IJITCE

ISSN 2347- 3657

International Journal of Information Technology & Computer Engineering

Email : ijitce.editor@gmail.com or editor@ijitce.com

International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 13, Issue 2, 2025

Agricultural Excellence Harnessing Precession Technology for Optimal Crop yield

V. Amani[1], G. Rupasri[2], P. Vasanthi[3], B. Harish[4], Aradhyula Badrinath[5]

[1] Assistant Professor, Department of Data Science Engineering, Chalapathi Institute of Engineering and Technology, Chalapathi Rd, Nagar, Lam, Guntur, Andhra Pradesh- 522034

[2,3,4,5] Students, Department of Data Science Engineering, Chalapathi Institute of Engineering and Technology, Chalapathi Rd, Nagar, Lam, Guntur, Andhra Pradesh- 522034

Email id: amanivuyyuru25@gmail.com[1], gopidesirupasri@gmail.com[2], vasanthiputluri@gmail.com[3], harishbandi@gmail.com[4], badrinath.aradhyula@gmail.com[5]

Abstract: In modern agriculture, optimizing crop yields and managing resources efficiently are critical for sustainable farming practices. Traditional approaches to crop monitoring often lack the precision needed to address variability in plant health, soil conditions, and pest management. This paper introduces a technology-driven solution that leverages advanced machine learning techniques to enhance precision agriculture. By integrating multispectral imaging, sensor data, and predictive analytics, the system provides real-time insights into crop health, soil moisture, nutrient levels, and potential pest threats. The proposed model analyzes large datasets collected from drone-based and ground sensors to detect anomalies, forecast crop performance, and recommend timely interventions to farmers. Unlike conventional practices, this approach offers a highly accurate and data-driven method for targeted irrigation, fertilization, and pest control, ultimately leading to improved crop quality and yield. Experimental results demonstrate significant efficiency in resource utilization and up to a 20% increase in crop productivity. This study illustrates the potential of precision technology to transform agriculture, fostering sustainable practices and enhancing food security by enabling farmers to make informed decisions at every stage of the crop cycle.

Keywords: Precision agriculture, Crop yield optimization, Machine learning, Sensor data, Real-time crop monitoring, Sustainable farming, Predictive analytics in agriculture, Smart farming, Resource-efficient farming, Agricultural technology.

1.Introduction

Agriculture is facing unprecedented challenges, from climate change and resource scarcity to the growing demand for food driven by population growth. Traditional farming methods are often inefficient and unsustainable, leading to lower yields and increased environmental impact. Precision agriculture offers a transformative solution by leveraging advanced technologies such as GPS, drones, sensors, and data analytics to optimize farming practices.

This proposal explores how precision agriculture can be harnessed to boost farm yields, improve resource management, and reduce environmental impact. By adopting data-driven techniques, farmers can make informed decisions that lead to higher productivity, greater efficiency, and long-term sustainability. The integration of technology in farming not only enhances crop performance but also addresses the global need for sustainable food production systems.

Technologies Powering the Transformation

1. **Global Positioning Systems (GPS):** GPS technology allows for accurate mapping of fields and real-time positioning of equipment, ensuring efficient planting, fertilizing, and harvesting.
2. **Geographic Information Systems (GIS):** GIS helps in analyzing spatial data, such as soil properties and crop health, enabling tailored field management strategies.
3. **Remote Sensing & Drones:** Drones equipped with multispectral sensors can detect issues like water stress, nutrient deficiency, and pest infestation before they become visible to the naked eye, enabling timely intervention.
4. **Soil and Crop Sensors:** These sensors provide real-time information about soil moisture, nutrient levels, and plant growth, allowing for precise input application.
5. **Data Analytics & AI:** Big data and artificial intelligence enable predictive analysis and automated decision-making, helping farmers forecast yield, identify risks, and plan accordingly.

Benefits of Precision Technology in Agriculture

- **Increased Crop Yield:** Precision technology ensures crops get exactly what they need, when they need it, leading to healthier plants and higher productivity.
- **Resource Efficiency:** Inputs like water, fertilizers, and pesticides are used more efficiently, reducing environmental impact and lowering costs.
- **Sustainability:** Precision farming promotes responsible land use, improves soil health, and supports long-term sustainability goals.
- **Risk Reduction:** Early detection of potential problems through sensors and drones allows for proactive responses, reducing crop loss.

2.Related work

Sustainable agricultural development presents a crucial solution to address rapid population growth, facilitated using ICT in precision agriculture. Precision agriculture has transformed agricultural practices since its inception in the 1980s by utilizing technologies like remote sensing, the geographic information system (GIS), and the global positioning system (GPS). This integration has transformed crop production methods, resulting in a significant shift in agricultural mechanization thinking [3]. The combination of Internet of Things (IoT) sensors and artificial intelligence (AI) enables precision crop production. This cutting-edge technology employs sensors and artificial intelligence to optimize crop growth and yield, allowing farmers to collect detailed data about their fields and use it to make informed decisions about irrigation, fertilization, and pest control. Moreover, the greatest output benefit of precision agriculture is decreased temporal yield changes, which has increased yield stability and climate change tolerance [4].

The agricultural industry faces several significant challenges related to effectively utilizing new technologies, including discovering knowledge and correlations from historical records, processing large volumes of unstructured data in an appropriate format, managing extensive amounts of image and video data, monitoring crops using multiple sensors, and effectively communicating and integrating these data. Additionally, the adoption and accessibility of emerging technologies can be cost-prohibitive for individual farmers, while a lack of low-technology expertise requires extra training and better information and communication technology (ICT) management equipment. Ensuring the security of these systems is also a critical concern within the agricultural community [5,6].

Precision agriculture has undergone a transformation over the past three decades, advancing from strategic monitoring using satellite imaging for regional decision making to tactical monitoring and control allowed by low-altitude remotely sensed data for site-specific field-scale applications. The incorporation of data science and big data technology into precision agriculture strategies has led to a rapid analysis of data, facilitating timely decision making [7,8]. Farming could move to a more effective, productive, and sustainable paradigm through the integration of technologies such ground IoT sensing and remote sensing, using both satellite and Unmanned Aerial Vehicles (UAVs), as well as utilizing data fusion and data analytics [9]. Wireless connection methods, such as Wi-Fi, Bluetooth, and cellular networks, are utilized to transmit sensor data to a central hub, allowing farmers to monitor their farms in real time and make informed crop production decisions.

The improvement of agricultural goods and services while reducing investment costs represents a critical objective for future farming. Big data can effectively support diverse precision agriculture functions and assist in the extraction of information and insights from data in order to process important farming decisions and difficulties. In the agricultural sector, ICT plays an important role in developing breakthrough data creation, transformation, and management technologies [10]. Site-specific data collection, characterized by the acquisition of comprehensive information regarding events occurring during the vegetation period, offers a practical solution to this issue. This methodology enables the identification of underlying processes and their causes, leading to precise intervention that reduces adverse environmental effects. It creates a monitored and controlled environment in both spatial and temporal domains and sets the stage for a more advanced decision support system than is currently available. Previous studies have advocated for this approach [11,12].

3.Methodology

The experimental study aims to forecast agricultural yields by conducting experiments at Latitude: 16.7437°N, Longitude: 81.4775° E during 2022-23. This dataset includes essential variables such as rainfall (mm), temperature (°C), fertilizer application (kg), phosphorus (P) and nitrogen (N) macronutrient levels, and potassium (K) content. The primary output variable analyzed is crop yield, measured in quintals per acre (Q/acres). This dataset captures crucial environmental and agronomic factors influencing crop productivity, providing a foundational resource for predictive modeling and analysis. Predicting crop yields with machine learning was a dynamic and successful tool, as was selecting which harvests to plant and how to handle them during the period of growth. The farming system relied on a massive volume of data generated by multiple variables, which made it extremely complex. AI techniques could help with intelligent system decision-making. The study explored several techniques for forecasting crop yields by utilizing diverse soil and environmental factors. The primary goal was to develop an XAI model that could generate predictions. We have selected variables such as nitrogen and phosphorus, emphasizing their critical roles in crop growth and productivity. Specifically, nitrogen and phosphorus were chosen due to their established impacts on plant development and yield outcomes; nitrogen is essential for chlorophyll production and overall plant Vigor, while phosphorus supports root development and energy transfer processes. Experimental research and field studies involving live plants, whether cultivated or wild, were conducted in strict adherence to relevant institutional, national, and international guidelines and legislation. All methodologies employed in the study, including the collection of plant materials, followed these guidelines to ensure ethical and responsible research practices.

Data collection and preprocessing

Data collection process

The data used in this study was sourced from multiple databases, combining agricultural data with climatic and soil information to form a comprehensive dataset. Primary crop yield data was obtained from national agricultural databases, such as [specific name of national agriculture database, e.g., Indian Council of Agricultural Research (ICAR)], providing regional yield information, crop variety details, and growth duration. Climate data, which included variables such as rainfall, temperature, humidity, and solar radiation, was acquired from meteorological databases, specifically from [name of meteorological sources, e.g., Indian Meteorological Department (IMD)] for daily and seasonal trends relevant to crop growth. Additionally, soil characteristics, including organic matter, pH, and nitrogen content, were derived from [name of soil database, e.g., Soil Health Card Database]. Preprocessing involved several critical steps:

Data Cleaning Outliers and inconsistencies, such as abnormally high or low values, were identified using interquartile ranges and visual inspection via box plots. Missing values were handled by either imputing them with average values (where values were missing sporadically) or applying forward-fill methods for time-series gaps in climate data, which allowed us to retain the temporal integrity of weather patterns.

Normalization and Standardization To facilitate accurate predictions, numerical features such as climate variables and soil properties were normalized to a range of [0, 1] using Min-Max normalization. This step was essential to ensure that larger numerical values did not disproportionately influence the model. For variables with normally distributed data, Z-score standardization was applied, transforming them into a common scale with a mean of zero and a standard deviation of one.

Feature Engineering Key interaction terms were engineered to capture the interplay between climatic and crop growth parameters. For example, we derived temperature anomaly indices and rainfall stress indicators based on historical data to measure how unusual climatic conditions could affect yields. Similarly, soil nutrient levels were aggregated to create composite indices representing soil fertility. Such features enabled the model to better account for non-linear interactions between the environment and crop performance.

Data Splitting

The dataset was split into training and testing sets, with 80% of the data used for training and 20% reserved for testing to validate model performance. To avoid seasonal biases in the data, stratified sampling was applied, ensuring that the training and testing sets included an equal representation of different crop cycles and climate conditions.

4. Results and discussion

This graph y axis indicates observed values crop yield at the time of winter season and x axis various crops yield attributes Rainfall measured in millimeters, or rainfall (mm), temperature in Celsius, or temperature (C), and kilograms, or kg, of fertilizer Quintals per acre is the yield (Q/acres) of crops, potassium (K) is

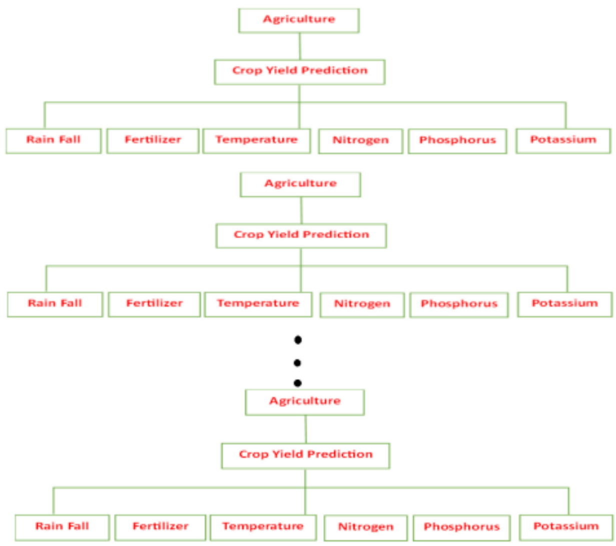


Figure: Crop yield prediction of agriculture random forest tree

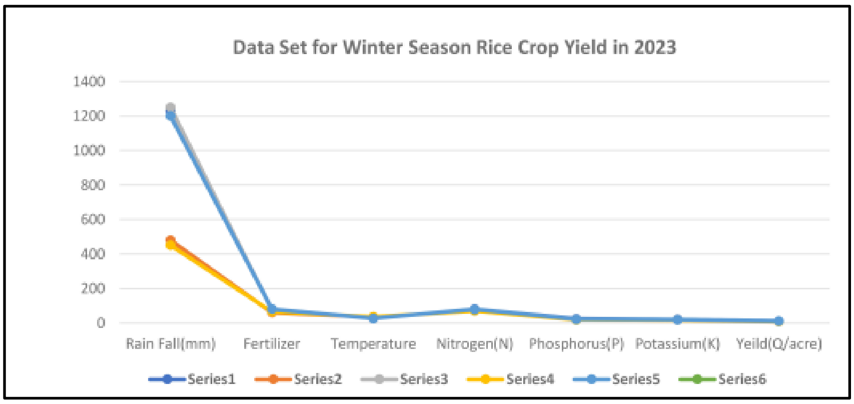
Table: Data set for winter season rice crop yield

S.No.	Rain Fall(mm)	Fertilizer	Temperature	Nitrogen(N)	Phosphorus(P)	Potassium(K)	Yield (Q/acre)
1	1230	80	28	80	24	20	12
2	480	60	36	70	20	18	8
3	1250	75	29	78	22	19	11
4	450	65	35	70	19	18	9
5	1200	80	27	79	22	19	11

International Journal of Information Technology & Computer Engineering

ISSN 2347–3657

Volume 13, Issue 2, 2025



A crop yield distribution graph is shown; two smaller maxima suggest that various crops grown on the same type of soil may generate different yields. The data analysis reveals two distinct crops and a relationship between crop yield and other columns. The first crop requires less rainfall, while the second requires more. Variations in crop production can be attributed to factors like soil type, temperature, fertilizer, and macronutrients. There is no direct correlation between fertilizer amount and crop output, suggesting high yields may be due to soil type and macronutrients. The first crop, rabi, is in the first cluster, while the second, kharif, is in the second. A linear relationship exists between crop output and nutrients In the Correlation Matrix Heat Map, the Explanatory Data Analysis shows that the dataset was collected for two different crops. There are two clusters in the dataset for temperature, precipitation, and crop production. Nutrient levels and crop yield appear to be proportionately correlated.

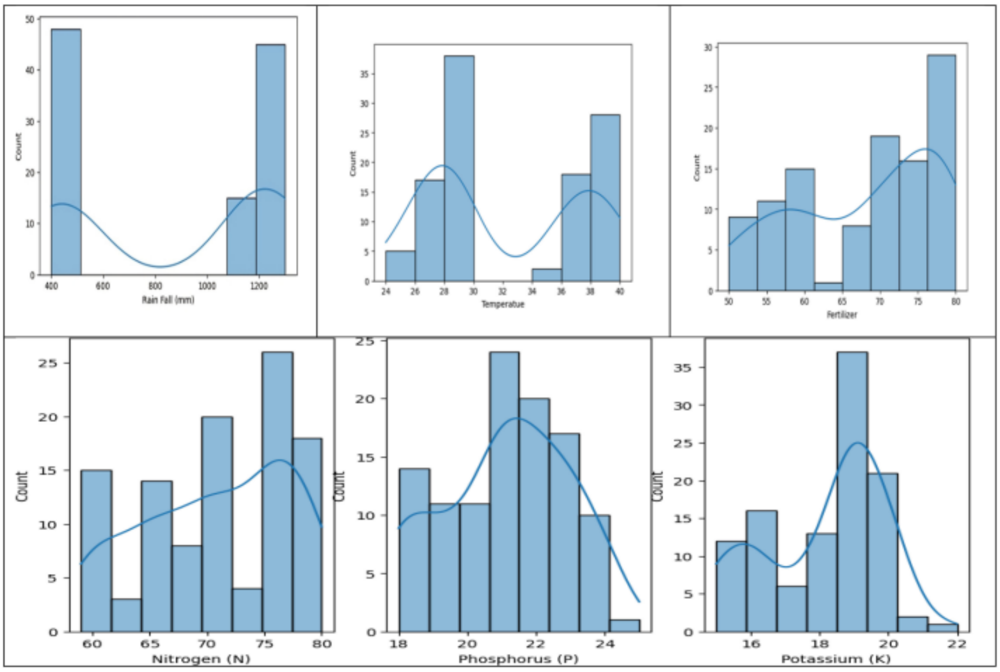


Figure: Histograms to Analyze Rainfall, Temperature, and Macronutrient distribution in rice fields during two seasons (Kharif and rabi) in the region

Discussion:

Recent studies have highlighted the potential of AI in improving crop yield predictions. For instance, deep learning models have been employed to analyze complex relationships between climatic factors and crop growth, achieving higher accuracy compared to traditional statistical methods (Raza, 2020). Furthermore, AI-driven approaches can dynamically update predictions based on real-time data, providing ongoing insights throughout the growing season. While AI models offer robust predictive capabilities, their 'black-box' nature often poses challenges in interpretability. This is where Explainable AI (XAI) becomes indispensable. XAI techniques aim to elucidate the decision-making processes of AI models, providing transparency and trustworthiness. By understanding the factors that influence model predictions, stakeholders can gain confidence in the results and apply them more effectively in agricultural practices. In this study, XAI methods such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) were integrated to interpret the AI models' outputs. These techniques identify key variables influencing crop yields, such as temperature, precipitation, and soil moisture levels, and explain their contributions in a human-understandable manner This transparency not only aids in validating model predictions but also provides actionable insights for optimizing crop management strategies.

Conclusion

The application of AI and XAI in predicting crop yields under climate change represents a significant advancement in agricultural technology. By combining the predictive power of AI with the transparency of XAI, this approach offers a reliable and interpretable solution for addressing the challenges posed by climate variability. As these technologies continue to evolve, they hold the potential to revolutionize agricultural practices, ensuring sustainable and resilient food production systems for the future. The integration of AI and XAI in predicting crop yields has significant implications for agricultural adaptation to climate change. By accurately forecasting yields, farmers can optimize planting schedules, select suitable crop varieties, and implement effective irrigation practices to mitigate the adverse effects of climate variability. Additionally, policymakers can use these predictions to devise strategic plans for food security, resource distribution, and disaster preparedness. Moreover, the explainability provided by XAI ensures that these predictions are not just accurate but also actionable. Farmers and agricultural advisors can understand the rationale behind the predictions, enabling them to make informed decisions that align with local conditions and sustainability goals. This approach fosters a data-driven agricultural ecosystem where decisions are backed by reliable and transparent AI insights. The article suggests that Light GBM Regressor, Decision Tree Regressor, and Random Forest Regressor are essential tools for predicting crop yield based on various factors such as temperature, potassium levels, rainfall, nitrogen content, and fertilizer application. Exploratory Data Analysis conducted in the study confirms the existence of distinct crop clusters in rainfall, temperature, and yield graphs, revealing a consistent relationship between nutrient levels and crop yield. Interestingly, this relationship appears unaffected by soil type, weather conditions, or crop variety. The study further demonstrates the superior performance of LightGBM Regressor, Random Forest Regressor, and Decision Tree Regressor in predicting crop yield using AI and XAI models.

References:

1. Cukier, K.; Mayer-Schönberger, V. The Rise of Big Data: How It's Changing the Way We Think about the World. In *The Best Writing on Mathematics 2014*; Princeton University Press: Princeton, NJ, USA, 2014; pp. 20–32.
2. Bhat, S.A.; Huang, N.-F. Big Data and AI Revolution in Precision Agriculture: Survey and Challenges. *IEEE Access* 2021, *9*, 110209–110222.
3. Zhang, N.; Wang, M.; Wang, N. Precision Agriculture—A Worldwide Overview. *Comput. Electron. Agric.* 2002, *36*, 113–132.
4. Yost, M.A.; Kitchen, N.R.; Sudduth, K.A.; Sadler, E.J.; Drummond, S.T.; Volkmann, M.R. Long-Term Impact of a Precision Agriculture System on Grain Crop Production. *Precis. Agric.* 2017, *18*, 823–842.
5. Khosla, R. Precision Agriculture: Challenges and Opportunities in a Flat World. In Proceedings of the 19th World Congress of Soil Science, Soil Solutions for a Changing World, Brisbane, QLD, Australia, 1–6 August 2010.
6. McBratney, A.; Whelan, B.; Ancev, T.; Bouma, J. Future Directions of Precision Agriculture. *Precis. Agric.* 2005, *6*, 7–23
7. Bendre, M.R.; Thool, R.C.; Thool, V.R. Big Data in Precision Agriculture: Weather Forecasting for Future Farming. In Proceedings of the 2015 1st International Conference on Next Generation Computing Technologies (NGCT), Dehradun, India, 4–5 September 2015; pp. 744–750.
8. Wolfert, S.; Ge, L.; Verdouw, C.; Bogaardt, M.-J. Big Data in Smart Farming—A Review. *Agric. Syst.* 2017, *153*, 69–80.
9. Alexopoulos, A.; Koutras, K.; Ali, S.B.; Puccio, S.; Carella, A.; Ottaviano, R.; Kalogeras, A. Complementary Use of Ground-Based Proximal Sensing and Airborne/Spaceborne Remote Sensing Techniques in Precision Agriculture: A Systematic Review. *Agronomy* 2023, *13*, 1942.
10. Ludena, R.D.A.; Ahrary, A. Big Data Approach in an ICT Agriculture Project. In Proceedings of the 2013 International Joint Conference on Awareness Science and Technology & Ubi-Media Computing (iCAST 2013 & UMEDIA 2013), Aizu-Wakamatsu, Japan, 2–4 November 2013; pp. 261–265.
11. Nyéki, A.; Milics, G.K.A.J.; Neményi, M. Improving Yield Advisory Models for Precision Agriculture with Special Regards to Soil Compaction in Maize Production. In *Precision Agriculture '13*; Stafford, J.V., Ed.; Wageningen Academic Publishers: Wageningen, The Netherlands, 2013; pp. 443–450.
12. Nyéki, A.; Milics, G.; Kovács, A.J.; Neményi, M. Effects of Soil Compaction on Cereal Yield. *Cereal Res. Commun.* 2017, *45*, 1–22.