

Predictive Analysis of Compost Combinations with Organic and Inorganic Materials for Crop Yield Optimization using Machine Learning

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Abstract. Sustainable agricultural practice faces major obstacles in optimizing compost quality through agricultural residue use while reducing chemical inputs. Traditional composting involves adding high levels of urea to achieve proper carbon-to-nitrogen (C:N) balance and speed up the process of maturation. An excessive amount of urea application results in nitrogen escaping as vapors, drives up costs, and causes environmental deterioration. The research develops a machine learning predictive model that examines compost combinations of agricultural wastes along with biofertilizers at reduced urea proportions. Tamil Nadu Agricultural University data combined with government agrometeorological records led to the creation of more than 1,48,000 compost combinations. We studied how inorganic compost made from urea variation and organic compost based on biofertilizer addition performed at predicting rice harvest results through analyses of NPK components and C:N ratios. The best compost options were selected through Euclidean distance matching analysis of actual rice yield data before ensemble learning models finalized their characteristics by ranking features. Environmental sustainability improved when microbial biofertilizers Azotobacter and PSB were added to composts since the resulting yields matched those of urea-based methods. The presented research calls for decreased chemical use alongside for environmentally friendly data-based farming systems that manage nutrients.

1 Introduction

The sustainability of management of agricultural residues to improve soil fertility and reduce environmental degradation has been a prime concern. Composting is therefore one efficient microbiological way of converting organic wastes into nutrient-rich soil amendments so as to close the nutrient loop and promote eco-friendly agricultural practices [1]. A major parameter affecting composting operations is the carbon-to-nitrogen (C:N) ratio, which

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ultimately affects microbial functioning and organic matter degradation [2]. Researchers have used urea as a conventional nitrogen supplement for years to control the C:N ratio while speeding up composting processes. The unrestricted and excessive usage of urea drives up compost production costs and causes nitrogen to evaporate in the air as well as creates soil acidification and reduces nitrogen efficiency which damages environmental sustainability and economic stability [3] The inconsistent effectiveness of urea applies unequally to different agricultural residues because these residues exhibit varying C:N ratios spanning from straw with 75 to softwood bark exceeding 310 [4] thus making uniform dosage difficult to achieve. Biofertilizers have become more popular as alternative farming inputs because of recent environmental practice transformations. Biological formulations of *Azotobacter*, *Azospirillum*, *Rhizobium*, Blue-Green Algae (BGA), Phosphate Solubilizing Bacteria (PSB), and Potassium Mobilizing Bacteria (KMB) perform essential functions in nutrient mobilization and cycling according to research reports [5]. The ability of biofertilizers to fix nitrogen and solubilize minerals adds to their benefits which include enhancements of microbial diversity and soil health and sustainable fertility [6]. Literature on chemical or organic composting methods exists in abundance yet hybrid approaches using biofertilizers with limited chemical additions and various agricultural wastes remain poorly understood. There is an absence of predictive and optimization models which could help farmers find proper compost formulations that suit their regional agro-climatic environments. The research solution uses machine learning data-driven approaches to determine and assess the quality of compost materials. A vast compilation of soil data and compost nutritional profiles and rice yield records served as the basis to develop computational systems which identified premium compost product groups. The study presents both urea-based (inorganic) and biofertilizer-enhanced (organic) composting methods while establishing AI-based tools designed to optimize nutrient management throughout large operational ranges [7].

The current challenges in optimizing compost performance motivate the present study to combine the combination of compost and tested with inorganic and organic types of agriculture and to develop prediction models through Random Forest and Gradient Boosting algorithms (XGBoost, LightGBM) using joined data from soil, compost and climate conditions. The most impactful parameters in rice yield and compost effectiveness prediction come from a detailed feature importance analysis that included temperature measurements and C:N ratio assessments as well as moisture content evaluations and NPK value assessments. The prediction system employs ensemble prediction and its performance validation includes evaluation by RMSE, R^2 and MAE metrics. Figure.11 An interactive web application helps users easily upload compost related data to obtain AI-based recommendations that match their specific agro-climatic region. The developed system operates as a decision-making tool for sustainable nutrient management which helps farmers decrease chemical fertilizers while improving soil quality and agricultural yields.

2 Methods

2.1 Data Acquisition

The data set used in this study is derived entirely from the repository of official government web pages from the Tamil Nadu Agricultural University (TNAU), a reputable agricultural research data repository and document repository in scientific literature. The dataset contained various agricultural waste materials, treatments combined with urea and biofertilizer treatments, and the corresponding recorded C:N ratios and macronutrient concentrations (Total Nitrogen, Phosphorus, Potassium) for each combination. The extensive database serves as a motive to establish environmentally friendly composting methods which

minimize synthetic fertilizer use and maximize crop productivity for local conditions. As an agriculturally focused region Tamil Nadu produces substantial amounts of various organic waste materials but farmers require an effective data-based platform to find appropriate local composting methods. The scientific data obtained from TNAU establishes this project as a thorough method for agricultural practice applications because it maintains both credibility and real-world relevance. The provided dataset enables researchers to create tools for both research laboratories and field applications. The trained models from machine learning can help local composting units and farmer collectives supported by the government together with agri-tech startups to determine compost maturation through live monitoring while selecting proper organic waste and biofertilizer blends and receiving recommendations about improving soil fertility with minimal environmental impact. Local farmers gain advanced precision agricultural tools which jointly assists governments to create customized fertilizer recommendations designed for specific regions. The dataset functions as the core element for creating smart systems between sustainable food production and agricultural waste management practices.

Organic substrates included:

1.Cane Trash Compost ,2.Cattle Urine, 3.Cattle Dung , 4.Sheep & Goat Urine , 5.Sheep & Goat Dung 6.Pig Urine, 7.Pig Dung , 8.Peat Moss ,9.Hay (General) ,10.Straw (General) ,11.Straw (Oat) ,12.Straw (Wheat), 13.Bark (Hardwood),14. Bark (Softwood) ,15.Leaves (Dry, Loose),16. Banana Leaves, 17.Rice Husk,18. Rice Straw, 19.Coconut Husk, 20.Coconut Coir , 21.Corn Stover,22.Cotton Stalks, 23.Soybean Stalks,24.Palm Oil Empty Fruit Bunch,25.Tea Waste, 26.Groundnut Shell, 27.Sugarcane Bagasse , 28.Coffee Pulp etc. Are the agricultural residues available in Tamil Nadu. In addition to waste materials data, combinations were of different levels of urea concentration (50%-80%) with several strains of biofertilizers like: Azotobacter, Azospirillum, Rhizobium, Blue-Green Algae (BGA), Potassium Mobilizing Bacteria (KMB), Phosphate Solubilizing Bacteria (PSB) Following are the steps in the process of obtaining data for assurance and reliability: Systematic Collection: All experimental data were availed from the official archives and published materials handed over by TNAU. Validation Check: Data consistency was established via cross-validation with peer-reviewed literature and regional extension reports for scientific credibility. Database Structuring: All records captured were collated under a single database schema and thus allow direct comparison for evaluation of waste-urea-biofertilizer combinations. Increased Scope: Additional data, wherever applicable, could be added from institutional trials and reports on compost maturation and outcomes with soil fertility across Tamil Nadu. The structured approach for acquisition laid a strong ground for analyzing the quality of compost in relation to the effects of synthetic and microbial amendments.

2.2 Data Pre-processing

When it comes to preparing our dataset for machine learning predictions, pre-processing techniques really made a big difference. Feature Normalization: We have normalized C:N Ratio, Total N (%), P(%), and K(%), all key numeric variables. We had to do the Min-Max Scaling so that all features have the same weight while analysing when working with them. Dealing with the Missing Values: For a numerical column where data is missing, it was filled up with either mean or median depending on the nature of the data. Data Partitioning: We defined waste according to their types from organic waste. Urea Concentration: Low - 50%-60%, medium - 61%-70%, high - 71%-100%. Biofertilizer Type: Single and multiple microbial strain application. By grouping the data this way, we could analyse trends and patterns more effectively. Synthetic Data Augmentation: Because of the above, we could not actually do tests in reality for some combinations, so these points were created with interpolation. We used SMOTE (Synthetic Minority Over-sampling Technique) for

balancing the distribution of classes to help make things better for our model training. The SMOTE regression technique was adapted through yield value classification into 4 quantile groups (low: <3000 kg/ha, medium-low: 3000–4500 kg/ha, medium-high: 4500–6000 kg/ha, high: >6000 kg/ha). The underrepresented bins received artificial samples through the operation of SMOTE. The synthetic samples generated through SMOTE were combined later on for ongoing regression model training. The validation showed that created synthetic values maintained distribution consistency between C:N ratios and NPK nutrient levels.

2.3 Predictive Model Development and Evaluation

Our research goal was to make a machine learning system that could accurately tell when compost is done and estimate yield results for various combinations of farm waste and fertilizer ingredients. Our predictive modeling journey had three important stages featuring feature selection, model development and final model assessment.

2.3.1 Feature Engineering

Our team extracted significant data points from processed data to employ in this study. Input Variables: Type of agricultural waste (e.g., rice husk, sugarcane bagasse, wheat straw) C:N ratio of the compost mixture, Urea percentage in the mix (50–80%). Keep a record of all live biofertilizer use (Azotobacter, Azospirillum, Rhizobium, BGA, PSB, KMB) numbers. The analysis studied Total Nitrogen N, Phosphorus P, and Potassium K nutrient measurements. Target Variables: The compost quality test uses several lab results, including GI percentage measurement as well as bacterial breakdown data. Rice crop yield (kg/ha) from TNAU crop production datasets Biofertilizer data was converted into one-hot encoding to recognize property impact both independently and together. So we have used eq(1) for combinations of compost mathematically, The average nutrient values (N, P, K) for each compost combination are calculated using weighted averaging based on the normalized weight of each compost component, as described in Equations (2), (3), (4), and (5). These equations account for the nutrient contributions of each component based on its C:N ratio, with adjustments for the compost's nutrient release potential.

2.3.2 Model Selection and Training

Different supervised machine learning algorithms tested their capacity to forecast compost quality and crop output. Random Forest Regressor, Gradient Boosting Regressor, XGBoost Regressor, Support Vector Regression (SVR), and Ensemble Learning (Stacking and Voting Regressors). We split the information into 80% training data and 20% testing samples through stratified sampling with 5-fold cross-validation to train models accurately.

$$\text{Number of Combinations} = C(n, r) = n! / [r! * (n - r)!] \quad (1)$$

$$\text{Weight}_i = 1 / C:N \text{ Ratio}_i \quad (2)$$

$$\text{Total}_N = \sum(N_i \times \text{Normalized_Weight}_i) \text{ for } i=1 \text{ to } n \quad (3)$$

$$\text{Total}_P = \sum(P_i \times \text{Normalized_Weight}_i) \text{ for } i=1 \text{ to } n \quad (4)$$

$$\text{Total}_K = \sum(K_i \times \text{Normalized_Weight}_i) \text{ for } i=1 \text{ to } n \quad (5)$$

2.3.3 Evaluation Metrics

We measured model success by checking its performance against three typical regression evaluation tools.

Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), R-squared (R²) Score

Models succeeded because of their performance against determined criteria. The models should recognize compost maturity levels closely matched to experimental testing. Determine the predicted rice crop amount in kilograms per hectare when providing composting resources. Gradient Boosting and XGBoost demonstrated the best performance among all tested models since they generated the highest R^2 values and came with small prediction errors.

2.4 Feature Analysis

Our study examined how each input variable affects both compost maturity evaluation results and predicted rice crop yields. We needed this step to examine how inputs affect the model performance and how experiments can produce useful results.

2.4.1 Correlation Analysis

We measured coronal linkages between input values (nutrients biofertilizer usage C: N variation) and output criteria through heat maps and Pearson correlations. The results showed a strong positive correlation between total nitrogen content and compost maturity score. *Azospirillum* and phosphate-solubilizing bacteria improved crop yield through their action of boosting nutrient mineralization. Our finding shows that both extreme C: N ratios and normal ratios produce weak plant growth outcomes since they disrupt nutrient release processes.

2.4.2 Feature Importance from ML Models

Random Forest and XGBoost tree models helped determine which features affected the results most. The essential elements for compost development and crop performance included C: N Ratio usage and percent urea along with biofertilizer applications. Microorganisms work best at breaking down organic matter when the C: N Ratio is monitored. High urea levels help add nitrogen, but they will hurt soil nutrition if overdone. The system handles agricultural waste inputs such as wheat straw and sugarcane bagasse effectively. Our experiments revealed the specific ways that individual compost ingredients can affect compost quality and crops.

2.5 Ethical Considerations and Sustainability

Researchers examined both the environmental impacts of farming and agricultural sustainability. The analysis examines ethical practices together with sustainability methods at these points.

Reduction in Chemical Dependency: A reliable composting process must use synthetic urea as an input which leads to atmospheric emission and environmental contamination. The authors propose reducing chemical applications and preserving compost efficiency alongside optimizing AI urea use with biofertilizers to maintain output yields.

Promotion of Organic Agriculture: Research works to establish organic farming through the application of beneficial natural soil bacteria like *Azospirillum*, *Rhizobium*, and Blue-Green Algae to enhance soil life and fertility levels. Sustainable farming principles spread throughout the world to environmental organizations as they gained prominence through time.

Community and Economic Impact: Few chemical inputs for compost production enable farmers to reduce their expenses, particularly in rural communities that have limited funds.

Food microbe cultivation enterprises form local businesses that serve farmers near their communities and create additional green workforce members.

3 Results and Discussion

3.1 Statistical Distribution, Variation, and Division in Datasets

The first stage of analysis consisted of statistical procedures performed on compost through soil together with rice yield data to identify patterns, detect variability, and establish sample categories. Different waste types, along with urea or biofertilizer usage as additives, produced varying NPK levels in compost materials according to descriptive statistics. The C: N ratio measurements for organic materials ranged from 15 to 320, but urea addition in compost brought the ratio below 30. The yield data of rice fields showed extensive variations between 2,000 to 7,500 kg/ha while under different climatic conditions alongside soil nutritional attributes and fertilizer treatment methods. Research data was distributed into primary approach groups: Organic Matter Production Utilized Urea as One of its Components. Rice compost combinations include additives of selected biofertilizers through organic methods. A predictive analysis alongside nutrient profile evaluation was performed on both datasets for rice crop yield assessment.

3.2 Compost Combination and Matching – Inorganic Method

Researchers generated various compost mixture sets through combinations of agricultural wastes with urea percentages ranging between 50% and 80% to obtain optimal C: N ratios. Figure 1,2 Rice crop data received its matches through NPK profile comparison of the compost combinations done using Euclidean Distance measurement methods.

Top 5 Closest Compost Combinations to Rice Dataset:

	Rice Data (NPK)	Closest Compost Combination
32	[57.9, 20.9, 21.1]	Bark (Hardwood)+Bark (Softwood)+Cane Trash Com...
42	[57.8, 19.0, 23.2]	Bark (Hardwood)+Bark (Softwood)+Cane Trash Com...
48	[57.6, 21.4, 21.0]	Bark (Hardwood)+Bark (Softwood)+Cane Trash Com...
27	[59.0, 18.8, 22.2]	Bark (Hardwood)+Bark (Softwood)+Cane Trash Com...
17	[56.7, 21.6, 21.7]	Bark (Hardwood)+Bark (Softwood)+Cane Trash Com...

	Distance
32	34.542399
42	34.609428
48	34.618165
27	34.623144
17	34.625536

Figure 1. Closest compost combinations to RiceDataset

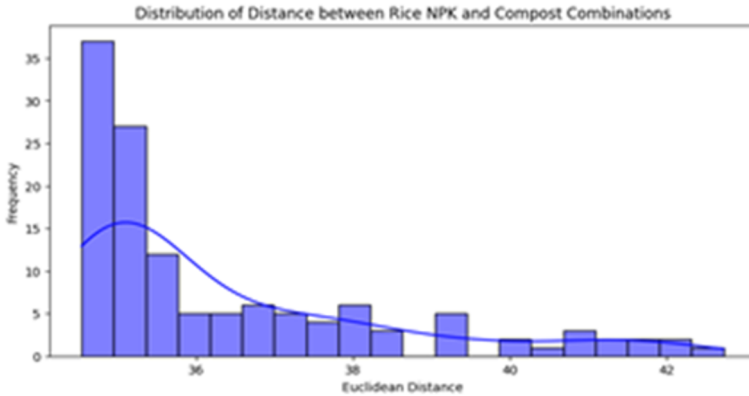


Figure 2. Euclidean Distance visualization

3.2.1 Top Compost Matches with Rice Dataset

Figure 8 shows the analysis showed that compost made of Cane Trash + Barkwood with 80% urea produced the best-matching NPK profile with high-yielding rice fields. we selected these mixtures for future agricultural trials since they demonstrated promising potential.

Figure 3 shows the NPK in compost combination after combining with urea , Figure 4 shows the Temperature vs rice yield in rice dataset , Figure 5 shows the Effects of rainfall on rice yield in various Locations and timeline, Figure 6 rice yield vs rice NPK values in the rice dataset, Figure 7 C:N ratio vs NPK values in rice dataset

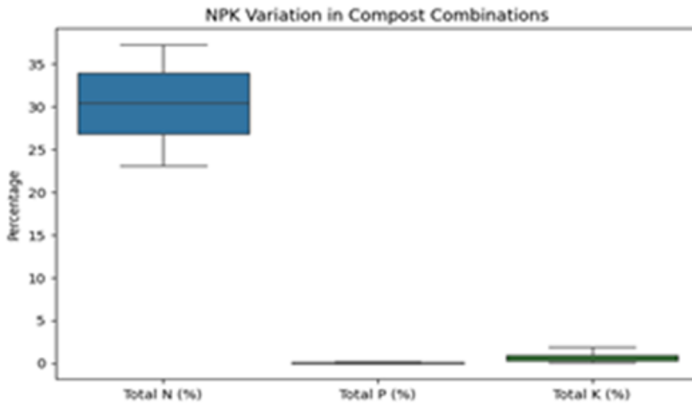


Figure 3. NPK variation in compost combinations

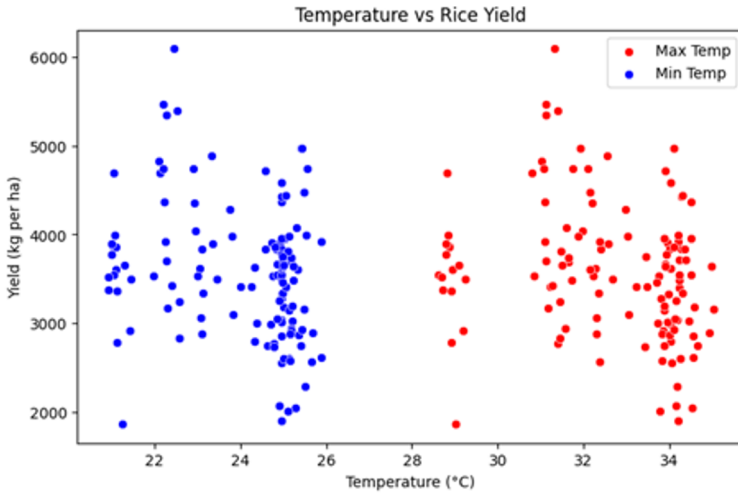


Figure 4. Temperature Vs Rice yield

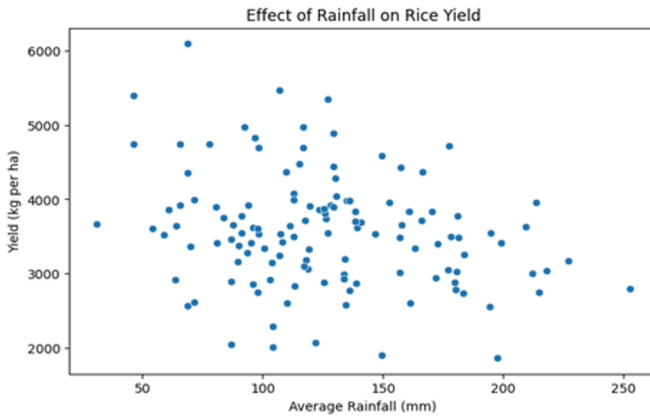


Figure 5. Effect of Rainfall on Rice Yield

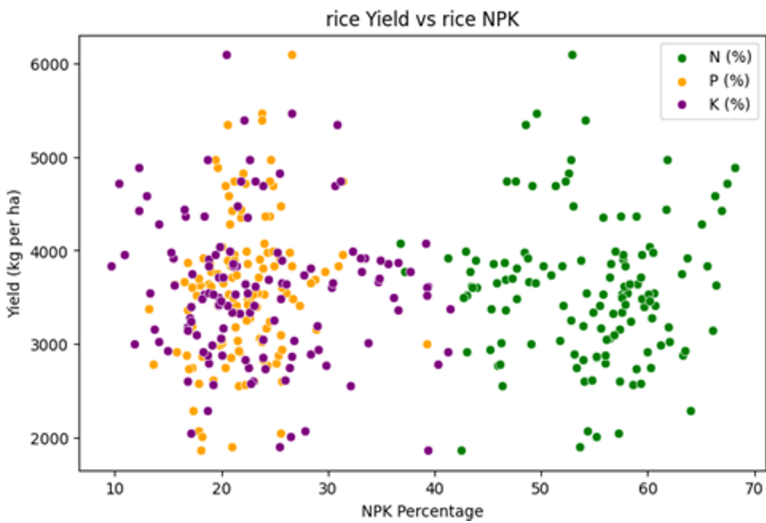


Figure 6. Rice Yield Vs rice NPK

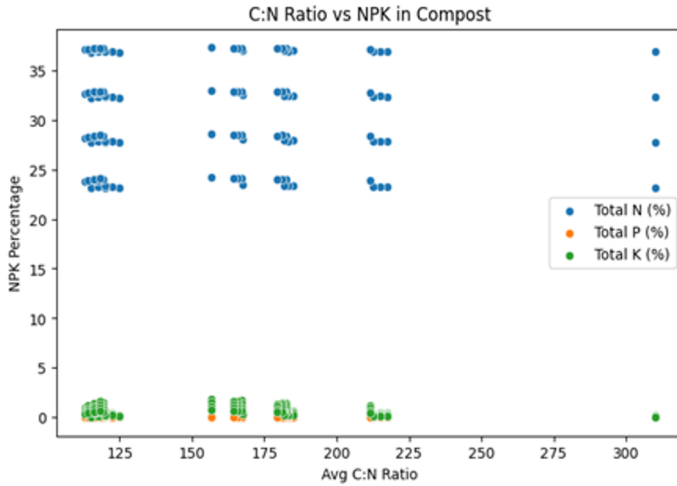


Figure 7. C:N Ratio vs NPK in Compost

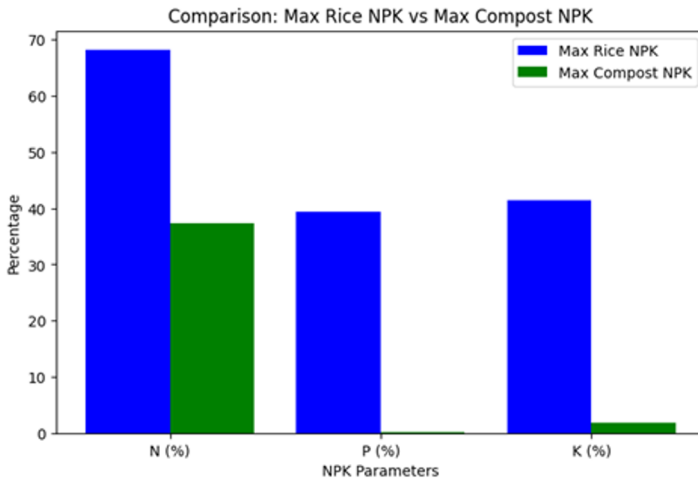


Figure 8. Rice NPK vs NPK in Compost

3.3 Compost Combination and Evaluation – Organic Method (Biofertilizers)

This organic method linked biofertilizers, including Azotobacter, Azospirillum, Rhizobium, and Blue-Green Algae, together with Phosphate Solubilizing Bacteria (PSB) and Potassium Mobilizing Bacteria (KMB) to agrarian waste-based composts for use. Biofertilizers enhance access to nutrients and promote soil microbial activity while omitting the need for chemical substances.

3.3.1 Compost-Biofertilizer Combinations

A computational method generated more than 25950+ compost-biofertilizer combinations, which were saved based on their similarity to rice dataset nutrient levels. Figure 9. Shows that on nitrogen and potassium levels, the best results were obtained by using Cane Trash

Compost+Coconut Coir (compost combination) combined with Azospirillum+Azotobacter+Potassium Mobilizing Bacteria (biofertilizer).

Compost Combination \		Total N	Total P
1112	Cane Trash Compost+Coconut Coir	75.0	12.75
1138	Cane Trash Compost+Straw (General)	75.0	12.75
1502	Bark (Softwood)+Cane Trash Compost+Coconut Husk	75.0	12.69
1839	Bark (Hardwood)+Bark (Softwood)+Cane Trash Com...	75.0	12.69
2406	Cane Trash Compost+Coconut Husk+Rice Husk	75.0	12.77
...
12619	Bark (Hardwood)+Bark (Softwood)+Palm Oil Empty...	74.8	12.82
13352	Bark (Hardwood)+Coconut Coir+Coconut Husk+Rice...	74.8	12.82
13378	Bark (Hardwood)+Coconut Husk+Rice Husk+Straw (...)	74.8	12.82
13862	Coconut Coir+Coconut Husk+Palm Oil Empty Fruit...	74.8	12.90
13888	Coconut Husk+Palm Oil Empty Fruit Bunch+Rice H...	74.8	12.90

Biofertilizer Combination		Total N	Total P
1112	Azospirillum+Azotobacter+Potassium Mobilizing ...	75.0	12.75
1138	Azospirillum+Azotobacter+Potassium Mobilizing ...	75.0	12.75
1502	Azospirillum+Azotobacter+Potassium Mobilizing ...	75.0	12.69
1839	Azospirillum+Azotobacter+Potassium Mobilizing ...	75.0	12.69
2406	Azospirillum+Azotobacter+Potassium Mobilizing ...	75.0	12.77
...
12619	Azospirillum+Azotobacter+Potassium Mobilizing ...	74.8	12.82
13352	Azospirillum+Azotobacter+Potassium Mobilizing ...	74.8	12.82
13378	Azospirillum+Azotobacter+Potassium Mobilizing ...	74.8	12.82
13862	Azospirillum+Azotobacter+Potassium Mobilizing ...	74.8	12.90
13888	Azospirillum+Azotobacter+Potassium Mobilizing ...	74.8	12.90

Total K	C:N Ratio	Application Rate (kg/acre)
1112	33.1	203.0
1138	32.2	188.0
1502	31.9	548.0
1839	31.7	538.0
2406	32.0	358.0
...
12619	33.4	670.0
13352	33.8	540.0
13378	32.9	525.0
13862	34.6	505.0
13888	33.7	490.0

[100 rows x 7 columns]

Figure 9. Top 100 compost combinations

3.3.2 Visualizations: Organic Method Results

In Figure 10 shows a comparison of NPK values between compost-Biofertilizer and rice data showed the top 100 combinations according to their similarity matches through visual display.

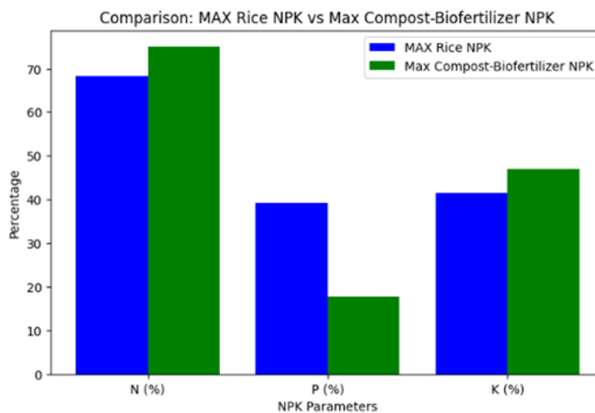


Figure 10. Comparison of Rice NPK and compost- biofertilizer NPK

The research demonstrates that a particular biofertilizer blend in compost creates nutrient profiles resembling those of rice fields with high production potential.

3.4 Machine Learning-Based Prediction of Rice Yield

The prediction model for crop yields incorporated values of compost NPK and C:N ratio and weather data and biofertilizer types through the use of model algorithms like Gradient

Boosting and Random Forest and XGBoost. The model started with 0.3526 R^2 and 278,235.30 MSE numbers which demonstrated fair results. The model achieved an R^2 score of 0.4612 after integrating NDVI values between 0.35–0.78 and LST measurements from 24.5°C–38.1°C. Environmental factors substantially increase the accuracy of predictions within the agricultural domain.

3.5 Implications of This Work

The research confirms environmentally sustainable agricultural practices since compost treatments incorporating Azotobacter and PSB biofertilizers serve as effective alternatives to chemical fertilizers for pollution reduction. Through machine learning optimization methods farmers gained enhanced capabilities to make precise choices regarding composting for their specific crops. The method reduces expenses and improves agricultural production rates particularly among farmers who operate small agricultural operations. The evaluation provides crucial knowledge about organic waste activity during composting that leads to better compost quality results. The completed work creates a solid research base for advanced studies concerning AI-based organic waste handling techniques and sustainable farming practices. Other studies should utilize this methodology to analyze composting wheat and maize plants along with spatial and climate data for strengthened predictive models.

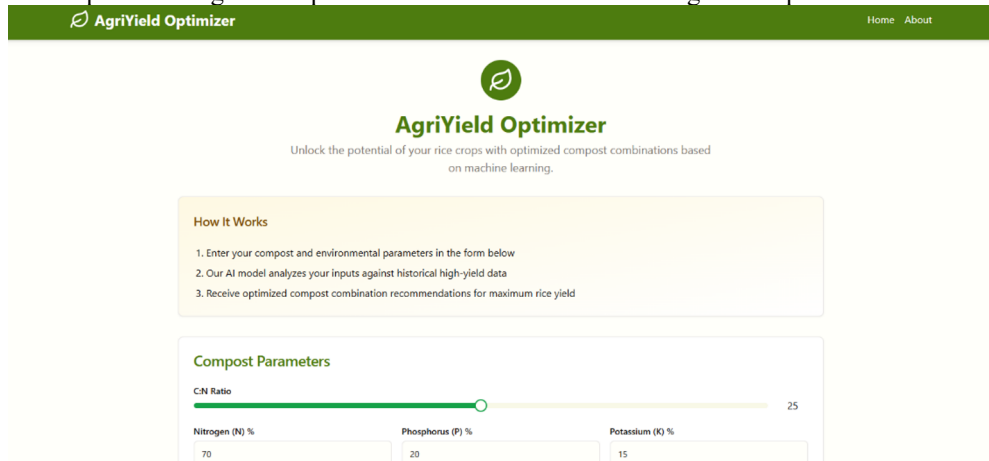


Figure 11. Screenshot of Web application

4 Conclusion

The research investigates rice yield enhancement through analyses of urea-based inorganic fertilizers and biofertilizer-enhanced organic materials. Through the use of Tamil Nadu Agricultural University datasets together with machine learning methods, we systematically created more than one thousand compost formulations for evaluation. The research demonstrates that biofertilizer-enriched compost combinations produce equivalent or better rice yields than traditional urea-based approaches after statistical analysis and normalization, and predictive modeling. Ensemble models Random Forest together with Gradient Boosting effectively determined critical yards such as nitrogen composition and C: N values in addition to weather elements including rainfall and temperature, which affect rice production. The computation of Euclidean distance between actual yield data and compost NPK values helped us develop effective maps to rank compatible combinations. The best compost formulations made with biofertilizers demonstrated their capability to be both environmentally sustainable and cost-effective and also highly effective in nutrient delivery for farmers' fields. The

research facilitates the evolution of climate-smart agriculture by removing dependency on chemical fertilizers and providing effective waste transformation methods. The research achieves two sustainable development goals (SDG 2 and SDG 13) by enhancing food security and reducing environmental consequences. This project proves how data-based methods transform contemporary farming by developing an adaptable system that bonds soil knowledge with agronomic expertise with AI for better decisions that support sustainable outputs.

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