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Smart Agriculture & System Advancements In Crop Field Integrating Machine Learning And Agriculture Data

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Abstract:
By using IoT (Internet of Things) along with artificial intelligence (AI) and data analytics tools, the "Smart Agriculture and System" project aims to transform conventional farming practices. Through the application of real-time data from an array of sensors installed throughout farm fields, the system will keep track of and optimize environmental variables like soil water content, temperature, humidity, and sunlight. The information gathered is processed and examined to offer actionable insights and automate aspects of farming such as irrigation, fertilization, pest control, and crop surveillance.

This project involves the use of an intelligent decision-support system that offers farmers real-time notifications, suggestions, and predictive analysis for maximum crop output. The use of AI models enables accurate forecasting of weather and crop conditions, lessening dependence on conventional guesswork. The system is also made remote-controllable, enabling farmers to view vital information and operate systems using smartphones or computers**.**

1. INTRODUCTION

Also known as smart farming, digital agriculture improves conventional agricultural practice techniques by combining new-age technologies such the Internet of Things (IoT), artificial intelligence (AI), robots and big data analytics. The system's goals are sustainable production, data-driven efficiency, and automated systems all working together to increase farming activity. Smart farming's several field sensors gather real-time data from the field comprising temperature and moisture levels as well as weather reports and crop status reports. The gathered data enables farmers to get strategic information that guides improved irrigation and teaches them how to handle pests and fertilizers together with crop production. Smart agriculture transforms farm operations for peak efficiency by using modern developing technologies such IoT, artificial intelligence, machine learning and robotics and big data.

Using real-time data, smart agriculture aims to increase production, support sustainability, and lower expenses. Sensors, drones, and other linked devices measuring vital traits such soil moisture, weather conditions, crop health, and pest infestations gather data. The obtained data is used to examine information for better decision-making on irrigation, fertilizer, pest control, and crop management, consequently raising yields and lowering environmental effect. By lowering running costs, smart agriculture increases farmers' profitability.

By automating and streamlining practices, farmers can reduce labor costs, maximize resource utilization, and make the entire farm more efficient. This results in increased yields and losses reduction, boosting profitability. Moreover, AI-based insights and data analytics provide personalized recommendations to farmers to enhance crop health and yield potential, so they can make informed and cost-effective choices. In summary, smart agriculture is the future of agriculture that combines technology to produce more efficient, sustainable, and profitable agricultural systems. Having the potential to revolutionize how food is produced, smart agriculture is the key to providing a growing global population with food while maintaining a healthy environment. With time, technology keeps improving, and the influence of smart agriculture will continue to increase, assisting farmers in meeting challenges of the new world alongside the contribution to a sustainable agriculture system.

RELATED WORK

Under smart agriculture, there are several projects and research studies that have been established or underway, targeting the use of multiple technologies such as IoT, AI, data analytics, drones, robotics, and others. The following are some examples of associated work and projects under the field of smart agriculture and systems:

IoT-Based Precision Farming: Research projects will work towards creating IoT-based solutions for collecting data through different sensors (e.g., weather, soil, moisture) to enable Farmers must utilize data-informed decision-making. The utilization of data enhances the efficiency of irrigation systems and the efficacy of fertilizer administration and pest control methods.

Our team built AI-driven machine learning algorithms that anticipate agricultural yields, disease outbreaks, and infestations.

• Relevant Literature: Researchers have illustrated how artificial intelligence models forecast future agricultural yields by examining environmental data and historical farming outcomes. This technology enables farmers to enhance planning and optimize agricultural management practices.

Example: The Agri-Tech Labs project employs machine learning models to forecast crop yield and detect potential pest or disease infestations using satellite imagery and past data.

Smart Sensor-Based Automated Irrigation Systems

•Description: Automated irrigation system projects utilize intelligent sensors and data analysis to maximize the use of water.

Related Work:

• Smart Irrigation Systems: Most projects aim at the design of automatic irrigation systems that switch on with soil moisture readings or weather conditions. This saves water and provides crops with the best amount of water.

Example: The Water-Smart Irrigation System incorporates IoT - based sensors that track soil moisture and weather information. It adjusts irrigation timings automatically, lessening water usage drastically

. Drone Technology for Precision Agriculture

•Description: Drones are employed for aerial monitoring of huge agricultural farms, providing information on crop health, soil health, and pest management.

Related Work:

Agricultural Drone Systems: Certain projects employ drones with cameras and sensors to track crop health and soil status. Drones can take high-resolution images to identify plant diseases, nutrient deficiencies, or pest infestations.

Example: The Precision Agriculture Using Drones project combines drone-based image acquisition

EXISTING SYSTEM

Various existing smart agriculture systems have been implemented to boost efficiency, save resources, and raise productivity. The systems use different technologies such as IoT, AI, drones, machine learning, and big data analytics. Some of the current smart agriculture systems and projects that have had a significant impact are mentioned below:

1. John Deere's Smart Farming System

• Overview: John Deere, one of the world's top agricultural machinery companies, provides various smart farming technologies in the form of Precision Agriculture tools incorporated into their products such as tractors, combine harvesters, and sprayers.

• Technology: The system utilizes GPS, IoT, and sensors to gather real-time information from the field. This information is processed in their Operations Center, which assists farmers in monitoring crop health, modify irrigation schedules, and maximize planting and harvests

2. REQUIREMENT ANALYSIS

In creating a Smart Agriculture System, it is necessary to perform a Requirement Analysis to guarantee that the system is aligned with the requirements of farmers and agricultural stakeholders. This process entails determining the objectives of the system, user requirements, technological specifications, and possible challenges. The following is a comprehensive outline of the Requirement Analysis for a Smart Agriculture System project.

1. STAKEHOLDER IDENTIFICATION

• Farmers: The end users who will be using the system directly for agricultural operations like irrigation, pest management, and crop monitoring.

• Agricultural Enterprises: Businesses that are part of the supply chain of agricultural produce, such as suppliers of fertilizers, pesticides, and seeds.

• Agricultural Advisors: Specialists or consultants who will give advice and recommendations to farmers based on information supplied by the system.

• Government Agencies: Government agencies responsible for regulating agricultural standards, crop monitoring, and environmental stewardship.

• Tech Providers: Entities or individuals that develop the IoT devices, sensors, cloud platforms, and AI algorithms employed in the system.

2. SYSTEM OBJECTIVES

• Optimize Resource Usage: Reduce the use of resources (e.g., water, fertilizers, pesticides) through real-time information and predictive analysis.

• Maximize Crop Yield: Leverage data to make crops healthier and more productive by giving farmers more insights into the health of the soil, climate conditions, and pest attacks.

• The future of agriculture necessitates sustainable practices that encompass waste reduction, water conservation, diminished chemical pesticide application, and enhanced soil health preservation.

• Remote Monitoring and Control: Enable farmers to oversee their farms and administer agricultural operations via mobile applications or web platforms.

• Data-Driven Decisions: Give actionable insights via data analytics and AI-based forecasts that enable farmers to make educated decisions.

3. FUNCTIONAL REQUIREMENTS

Functional requirements establish the key functionalities of the system. The following are some important functional requirements for a Smart Agriculture System:

3.1 Real-Time Monitoring

• Data Collection: Gather information from IoT-based sensors (soil moisture, temperature, humidity, light, pH levels).

• Sensor Integration: Integrate multiple sensors for environmental and crop condition monitoring (e.g., moisture sensors, weather stations, drones for crop health monitoring).

• Data Transmission: Transmit sensor data securely to a cloud server or local processing unit.

3.2 Automation and Control

• Irrigation Control: Automate irrigation systems using real-time soil moisture levels and weather forecasts.

• Fertilization Control: Control automated fertilizer application systems using soil nutrient levels.

• Pest and Disease Management: Initiate automated pest control actions or suggest pesticide application when specific thresholds are reached.

3.3 Data Analytics and Visualization

• Predictive Analysis: Utilize machine learning models to forecast future crop production, pest outbreaks, or weather patterns.

• Visualization Dashboards: Give an easy-to-understand interface that depicts data in visual representations such as graphs, charts, and maps for farmers to make informed decisions.

• Alerts & Notifications: Send notifications or alerts regarding crop health, weather conditions, irrigation needs, pest attacks, etc.

3.4 Mobile and Web Interface

• Mobile Application: Offer an application that farmers may use to receive alerts, system control (e.g., irrigation), and crop management functionalities.

• Web Portal: More in-depth dashboard for agricultural consultants, farm managers, and administrators to remotely access the system.

3.5 Integration with External Systems

• Weather APIs: Incorporate weather forecasting APIs to make adjustments to irrigation and other processes in accordance with weather forecasts.

3. PROPOSED SYSTEM

Proposed Framework for Intelligent Agriculture

An advanced agricultural system utilizing IoT technology and cloud analytics, together with automation and data analysis, provides a comprehensive solution for agricultural improvement. The next section delineates the critical architectural components of the proposed system, accompanied by an exhaustive inventory of necessary functional elements.

1. OVERVIEW OF THE PROPOSED SYSTEM

The Smart Agriculture System (SAS) proposed will streamline agricultural processes with automation and real-time data capture. Through the use of IoT devices such as soil moisture.

Benefits:

Smart Agriculture System has many benefits to farmers, the environment, and the agricultural industry as a whole. The integration of IoT solutions with data analytics, AI capabilities, and automation technologies revolutionizes agriculture, enhancing sustainability and increasing production metrics. A Smart Agriculture System offers three primary benefits as part of its operation.

1. HIGHER CROP YIELD

• Decisions Based on Data: Agriculturalists use real-time data from monitors, weather forecasts, and predictive analytics to help them make choices about what to plant, how much water to use, fertilizer, and how to get rid of pests.. This results in optimized crop growth conditions, leading to increased yields.

• Optimized Resource Utilization: Effective soil moisture, nutrient, and pest control management ensures crops get the correct amount of resources, increasing productivity.

2. EFFECTIVE RESOURCE MANAGEMENT

• Water Conservation: Intelligently controlled irrigation systems employ soil water status and weather information to initiate irrigation only when required. This prevents wastage of water and allows farmers to save water, particularly in areas with water scarcity.

• Minimized Fertilizer and Pesticide Utilization: With accurate tracking of soil health and pest infestations, the system can provide or automate advice on the release of fertilizers and pesticides. This minimizes waste, helps to target more effectively, and reduces environmental contamination.

HARDWARE REQUIREMENTS

- System : Pentium IV 2.4 GHz.
- Hard Disk : 40 GB.
- Floppy Drive : 1.44 Mb.
- Monitor : 15 VGA Colour.
- Mouse : Logitech.
- Ram : 512 Mb.

SOFTWARE REQUIREMENTS

- Operating system : Windows XP/7.
- Coding Language : python
- IDE : anaconda navigator

MATERIALS AND METHODS

A. STUDY AREA AND EXPERIMENTAL DESIGN

Research data originated from the wheat experimental field located at the National Agricultural Research Centre (NARC) in Islamabad Pakistan at a geographic position of 33.6692481◦ N, 73.1076928◦ E. The experimental field organizes three main plots that introduce wheat sowing dates on Nov 15, 2021 as well as Dec 15, 2021 and Jan 15, 2022. The suspended wheat varieties are arranged in 15 different samples measuring 1.5m X 6m within each replication of three planned systems. Every replication features 112.5 g/plot seed planting of 15 variety lines (V1, V2, V15). The research reduces errors in statistics with 45 experimental plots arranged into three replicates each containing 15 wheat seed varieties. RCBD design served to organize the experiment based on Figure 2 as illustrated in the research.

B. PREPARATION OF DATA

1) COLLECTION OF DATA

The assessment of wheat yield requires collection of information about

Multiple bands together with agronomic measurements of different characteristics are collected from the start to completion of each wheat growth season. The DJI Phantom 4 drone collects multispectral data through its Sentera multispectral imager that obtains data from terrestrial and red wavelengths.

near in- and red bands. The aerial field images are acquired with automated flight planning through dedicated Sentera 'Flight Agent' software which controls the drone operations. DJI Phantom 4 drones acquire multiple flights at 80ft height while exceeding 80% ground coverage during clear weather conditions with limited wind on selected days between 10:00 am and 11:00 am local time. The drone data collection process started when the crops under SD3 reached the single shot stage during February 2022 and finished as the SD1 crop reached its ripening stage. Raw datasets were collected through eight drone missions which took place starting from February 10 to April 15 in 2022. The raw images require processing through Web ODM developed by Open Drone Map as an open-source software to generate mosaics [22]. Web ODM functions as an advanced tool to generate point clouds together with geo referenced models and elevation models as well as 3D maps. The platform works with multiple processing engines to boost its operational effectiveness.

Structure from Motion (SfM) and Multi-View Stereo (MVS) methods are used to process images from UAVs and satellites.

This web-based interface from the software makes it easy to apply complex image processing algorithms..

The system functions to analyze enormous datasets before turning photographs into exact geographic coordinates.

The outputs find industrial applications in agriculture together with urban planning and environmental monitoring as well as other sectors.

Web ODM creates mosaic images that subsequently get split into 135 polygonal forms before researchers extract meaningful crop information from each field sector. Wheat crop development stages were measured through ground surveys which took place in March and April 2022 based on the fields' different sowing dates. The assessment of wheat yield parameters begins with tiller counts per square meter and bundle weight measurement per square meter and grains weight count per square meter to determine the wheat yield estimation.

2) DATA PREPROCESSING

Supporting data transformation occurs prior to sophisticated analysis techniques through the application of multiple skill-based procedures. All efforts during this phase address data cleaning together with feature engineering and data scaling alongside categorical feature handling and integration steps and feature selection procedures. Multiple preprocessing steps were performed to improve our dataset quality for regression analysis while considering its characteristics.

- The high performance of the ML model depends on the essential data cleaning step which results in successful implementation of the regression method. The gathered data receives thorough analysis to detect anomalies along with missing data points and data noise while inspecting data point consistency. The application of ML begins after researchers eliminate all detected anomalies from the dataset.

- Feature Engineering serves as a data manipulation process to find important domain-based patterns which influence ML algorithm performance strongly. An analysis of gathered data yielded nine features from six VIs and agricultural stage information and number of tillers/m2 and bundle weight/m2 records. The regression models use these features for making predictions about grain yield.

- The technique of data scaling transforms data points to achieve a predefined range as a means to improve the performance of ML models. The subsequent data scaling procedure applies to the derived features to normalize their values between 0 and 1.

- On the other hand One hot Encoding creates new variables from categorical data according to the specified method. The wheat grain yield prediction feature set includes growth stage as a categorical variable through one-hot encoding technique to generate numerical values.
  • Feature selection is a crucial preprocessing technique that enhances the performance of ML regression models by preventing data overfitting situations. Regression analysis becomes possible through selecting a feature subset of importance from an extensive collection of features. The wheat grain yield prediction model includes nine selected features as part of its feature set. To determine the most influential features for selection the researcher calculated the correlation between every feature and the target variable.

4. RESULTS

The process of wheat grain yield prediction employed execution from three regression systems: random forest, LASSO and XGB. All three regression methods prove widely selected in data scenarios which present many attributes but seek to prevent overfitting issues.

Nine traits from the gathered dataset included the number of tillers, bundle weight, SR, SAVI, OSAVI, IPVI, NDVI, TSAVI together with growth stage characteristics. Grain weight represented the most important variable for prediction purposes..

The investigation between feature variables and the target variable was performed through correlation matrix analysis at each stage of wheat crop development as shown. The correlation values within these matrices adjust according to wheat crop growth pattern. The target variable shows significant correlation with all computed VIs during February before March and April measurements result in declining correlation values.

The measurements of different VIs arise from chlorophyll levels in plants as they grow until grain filling before chlorophyll amounts decrease until the end of development. The Bundle weight and Number of tillers measurements were unavailable when performing the February data collection because they became accessible during March 2022.

Feature variables create multi collinearity patterns since they correlate with additional features so we cannot separately identify the target variable impacts of each feature. Developing 'k' most important and relevant attributes requires implementing correlation statistics as the solution to this problem. After correlating feature and target variables the F-value works as an importancce score for each feature. The F-values for each numerical feature are shown for all wheat crop developmental periods. The regression feature selection process finds its main characteristics through F-values which then eliminate all other elements to stop overfitting conditions from occurring. The analyzed features for February included 'NDVI' in addition to 'IPVI', 'SAVI', 'TSAVI' and 'OSAVI' while the rest of the features remained excluded. The month of March reveals bundle weight as the feature with the highest F-value which stands ahead of SR and TSAVI. Selection of 'NDVI' was made based on its effect analysis on regression because the other four VI features contain equal F-values. Each of these features – 'Bundle Weight', 'No of Tillers', 'Growth Stage Heading Complete' and 'NDVI' – is chosen for April prediction. The research achieved its first goal of identifying optimal predictive variables through the feature selection procedure. The regression models apply their function at different wheat crop growth stages where performance is assessed through R2, MAE, and RMSE evaluation metrics. The total record containing sowing dates undergoes partitioning into training and testing subsets with a proportion of 7:3. The February 2022 data collection gave rise to performance comparisons shown in Table 2 while Figure 10 depicts how measured wheat grain yield matches with estimated wheat grain yield through a 37-point test split. LASSO delivers the best performance for predicting wheat grain yield yielding 0.92 R2 alongside 27.95 g/m2 MAE and 33.32 g/m2 RMSE. Random Forest delivered superior results compared to XGB because it achieved R2 of 0.90 accompanied by MAEof28.49 g/m2. The evaluation of regression methodologies for March 2022 data collection appears in Table 3. The performance of LASSO led to most optimal results as its R2 reached 0.93 alongside MAE of 22.91 g/m2 and RMSE of 31.06 g/m2. Three regression methods evaluated the measured grain yield against actual yield from March observations through Figure 11. The findings from the three regression models appear in Table 4 which employs data collected during April 2022. The different regression methods generate predicted grain yields which are analyzed against actual recorded yields. The research data from April demonstrates that LASSO delivered superior performance compared to Random Forest and XGB.

For analyzing regression performance individual features, researchers use the SHAP (Shapley Additive explanations) methodology. The SHAP feature importance plots present an all-inclusive view of complete feature importance.

overview of the model's sensitivity to personal traits and their impact on predictions as well as its interpretability. A quantitative measure for feature performance in prediction models can be obtained through an analysis of every possible feature combination while calculating the prediction difference before and after adding or removing each individual feature. Using SHAP value calculation the model estimated the amount of prediction modification that results from adding a feature to the dataset. The SHAP feature importance plots analyze the gathered datasets from February 2022 through March 2022 to April 2022.

5. CONCLUSION AND FUTURE WORK

Wheat crop yield prediction plays a critical role for establishing global food security because of its importance. The study presents a predictive model which serves to determine wheat grain yield predictions. Multiple spectral data from three fields testing different sowing dates are acquired using drone sensors during wheat crop growth. The research continues through three steps that include predictor determination and implementation of Random Forest XGB regression and LASSO regression as popular ML regression models to predict crop yield. LASSO yielded the superior prediction results with an R2 value of 0.93 and 21.72 g/m2 as the Mean Absolute Error (MAE). The predicted yearly production amounts to 260.54 g/m2, 201.64 g/m2, 47.29 g/m2 for wheat fields planted in November (SD1), December (SD2), and January (SD3) respectively. The observations from April month deliver the highest predictive accuracy according to the results. This research will help farmers together with agronomists estimate their crop yields precisely in a timely manner to organize crop resource handling before harvesting. Wheat grain yield estimation uses multispectral data in combination with machine learning approaches at present. We will conduct research on deep learning CNN and LSTM technologies in the future to analyze drone-sourced optical data for crop yield forecasting. Soil and climate data will be integrated as predictors in our system which aims to enhance the prediction accuracy of yield outcomes.

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