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Research Article

Explainable AI for Climate-Smart Agriculture

Ayush Kumar [1*], Priyanka Srivastava [2], Aditya Kumar Pandey [3], Binod Kumar [4]
[1,3,4] Students, Sarala Birla University, Ranchi, Jharkhand, India
[2] Associate Professor, Sarala Birla University, Ranchi, Jharkhand, India

Corresponding Author: *Ayush Kumar

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Abstract

The rapid adoption of Artificial Intelligence in agriculture has improved the production of crops, monitoring of the overall process of farming, resource management, and what type of resources will be used for more and better production of the crops in today's era.

So, for that AI helps us a lot. The reason behind the use of AI in farming is that better production is what each and every farmer wants. Transparency-like, if the crops got damages, then the farmers have clear and accurate knowledge about the failure of the crop. Explainable Artificial Intelligence addresses this challenge by providing clear, interpretable insights into how the AI system makes decisions. This paper explores how AI is beneficial in farming, focusing on several techniques such as feature importance, visualization, and rule-based explanations that improve decision-making in crop management. This also explores several tools-like, the weather condition, equipment required that gives more than expected outcome, and much more. By this study, some of the features I want to add through technology which helps farmers for better production. The addition of technology in farming enhances transparency, trust, and sustainability in modern farming practices.

The importance of XAI in agriculture forms the foundation of this research paper, which intends to present various explanation techniques and study how they will lead to trustworthy decision-making in crop management. This study also presents the use of technological tools such as climate monitoring systems, automated equipment, soil sensors, and data-driven forecasting models that work in harmony with XAI for delivering superior results. XAI provides clear and understandable explanations-such that farmers would not only use the AI-based tool but fully trust and utilize it to truly make farming smarter and more resilient.

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KEYWORDS: Explainable Artificial Intelligence (XAI), Climate-Smart Agriculture, Precision Farming, Machine Learning, Sustainable Agriculture.

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1. INTRODUCTION

Agriculture is the main and only source for feeding and growth. It is the cultivation of land, the rising of animals, the growth of human beings, the production of diet that we are taking every day, the production of crops and added essential crops for social use. It is vital for manufacturing, particularly in terms of the food and raw supplies needed to support human life and economic expansion [1]. In the past, the traditional agricultural practices were very difficult; faces many challenges such as climate change, resource limitations, water supplies, technical support, need for more efficiency [2, 3, 4, 5, 6, 7].

But when we use such technologies like AI, Machine Learning, and several AI tools, farming becomes easier. Smart agriculture offers real-time crop, soil, and weather conditions monitoring and management [8]. It is such a methodology that improves the farming process, enhances efficiency, and minimizes the conservational influence. It transforms conventional farming to efficiently use available resources, saves money, and reduces generated waste with the help of IoT sensors and data analytics [9]. In contrast, data-driven machine learning algorithms have rapidly developed in recent years and come forth with huge potential in agriculture [10]. However, the reasons for deploying ML models in agriculture are less common due to issues like poor data groundwork, expensive sensors, and specialized expertise. Now a day's deep neural networks are increasingly deployed for time series forecasting applications [11]. Standard DNN models such as Transformer models, encoder-decoder models, GRU, LSTM, and CNNs are deployed widely in many domains such as natural language processing, timeseries prediction, computer vision, image classification.

With clear and intelligible AI-based recommendations that farmers can trust and understand, AI significantly increases the adoption and effectiveness of innovative agricultural technologies [13]. From these references, we design an AI-based recommendation framework for a smart agriculture system to make the precision farming better by optimizing

Irrigation scheduling and strategic crop rotation. The major contributions of this proposed Framework are elaborated as follows:

1. **Data synthesis:** We carefully compiled an extensive data set of weather, soil, and crop information from authentic Indian sources, including:
   Geoportal.natmo.gov.in (soil data), data.icrisat.org (crop production) and power.larc.nasa.gov (meteorological data).
2. **Advanced feature extraction:** Using XL Net on the curated dataset extracted profound features, capturing intricate patterns and insights that are necessary to make accurate predictions.
3. **Improved Optimization:** An Enhanced Barnacles Mating Optimization algorithm was proposed to overcome high-measure mentality and computational complexity encountered in agricultural data analysis.
4. **Holistic analysis:** The optimal features chosen were analyzed to provide comprehensive recommendations on precision farming using established machine learning models such as support vector machines, random forests, decision trees, and neural networks.
5. **Interpretable insights:** Integrating XAI frameworks such as S Haply Additive explanation (SHAP) and Local Interpretable Modelagnostic Explanation (LIME), we present insights in a transparent and actionable manner to ensure recommendations for optimizing agricultural practices.

This research fills these gaps by assuming a justice lens for the examination of AI adoption in Non-Chemical Agriculture Methods. Using discourse and thematic analysis, it assures the capturing of the lived experiences of smallholders on how narratives and local contexts shape adoptions [13]. NCAM is climate-resilient, biodiversity-rich farming that inherently emanates from traditional practices but nonetheless requires modern support. Sir Albert Howard (1945) [14] eluded to the resilience of India's chemical-free farming. Recent challenges of labour shortages and climate stress can be further assisted through AI-enabled pest detection, soil monitoring, and yield prediction [16]. Indeed, notwithstanding its potential, AI adoption in NCAM is further confronted with obstacles like high costs, limited digital literacy, and incoherent rural infrastructure [17, 18]. Indeed, dealing with these infrastructural gaps is an important way of dealing with equitable access to AI technologies. Further, the resistance of traditional farming communities is also posing challenges. Inclusive, transparent deployment strategies are vital in developing trust and assurance of equitable access [19]. In furthering farmers' strategic communication needs, there is the enhancement of cognitive, social, and emotional capacities [20, 21]. Trust is evoked by educational programs, peer learning, and success stories [22]. Human-centered, explainable AI further assures farmer control and supports sustainable practices through transparent and autonomous technologies [23, 24]. This study therefore pursues three major objectives:

To investigate possible applications of AI technologies for enhancing sustainable practices like NCAM. To obtain a better understanding of the problems and opportunities in adopting AI technologies among farmers engaged in NCAM through Focus Group Discussions. To develop a refined conceptual framework integrating holistic understanding of AI adoption from the farmer-centric perspective. The Purdue food and agriculture vulnerability index in collaboration with Microsoft served as a baseline in terms of establishing what scholarly work is already Available, and identifying what can be improved upon. Purdue University "combined data on the number of Covid-19 cases in each U.S. County with the county's total population, the U.S. Department of Agriculture data on the number of farmers and hired farm workers in Each county, data on agricultural production of each county, and lastly was able to estimate the share of agricultural production at risk" (Purdue, 2020). Visualization of loss of production within various states was

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useful in developing a deeper understanding of the struggles within the agriculture industry, more specifically during an outlier event. Though the loss of production impact for a given commodity is an aspect of agriculture research, It cannot serve usefully for the forecasting of the other outlier events discussed in this study and their relationship with economic indices. For these reasons, we can differentiate this piece of research from an already published research work by Purdue University.

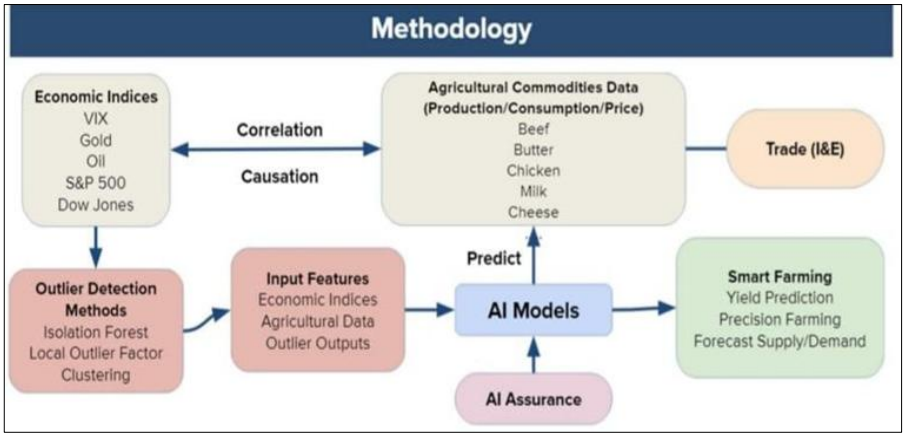


Fig 1: The Application of Artificial Intelligence assurance

AI For Smart Farms

Starting from the far right and moving left in Fig. 15.1 of the AI2Farm model, the commodity of interest is shown with the six selected economic indices to understand their relationship when fluctuation occurs. Detection of an outlier develops through the use of ML algorithms such as isolation forest, autoencoder, K-means clustering, support

Vector machine) to detect unusual/outlier points on VIX, S&P500, gold, DOWIA, and crude oil indices. With proper labeling of outlier data points, we are then able to predict those in the future from the models. The definitions for outlier events mentioned within the data refer to any anomalous dataset that exhibits an abnormal behavior among the rest of the population. These, in turn, indicate certain real-world events that force the abnormal behaviors of these datasets. In turn, successful detection of outlier events deepens one's understanding of how social and political impacts sway smart farms. In comparing each of the model's performance matrices, both supervised and unsupervised learning models are deployed. As it relates to the desire to centrally focus on AI for econ and international outlier events for the purposes of technology and science policy, we're inclined to ask:

a) Can policy scenarios be built in order to validate the outcomes and optimize different data-driven policies?
b) Can an economic causality model define the causes and effects of global outlier events? Learning with assurance from economic indices using AI?
c) Can AI models incorporate outlier events into economic predictions to support farming?

make decisions differently during outlier events vs. "conventional times"? The three questions above differentiate our research from current standing studies that Merely focus on COVID-19 or another singular outlier event for that manner Gruère and Brooks, 2021; Ellery *et al*., 2020). It is here we shift our focus towards weather; an outlier event that has been Documented for centuries, weather conditions have included temperature, rain, humidity, Moisture, and wind speed all impact yield production.

Although documentation of such conditions through the USDA weather archives remain in use by farmers, rise in temperature caused by global warming will result in more persistent weather anomalies that will increase the need of better weather forecasting and question the use of traditional farming methods (D'Agostino and Schlenker, 2016). The urgency to implement a new form of predictive modeling pertains only to weather, just one outlier of many, all the while farmers are still subject to the impacts of supply and demand and market prices. This scenario illustrates that focusing on just one outlier event is not enough?

This is because, in real life, farmers have to explore several avenues to make an optimum decision regarding their commodities. The aforementioned is the reason why initiatives like the USDA's Natural Resources Conservation Service and the National Water and Climate Center-NWCC, as traditional as it may be, might be losing their value. As D'Agostino and Schlenker 2016, solely Remaining responsible to produce and disseminate accurate and reliable forecasts and other climatic datum are trivial if it isn't specific towards a particular commodity or does not address other worldly events. Moreover, the manner in which they are collected and Distributed to farmers is of no use. Generation of forecasts in near real-time is what is needed. Result of new and upincoming models, such as the AI2Farm model presented in this Chapter. The cost of production forecasts for US major field crops, for instance, is centered upon projecting net returns at the national level. The projected costs are based upon the previous year's production costs and projected changes in the coming year's indexes of

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prices paid for farm inputs (Knoema, 2021). Although the long-term baseline projections are in a sense reliable, they fail to provide an explanation as to why the fluctuation in prices occurred to begin with. The inclusion of economic indices is a starting point, but the lack of awareness surrounding outlier events and their impacts is lacking, and an area in which this research expounds. Conversely, research by the International Production Assessment Division (IPAD) of the USDA's Foreign Agricultural Service (FAS) does take outlier events into consideration. The primary mission of IPAD is to produce the most objective and accurate assessment of global agricultural production and the conditions affecting food security around the world (Becker-Reshef *et al*., 2010). Outcomes of the IPAD are monthly crop production estimates and early Warnings of crop disasters. Though the outcome is similar in terms of early warning of crop disaster through the detection of weather outlier events, the method of collecting data is different in that it only focuses on one outlier event (weather) and doesn't concern economic indices. What continues to distinguish this research is that we have identified a new relationship that has not been studied before; considering the impact of both economic indices and outlier events? Observing one without the other is what separates research pertaining to localized versus global knowledge.

2. METHODOLOGIES

RESEARCH DESIGN

The study will employ a qualitative and analytical research design to understand how
Explainable AI techniques can be applied within the agricultural AI system. It focuses on the methodology of analyzing the existing AI models deployed in farming and evaluating how interpretability tools improve the transparency and decision-making of farmers.

3. DATA COLLECTION

Data was collected from the following sources:

- Published research papers on AI and XAI in agriculture
- Open-Source agriculture datasets - crop image, soil data, weather data
- Case studies from smart farming systems
- Government and industry reports on precision agriculture

These datasets include a number of features that characterize soil properties, weather conditions, pest symptoms, or crop growth indicators.

AI Model Development

A suitable model in machine learning was selected - Random Forest, CNN, or Boost-to achieve the following:

- Crop disease detection
- Yield prediction

Soil Moisture Forecasting

The model was trained using standard preprocessing steps:
Data Cleaning

- Feature selection
- Train-test split
- Model evaluation through accuracy, precision, and recall

Review of Interpretability Explanation quality

- Interpretability metrics: simplicity, clarity, relevance
- Farmer feedback through hypothetical scenarios
- Black-box model versus XAI-enhanced model comparison

The evaluation examined whether explanations improved:

- Trust in the AI system
- Understanding of predictions
- Decision-making accuracy
- Adoption readiness in farming

Result Interpretation

Output from the XAI tools were analyzed to understand the following:

- Most influencing factors of crop predictions
- How explanations help farmers avoid certain risks that might include diseases or over-irrigation
- How transparency improves model acceptance.

Related Work

Explainable AI

Transparency of decisions made by artificial intelligence and machine learning algorithms is becoming increasingly important, especially when people's everyday lives are directly affected. A decision justified only by "because the computer said so" is no longer good enough and can thus give rise to legal problems in cases of suspected unfairness and discrimination, such as in recruitment or credit granting decisions (Dosilovic *et al*. 2018; Guidotti *et al*. 2019). Some lawmakers even envisage a "right to an explanation"
While Edwards and Veale 2017 present different applications of black box machine learning and artificial intelligence methods, such as artificial neural networks, which are among the most powerful algorithms for prediction and classification tasks. There is, however, a trade-of between performance and interpretability in light of the complexity of these algorithms compared to white-box counterparts, including decision trees and linear regression.
Therefore, XAI became a popular field of research recently to make black-box algorithms transparent. In fact, the term XAI encompasses a very wide range of different approaches and so are the efforts to catalog and categorize those methods ((Barred Arietta *et al*. 2020; Raps *et al*. 2018; Tajo and Guan 2020). The most straightforward distinction is Between global and local explanations. While local explanations try to explain one individual predication, global explanation methods aim to explain the underlying model and its internal relations in a more general way, but these usually come at higher computational

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cost. Among the most commonly used, and frequently mentioned, are Local Interpretable Model-Agnostic Explanations (Lime) (Ribera *et al*. 2016), Anchors High-Precision Model-Agnostic Explanations (Anchors) (Ribera *et al*. 2018), and Shapley Additive explanations (SHAP) (Lundberg and Lee 2017) [27].

Data Farming Output Analysis Using Explainable AI

Data farming integrates large-scale simulation experiments with high-performance computing and sophisticated big data analysis techniques. The portfolio of analysis methods for these huge volumes of simulation data still holds development potential, and new methods are under constant development. As an extension, the concept of knowledge discovery in simulation data was developed to take a deep dive into the analysis side of data farming by providing a process model and workflow for using data mining methods and suitable, interactive visualizations (Feldkamp *et al*. 2015). In particular, this is helpful when models feature large number of relevant outputs that exhibit a complex, multidimensional response surface. When outputs are congregated into groups of disparate system behavior by using unsupervised data mining algorithms such as clustering, the relation between factors and outputs can then be investigated to conclude knowledge about the system (Feldkamp *et al*. 2020). For this purpose, supervised learning algorithms can create models that represent the relations between simulation input data and previously created clusters, from which in turn we can derive rules that can contribute to knowledge creation through human-interpretation. For a supervised algorithm, each simulation experiment is one training record (Feldkamp *et al*. 2020). More precisely, there is a classification problem to be solved. The underlying decision rules of such a classification can be easily extracted from white-box algorithms such as decision trees since those are explicitly visible. Other classification algorithms, like artificial neural networks or random forests, are very good at approximating a given input-output relation for the purpose of prediction but less good at actually and it is this that we need with respect to the derivation of analyses and knowledge. We can overcome this lack of understanding caused by such black-box algorithms with the help of XAI since such rules and their relations can be made visible by XAI and explained in an understandable and comprehensible way. Figure 1 shows the workflow that we proposed in. Easy-to-calculate relevance measures are the starting point, such as the importance of permutation features. These measures can only provide a rough overview since they assess the overall importance of a factor for the output of the model. For example, extending the analysis to the actual classifications, i.e., the assignment of factors to clusters, is the next logical step at the global level. Using these methods, we can draw conclusions about the differences between clusters, i.e., which factor scores contribute to which cluster assignments. Many XAI methods support explanations only for binary classifications. However, when using the KDS workflow, the data is typically categorized into several clusters, thus naturally leading to a multi-class classification problem. One could circumvent the latter by transforming their analysis into a one-versus-rest classification. That is, we compare each cluster of interest with the rest of the data. The disadvantage of such a process is that all these comparisons need a separate classification model and further XAI evaluation. The final step is to use local explanation methods, that can be used for the analysis of It selects representative points, such as the cluster medoid, which represents the mean of a given cluster.

Challenges

AI can modernize and optimize agricultural operations by allowing better decision-making, higher accuracy, and a reduction in wasted resources. Nonetheless, there are a lot of challenges that hold back the agricultural industry from fully embracing AI technologies due to data scarcity, economic limitations, environmental complexity, and trust-related issues.

The subsequent section discusses these challenges in detail, supported with references.

One of the biggest challenges involves a lack of good, large agricultural datasets, which are extremely important for the training of AI models. Agricultural data contains a lot of missing values, inconsistent measurements, and poor labeling. Liakos *et al*. [25] state that the absence of robust and standardized datasets greatly reduces the performance of AI in real-world farming scenarios. Kamilaris & Prenafeta-Boldú [26] point out that agricultural data can vary greatly from region to region because of different types of soil, climate, and varieties of crops. For such a varied agricultural context, generalization by AI algorithms is quite difficult.

Another big challenge is the low level of digital literacy among farmers, particularly in developing countries. Farmers usually lack necessary training in the usage of any digital tool, mobile app, or sensor or AI systems. Choudhary *et al*. [27] indicate that limited digital literacy is one of the main barriers preventing farmers from using advanced agricultural technologies. The given digital gap results in hesitation to use, misuse, or complete avoidance of AI tools that could otherwise support decision-making.

Another critical issue is the black-box nature of AI models. The majority of machine learning and deep learning models propose results without presenting how these results were generated. According to Lundberg & Lee [28], who introduced SHAP values, the absence of interpretability reduces trust among users. Explanations are needed in farming, since decisions influence crop yield, income, and risk. Lack of transparency requires farmers to treat AI outputs as unreliable or incomprehensible; thus, XAI is of great importance.

Economic factors also play a big role in the limited adoption of AI in farming. Most AI technologies require expensive equipment like drones, IoT sensors, automated tractors, and monitoring devices. Wolfert *et al*. report that small and marginal farmers face a financial burden while trying to buy

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and maintain these technologies. Even in cases where subsidy support is provided by the government, the cost of installation and updates remains a major concern.

Another major challenge pertains to limited Internet connectivity and technological infrastructure. Many AI applications rely on cloud computing, real-time updates, and constant access to the Internet. Jayaraman *et al.* [30] point out that rural areas often do not have stable Internet networking, which makes it hard to use AI-based tools effectively. Poor infrastructure restricts real-time farm data collection and the usability of mobile-based AI applications.

Performance of AI systems is also influenced by environmental variability. Soil properties, climate patterns, rainfall, temperature, and pest behavior vary from region to region.

According to Pantazi *et al.* [31], the diversity in these environmental conditions makes it challenging to develop universal working models of AI. A model trained in one region cannot be applied directly to another region without retraining or customization.

More specifically, there are socio-cultural barriers, such as resistance to the replacement of traditional farming techniques with systems using AI. Usually, farmers have a basis on intuition or hereditary knowledge and may view AI tools as unfamiliar or risky. According to Rose *et al.* [32], behavioral resistance and lack of trust reduce the pace of technology adoption in many agricultural communities. Training and demonstration projects should be conducted to overcome such resistance.

There are also several challenges regarding ethical concerns and data privacy. Farmers can be concerned about how their data, such as yield details, land information, or patterns of production, are eventually going to be utilized or by whom. Bronson & Knezevic [33] caution that ambiguous data governance policies can lead to mistrust, particularly when agricultural data passes through private companies. Finally, there is a lack of standardization across different AI models, their tools, and their data formats. Different companies create different systems with no universal guidelines. Bechar & Vigneault [34] note that without standard protocols, comparing AI solutions or ensuring reliable long-term performance becomes quite impossible. In conclusion, though AI certainly has the potential to enhance agriculture, the adoption of AI in agriculture is confronted with various challenges related to data quality, digital literacy, cost, trust, infrastructure, environmental variation, and ethics. Overcoming these barriers most especially with Explainable AI is crucial for creating a more accessible and farmer-friendly technological future.

4. CONCLUSION

This extensive review and methodological framework underline the critical juncture at which India's agricultural sector currently finds itself, along with the absolute urgency for systemic inefficiencies and climate vulnerability to be met head-on with AI computational solutions. We chronicled the transformational journey so far, stating how the tendency shifted from resource-intensive limitations of traditional and mechanized farming to precision- and data-centric requirements of Agriculture 4.0. The need for this progress beyond rudimentary techniques is reflected in both increasing populations and acute risks related to unpredictable weather patterns.

Our analysis has confirmed the transformational capability inherent in advanced analytical models, comprising different Machine Learning classifiers, high-speed Deep Learning architectures like the Extreme Learning Machine, and traditional Time Series methods such as ARIMA and RNN-essential in the attainment of the ultimate goals of crop selection and yield forecasting. However, the robust capability of such powerful models automatically implies a related commitment to interpretability.

The main distinctive methodological contribution of this work is the imperative integration of XAI, using SHAP and LIME methodologies, directly into the predictive framework. This moves decisively past a focus on simple accuracy metrics. It ensures that nonlinear relationships between critical inputs, like localized soil nutrients, rainfall, and thermal variations, are modeled in a fully transparent and comprehensible way. Further, this clarity enables farmers and policymakers alike to disaggregate complex predictions and render what are otherwise abstract algorithmic outputs as tangible, site-specific strategies consistent with the resource efficiency principle of the "five Rs ".

Looking ahead, realizing the full potential of this computational transformation requires overcoming significant practical hurdles. Future efforts must place a strong focus on engineering highly efficient AI models that can execute robustly with limited data and computation resources, especially in tightly constrained rural environments. We also realize that we cannot afford to make predictions based solely on historical data in a time when climate volatility is increasing every day. Thus, any further research must be based on dynamic climate simulation models, most importantly incorporating real-world constraints that have been ignored so far, including market dynamics, resource accessibility, and diverse socio-economic factors.

In all, this marriage of advanced, high-performance ML/DL techniques with federally mandated transparency via XAI is not just a technical refinement but a basic requisite to build resilient agriculture in the face of climate change. This systemic approach offers the best pathway toward mitigating farmer distress, improving food security, and ensuring sustainable resource management in a critical sector. It calls for continuous interdisciplinary collaboration of technologists and domain experts to realize its full benefits.

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