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Data-Driven Prediction of Nitrogen Stress and Crop Yield in a Maize - Wheat Cropping System

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Abstract:

The study has attempted to determine leaf-N content in a cropping system consisting of Wheat and Maize using plant sensors like GreenSeeker and SPAD meter (chlorophyll meter) and use machine learning models so that crop yields based on inputs can be predicted of data on nitrogen doses, NDVI values, SPAD values, and leaf N content. The data recorded from field experiments on wheat and maize crop variable fertilized by N (wheat: 0, 30, 60, 90, 120, 150, 180 and 240 kg N/ha; maize: 40, 80, 120, 160, 200, 240 and 300 kg N/ha) were used. A pair plot analysis showed a positive association between leaf N and NDVI, between leaf N and SPAD values, and between NDVI and SPAD values; all these parameters had a positive correlation with N-application rates. For yield prediction, the model calibrated for wheat could validate yield prediction for maize as well. Random Forest and Support Vector Machines showed reproducible performance (consistent) on both datasets (maize and wheat), with accuracies of 85.71% and 100%, respectively, on the original dataset.

Keywords: Nitrogen Stress, Crop Yield , Wheat Cropping System.

Introduction

Maize (*Zea mays* L.) – wheat (*Triticum aestivum* L) span over about 2.90 million hectare (mha)area and holds the distinction of being India's third most widely adopted cropping system, rice-wheatand rice-cotton being first and second, respectively (Singh et al., 2014). Individually, maize isgrown on 9.98 mha and wheat 29.8 mha, which speaks about the importance of these two cropsin the country's agri-food systems. India produced 38.1 million tonnes (mt) of maize in 2022- 23 and 110.6 mt of wheat together contributing 37% to the country's total food grainproduction. Food and nutritional food security depend largely on the production of these two staple food crops not only in India but also worldwide. These two cereal crops no doubt give high grain yield but require heavy amounts of nutrients. A maize crop yielding 9.5 t grain/ha can remove 191 kg/ha N, 89 kg/ha P_2O_5, and 235 kg K_2O; while nutrient removal by wheat producing 6.7 t/ha grain is 200 N, 55 kg P_2O_5, and 252 kg K_2O/ha (Roy, 2006). Plants get nutrient supplies partly from the soil's inherent available nutrient pools and applied fertilizersand manures. Due to the requirements of achieving higher yields and a large deficiency of nutrients in Indian soil, an external supply of nutrients is essentially required.

Among 17 plant nutrients essentially required for plant growth and yield, N is required to be supplied in larger amounts as it is required for many metabolic activities, chlorophyll-, protein- , enzymes and- synthesis, shoot growth, root growth, and yield formation, and soils are mostlylow in N contents. Out of more than 50 million samples analyzed, 97% showed N deficiency with 27 states and UTs showing N deficiency in 90% of samples (Kumar, 2022). It has been observed that when N supply is omitted yield losses are significant (Lalfakzuali and Sharma, 2021). Thus, food production cannot be sustained without the application of N fertilizers. Managing nitrogen fertilizers in agri-food systems with higher efficiency has been a challengefor the last 50–60 years. As the food requirement grew the fertilizer consumption also rose, most of which had been N fertilizers. There has been a 6% yearly increase in fertilizer consumption in India since 1970 (Sutton et al., 2017; FAO, 2016)**.** The increase in fertilizer use especially N causes serious issues; the heavy losses of applied N into the environment threaten the air quality, soil environment, and freshwater ecosystem. Because of this, the stability of climate, ecosystems, and human health are hampered. The current global food systems comprising crop and livestock integration exhibit an utterly low N-use efficiency of 15% (Sutton et al., 2013 and Sutton et al 2017). Thus, 85% of applied N is lost in air, leached down, washed off polluting and damaging the environment including soils, groundwater, and river/lake/pond water ultimately affecting human health and ecosystems (Galloway J. N. et al., 2008; Aneja et al., 2009; Sutton et al., 2011; Fowler et al., 2013). To close the food gap and ensure everyone hasenough to eat, the doubling of fertilizer consumption by 2050 has been foreseen; this invokes for re-designing of N fertilizer management strategies through scientific interventions (Moring et al., 2021).

Real-time monitoring and assessment of N deficiency have been advocated by many researchers for scheduling N applications to avoid N stress beyond a critical level (Dass 2012,2014, 2015 2018; Okasa et al, 2024). Rapid and user-friendly methods for plant nitrogen measurement are essential. Current lab techniques are too slow and cumbersome. Collecting, drying, processing, and analyzing plant samples takes time apart from being costly, and is proneto contamination and inaccuracies. By the time results are obtained, the plants would have suffered from deficiency. The Plant N sensors like GreenSeeker, Crop Circle, spectro-radiometers, SPAD meter, LCC are now available and being used for assessing plant N status.The sensor indices give and idea of N stress. Of late, machine learning tools have emerged as potential aid in predicting and quantifying different stresses, which constitutes precursor information for developing nutrient prescriptions. The current study was designed to develop,calibrate and validate machine learning models for N and yield prediction in wheat and maize crops.

Materials And Methods

The basic data used for machine-learning based yield prediction included leaf N, normalized vegetation index (NDVI), SPAD (Soil plant analyses Development) values, plant dry weight, grain yield and straw yield measured periodically, baring yields, for wheat and maize crops fertilized with variable rates of N (wheat: 0, 30, 60, 90, 120, 150, 180 and 240 kg/ha; maize: 0, 40, 80, 120, 160, 200, 240 and 300 kg/ha). A field experiment on wheat was conducted duringthe *rabi* season (December-April), the crop was sown in the early December and yielded in 3rd week of April. The experiment of maize was undertaken during the *rainy (kharif)*season (3rd week of July to early November). Both experiments were conducted in the same plots (fixed plots) using the same field layout. Each experiment had a total of 21 plots; 7 N application rates had 03 replicates. Other fertilizers including P, K, and Zn were added homogeneously to all experimental plots at the prescribed rates. Wheat was planted at a row distance of 0.225 m while spacing for maize was kept at 0.60 m row-to-row and 0.20 m plant-to-plant. Irrigation was applied as per recommended irrigation schedules. Crops were kept free of weeds by using recommended herbicides and hand weeding. Nitrogen was applied in three splits, at sowing, attillering (wheat) / knee high (maize) and booting (wheat) and pre-tasseling (maize).

The study site, ICAR-IARI, New Delhi (28◦28’ N; 77◦09’ E and of 228.6 m above sea level) has subtropical and semi-arid climate characterized by dry, hot summers and cools winters. In peak winter months December / January, temperature approaches zero degree Celsius. Both major crop seasons (*kharif and rabi*) receive rainfall but the majority (80%) of the mean annual rainfall of 650 mm occurs in the *kharif* season, winter and summer seasons are blessed with only a few showers. The experimental field's soil texture is sandy loam with moderate levels of N and P and a high level of K, 8.1 pH.

The NDVI was measured using a GreenSeeker and SPAD value using a SPAD meter also called a chlorophyll meter (Dass et al., 2015; Dass et al., 2018; Okasa *et al*., 2024) four times. Leaf N was determined by alkaline permanganate (KMnO4) method (Subbiah, B.V.; Asija, 1956, Rana *et al*., 2014)

Model Definition and Significance

The model refers to the machine learning classifiers trained in the code (Decision Tree, NaiveBayes, Logistic Regression, SVM, Random Forest). These models carry a great significance because theyare trained to predict crop yield based on various features such as weight, SPAD, NDVI, and N Content. The significance of the models lies in their capability to analyze/examine previous data and learn and identify patterns that could help predict future crop yields. These predictions can be valuable for farmers and agricultural experts in building quick and large information-driven decisions regarding crop management, apportioning farm resources, and maximizing yield.

The purpose of the model is to provide predictive analytics for crop yield estimation. By training different machine learning algorithms on historical crop yield data, the model aims to learn the underlying relationships between various features and crop yield. After training, the model could be employed to make predictions on new or unseen data, helping stakeholders anticipatecrop yield under different conditions. The overall objective is to facilitate producers, agricultural researchers, and policymakers in augmenting agricultural practices, raining crop yields and crop production, and ensuring food security.

Model Summary

The summary refers to the output generated by various methods such as `describe ()`,

`classification_report ()`, and `cross_val_score ()`. They offer perceptions into the conduct and performance of the trained models. To illustrate the model's prediction power, the `classification_report()`, for instance, offers metrics for each class such as F1-score, recall, and precision. Cross-validation scores are provided by the `cross_val_score()}, which show how well the model generalises to new data. All things considered, they aid in assessing the models' efficacy and directing possible areas for improvement.

About Algorithms

Decision Tree

A well-liked supervised learning technique for tasks involving regression and classification is the decision tree. Recursively dividing the dataset into subsets according to the most important feature at each node is how they operate. Either maximizing information gain or minimizing impurity metrics, like entropy or Gini impurity, determines the divide. Decision trees may handle category and numerical data and are interpretable. Without appropriate regularisation, they may not generalise well to previously unknown data and have a tendency to overfit the training set.

Naive Bayes (Gaussian)

Naive Bayes, a probabilistic classifier with an assumption of feature independence, is based on Bayes' theorem. Although it can be used in other fields, text categorization jobs benefit greatly from its application. Gaussian Features are assumed to have a Gaussian (normal) distribution by Naive Bayes. In fact, Naive Bayes frequently performs well despite its simplicity and the "naive" assumption of feature independence, particularly for datasets with a high dimensionality.

Logistic Regression:

A linear model used for binary classification problems is called logistic regression. It uses the logistic function (sigmoid) to model the likelihood that an input falls into a specific class. In order to minimise the logistic loss function, logistic regression estimates the coefficients for each feature. It offers insights into the significance of traits and is comprehensible. Despite its efficiency and robustness, logistic regression relies on a linear relationship between characteristics and the response variable's log-odds.

Support Vector Machines

A potent supervised learning technique for regression, outlier identification, and classification is support vector machines (SVM). The way it operates is by locating the feature space hyperplane that best divides the classes. SVM seeks to improve generalisation by maximising the margin between classes. Using various kernel functions, SVM can handle both linear and non-linear decision boundaries. Despite their usefulness, SVMs may need to be carefully tuned because they are sensitive to the kernel and parameter choices.

Random Forest

Random Forest is a learning method which is based on decision trees.During training, it builds multiple decision trees and merge their outcomes throughaveraging (for regression) or voting (for classification). Random Forest introduces randomnessby bootstrapping the data as well as selecting a random subset of features at each split. It reduces overfitting and increases robustness if we compare it to decision trees individually. Random Forest is versatile, scalable, and effective for both classification and regression tasks.

The model described in the provided code is a classification model aimed at predicting crop yield based on various features such as weight, SPAD, NDVI, and nitrogen content. Here's a detailed overview of the model, including its components, performance, and results:

Calibration for Wheat Datasets

Data Preprocessing

The dataset is loaded using pandas, and basic EDA (exploratory data analysis) is performed so that the structure and characteristics of the data can be understood. Pre-processingsteps include handling missing values, checking for data types, and exploring correlations between features using a correlation matrix and pairplot. Steps of Data preprocessing such as selecting relevant features, handling missing values, converting continuous target labels into categorical labels, and breaking the dataset into testing and training set are performed.

Feature Selection

Relevant features such as weight, SPAD, NDVI, nitrogen content, and yield are selected for model training and testing.

Model Selection

Several classification algorithms were employed, including XGBoost, Logistic Regression, Naive Bayes, Random Forest, Support Vector Machines (SVM), and Decision Tree. Each and every model is trained as well as evaluated using accuracy scores along with classification reports.

Model Evaluation

Meticulous evaluations of the model's performance include accuracy, precision, recall, and F1-score. To verify the models' resilience, cross-validation is also carried out. To gain insights into the model's performance across several classes, `classification_report()} is used to generate classification reports. To validate the robustness and generalisation capabilities of the models, `cross_val_score()} is used to produce cross-validation scores.

Model Calibration for Maize

The model is calibrated using new data by following similar pre-processing steps, training the models, and evaluating their performance on the new dataset. Theperformance of the models on the new dataset is assessed and compared with their performanceon the original dataset. The best-performing model (Random Forest) is used to make predictions on new data. Given a set of features representing a particular crop, the model predicts the corresponding crop yield.

Validation for Maize Datasets

This outlines a process for adapting a machine learning model trained on a wheat crop datasetto a new dataset containing data for maize crops.

Acquire Additional Data:

In this case, the model trained on wheat crop data is being adapted to potentially work with maize crop data.

Preprocess the Data:

Similar preprocessing steps as before need to be applied to the data set of maize. This includes handling missing values, encoding categorical variables, scaling numerical features, and any other necessary preprocessing steps. Thesignificance here lies in ensuring that the new dataset is prepared in a format suitable for modelling and consistent with the preprocessing applied to the original wheat dataset.

Model Validation:

The significance lies in adapting the existing models to work withthe characteristics of the new maize crop dataset.

Evaluate Model Performance:

The performance of each calibrated model on the newdataset (maize) needs to be evaluated. This involves making predictions on the test setof the new dataset and calculating relevant evaluation metrics such as accuracy. The significance is in assessing how well the adapted models perform on the new maize crop dataset compared to their performance on the original wheat dataset.

Comparison

Finally, the performance of models trained on the original wheat datasetis compared with the performance of models trained on the new maize crop dataset. Any improvements or differences in performance are assessed. The significance here lies in determining whether the adapted models generalize well to the new crop type and whether any adjustments or further tuning are necessary.

Overall, this process is significant as it demonstrates the adaptation of a machine-learning model from one crop type to another, showcasing the importance of data adaptation and generalization in agricultural modeling tasks. It also highlights the iterative nature of model development, where models are continuously refined and adapted based on new data and insights.

Model Comparison and Visualization

A bar plot is generated to compare the accuracies of different models on both the original andnew datasets. The accuracies of different models are printed for comparison. Additional visualization techniques such as pair plots are used to visualize relationships between featuresand target variables.

Analysis of data: Pairplot

In the pairplot generated by Seaborn, each subplot represented the relationship between two variables in the dataset. In scatterplots, the main diagonal of the pairplot grid consisted of scatterplots. These scatterplots show the relationship between each variable and itself, which essentially represents the univariate distribution of each variable. In this dataset, the pairplot generated using Seaborn visualizes the relationships between the variables 'Weight', 'SPAD', 'NDVI', 'N Content', and 'Yield_B'.

RESULTS AND DISCUSSION

Based on the provided dataset and code, the pairplot graph visualizes the relationships betweendifferent variables. The following relationships based on the variables included in the pairplotwere analysed.

N-Rates Vs. Spad Value

In both wheat and maize, there was a positive correlation between N application rate, and SPAD values indicating that as the N-rate increased, the SPAD value (a measure of chlorophyllcontent) tended to increase. N is a constituent of chlorophyll, increased supply of N increasedchlorophyll content and thus the SPAD value.

N-Rates Vs. NDVI

The Normalized Difference Vegetation Index (NDVI), a measure of vegetation density and health and greenness showed a positive association with N-application rate. N apart from imparting green colour also improves plant growth and vigor, which resulted in the positive association between N level and NDVI both for wheat and maize.

N-Rate Vs. Leaf N Content

Application increased amount of N increases its availability which, in turns, leads to enhanced accumulation of N by plants. Thus there existed a positive correlation between N rate and leafN concentration.

N-Rates Vs. Grain Yield and Straw Yield

As N is an important constituent of chlorophyll responsible for green colour and photosynthesis, thus increased N supply improved production, storage, and translocation of photosynthates, leading to increments in both grain yield and straw yield with increasing ratesof N application. Thus, a positive correlation existed between grain/straw yield and N application rate.

SPAD vs. NDVI

Both SPAD and NDVI are measures related to plant health and chlorophyll content. Both areinfluenced by increase or decrease in N supply, both show positive correlation with N rates andthus with each other. A positive correlation here would implies that a higher chlorophyll content, as measured by SPAD, corresponds to higher NDVI values.

SPAD vs. N Content, SPAD vs. Straw Yield

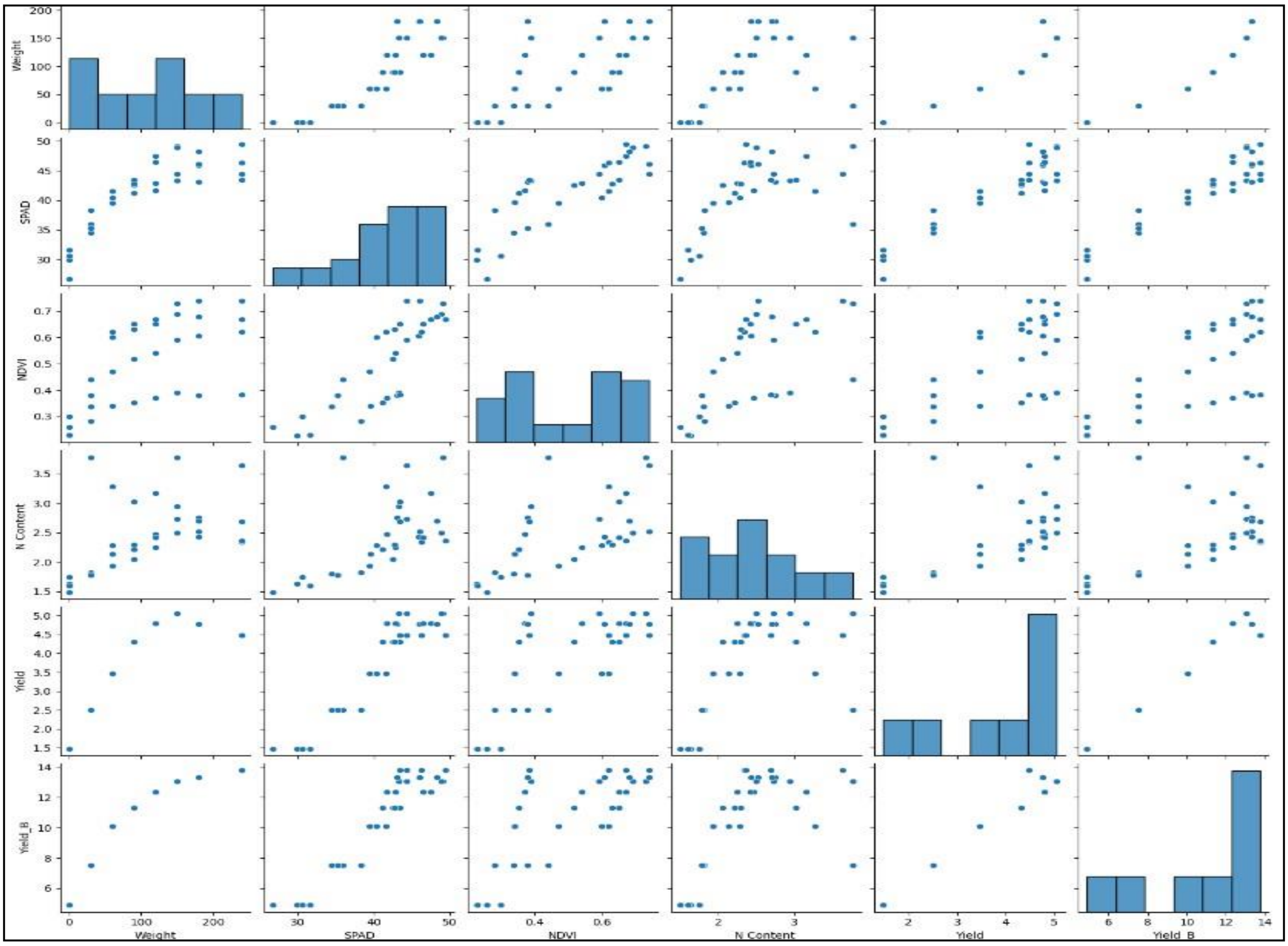
Similar to the above relationships, positive correlations would suggest that higher chlorophyllcontent is associated with higher nitrogen content and higher yield according to Yield_B.

NDVI vs. N Content, NDVI vs. Straw Yield

Positive correlations here revealed that higher NDVI values are associated with higher nitrogen content and higher straw yield

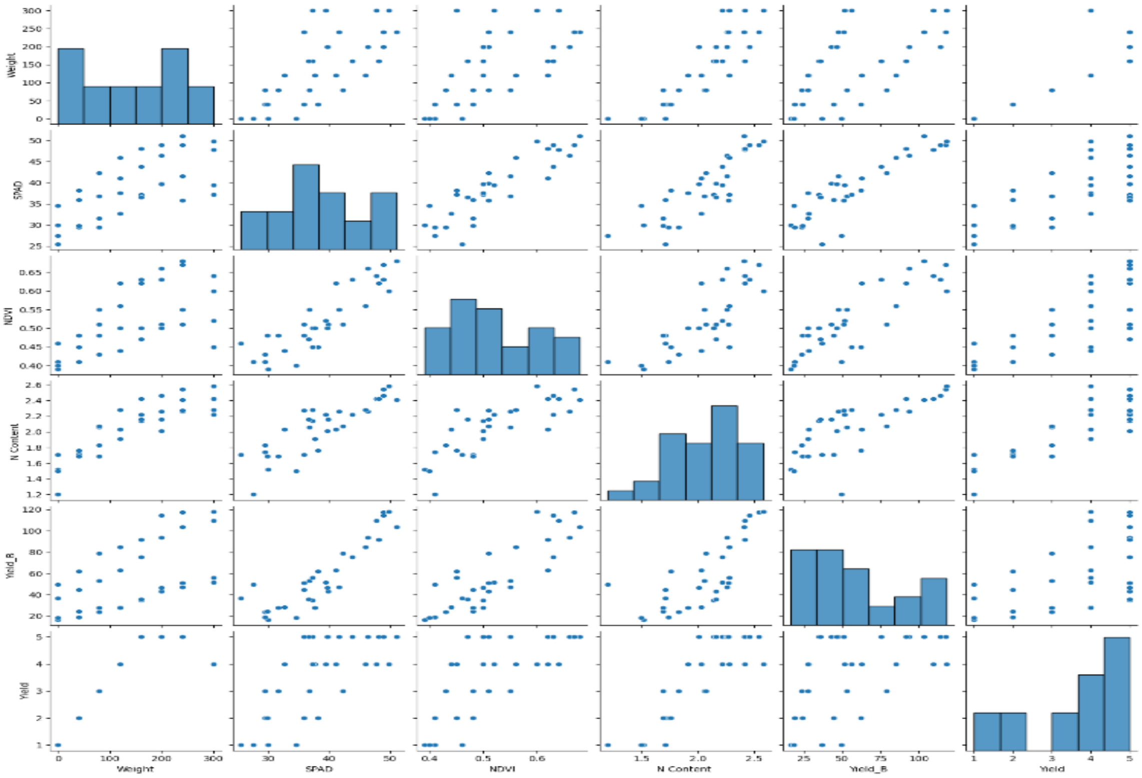
N Content vs. Grain Yield

There existed a positive correlation between leaf N concentration and grain yield of both wheat and maize, suggesting that higher nitrogen content in the crop corresponds to higher yields. These interpretations are based on typical expectations of how these agricultural parameters might relate to each other. The pairplot provides a visual tool to validate or identify these relationships and can be crucial in understanding the dataset and guiding further analysis. By examining these pairwise relationships in the pairplot, you can gain insights into how thesevariables interact with each other, potentially revealing patterns that can inform further analysisor modeling decisions.



Note: Weight mean N-application rates and yield B straw yield

FIG. 1. Pairplot for wheat dataset



Note: Weight mean N-application rates and yield B straw yield

FIG. 2. Pairplot for maize dataset

Decision Tree

Achieved an accuracy of 71.43% on the original dataset (wheat). Naive Bayes and Logistic Regression also obtained an accuracy of 71.43% on the original dataset (wheat data). The SVMachieved a higher accuracy of 85.71% on the original dataset. However, Random Forest: Achieved thehighest accuracy of 100% on the original dataset **(Fig 3).**

Model Comparison

A bar plot is generated for assessing and comparing the accuracies of different models on both the original and new datasets (maize). SVM and Random Forest showed consistent performance on both datasets, with accuracies of 85.71% and 100%, respectively, on the original dataset.

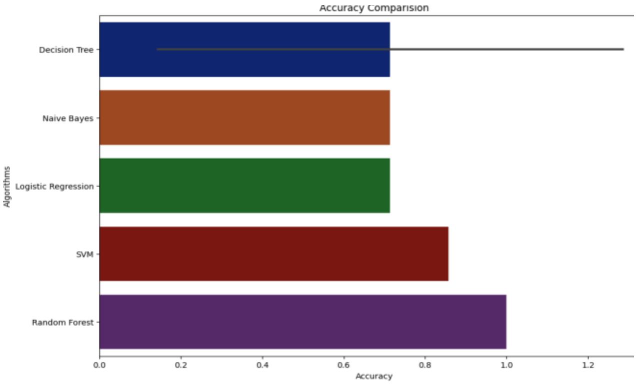


FIG. 3. Accuracy comparison of different models for yield prediction in wheat

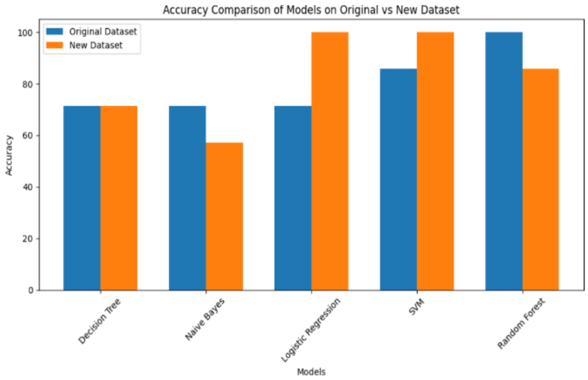


Fig. 4. Comparative accuracy of each model (original data set pertains to wheat; new dataset pertains to maize)

Yield Prediction

Finally, the Random Forest model is used to make a prediction on new data, yielding a predicted crop yield value. The prediction by all models, barring logistic regression, were comparable between wheat data set and maize data set (Fig. 4).

CONCLUSION

The NDVI and SPAD values can be used for estimation of plant N –status and predicting cropyields with a fair accuracy both in wheat and maize, two important food crops. The Random Forest model stands out as the best-performing model with consistent accuracy across datasets. SVM also demonstrates robust performance. The model's predictive capabilities are showcasedthrough a sample prediction on new data. The main functioning of the code involves data pre-processing, model training, evaluation, prediction, and comparison. The ultimate objective is to build a robust machine learning model that predicts crop yield accurately based on agronomicfeatures. The insights derived from the models could be employed to optimize crop management protocols, and thereby improve agricultural productivity. In summary, the model effectively predicts crop yield based on various agronomic features, providing valuable insights for agricultural decision-making.

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References

[1] A. Dass, K. Kumari, S. Sudhishri, R. Kaur, R.N Sahoo and M.C. Meena, “Assessment of leaf N content using optical sensors in maize under variable irrigation and nitrogen application rates” in Re designing Agronomy for Nature Conservation and Economic Empowerment, Proceedings of National Agronomy Congress (organized by the Agronomy Society, Department ofAgronomy, College of Agriculture G.B.P.U.A. & T., Pantnagar, India, during 20–22 February, 2018), pp. 139– 140.

[2] Dass, B.G. Shivkumar, S. Dhar and K. Kumar, Annals of Agricultural Research, **36** (4), 358-363 (2015).

[3] Dass, D.K. Singh and S. Dhar, “Precise supply of nitrogen and irrigation to hybrid maize using plant sensors,” in Agriculture, Diversification, Climate Change management and livelihoods, Proceedings of International Agronomy Congress (ISA, IARI, New Delhi, Oral presentation during 26-30, November, 2012) Pp. 534-535. 2012.

[4] D. Fowler, M. Coyle, U. Skiba, M. A. Sutton, J. N. Cape and S. Reis, Philos. Trans. R. Soc., **368** (1621), 20130164 (2013).

[5] J. N. Galloway, A. R. Townsend, J. W. Erisman, M. Bekunda, Z. Cai and J. R. Freney, Science **320**, 889–892 (2008).

[6] N. Gupta, Y. Singh, H.S. Jat, L.K. Singh, K. M. Choudhary, H S. Sidhu, M.K. Gathala and M.

[7] L. Jat, Sci. Rep. **13**:12060 (2023).

[8] V. Kumar, “How nutrient-deficient are Indian soils?” in Down to Earth (2022).

[9] M. Lalfakzuali and Y.K. Sharma, Ann. plant soil res. **23** (4), 397-401 (2021).

[10] A. Móring, S. Hooda, N. Raghuram, T.K. Adhya, A. Ahmad, S.K. Bandyopadhyay, T. Barsby, G. Beig, A.R. Bentley, A. Bhatia, U. Dragosits, J. Drewer, J. Foulkes, S.D. Ghude, R. Gupta, N. Jain, D. Kumar, R.M. Kumar, J.K, Ladha, P.K. Mandal, C.N. Neeraja, R. Pandey, H. Pathak, P. Pawar, T.K. Pellny, P. Poole, A. Price, D.L.N.

Rao, D.S. Reay, N.K. Singh, S.K. Sinha, R.K. Srivastava, P. Shewry, J. Smith, C.E. Steadman, D.,Subrahmanyam, K. Surekha, K. Venkatesh, V. Singh, A. Uwizeye, M. Vieno and M.A. Sutton, Front. sustain. food syst. **5**, 505347 (2021).

[11] H. Okasa, Shreya, G. Arya, A. Dass, M.C. Meena, R.N. Sahoo, S. Sudhishri and M. Khanna, Grenze International Journal of Engineering and Technology, (2024).

[12] K. S. Rana, A. K. Choudhary, S. Sepat, R. S. Bana and A. Dass, Methodological and AnalyticalAgronomy Indian Agricultural Research Institute New Delhi, (2014)

[13] R.N. Roy, FAOFertilizer and Plant Nutrition Bulletin **16**, 348 (2006).

[14] B.V. Subbiah and G.L. Asija, Curr. Sci. **25,** 259–260 (1956).

[15] M. A. Sutton, J. Drewer, A. Moring, T. K. Adhya, A. Ahmed and A. Bhatia, “The Indian nitrogen challenge in a global perspective,” in The Indian Nitrogen Assessment: Sources of Reactive Nitrogen, Environmental and Climate Effects, Management Options, and Policies, edited by Y. P. Abrol, T. K. Adhya, V. P. Aneja, N. Raghuram, H. Pathak and U. Kulshrestha (Elsevier, Cambridge, 2017), pp. 9–28.

[16] M. A. Sutton, C. M. Howard, J. W. Erisman, W. J. Bealey, G. Billen and A. Bleeker, “The challenge to integrate nitrogen science and policies: the European Nitrogen Assessment approach,”in The European Nitrogen Assessment: Sources, Effects and Policy Perspectives, edited by M. A. Sutton, C. M. Howard, J. W. Erisman, G. Billen, A. Bleeker and P. Grennfelt (Cambridge University Press, Cambridge, 2011), pp. 82–96.

[17] V. P. Aneja, W. H. Schlesinger, D. Nyogi, G. Jennings, W. Gilliam and R. E. Knighton, Trans. Am. Geophys. Union **87**, 25–29 (2006).

[18] Dr. S. A. Sivakumar, "Artificial Intelligence and Machine Learning Algorithms in Engineering: A Mathematical Perspective", MathInnoTech: Innovations in Engineering Mathematics Journal, Volume 1 Issue 1, pp: 22-33, 2024.

[19] Nora Zilam Runera, "Mathematical Techniques in Signal Processing for Telecommunications Engineering", MathEngage: Engineering Mathematics and Applications Journal, Volume 1 Issue 1, pp: 01-11, 2024.