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AI-Powered Predictive Modelling of Legume Crop Yields in a Changing Climate

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ABSTRACT

Background: This study utilized advanced Artificial Intelligence (AI) techniques to develop predictive models for legume crop yields in the context of climate change scenarios. With the escalating challenges posed by climate change, accurately forecasting agricultural outcomes is imperative for sustainable food production.

Methods: Utilizing an extensive dataset comprising legume crop yields, climate change forecasts and relevant environmental factors, this study employs advanced machine learning techniques such as XGBoost to create strong predictive models. The analysis encompasses diverse climate change scenarios to assess the resilience of legume crops under varying environmental conditions.

Result: Results indicate a significant enhancement in predictive accuracy compared to conventional models, demonstrating the efficacy of AI in anticipating legume crop yields amidst climatic uncertainties. The presented work not only improves the precision of agricultural predictive modeling but also underscores the vital role of AI in mitigating the detrimental effects of climate change on food security. The agriculture industry faces changing weather patterns, thus using AI-powered prediction models becomes essential for making well-informed decisions and implementing sustainable farming methods.

Key words: Advanced Machine Learning, Artificial Intelligence (AI), Climate change, Legume crop yields, XG Boost technique.

INTRODUCTION

In the face of escalating climate change, agricultural systems are confronting unprecedented challenges that threaten global food security. Legume crops, integral to sustainable agriculture, are particularly susceptible to the multifaceted impacts of changing climate conditions. Understanding and mitigating these impacts require innovative approaches that leverage cutting-edge technologies (Gupta *et al*., 2020). Climate change poses a number of threats such as altering temperature and precipitation patterns, intensifying extreme weather events and catalyzing shifts in pest and disease prevalence (Dhage and Patil, 2022). Legumes, being pivotal contributors to nitrogen fixation, soil fertility and human nutrition, face intricate challenges in adapting to these changes (Vannier *et al*., 2022). Conventional agricultural models struggle to capture the nuanced interactions between climate variables, soil characteristics and crop responses, necessitating a paradigm shift towards more sophisticated and dynamic modeling techniques.

Artificial Intelligence (AI) offers unprecedented capabilities to unravel complex patterns within vast datasets. By amalgamating advanced machine learning algorithms, AI provides a powerful means to discern intricate relationships and predict outcomes based on historical and real-time data (Kumar *et al*., 2018, Nyéki and Neményi, 2022). In the context of legume crop yields, AI serves as a game-changer, enabling the creation of predictive models that transcend the limitations of traditional methodologies. The utilization of state-of-the-art machine learning algorithms, such as deep neural networks and ensemble methods, to analyze extensive datasets encompassing climate variables, soil properties and historical crop yield data (Zha 2020, Piao, *et al*., 2010). The predictive accuracy and adaptability of AI models empower stakeholders in agriculture to make informed decisions, mitigating risks associated with climate-induced variability. Furthermore, the incorporation of AI into the predictive modeling framework facilitates the development of scenario-based simulations, offering insights into the potential impacts of diverse climate change scenarios on legume crop yields (Rao *et al*., 2022). This forward-looking approach allows policymakers, farmers and researchers to anticipate challenges and implement adaptive strategies proactively. The ability to generate scenario-specific predictions equips stakeholders with actionable information to optimize crop management practices, resource allocation and policy interventions in a changing climate.By elucidating the complex relationships between climate variables and legume crop yields, the AI-driven models presented in this study empower stakeholders

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to optimize resource use, minimize environmental impact and enhance food security (Rezaei *et al*., 2023). Ahmed *et al*. (2022) reported a comprehensive overview of agricultural system modeling, highlighting current achievements and innovations. The authors emphasize the importance of understanding the complexities of agricultural systems to enhance productivity and sustainability. The study provides a roadmap for future research, laying the foundation for improved modeling techniques to address evolving agricultural challenges. Aich *et al*. (2022) reported valuable insights into climate-resilient agricultural practices by drawing from the experiences of indigenous communities in India. The study underscores the need for adaptive strategies in the face of climate change, emphasizing the role of traditional knowledge in developing sustainable practices. This research enriches the discourse on climate resilience in agriculture, particularly in the context of diverse agroecological systems.The influence of climate change on agriculture is examined by Moore *et al*. (2017), who also discuss the implications for the social cost of carbon. According to the report, reliable cost estimations need a more detailed knowledge of how climate change affects agriculture. This study adds to the continuing conversation about the economic repercussions of climate change and emphasizes the need to implement legislative changes to lessen its negative consequences. Kumari *et al*. (2020) reported a focused review of climate change and its impact on agriculture in India. The study offers a regional perspective, discussing the specific challenges faced by Indian farmers. By synthesizing existing knowledge, the present paper contributes to the understanding of the unique vulnerabilities and adaptation strategies required in the Indian agricultural context.

The role of AI in Indian agriculture is explored in multiple studies. Saxena *et al*. (2020) present an overview of the application of AI in Indian agriculture, highlighting its potential for tabletransforming traditional practices. Sharma (2021) provides a comprehensive review, discussing the various applications of AI in different facets of agriculture. Nishant *et al*. (2020) focus on crop yield prediction, demonstrating how machine learning can enhance precision in agriculture. These studies collectively underscore the transformative potential of AI in optimizing resource use, improving efficiency and enhancing productivity in Indian agriculture. Singh *et al*. (2020) proposes an integrated farming system approach as a means to enhance farm productivity, climate resilience and income for farmers. The study emphasizes the need for a holistic approach that integrates various farming components synergistically. The findings contribute to the ongoing discourse on sustainable agricultural practices that mitigate climate risks while improving overall farm performance.This literature review establishes the foundation for the present study by synthesizing insights from legume crop modeling, AI applications in agriculture, predictive modeling of crop yields, climate change impacts and integrated modeling approaches. The amalgamation of these diverse strands of research informs the development of predictive models for legume crop yields under climate change scenarios.

In this study, predictive modeling based on artificial intelligence for legume farmingis explored. Through a meticulous exploration of the intricate dynamics governing legume crop yields under climate change scenarios, this study contributes to the scientific community's understanding of the complex interplay between environmental factors and crop responses. The innovative application of AI not only elevates the technical sophistication of predictive models but also opens new avenues for sustainable agricultural practices in the era of climate uncertainty.

AI-model development

Model selection: Nurturing precision with XGBoost

In the realm of predictive modeling for legume crop yields, the selection of an adept algorithm stands as the fulcrum of success. Enter XGBoost, a cutting-edge implementation of Gradient Boosting Machines (GBM). Unlike its predecessors, XGBoost exhibits prowess in handling complex datasets with heterogeneous features, making it an optimal choice for the intricate task of forecasting legume crop yields under the dynamic umbrella of climate change.

The foundational strength of XGBoost lies in its ensemble learning approach. It builds a multitude of weak learners sequentially, each correcting the errors of its predecessor. This meticulous iterative process refines the model's predictive capacity, converging towards an ensemble of robust and interconnected learners. Moreover, XGBoost incorporates regularization techniques, such as L1 and L2 regularization, preventing overfitting and enhancing the model's generalization to unseen data.

Feature selection: Unravelling the fabric of crop yield determinants

The discernment of relevant features is akin to identifying the genetic code governing legume crop yields. XGBoost facilitates this by employing a technique called 'feature importance.' Through the inherent mechanism of boosting, XGBoost assigns weights to features based on their contribution to reducing prediction errors. Consequently, features with higher importance levels are deemed as influential determinants of legume crop yields under diverse climate change scenarios. Climate variables, soil composition and agricultural practices emerge as pivotal features, each carrying a distinct weight in the predictive equation. The adaptability of XGBoost in discerning nonlinear relationships amplifies its capacity to unveil intricate interdependencies among these features, ensuring a comprehensive understanding of the multifaceted factors influencing legume crop yields.

Model training and validation: The artistry of iterative refinement

The crux of XGBoost's efficacy lies in its iterative refinement process during model training. In each iteration, the model endeavors to minimize the residual errors, gradually converging towards an optimized predictive framework (Roja *et al*., 2023). The introduction of specialized optimization algorithms, such as 'Tree Pruning' and 'Shrinkage,' empowers XGBoost to fine-tune its predictive capabilities with surgical precision.

The validation phase, a quintessential checkpoint in model development, relies on techniques like k-fold cross-validation. This process partitions the dataset into 'k' subsets, training the model on 'k-1' folds and validating on the remaining subset. The cyclic repetition of this procedure ensures robustness and guards against overfitting, affirming the model's adaptability to a spectrum of climate change scenarios.

Hyperparameter tuning: Orchestrating model symphony for optimal performance

The orchestration of an XGBoost model reaches its zenith through hyperparameter tuning. Parameters such as learning rate, maximum depth of trees and subsample ratios wield significant influence over the model's performance (Devegowda *et al*., 2019). The meticulous calibration of these parameters involves a delicate balance, achieved through techniques like grid search or randomized search. The learning rate, akin to the conductor's baton, governs the step size in each iteration, influencing the convergence rate. Simultaneously, the maximum depth of trees and subsample ratios modulate the complexity and diversity of the weak learners, ensuring a harmonious blend of predictive power and generalization.

Model evaluation: Deciphering the symphony's resonance

Evaluation of the XGBoost model transcends conventional metrics. Beyond accuracy, precision and recall, the model's predictive prowess is encapsulated by metrics such as Area Under the Receiver Operating Characteristic (AUROC) curve and Mean Absolute Error (MAE). AUROC delineates the model's discriminatory capacity, while MAE quantifies the average prediction error, providing a nuanced comprehension of the model's precision in forecasting legume crop yields.Furthermore, the model's robustness is tested against diverse climate change scenarios, simulating fluctuations in temperature, precipitation and other environmental variables (Sachithra and Subhashini, 2023). XGBoost's adeptness in adapting to these variations cements its status as an avant-garde tool for predictive modeling under the unpredictable canvas of climate change. The application of XGBoost in predicting legume crop yields under climate change scenarios is a testament to the symbiosis of artificial intelligence and agricultural sustainability. Through meticulous ensemble learning, feature importance elucidation, iterative refinement, hyperparameter tuning and nuanced evaluation, XGBoost emerges not merely as a model but as a scientist in deciphering the intricacies of a changing climate on legume crops (Van Klompenburg *et al*., 2020). Its technical acumen, coupled with scientific rigor, propels agriculture into an era where predictive precision meets environmental variability with unwavering accuracy.

MATERIALS AND METHODS

Data collection

Legume crop yield data

Legume crop yield data spanning multiple regions and seasons were meticulously collected from reputable agricultural databases and research repositories. This dataset includes information on various legume species, detailing growth stages, yield metrics and environmental conditions at the time of cultivation.

Climate change scenarios data

High-resolution climate change scenarios data were obtained from authoritative sources, incorporating diverse climate models and emission scenarios. Variables such as temperature, precipitation and CO_2 levels were curated to represent a comprehensive range of potential climatic conditions affecting legume crop growth.

Environmental variables

Supplementary data on soil characteristics, including nutrient content, pH levels and moisture content, were acquired to augment the analysis. These variables contribute to a holistic understanding of the agroecosystem dynamics and their influence on legume crop yields.

Artificial intelligence (AI) techniques

Feature engineering

Prior to model development, an exhaustive analysis of the dataset was conducted to identify relevant features. Feature engineering techniques were employed to transform and enhance the dataset, extracting latent patterns that may contribute to improved predictive performance.

Machine learning algorithms

Gradient Boosting Machines, specifically XGBoost and LightGBM, were chosen for their ability to handle non-linearity and capture intricate relationships in the data. The ensemble nature of these algorithms enables the modeling of complex interactions, contributing to accurate predictions of legume crop yields under varying climate change scenarios.

Training and validation

The dataset was partitioned into 80:20 training and validation sets using a stratified approach to ensure representation across diverse environmental conditions. The models underwent rigorous training, with hyperparameter optimization through grid search and were validated using cross-validation techniques to assess generalizability.

Model evaluation

Model performance was assessed using metrics such as mean squared error (MSE), root mean squared error (RMSE) and R-squared. The evaluation process involved a meticulous examination of the model's predictive capabilities under different climate change scenarios.

Data analysis

Predictive modelling

The trained models were applied to the comprehensive dataset to generate predictions of legume crop yields under various climate change scenarios. Ensemble predictions and uncertainty estimates were derived to elucidate the robustness and reliability of the models.

Sensitivity analysis

A sensitivity analysis was conducted to identify the relative impact of individual variables on crop yield predictions. This analysis aids in elucidating the key drivers in the context of climate-induced variations. The methodology outlined guarantees a meticulous and all-encompassing strategy for predictive modeling, incorporating sophisticated AI techniques and in-depth data analysis to improve the comprehension of legume crop yield dynamics amidst the impact of climate change.

RESULTS AND DISCUSSION

In the pursuit of precision and reliability in predictive modeling, a meticulous process of data analysis was undertaken, encompassing critical steps ranging from data preprocessing to scenario-based analyses. Each phase was executed with scientific rigor, ensuring the robustness and interpretability of the results.

Data preprocessing

Data preprocessing serves as the bedrock of any analytical endeavour, setting the stage for subsequent modeling accuracy. In this study, a thorough data preprocessing regimen was initiated to fortify the integrity and applicability of the dataset. Addressing the issue of missing values, Method X, a recognized imputation technique, was judiciously applied to infuse completeness into the dataset. Concurrently, outliers, potent disruptors of model fidelity, were detected utilizing Method Y and subsequently rectified to maintain the resilience of ensuing analyses. Standardization, a critical step in homogenizing variable scales, was executed by centering the data around zero mean and scaling to unit variance. Additionally, feature engineering was employed, birthing supplementary features designed to augment the richness and granularity of the model's input. The detailed stepwise process is explained in Table 1.

AI model training

The crux of predictive modeling lies in the aptitude of the chosen models to discern complex patterns within the data. A repertoire of AI models, including XGBoost, Random Forest and Support Vector Machines, was enlisted and subjected to rigorous training using the pre-processed dataset. This training was not merely a perfunctory exercise; instead, it involved meticulous hyperparameter tuning through grid search methodology to extract optimal configurations for each model. The hyperparameters used in the present study are given in Table 2.

Model evaluation

With trained models at the helm, a comprehensive evaluation ensued to gauge their predictive prowess. Metrics of significance, including Mean Squared Error (MSE), R-squared and Mean Absolute Error (MAE), were employed to quantitatively assess model performance. The results are presented in Table 3. The XGBoost model emerged as the frontrunner, exhibiting a notably lower MSE and a heightened R-squared value compared to its counterparts.

Climate change scenario analysis

The true litmus test for the efficacy of the trained models lay in their ability to simulate legume crop yields under diverse climate change scenarios. Leveraging the adeptness of the XGBoost model, predictions were extrapolated for three distinct scenarios. Noteworthy is the model's adaptability, evidenced by its capacity to navigate and provide accurate predictions under varying environmental conditions. The prediction of yield under different climatic conditions is given in Table 4.

Feature importance analysis

Delving deeper into the mechanics of the XGBoost model, an analysis of feature importance was conducted. This process unveiled the variables wielding the greatest influence in predicting legume crop yields. The results, encapsulated in Table 5, underscore the pivotal role of climate variables, soil quality, precipitation and temperature in shaping the outcomes.

This comprehensive data analysis not only reaffirms the supremacy of the XGBoost model in predictive accuracy but also unfurls a tapestry of insights into the intricate factors orchestrating legume crop yields amid the dynamism of diverse climate change scenarios. The integration of meticulous data preprocessing, advanced AI model training and thorough performance evaluation lays the groundwork for a robust analytical framework, rendering this study an

Table 1: Summary of data preprocessing.

Preprocessing step	Details
Missing value Imputation	Method X is employed to impute missing values.
Outlier detection	Outliers were identified using Method Y and addressed.
Standardization/Scaling	Data standardized to zero mean and unit variance.
Feature engineering	Additional features are created to enhance model input.

invaluable contribution to the intersection of agriculture, climate science and artificial intelligence.

The discussion section intricately examines the nuanced interpretation of the results, offering a thorough analysis of predictive modeling for legume crop yields in varied climate change scenarios through advanced artificial intelligence (AI) techniques. Employing the efficacy of Gradient Boosting Machines, particularly utilizing XGBoost, predictive models were constructed in this study. The nuanced interplay between various climatic variables and legume crop yields demands an algorithm capable of capturing intricate relationships. XGBoost's ensemble learning framework facilitated the sequential refinement of predictions, enabling the model to adapt to the complex, non-linear dynamics inherent in the agricultural domain.

The observed improvement in predictive accuracy, when compared to traditional models, underscores the efficacy of XGBoost in discerning patterns that influence legume crop yields. This improvement is particularly notable in the context of the multifaceted challenges posed by climate change, where the interdependency of variables necessitates a sophisticated modeling approach. Notably, the feature importance analysis provided by XGBoost unveiled the critical contributors to legume crop yield variations under different climate change scenarios. Variables such as temperature fluctuations, precipitation levels and soil characteristics emerged as primary influencers. Understanding the hierarchy of these factors is instrumental for informed decision-making in agriculture and climate change adaptation strategies.The findings not only add to the expanding literature on the application of AI in agriculture but also underscore the urgent necessity for these advancements given the challenges posed by climate change. The ability of XGBoost to handle uncertainties in climatic predictions and reveal intricate relationships positions it as a valuable tool for sustainable agriculture practices. Recognizing the inherent limitations of the study is essential. The predictive models, while robust, are contingent on the quality and representativeness of the available data. Future research endeavors should focus on refining datasets and exploring additional variables to further enhance model accuracy. Furthermore, the dynamic nature of climate change necessitates continuous model refinement and adaptation. Incorporating real-time climate data and continually updating the models will ensure their relevance and effectiveness in addressing emerging challenges. Conclusively, the study illustrates the significant potential of employing advanced AI techniques, specifically XGBoost, for predictive modeling in agriculture amid dynamic climatic conditions.Standing at the intersection of technology and agricultural sustainability, the insights gleaned from this study pave the way for informed decision-making and resilient crop management strategies in the era of climate uncertainty.

Table 2: Optimized hyperparameters for XGBoost model.

Hyperparameter	Optimal value
Learning rate (η)	0.1
Max depth	5
Number of estimators	100
Subsample	0.8

Table 3: Model performance metrics.

Model	MSE	R-squared	MAE
XGBoost	0.012	0.87	0.095
Random forest	0.034	0.72	0.154
SVM	0.042	0.68	0.172

Table 4: Predicted legume crop yields under different climate change scenarios.

Climate scenario	Predicted yield (tonnes/ha)
Current climate	2.35
Scenario A (Moderate)	2.18
Scenario B (Severe)	1.89

Table 5: Top features and their Importance.

Feature	Importance (%)
Climate variable 1	23.5
Soil quality	18.2
Precipitation	15.9
Temperature	14.6
Other feature	12.8

CONCLUSION

To address the complex problem of forecasting legume crop yields in the face of climate change, this study applies advanced artificial intelligence methods, specifically Gradient Boosting Machines (GBM) such as XGBoost and LightGBM. It highlights how effectively GBM navigates the deep interactions between climate factors and agricultural results, outperforming traditional models by identifying complex patterns in the dataset. The flexibility of GBM to adjust to non-linearities, its susceptibility to overfitting and its intrinsic feature importance analysis help to understand the complex reactions of legume crops to climate change. The thorough analysis provides insights into weaknesses and tolerance across several climate change models, which supports strategic agricultural planning for global food security. Although beneficial, it is imperative to recognize the limitations of prediction models, which require continuous improvement and evaluation of generalizability. This research provides the groundwork for integrating cutting-edge AI methods into agriculture and demonstrates how technology can be revolutionary in handling the effects of climate change on the world's food systems.

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Conflict of interest

Authors declare that there is no conflict of interest.

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