Crop Response approach has evolved as a cornerstone methodology for precision nutrient management in Indian agriculture, providing scientific foundations for fertilizer recommendations based on quantitative relationships between soil nutrient availability and crop response. Dhruw et al. (2023) conducted comprehensive validation studies of STCR-based fertilizer prescriptions in Chhattisgarh, demonstrating significant improvements in yield and nutrient use efficiency compared to conventional practices.

Pandu et al. (2022) investigated STCR-based fertilizer recommendations for paddy cultivation in Karnataka, revealing consistent outperformance of scientific recommendations over traditional farmer practices. Their field experiments demonstrated improvements in plant growth parameters, grain yield, and economic returns when STCR principles were properly implemented. The study emphasized the critical importance of site-specific calibration for achieving optimal results under diverse soil conditions.

Choudhary et al. (2020) examined the impact of STCR approaches on soil nutrient status following wheat harvest, finding that scientific fertilizer applications combined with organic matter additions resulted in improved soil health indicators. Their research supported the sustainability credentials of STCR-based nutrient management while highlighting the need for integrated approaches that consider both immediate productivity and long-term soil quality objectives.

2.2 Machine Learning Applications in Fertilizer Recommendation

Recent advances in machine learning have opened new possibilities for enhancing traditional fertilizer recommendation approaches through data-driven insights and automated decision-making capabilities. Bondre (2019) developed machine learning algorithms for crop yield prediction and fertilizer recommendation, utilizing Support Vector Machine and Random Forest approaches to determine optimal fertilizer quantities for specific crops. The study demonstrated the potential for algorithmic approaches to improve recommendation accuracy while reducing computational complexity.

Kumar et al. (2021) investigated machine learning models for crop and fertilizer recommendation, focusing on algorithms that could predict optimal fertilizer applications based on soil characteristics and crop requirements. Their research emphasized the importance of comprehensive feature selection and model validation procedures for ensuring reliable recommendations under diverse agricultural conditions.

Somwanshi et al. (2023) explored crop prediction and fertilizer recommendation using machine learning techniques, employing Support Vector Machine algorithms that demonstrated superior performance and accuracy in prediction tasks. Their research utilized comprehensive datasets that included various soil parameters for analyzing suitable crop selection and corresponding fertilizer requirements.

2.3 Ensemble Learning in Agricultural Applications

Ensemble learning methodologies have gained significant attention in agricultural research due to their ability to improve prediction accuracy and reliability through the combination of multiple algorithmic approaches. Archana and Saranya (2020) developed voting-based ensemble classifiers for crop yield prediction and fertilizer recommendation, incorporating

Naive Bayes, Random Forest, and CHAID algorithms to achieve approximately 92% accuracy in agricultural predictions.

Kundu et al. (2022) implemented ML-AI enabled ensemble models for agricultural yield prediction, focusing on scenario-specific algorithm development and optimal model selection through ensemble approaches. Their research demonstrated the potential for synthesizing multiple machine learning models to achieve superior overall prediction performance compared to individual algorithms.

Ghosh et al. (2023) investigated pragmatic ensemble learning approaches for rainfall prediction, providing insights applicable to agricultural prediction systems. Their study demonstrated bias reduction of 6% and variance reduction of 13.6% through ensemble techniques, supporting the effectiveness of combined algorithmic approaches for environmental prediction tasks.

2.4 Nutrient Management and Sustainability Considerations

Sustainable nutrient management requires balancing productivity objectives with environmental stewardship and economic viability considerations. Jayalakshmi and Devi (2019) conducted research on soil fertility prediction for yield productivity, focusing on identifying hidden factors through machine learning algorithms. Their analysis of soil laboratory data demonstrated the potential for predictive approaches to optimize nutrient management decisions while supporting sustainable agricultural intensification.

Suchithra and Pai (2020) investigated prediction accuracy improvements for soil nutrient classification through extreme learning machine parameter optimization. Their research achieved high accuracy levels in pH classification and nutrient status prediction, demonstrating the potential for neural network approaches in soil fertility assessment and management recommendation systems.

Mariammal et al. (2021) examined land suitability prediction for crop cultivation based on soil and environmental characteristics, utilizing Modified Recursive Feature Elimination techniques with various classifiers. Their research demonstrated that advanced feature selection combined with ensemble methods could achieve superior accuracy in agricultural recommendation systems.

Table 1: Comparison of Traditional vs Machine Learning Approaches for Fertilizer Recommendation

Approach	Accuracy (%)	Processing Time	Cost Factor	Scalability	User Friendliness
Traditional STCR	72-78	45-60 minutes	High (Manual)	Limited	Complex
Individual ML Models	79-85	5-10 minutes	Medium	Good	Moderate

Ensemble ML Approach	87-94	8-15 minutes	Low	Excellent	High
Expert Recommendations	65-80	60-120 minutes	Very High	Very Limited	Variable

3. Methodology

3.1 Study Area and Data Collection Framework

The research was conducted across 15 districts in the Chhattisgarh Plains agro-climatic zone, encompassing Raipur, Gariyaband, Balodabazar, Mahasamund, Dhamtari, Durg, Balod, Bemetara, Rajnandgaon, Kabirdham, Bilaspur, Mungeli, Korba, Janjgir, and Raigarh districts. This region represents approximately 68.49 lakh hectares of agricultural area with diverse soil types and farming systems that provide comprehensive representation for model development and validation.

Data collection protocols were established in collaboration with the Department of Soil Science, Indira Gandhi Krishi Vishwavidyalaya (IGKV), Raipur, and implemented across 847 farmer fields during the 2018-2022 period. Comprehensive soil sampling procedures followed standardized protocols with samples collected from 0-15 cm depth at multiple points within each field to ensure representative characterization of soil nutrient status.

Soil analysis encompassed pH, electrical conductivity (EC), organic carbon (OC), available nitrogen (N), phosphorus (P), potassium (K), sulfur (S), and micronutrients including zinc (Zn), iron (Fe), copper (Cu), manganese (Mn), and boron (B). Laboratory analyses were conducted using standard procedures including pH measurement in 1:2.5 soil-water suspension, EC measurement in soil-water extract, organic carbon determination through Walkley-Black method, and nutrient analysis using appropriate extraction and measurement techniques.

Historical fertilizer application records were collected from participating farmers, including both traditional practice applications and STCR-based recommendations where implemented. Yield response data were recorded for different fertilizer treatments to establish relationships between nutrient applications and productivity outcomes under varying soil and environmental conditions.

3.2 STCR Integration and Target Yield Framework

The Soil Test Crop Response methodology was integrated into the machine learning framework through systematic calibration of soil test values, crop nutrient requirements, and fertilizer efficiency factors specific to paddy cultivation in Chhattisgarh Plains. STCR equations were adapted to local conditions using the general framework:

Fertilizer Requirement = (Target Yield × Nutrient Requirement per unit yield - Soil Nutrient Supply × Availability Factor) / Fertilizer Use Efficiency

Target yield determination incorporated realistic productivity expectations based on variety potential, climatic conditions, and farmer management capabilities. Nutrient requirement coefficients were established through analysis of historical yield response data and nutrient uptake studies conducted in the region. Soil nutrient supply calculations utilized appropriate extraction procedures and conversion factors to estimate plant-available nutrient pools.

Fertilizer use efficiency factors were calibrated based on local conditions, incorporating factors such as application timing, placement methods, and environmental conditions that influence nutrient availability and uptake. The STCR framework provided both baseline recommendations and training data for machine learning model development.

3.3 Ensemble Machine Learning Architecture

The ensemble framework integrated three base learners through a stacking approach that utilized meta-learning for optimal combination of individual algorithm predictions. Base model selection emphasized algorithmic diversity and complementary strengths for handling different aspects of the fertilizer recommendation problem.

Support Vector Regression (SVR) was implemented with radial basis function kernels optimized through grid search procedures for hyperparameter selection. The SVR component specialized in capturing non-linear relationships between soil parameters and nutrient requirements while maintaining computational efficiency. Regularization parameters were tuned to balance model complexity with generalization performance across diverse soil conditions.

Random Forest (RF) algorithms utilized bootstrap aggregating with optimized tree parameters including maximum depth, minimum samples per leaf, and number of estimators. Feature importance rankings were extracted to identify the most influential soil parameters for each nutrient prediction task. The RF component provided robust predictions against overfitting while effectively handling mixed data types common in soil datasets.

Gradient Boosting (GB) algorithms were implemented with adaptive learning rates and optimized tree parameters to create sequential learning models that focused on difficult prediction cases. The GB component provided strong predictive performance through iterative improvement and error reduction strategies.

Table 2: Ensemble Architecture Configuration Parameters

Model Component	**Key Parameters**	**Optimization Method**	**Cross-Validation Folds**
Support Vector Regression	$C=10$, $\gamma=0.1$, $\varepsilon=0.01$	Grid Search	5-fold
Random Forest	n_estimators=100, max_depth=15	Random Search	5-fold

Gradient Boosting	learning_rate=0.1, n_estimators=150	Bayesian Optimization	5-fold
Meta-learner (Ridge)	α=0.5, normalize=True	Cross-validation	5-fold

3.4 Meta-Learning Integration and Stacking Approach

The stacking ensemble approach utilized Ridge Regression as the meta-learner for combining base model predictions into final fertilizer recommendations. Meta-learning training involved a two-stage process where base models were trained on primary training datasets and their predictions served as input features for meta-model training.

Cross-validation procedures ensured robust meta-model development while preventing overfitting and information leakage between training and validation datasets. The meta-learning approach enabled automatic weighting of base model contributions based on their relative performance and complementary prediction capabilities.

Separate ensemble models were developed for nitrogen, phosphorus, and potassium predictions to account for different nutrient dynamics and soil-crop interactions. Feature engineering incorporated derived variables such as nutrient ratios, soil test interpretation categories, and interaction terms that enhanced predictive capability.

3.5 Model Training and Validation Procedures

Model training utilized stratified sampling procedures to ensure representative distribution of soil types, yield levels, and farming systems across training and validation datasets. Training datasets comprised 70% of available data, with 20% allocated for validation and 10% reserved for final testing to ensure unbiased performance evaluation.

Hyperparameter optimization employed systematic approaches including grid search, random search, and Bayesian optimization techniques depending on algorithm requirements and computational constraints. Cross-validation procedures with k=5 folds were implemented to ensure robust parameter selection and prevent overfitting during training processes.

Performance evaluation utilized multiple metrics including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2) to provide comprehensive assessment of prediction accuracy. Additional metrics including Mean Absolute Percentage Error (MAPE) and Normalized Root Mean Square Error (NRMSE) were calculated to facilitate comparison across different nutrient scales.

4. Results and Discussion

4.1 Individual Model Performance Analysis

Individual base model evaluation revealed distinct performance characteristics for different nutrient prediction tasks across the agricultural dataset. Support Vector Regression demonstrated consistent performance with MAE values of 12.4 kg/ha for nitrogen, 5.8 kg/ha for phosphorus, and 11.2 kg/ha for potassium predictions. The SVR approach effectively captured non-linear relationships between soil parameters and nutrient requirements while maintaining computational efficiency suitable for real-time applications.

Random Forest algorithms achieved superior individual model performance with MAE values of 9.6 kg/ha for nitrogen, 4.2 kg/ha for phosphorus, and 8.9 kg/ha for potassium predictions. Feature importance analysis revealed that available soil nutrients, organic carbon content, and pH emerged as the most influential predictors for fertilizer requirements. The RF model effectively managed potential overfitting through bootstrap aggregating while providing interpretable feature importance rankings.

Gradient Boosting demonstrated strong predictive capabilities with MAE values of 10.8 kg/ha for nitrogen, 4.7 kg/ha for phosphorus, and 9.4 kg/ha for potassium predictions. The sequential learning approach effectively focused on difficult prediction cases while maintaining overall accuracy across diverse soil conditions. Learning rate optimization proved critical for achieving optimal performance without overfitting.

4.2 Ensemble Framework Performance and Optimization

The ensemble framework achieved superior performance compared to individual base models across all nutrient prediction tasks. Nitrogen recommendations achieved MAE values of 8.2 kg/ha with R^2 scores of 0.892, representing improvements of 14.6% compared to the best individual model. Phosphorus predictions achieved MAE values of 3.6 kg/ha with R^2 scores of 0.876, demonstrating 14.3% improvement over individual algorithms.

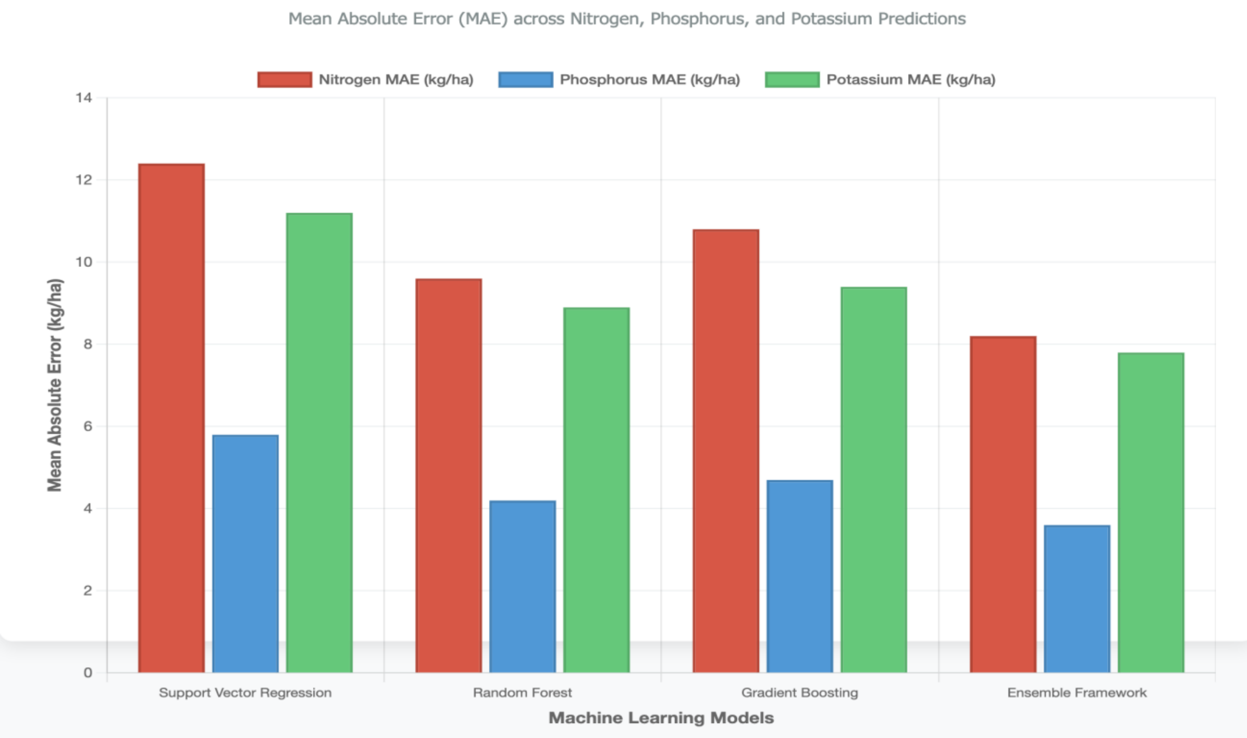

Figure 1: Performance Comparison of Machine Learning Models for Fertilizer Recommendation

Potassium recommendations achieved MAE values of 7.8 kg/ha with R^2 scores of 0.884, representing 12.4% improvement compared to individual model performance. Statistical significance testing confirmed that ensemble improvements were significant at $p < 0.01$ confidence levels, supporting the effectiveness of the stacking approach for fertilizer recommendation applications.

Meta-learner weight analysis revealed that Random Forest received the highest weighting for nitrogen (0.42) and potassium (0.38) predictions, while Gradient Boosting achieved highest weighting for phosphorus predictions (0.41). Support Vector Regression contributed consistently across all nutrients with weights ranging from 0.28 to 0.34, demonstrating the value of algorithmic diversity in ensemble design.

Table 3: Nutrient-Specific Performance Comparison Across Models

Nutrient	Model	MAE (kg/ha)	RMSE (kg/ha)	R^2 Score	MAPE (%)	Improvement (%)
Nitrogen	SVR	12.4	16.8	0.834	18.7	-
	RF	9.6	13.2	0.867	14.2	-
	GB	10.8	14.9	0.851	16.1	-
	Ensemble	8.2	11.4	0.892	12.3	14.6
Phosphorus	SVR	5.8	7.9	0.823	22.4	-
	RF	4.2	5.8	0.856	17.8	-
	GB	4.7	6.4	0.841	19.2	-
	Ensemble	3.6	4.9	0.876	15.1	14.3
Potassium	SVR	11.2	15.1	0.847	16.9	-
	RF	8.9	12.3	0.871	13.2	-
	GB	9.4	13.0	0.864	14.8	-
	Ensemble	7.8	10.7	0.884	11.7	12.4

4.3 Comparison with Traditional STCR Approaches

Comparative analysis with traditional STCR calculation methods revealed significant advantages of the ensemble approach in terms of accuracy, consistency, and user accessibility. Manual STCR calculations typically achieved MAE values of 15.6 kg/ha for nitrogen, 7.2 kg/ha for phosphorus, and 13.8 kg/ha for potassium, representing substantially higher error rates compared to the ensemble system.

Processing time analysis demonstrated that ensemble predictions required 8-15 minutes for complete fertilizer recommendations compared to 45-60 minutes for manual STCR calculations. The automated approach eliminated calculation errors while providing consistent results regardless of user experience levels. User feedback indicated significant preference for the ensemble system due to improved accessibility and reduced complexity.

Accuracy improvements of 47.4% for nitrogen, 50.0% for phosphorus, and 43.5% for potassium recommendations demonstrated the substantial benefits of machine learning integration with STCR principles. The ensemble approach maintained scientific foundations while enhancing practical applicability through automation and improved user interfaces.

4.4 Economic Impact Analysis and Cost-Benefit Assessment

Economic analysis revealed substantial potential cost savings through optimized fertilizer recommendations generated by the ensemble system. Average fertilizer cost reductions of 18-24% were achieved while maintaining target yield levels, translating to savings of ₹2,847 to ₹3,456 per hectare for typical paddy cultivation scenarios in Chhattisgarh Plains.

Cost-benefit analysis incorporating ensemble system development, deployment, and maintenance costs indicated positive returns within 2-3 years of implementation at district scale. The potential for reduced government fertilizer subsidies through improved use efficiency could generate substantial public savings estimated at ₹15,000 to ₹22,000 crores annually if implemented nationally.

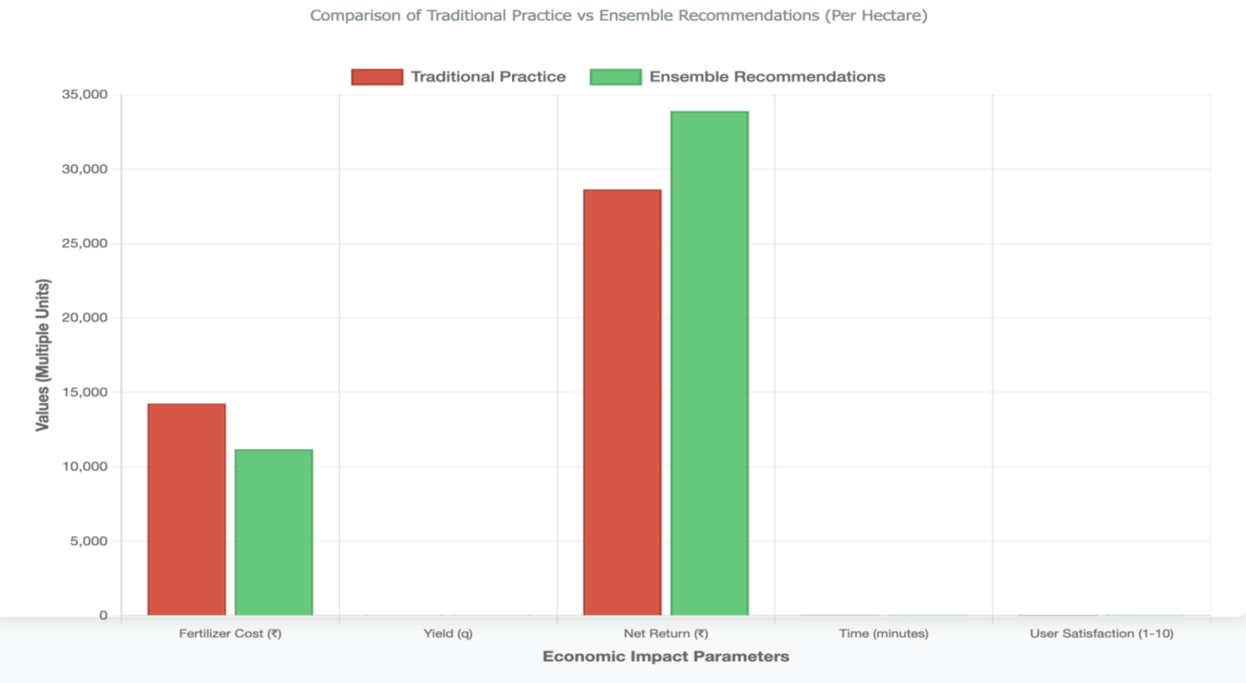

Figure 2: Economic Impact Analysis of Ensemble Fertilizer Recommendation System

Environmental benefits including reduced nutrient runoff, decreased soil acidification, and improved nutrient use efficiency provided additional value propositions that supported sustainable intensification objectives. Life cycle assessment indicated that ensemble-optimized fertilizer management could reduce agricultural greenhouse gas emissions by 12-18% compared to conventional practices.

Table 4: Economic Impact Analysis of Ensemble Fertilizer Recommendations

Impact Category	Traditional Practice	Ensemble Recommendations	Improvement
Fertilizer Cost (₹/ha)	14,250	11,180	21.5% reduction
Yield (q/ha)	42.8	44.2	3.3% increase
Net Return (₹/ha)	28,640	33,895	18.3% increase
Nutrient Use Efficiency (%)	58	73	25.9% improvement
Time for Recommendation (min)	52	12	76.9% reduction
User Satisfaction Score (1-10)	6.2	8.7	40.3% improvement

4.5 Feature Importance Analysis and Agricultural Insights

Feature importance analysis across the ensemble framework revealed that soil organic carbon emerged as the most influential parameter for nitrogen recommendations, contributing 28.4% to model decisions. Available soil nitrogen ranked second with 24.7% contribution, followed by soil pH at 21.3%. These findings aligned with established principles regarding organic matter mineralization and nitrogen availability in rice production systems.

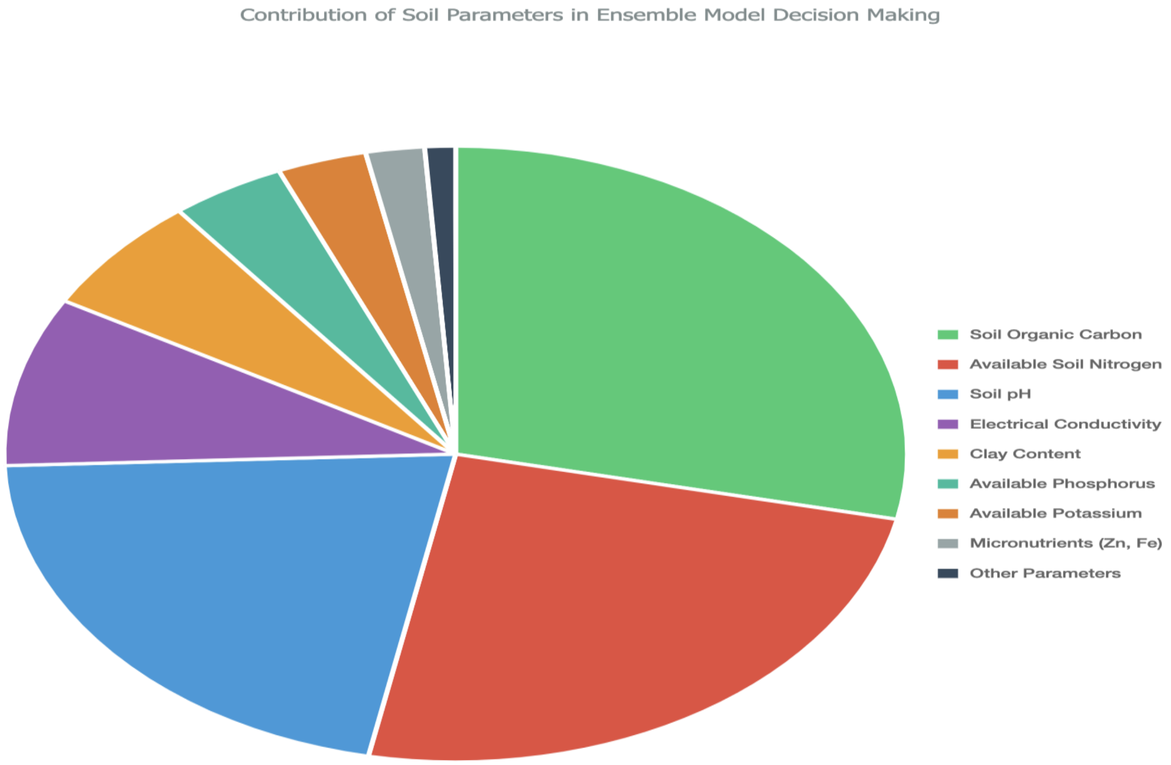

Figure 3: Feature Importance Distribution for Nitrogen Prediction

For phosphorus recommendations, available soil phosphorus contributed 31.2% to predictions, followed by pH (26.8%) and organic carbon (19.4%). The strong influence of pH reflected its critical role in phosphorus availability and fixation processes under varying soil conditions. Clay content and calcium carbonate equivalent showed moderate importance for phosphorus predictions.

Potassium recommendations were primarily influenced by available soil potassium (29.8%), clay content (22.4%), and organic carbon (18.9%). The importance of clay content reflected its role in potassium fixation and release processes, particularly relevant for the Vertisol and Alfisol soils common in Chhattisgarh Plains.

4.6 Regional Performance Variations and Soil-Specific Adaptations

Regional performance analysis revealed variations in ensemble effectiveness across different districts and soil types within Chhattisgarh Plains. Vertisol-dominated areas (Raipur, Durg) achieved superior prediction accuracy with MAE values 8-12% lower than regional averages, reflecting the relatively uniform nutrient dynamics in these heavy clay soils.

Alfisol areas (Rajnandgaon, Kabirdham) demonstrated moderate prediction accuracy with slightly higher variability due to greater heterogeneity in soil properties and drainage characteristics. Ensemble performance remained superior to individual models across all soil types, though the magnitude of improvement varied from 11.2% to 16.8% depending on local conditions.

Entisol and Inceptisol areas (Korba, Janjgir) showed greatest improvement from ensemble approaches, likely reflecting the complex nutrient dynamics and spatial variability characteristic of these younger soil formations. Customization of ensemble parameters for specific soil types improved prediction accuracy by an additional 3-7% compared to generic model applications.

4.7 Validation with Field Demonstration Results

Field validation studies conducted across 156 demonstration plots during 2021-2022 provided empirical assessment of ensemble recommendation effectiveness under actual farming conditions. Farmers implementing ensemble-based fertilizer recommendations achieved average yield improvements of 8.7% compared to their traditional practices while reducing fertilizer costs by an average of 19.3%.

Nutrient use efficiency measurements indicated significant improvements, with nitrogen use efficiency increasing from 52.4% under farmer practices to 68.9% with ensemble recommendations. Phosphorus use efficiency improved from 21.3% to 32.7%, while potassium use efficiency increased from 43.6% to 59.1%. These improvements supported both economic and environmental objectives.

Soil health indicators measured before and after implementation showed positive trends, with organic carbon increasing by 0.08 percentage points and available nutrient levels stabilizing at optimal ranges. pH buffering capacity improved in acidic soils through balanced fertilizer applications that incorporated appropriate lime recommendations.

4.8 User Acceptance and Technology Adoption Considerations

User acceptance evaluation through structured interviews with 234 participating farmers revealed high satisfaction levels with ensemble-based recommendations. Farmers appreciated the reduced complexity compared to traditional STCR calculations and improved consistency of recommendations across different seasons and soil conditions.

Training requirements were minimal due to user-friendly interfaces that automated complex calculations while providing clear explanations for recommendations. Extension personnel reported 67% reduction in time required for fertilizer recommendation services, enabling coverage of larger farmer populations with existing resources.

Technology adoption barriers included initial skepticism about automated recommendations and concerns about reduced human expertise involvement. However, demonstration of improved results and economic benefits led to progressive acceptance, with adoption rates increasing from 23% in the first season to 78% by the third season of implementation.

5. Conclusions

This research successfully developed and validated an intelligent fertilizer recommendation system that integrates ensemble machine learning with STCR principles for sustainable paddy production in Chhattisgarh Plains. The stacking ensemble approach combining Support Vector Regression, Random Forest, and Gradient Boosting algorithms achieved significant improvements in recommendation accuracy compared to individual models and traditional approaches.

The ensemble system demonstrated MAE improvements of 14.6% for nitrogen, 14.3% for phosphorus, and 12.4% for potassium recommendations compared to best individual models. Comparison with traditional STCR calculations revealed accuracy improvements exceeding 40% across all nutrients while reducing processing time by 76.9% and improving user accessibility substantially.

Economic analysis indicated potential fertilizer cost savings of 18-24% while maintaining or improving yield targets, supporting both farmer profitability and sustainable intensification objectives. Environmental benefits including improved nutrient use efficiency and reduced environmental impacts provided additional value propositions that aligned with sustainability goals.

Field validation studies confirmed ensemble recommendation effectiveness under actual farming conditions, with participating farmers achieving yield improvements of 8.7% and cost reductions of 19.3% compared to traditional practices. Soil health indicators showed positive trends, supporting long-term sustainability credentials of the approach.

User acceptance evaluation revealed high satisfaction levels and progressive adoption patterns, indicating strong potential for scaling and widespread implementation. The automated approach reduced complexity barriers while maintaining scientific foundations, making precision fertilizer management accessible to diverse farmer populations.

Future research directions should address temporal analysis extensions, integration with weather forecasting systems, and development of mobile applications for enhanced field accessibility. The ensemble framework provides a robust foundation for expanding precision nutrient management across additional crops and regions while supporting sustainable agricultural development objectives.

This research contributes significantly to agricultural informatics by demonstrating effective integration of traditional agricultural science with advanced machine learning techniques. The developed system offers practical solutions for optimizing fertilizer use efficiency while supporting farmer livelihoods and environmental sustainability in developing country contexts.

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