AI-Driven Grid-Based Crop Allocation and Precision Farming

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Abstract

There is rapid increase in precision agriculture and the key aim of any developed farming program is to derive maximum value per square meter and at the same time ensuring long term sustainability. In line with the above description, our research project assigns the concept of Smart Crop Grid Planner, an online tool that would combine machine-learning models and on-farm data to provide a decision-maker with relevant and reliable information based on which one can make an agricultural decision. The user requires specifying the farm extent, soil ph, soil nutrients profile, irrigation potential, and the geographical coordinates in order to use the planner. The platform then divides the ground into a grid map and, assuming a multi-objective optimization approach, suggests in each grid cell which crop should be used given existing soil fertility, crop rotation constraints, the local weather conditions and current market rates. Soil, weather, and water data that is given in real time through application programming interfaces (APIs) guarantees that the recommendations can be applicable in various geographical areas. The end product map provides a graphical key in showing which crop has been recommended in each of the grids and comes along with prescriptive advice on the seeding rates, ratio of applying fertilizer and irrigation method to be applied on every location. This platform aims to improve the productivity and the environmental impacts of contemporary farming businesses by improving resources allocation, production predictions, and the adoption of the sustainable agriculture principles, especially in the districts that are data-scarce and where farming is more sensitive to climatic forces.

Keywords: *AI in Agriculture, Crop Recommendation, Smart Farming, Precision Agriculture, Grid-Based Land Segmentation, Machine Learning, Soil and Weather APIs, Multi-Objective Optimization, Variable Rate Seeding, Sustainable Farming*

1. Introduction

The main form of economic activity classified as cultivation of cash crops dominates across most of the developing economies with majority of the regions experiencing more than 70 percent of the economic activity. However, the farm cultures still remain which in most cases is a source of mismanagement of land, unsustainability and overuse of resources. At the same time, an increased climatic unpredictability, the rise in the rate of soil erosion, and the change in market requirements make the process of controlling agricultural production quite challenging. The modern agricultural industry should respond to those new challenges with data-driven and innovative technologies that would allow developing synthetic solutions to different problems.

The smart crop grid planner works hand in hand on these needs. Instead of in-depth planning of the agricultural lands and maximizing the yield by using machine-learning algorithms, the platform is supported by artificial intelligence and has a graphical display of every needed detail to plan the works. The system allows overlapping of data on land area, soil type and pH, irrigation potential, geographic location and season and thus parcels the land into grids and employs multi objective optimization to come up with the most appropriate crops in the most effective way. As a result, there is integration of weather forecast, soil property parameters and APIs regarding water availability. Thus, results are delivered in real time and very site specific to the farmer.

It has a system that has optimized density of seeds, quantity of fertilizers, and irrigation needs per each square cell supplying sustainable farming plans. The findings will be provided in the form of an interactive map where the colour-coded crop zones make information instantly understandable. At the end, the goal is strategic, where the aim is to bridge the gap between agri-technology and small- or medium scale farmers on a user-friendly, technology driven, and space oriented platform which promotes precision agriculture, crop growth, and environmental sustainability.

2. Literature Survey

Kumar, Roy and Sharma [1] have proposed a CR system powered by machine-learning technique that is built upon soil characterization, climatic conditions and historical cultivation data to suggest the best crop to be sown. Their architecture utilizes the techniques of it and looks into the content of soil nutrients, pH, seasonal records, and weather forecasts using techniques such as Decision Tree and Random Forest and XGBoost to increase the agronomic performance.

The API that Moreau, Lefevre, and Dubois [2] proposed was Weather API, oriented to agricultural use, which allows one to get the necessary climate indicators rainfall, humidity, and temperature in real time. Concurrently, Batjes and Hengl [3] also published SoilGrids, a collection of gridded soil information about the whole world, and therefore, offered precision agriculture in form of accurate descriptions of the soil properties, water content, and fertility.

As exemplified by Fernandez, Liu, and Schmitz [4], land segmentation via satellite imagery was analyzed through the means of grid-based approach and with K-means clustering. Their results indicate a clear representation of the agricultural properties through the grid cells which are lastly streamlined through the use of linear programming to provide nuances to the land allocation processes in terms of recourse supply, irrigation potential and reasonable exerted demand in the market.

Banerjee, Wang, and Verma [5] emphasize the leading importance of Explainable AI (XAI) in the sphere of agriculture. Helps them understand the AI models which drive crop forecasting and make it more transparent thus improving the transparency given to farmers and leading towards more trust and decision making.

Systematically, Thomas, Raj, and Nair [6] found out the performance of the Variable Rate Seeding (VRS), which is a modern precision-farming approach to calibrating the density of planting with site-specific conditions. Their results showed that VRS improved crop yields and efficiency of the resources through a unit by unit grid-based distribution of the seeds in accordance to real time data.

Miller & Johnson [7] prove the effect of artificial intelligence on the modern agriculture by analyzing John Deere. Their analysis shows that: With smart systems in place, e.g. live dashboards and triggered alerts, farmers are able to inspect the conditions of their fields, and make evidence-based decisions based on a real-time analysis of quantitative data.

Famonaut by Rao, Gupta, and Das [8] provide an API that has real-time information on the crop health and soil moisture. The research reveals that when these APIs are implemented in the farming mechanism, the farmers can use them to picture their fields as grids in colour and get usable notifications regarding requirements of irrigation and fertilization.

3. Proposed methodology

The system will be an artificial intelligence powered tool that could assist farmers with making crop planning decisions supported by data. It divides agricultural lands into squared grid areas and then

proposes crops to grow on the unit that should suit the local environment and agronomic requirements. In order to begin a user will input data into land size, soil type, pH level, irrigation capacity, location, and the season of the year. The platform uses real time APIs including ISRIC SoilGrids, Weenat, and Farmonaut to gather information on the soil nutrients, moisture and weather conditions. Then machine-learning models, i.e., Random Forest and XGBoost will be used to make predictions as to which crop will be the most effective in each of the grid segments.

The system turns to multi-objective optimization techniques like Linear Programming (LP), weighing soil health, crop rotation, water availability, and market value to recommend crops that balance yield and sustainability. Coupled with that, the platform gives grid-specific instructions on seed rate, fertilizer and irrigation. All the outcomes are displayed through interactive map color-coded, and Explainable AI tools such as SHAP or LIME are included, so the users would know the specifics of how the system came to its decisions.

3.1 Proposed model diagram

The proposed AI-Driven Grid-Based Crop Allocation grid-based crop allocation architecture is structured such that it will streamline crop planning since it will automate the decision-making processes via intelligent data analysis. A sequential workflow incorporates user input in combination with streamed real-time data, entwines the information with machine-learning estimations formed of streaming information, and ends with a multi-objective representation module. The combination results in very precise, sustainable, and tailored recommendation to each cluster of land grids as depicted in the diagram below:

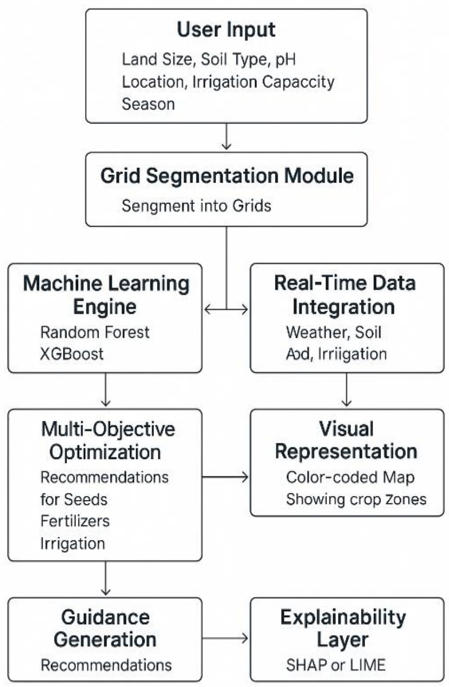

Figure 3.1.1 Flow of Proposed model

3.2 Block diagram of ML module

The machine learning module carries out the mathematical reasoning which converts the inputs into a reliable crop prediction. The block diagram of the functioning of the system is shown below.

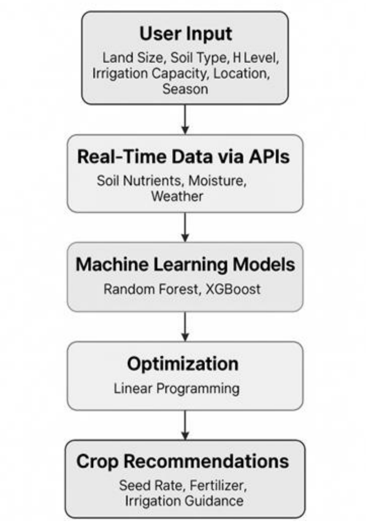

Figure 3.2.1 Model flow diagram of ML module

The system will first accept the input parameters consisting of the soil type, amount of fertilizer, geographical location and available irrigation capacity besides the real time data that will be obtained through external APIs. Light preprocessing is being performed on such information and then the information is trained employing various available ML algorithms: Random Forest, Decision Tree, and XGBoost. Each of the algorithms is trained using historical agricultural data sets in order to provide a suitable score on crop suitability. Based on the developed models, their performance is tested using such parameters as accuracy, F1-score, mean absolute error, and the best model is chosen. They are used to make predictions that are fed to an optimization engine to place crops in grid-wise locations upon verification. Such stringent process eliminates demotion of the model output in terms of accuracy, interpretation, and sensitivity to local aspects.

4. Mathematical Formulas

Targeted architecture combines processes in machine-learning and crosses them with multi-objective optimization to combine the features of Random Forest and XGBoost processes with exact crop suggestions and grid partition land coverage. Equations of the system are the following:

4.1. Crop Suitability Score Calculation (Regression Output)

In this case, the suitability of a crop, c, in a grid, g is predicted using a regression: either Random Forest or XGBoost.

$$S_{g,c}=f(X_g)$$

Where:

- $S_{g,c}$: Predicted suitability score of crop c in grid g
- X_g : Feature vector for grid g (includes pH, NPK values, temperature, rainfall, etc.)
- f: Trained machine learning model

4.2. Multi-Objective Linear Programming (Crop Allocation)

To maximize productivity and profitability simultaneously with lower use of resources, a multi-objective linear programming is implemented.

$$\text{Maximize: } Z = \sum_{g=1}^{n} \sum_{c=1}^{m} (Y_{g,c} \cdot P_c)$$

Subject to:

- Land constraint:

  $\sum_{c=1}^{m} Y_{g,c} = 1, \forall g \in [1,n]$

- Water constraint:

  $\sum_{g=1}^{n} \sum_{c=1}^{m} Y_{g,c} \cdot W_c \leq W_{total}$

- Soil nutrient constraint (e.g., Nitrogen):

  $N_g \geq N_{min,c} \cdot Y_{g,c}, \forall g,c$

Where:

- $Y_{g,c} \in \{0,1\}$: Binary decision variable (1 if crop c is assigned to grid g, else 0)
- P_c: Expected profit or market value of crop c
- W_c: Water required for crop c
- N_g: Available nitrogen level in grid g
- $N_{min,c}$: Minimum nitrogen required for crop c
- W_{total}: Total available water for all grids

5. Graphs

5.1. Model Accuracy Comparison:

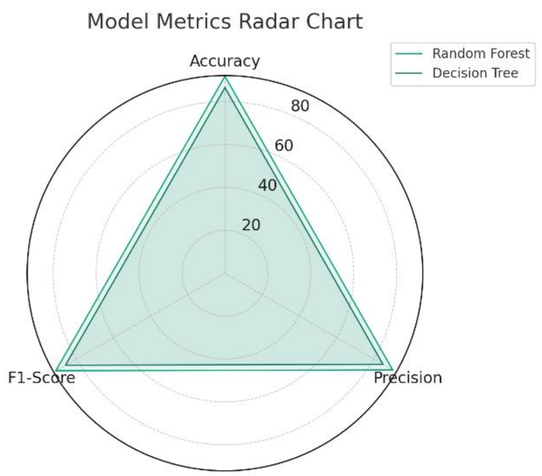

Figure 5.1.1 Model metrics radar chart displaying Model accuracy comparison

In the analysis of the different machine-learning models that are to be taken as effective regarding crop suitability predictions, the reviewers used the overall accuracy. The results are unambiguous, the Random Forest classifier obtained the best score and received 91.8 %. The Decision Tree model, in comparison was able to come second with a percentage level of 86.5 %. Such difference in outcomes demonstrates that the ensemble methods, in this case, Random Forest can be defined as more stable and able to generalize on crop-recommendation tasks compared to individual decision trees.

5.2. Predicted Crop Yield Distribution:

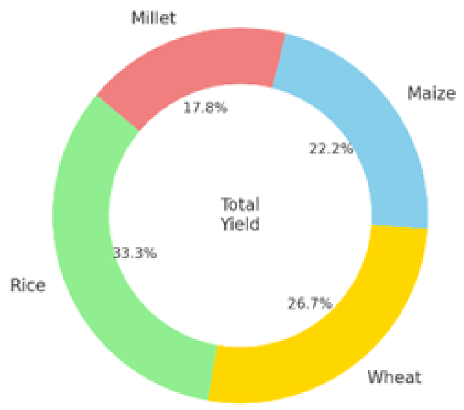

Figure 5.2.1 Donut Chart Showing Predicted Yield per Crop

The following chart is the estimation of the yield of particular crops according to the machine-learning models that were used in our study. Following these models, the highest contribution of Rice is expected to be at 33.3 percent followed by other crops on the list namely Wheat (26.7 percent), Maize (22.2 percent), and Millet (17.8 percent).

These predictions were made on the basis of the environmental conditions like nutrients, PH and moisture content of soil and climatic parameters like temperatures, and rains coupled with grid-related characteristics. This chart enables farmers to consult and know which crop will be most productive at a particular time on their farm land thus improving the decision making process that is associated with increased productivity and profitability.

6. Experimental results

The observation of the literature related to the demonstration of machine learning model deployment with agricultural applications and the use of AI-driven systems enables proving the potential of the Smart Crop Grid Planner. Overall views about key results of experiments are presented in the below table.

System/Model	Task	Key Algorithms	Performance Metric	Best Value
Crop Recommendation System	Crop Recommendation	Random Forest, SVM, Logistic Regression, Decision Tree, GNB	Accuracy	Up to 99%
RFXG Ensemble	Crop Recommendation	Random Forest + XGBoost	Accuracy, 10-fold Cross-Validation	98%, 0.981 ± 0.0119
TCRM (Cloud-based)	Crop Recommendation	RF, Extra Trees, Dense, Multi-head Attention	Accuracy, Precision, Recall, F1 Score	Accuracy: 94%, F1: 93.97%

Standalone Models	Crop Recommendation	RF, XGBoost, Extra Trees, MLP, DT, LR	Precision, Recall, F1 Score	Up to 96% (RF/XGB), MLP only 43% F1
Forecasting Model	Optimal Harvest Prediction	Decision Tree	R^2 Score	99%
Crop Yield Prediction	Yield Estimation	LR, RF Regressor, LightGBM, DT Regressor	Accuracy, R^2, MSE, MAE	Accuracy: 95.87%, R^2: 0.92, MSE: 0.02
Hybrid Model (E-Kisan)	Crop Yield Prediction	RF, LSTM, XGBoost	R^2 (Yield Prediction)	0.9827 (Overall), 0.9721 (Rice)
Fertilizer Recommendation	Nutrient Optimization	Gradient Boosted Trees, XGBoost	Accuracy, Precision	Accuracy: 99%, Precision: 99.1%
Smart Irrigation System	Water Management	Fuzzy Logic	Water Savings, Calibration Rate	61% Savings, 66.23% Faster
John Deere ExactEmerge™	Planting Efficiency	AI Sensors, ML, GPS	Planting Efficiency	20% Higher

7. Conclusion

Artificial intelligence-based Smart Crop Grid Planner represents a brand new technological tool to have a real breakthrough in modern agrarian management. Using machine-learning algorithms and instantaneous input of environmental parameters, it makes weather, soil moisture, and the associated data actionable field plans. The device splits cultivated land into a grid mesh pattern and practically the best places to plant each crop are identified through multi-objective optimization to ensure the best turnout in terms of suitability and productivity. The use of Smart Crop Grid Planner also leads to improvement in the financial stewardship, cost-cutting on operating costs and soil preservation, thus achieving a balance between economic demand and environmental factors.

In spite of these favourable properties, the Smart Crop Grid Planner has a number of issues that can be observed during its implementation. The most important are technical barriers, i.e., data quality, interoperability, and reliability of supportive infrastructure as well as socioeconomic ones, i.e., the digital divide, high initial capital demands, and reluctance of the agricultural producers caused by a lack of awareness or confidence in the use of technologies based on artificial intelligence. Eliminating these obstacles will require creation of strong data platforms, development of user friendly interfaces that could be understood and used by end users, and development of focused training programs to farmers. Favourable policy surroundings and economic encouragements towards its adoption will also play a vital role in its widespread auto adoption. With such additions of complementary measures, the AI-Powered Smart Crop Grid Planner can be an instrument of change to redesign agricultural procedures in the future by focusing on resilience, productivity, and sustainability.

8. Future enhancement

At present, the Smart Crop Grid Planner, which is the advancement of precision agriculture, driven by AI, although it is a worthy breakthrough, does not lack limitations that should be evaluated systematically. The most important issues related to these are data quality and interoperation of systems. Strict schedule of validation, integration, and standardization should thus be exercised over a vast volume of heterogeneous sensors, platforms, and application programming interfaces (APIs) so that the planning agency would be able to maximize its area of coverage. At the same time, transitioning to universal data formats would also help the effortless integration of various technologies across the field of agriculture and eventually contribute to the development of a more structured technological environment.

The necessity to promote Explainable AI into the planner is also imminent such that its outcomes are executable and transparent to the final user. In addition, more up-to-date methods of optimization, already implemented in the system as multicriteria optimization, are suited well to capture dynamic crop rotation schemes and multi-year planning thus entailing longer-term soil health, pest resistance and market adaptability. A stronger collaboration of the planner with robotics and automation, especially tractor automation and drones equipped with the AI tools can reduce the amount of necessary labour and increase the efficiency of operations. Offensively predictive maintenance is also AI-enabled, capable of extending the service life of farm equipment and the reduction in shutdowns. The forecasting models of pest and diseases based on granular biological and climatic data can also be added to the existing architecture, with the interventions (timely and on-site) minimizing the use of chemicals.

Additional developments and enhancements can potentially use blockchain technology and hence provide full transparency across the agricultural supply chain, an improved direct market place access of the farmers and greater traceability of the products. As per the bridge of the digital divide, low-cost, mobile-first edition of the planners should be warranted, which is designed with uncomplicated interfaces of the small and periphery farming communities. Moreover, it must incorporate the ability to carry out adaptive learning throughout the process by making the AI model constantly adapt to data related to the farm in question,That will improve personalization and accuracy as time goes on. Lastly, in order to address the upcoming issue arising out of climate change, the planner ought to incorporate options that enhance resilience to drought, optimal water use, and carbon-limiting activities. All these improvements will complement the Smart Crop Grid Planner as a sustainable, inclusive, and immortal system of sustainable agriculture.

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