Machine Learning Models for Intelligent Farmer Support Systems: A Comparative Approach Using Random Forest, Prophet, and YOLOv8

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Abstract—**In this article, we highlight the role of agriculture in modern societies, not only for the economic development of many countries, but especially for regions with pressing needs and underdevelopment where the majority of the population relies on agriculture for survival. Today, with great technological advances, agriculture has moved beyond rudimentary methods, adopting a gigantic advancement with artificial intelligence (ML), which has transformed and given a boost to farmers, making production more relevant and improving its performance. This sector has been crucial for the development and economic growth of many nations, contributing to and positively impacting the gross domestic product of many developed and non-developed countries.**

The challenges for farmers are still many, ranging from soil preparation, seed selection, auxiliary technological means, paced support platforms, disease detection, non-mechanized irrigation, self-sufficient harvesting with autonomous systems, yield forecasting, weed control, etc. This study presents an in-depth analysis of the significant advancements in information and communication technologies in this sector, which have revolutionized it. From machine learning, which has naturally been the biggest and most effective driver of this activity through autonomous data monitoring and control processes and methods, this study presents the different machine learning methods employed in agriculture, highlighting their advantages and challenges, and generating tangible and visible results aimed at bringing autonomy to farmers. Models such as Random Forest, YOLOv8, and Prophet are ML-based models coupled with artificial intelligence, capable of providing prompt and effective real-time responses. The study also includes a comparison focused on these models, their operations, and their major advantages in the world of technological modernity.

Index Terms—**Machine Learning, Agriculture, Farmers, Livelihood, Crops, Harvesting, Gross Domestic Product, Irrigation, Planting, Yields, Weed Control**

I. Introduction

Agriculture is one of the fastest-growing and most economically developed sectors worldwide, guaranteeing food securities in many countries, particularly in rural areas. Farmers, as the focal point of this chain, often face serious difficulties in obtaining and accessing timely information and specialized guidance that would allow them to perform this activity optimally. Agriculture is the major source of employment for people living in rural areas, especially in developing nations like India, the productivity and production of agriculture determine the socioeconomic welfare of India's 1.3 billion (45%) agriculturally dependent population. As a result, agriculture plays a significant role in the national economy.

Many farmers lack reliable support related to crop management, pest control, weather conditions, pest and disease outbreaks, insufficient modern techniques and modern farming techniques which can reduce and affect negatively the productivity and sustainability as well as inefficient farming practices, with the rapid advancement of Machine learning and digital technologies, mobile and web based platforms have emerged as effective tools for delivering agricultural information and support services.

[3] ML is an interdisciplinary field that merges computer science and statics to perform tasks that are typically performed by humans, in recent years the integration of ML with big data technologies and high performance computing has gained popularity in agriculture, facilitating the analysis of data intensive processes.

Also to enhance the accuracy of ML applications and predictions, researchers and practitioners integrated data from multiple sources, a process known as information fusion, ML and data fusion have become an essential tool in agriculture and have found applications in various scientific fields such as bio informatics, biochemistry, medicine, meteorology, economic sciences, robotics, aquaculture, food security, and climatology.

[4] ML models have become essential tools in precision agriculture due to their ability to analyze large volumes of agricultural data and generate accurate predictions. Among the various techniques available YOLOv8 is one of the most algorithm used that is applied for real time crop analysis disease and pest detection, it enhances decision making by providing immediate visual analysis, for automated crop disease detection from uploading images, based on this the algorithm is able to provide and detect issue reporting the name of disease, type of leaf or plant, the percentage of disease affecting the leaf or plantation and finally providing recommendation of the type of product to be used to solve the problem affecting production.

While Random Forest and Prophet are ML algorithms that assist in predicting statistical data related to occurrences and facts, Random Forest is a combined ML algorithm applied for classification and regression tasks that operates by constructing multiple decision trees throughout training and generating predictions found on the aggregation (majority voting for classification or averaging for regression) of individual tree outputs.

The time series forecasting model called Prophet is a proposed chain system to generate highly accurate and precise forecasts of crop prices and current market trends, it makes easy for farmers and others to make informed and accurate decisions about the ideal time to market their products.

Based on predictive intelligence, this robust and effective mechanism facilitates the reduction of exposure to make volatility and congruent uncertainties in the financial market, strongly contributing to the analysis and stability of yield increase s and improvements, and a more efficient strategic plan in agriculture practices.

These algorithms work on the classification and regression of trees, classifying them as majorities when related to classification and averaging for regression, since prophet is an algorithm that works in cadence with time series where trends, holiday effects, errors and seasonality are the behavioral patterns of this algorithm working especially for long term forecasts, while random forest is for short term.

The main research presents a comparative approach using these main algorithms Random Forest, Prophet, and YOLOv8 to explore their roles and effectiveness in smart agriculture applications, the research aims to evaluate and analyses how these models contribute to prediction, forecasting and visual detection tasks within agricultural environments.

By integrating these technologies the study seeks to support the development of intelligent farmer support systems capable of improving decision making, resource management, and agricultural productivity in the era of agriculture 4.0.

II. LITERATURE REVIEW

A. Information Fusion in Smart Agriculture: Machine Learning Applications and Future Research Directions

[1] It is worth highlighting that recent advances in ML have brought about a significant transformation in the new model of doing agriculture, what we are now calling modern agriculture, where production undergoes a major improvement, ensuring sustainability in decision-making processes. The study related to "Information Fusion in Smart Agriculture: Machine Learning Applications and Future Research Directions" highlights the strong integration of ML with the conviction of merging data from various sources, from remote sensing, IoT devices and climate analysis, to improve precision agriculture.

It is important to note that the authors present fundamental data related to ML in the various stages of pre-harvest, as well as harvest and post-harvest, which to a great extent has demonstrated the merging of data that is increasingly improving the accuracy of prediction and supporting informed agricultural decision-making. The computer has provided a vision of applying centralized and intelligent processes in agriculture, receiving particular attention through the structural chain of YOLO (You Only Look Once) object detection, which in agriculture highlights "Agricultural Object Detection with the YOLO Algorithm: A Bibliometric and Systematic Literature Review." The authors worked with approximately 257 research articles, concluding that these models that operate based on YOLO are becoming increasingly important for monitoring agricultural crops in real time, as well as in crop management and the automatic recognition of objects that affect the agricultural planting chain.

The focus of this study is on the ability of this YOLO algorithm to reduce costs and labor, thus improving resource efficiency and supporting the level of intelligence of farmers through great technological advances as well as advanced detection and surveillance systems.

B. AI-Powered Cow Detection in Complex Farm Environments

[2] Effectiveness in agricultural environments is a major requirement, and the challenge lies in demonstrating its effectiveness in detecting cows using artificial intelligence in complex agricultural settings. Based on this, researchers proposed the comprehensive YOLOv8-CBAM model, which centers on the robust Convulsive Block Attention Module (CBAM) to address real-world issues affecting this chain, such as poor lighting conditions, occlusions, and complex backgrounds.

Experiments yielded results demonstrating the model's improved performance, achieving greater accuracy and generalization compared to the standard YOLOv8 model, thus confirming its suitability for real-world cattle monitoring applications.
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C. A Survey on Machine Learning Applications in Agriculture

[5] This survey showcases the extensive research of "A Survey on Machine Learning Applications," which itself provides an analysis that touches on the adoption of machine learning techniques based on time and patterns of long agricultural life cycles. This study focuses on discussing machine learning as a tool to overcome pressing challenges such as pest infestations, inefficient irrigation, climate variations, and consequently, the decline of natural resources. The authors discussed real and correlated process chains, concluding that artificial intelligence-based systems generate precision processes as well as robustness and sustainability, with superior enhancement of data collected through comparative mechanisms and traditional agricultural methods, making these processes essential to meet future agricultural demands.

III. METHODOLOGY

This study adopts a quantitative and qualitative comparative research methodology to evaluate the effectiveness of three ML models, Random Forest, Prophet, and YOLOv8 within an intelligent farmer support system. The research focuses on comparing the performance of these models in agricultural prediction, forecasting, and image based detection tasks, the methodology aims to determine how ML techniques can support precision agriculture and improve decision making processes of farmers under Agriculture 4.0.

A. Data collection and Preprocessing

The effectiveness of this study depends on the availability of the diverse, accurate and well-structured data to support its core modules, including market insights, disease detection, smart advisory and user interaction services, this study adopts a multi-source data collection strategy to guarantee that the platform addresses real world agricultural challenges in a comprehensive manner.

B. Data Collection

Data for this study was collected from multiple reliable sources, including government agricultural databases such as the Government of India Open Data Platform and Agmarknet (Agriculture Marketing Information Network), public datasets like PlantVillage and Kaggle, and international organizations such as FAO (Food and Agriculture Organization), ICAR (Indian Council of Agricultural Research). In addition, real time user input data was collected through the application to provide personalized and context aware recommendations.

C. Data Pre-processing

To ensure high data quality and optimal model performance, the collected data undergoes several pre-processing steps:
Data cleaning: Elimination of missing duplicate and inconsistent records to improve data reliability.
Data Transformation: Conversion of categorical variables into numerical formats and normalization, and augmentation techniques to enhance disease detection accuracy.

Image Pre-processing: Standardization of plant images through resizing normalization, and augmentation techniques to enhance disease detection accuracy.
Feature Selection: Identification and selection of the most relevant features to improve model efficiency and reduce computational complexity.

Data integration: This involves consolidating and grouping data from various modules into a unified and consistent dataset.

Data splitting: These same datasets are subsequently divided separately into training and test subsets in order to ensure proper validation of the models and provide robust and effective evaluation performance.
The main objective is to build a robust structure capable of ensuring the unified and paced collection and pre-processing of data so that the data is reliable and of high quality, thus guaranteeing better accuracy and high-quality disease detection performance, anticipating that the consulting services that work with this data will be global.

This will ensure greater analysis and consequently support data-driven decision-making with improved farmer productivity.

D. Model Implementation

In order to model supervised learning, which is widely used in large agricultural support systems, in this system we use Random Forest, which focuses on its robustness in the proportionality of predicting agricultural market prices based on historical data.

Based on various inputs such as crop type, month, year, and market location, the algorithm can predict and estimate future crop prices with a fairly high degree of accuracy.

By constructing multiple precision trees, this algorithm works using a subset of training data and randomly selected features, where each of the various trees is trained and designed to predict the price of a given crop in a unique and independent way. The final prediction is then maintained by calculating the average of the outputs of all the trees that make up the system. This unified conjunction approach ensures improvement as well as accuracy, significantly reducing over fitting and relatively increasing the stability of the model in question.

The forecasting process begins with the data collection phase from the largest agricultural markets, which, in a structured and organized manner, ensures the operability of this data, including crop prices and market information, also monitoring categorical variables such as crop names and market locations, which are automatically converted into numerical values through a highly advanced technique called coding, which gives the algorithm efficiency in data processing.

The Random Forest algorithm works with the learning mechanism of complex relationships and hidden patterns in agricultural datasets, including seasonal price fluctuations, regional market differences, and long-term economic trends. In this aspect, factors such as the month have been taken into account, as it strongly influences the model's ability to identify and manage seasonal variations in supply and demand, while the year works to capture inflation and market evolution over time. Therefore, the market location provides an understanding of regional price differences, which in this case are caused by high transportation costs, product inventory levels, and consumer demand.

This model, as we have mentioned, is trained based on a set of historical data that are unified and divided into training and test sets to ensure the best model response based on the data the system loads. During the forecast, the trees work independently, each producing an estimated price for the crop, and the algorithm calculates the final result, ensuring the average of all forecasts.

Random Forest is designed for non-linear operations based on fluctuations, particularly suitable for agricultural applications focusing on large datasets as well as mixed data types, while maintaining high forecast accuracy. This model reduces uncertainty, improves crop planning, supports decision-making, and assists in price forecasting.

E. Prophet

This article also features Prophet, one of the most powerful time series forecasting models focused on supporting farmers. Its key component is forecasting future prices of agricultural crops based on historical market data. The model focuses on effectiveness, particularly in agricultural forecasting, as it provides standardized and time-dependent analyses such as seasonal variations, long-term trends, and recurring market behaviors.

This rather delicate process begins with the collection of historical price data for agricultural crops. Prophet works with columns: a date column (ds) and a target value column (y) containing crop prices over time. This intelligent model automatically learns recurring seasonal behaviors, allowing it to predict crop values, annual market trends, and constant periodic price fluctuations.

We must emphasize that the type of crop, the month, the year, and the market location have a significant influence on this forecasting process. The month factor helps the model identify seasonal agricultural cycles, such as harvest and off-season periods, while the year captures long-term economic changes, inflation, and the evolution of market conditions. We must not forget the market location, which allows us to recognize large and significant regional price variations caused by convergent and concise supply factors, as well as local transport and demand. This algorithm also offers the great advantage of being able to develop forecasting models separately, emphasizing the differentiation of crops and markets in order to improve forecast accuracy.

Prophet is an algorithm heavily focused on analyzing and tracking the historical evolution of prices in order to generate future forecasts for specific crops and markets. This algorithm offers a high standard of detection of recurring agricultural patterns and an estimate of future crop prices, which helps farmers identify profitable sales periods, as well as plan agricultural activities in a structured and organized way, prioritizing process efficiency.

The strong capabilities of seasonal forecasting, automatic trend analysis, robustness in handling faulty data, and ease of implementation are the great advantages of this algorithm, whose versatility extends beyond the normal mechanisms of agricultural applications. This algorithm specializes in agricultural datasets, since crop prices naturally follow cyclical and seasonal patterns.

Prophet has a significant impact on intelligent agricultural decision-making, helping farmers to predict market prices, reduce uncertainty, optimize sales strategies, and improve overall farm planning through insights based on unified and value-adding data.

F. YOLOv8

In this vein, we present YOLOv8 in its version 8, which is also a quite advanced version compared to previous ones, with profound object detection capabilities using a farmer support system. Its core function is to analyze agricultural images and provide clear visual information that helps predict diseases affecting the crop chain. This algorithm is not directly linked to price prediction; it detects ripening quality, the presence of diseases, pest infestation, and yield conditions. It works based on neural networks composed of three main components: the spine, the neck, and the detection head.

The spine extracts important image features such as shape, color, texture, and disease patterns. The neck combines features from different image scales to improve accuracy, while the detection head predicts object classes, bounding boxes, and confidence scores.

YOLOv8 processes agricultural images by dividing them into grid regions and identifying objects within each region. For each detected object, the model predicts the object's category, its location, and a confidence probability.

YOLOv8 analyzes crop images sent to the system to identify agricultural conditions affecting these products, thus preventing them from growing and developing with diseases that can significantly affect the product and its normal development. This prevents low-quality products from being injected into the market, which can consequently affect the lives of consumers. This model analyzes the images and automatically detects the type of disease affecting the crop, the percentage of the crop affected by the disease, the name of the affected crop, and consequently the recommendations to overcome this problem, even suggesting fertilizers to cure the disease affecting the crop.

This intelligent model works in a coordinated and synchronized manner, providing several advantages to the agricultural system, including real-time crop monitoring, automatic disease detection, high detection accuracy, and reduced manual inspection effort. YOLOv8 contributes to intelligent agricultural decision-making, allowing farmers to assess crop quality, identify diseases early, optimize crop management, and improve market planning through computer vision technology.

G. Farmer Support System Workflow

This system follows a workflow comprised of 5 synchronized steps that function integrally in a cadenced manner, such as input, processing, machine learning models, and finally, output and support for farmer decision-making.

1-Input

The system initially captures agricultural data from numerous sources, including information on crops, market prices, month, year, market location, weather conditions, and crop images sent by the system. These inputs provide the raw data necessary for analysis and forecasting.

2. Processing

Once collected, the data is cleaned, organized and prepared for analysis. Numerical and categorical data are transformed into machine readable formats, while images sent by system are pre-processed for computer vision analysis. This phase brings consistency and reliability, ensuring that the data has the authenticity necessary for ML operations.

3 – Machine Learning Models

The data, due to their specificity and nature, are carefully analyzed using advanced techniques and robust, authentic standards, utilizing ML models.

Random Forest, in a random fashion focuses on the utility of predicting crop prices based on multiple agricultural characteristics.

When it comes to time series forecasting, Prophet emerges as an algorithm for analyzing seasonal market trends.

With its high robustness, YOLOv8 stands out in the analysis of agricultural crop images as well as in the detection of disease, focusing on quality assessment.

4 – Results

After analyzing the system, the results of this article are relevant given the projected prices of crops, their future market trends, crop quality assessments, as well as the detection of diseases that endanger the plantations.

These results are presented in a functional way to farmers through an application interface in a simple and understandable format.

5 – Farmer Decision Support

Farmers have access to a range of generated information that, in turn, helps in making decisions about crops, such as the timing of sales, markets and their types, and finally, diseases or pests, often following an agricultural plan. This information significantly improves productivity, more effectively reducing uncertainties and thus promoting best agricultural practices based on data.

H. System Diagram

This research model and its architecture stand out in the way it was designed to be a highly data-driven intelligent platform that bridges the gap between advanced computing technologies and the greater practical needs of agriculture.

This architecture follows a fairly modular design pattern that is typically managed in layers, which in turn ensures efficient communication between system components, maintaining scalability, reliability, and performance. Initially, the farmer (user) will integrate or interact with the system through its simple and completely intuitive interface, developed with web technology. Due to the complexities and to allow convenient access to the system's functionalities, layers were developed to minimize the complexity of processes for users with limited technical knowledge.

In this way, there are user inputs that include agricultural data or images, which in turn are transmitted to the backend server that is strictly connected to Flask, which serves as a central processing unit of the system, while the backend, in its scope, aims to handle requests as well as perform data pre-processing and subsequently intelligently forward this data to the appropriate machine learning models.

The system's core integration is achieved through multiple models that form the machine learning suite: the Random Forest model, which performs predictive analyses; Prophet, which plays a significant role in forecasting time series to identify various seasonal trends; and finally, the model that serves as a real-time detector and analyst of diseases and pests affecting crops and the entire agricultural chain.

These models are comprehensive and work in a synchronized and collaborative manner to provide comprehensive insights that address numerical and visual aspects for better agricultural decision-making. All proposed and historical data can be managed in a single data storage layer, which in turn can include structured datasets stored in CSV files or databases, ensuring that data consistency can support model training and allows for accurate and authentic predictions.

Finally, the results obtained are returned in a set of blocks to the backend for the frontend to present them to the user in a clear and practical format, thus ensuring that the closed-loop architecture generates complex calculations that are subsequently abstracted from the user at the moment the insights are provided, guaranteeing support for informed decision making.

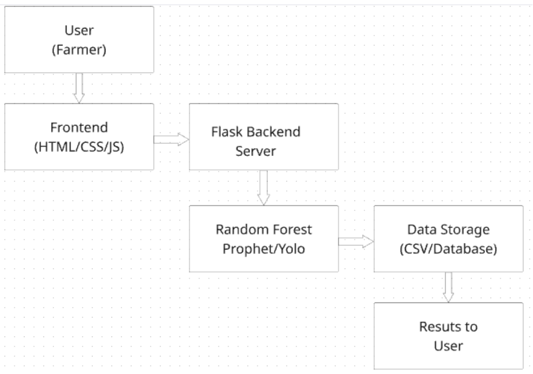

Fig.1 System Diagram

H. Comparative Analysis

It is worth highlighting that this system operates normally based on three major advanced machine learning and artificial intelligence models: Random Forest, Prophet, and YOLOv8, each playing a highly relevant role in the model, emphasizing intelligent agricultural decision-making. Random Forest is widely used for specific precision tasks with strongly structured agricultural data, such as crop type, month, year, and market location. In this case, it uses agricultural data collected during the system's testing and verification phase, which are typically structured data with high predictive accuracy generated from the combination of several decision trees. It is quite effective for handling non-linear relationships in highly relevant agricultural datasets, although it requires a significant amount of moderate processing time and a medium degree of implementation complexity. Prophet is widely used to forecast a range of time series based on historical market trend analysis, with constant seasonal variations and recurring agricultural patterns that work with forecasting future crop prices.

This ensures a high forecast rate and high processing speed with lower implementation complexity, making it a suitable alternative for seasonal analysis of the agricultural market. In contrast, YOLOv8 focuses on the pressing tasks of detecting and recognizing agricultural crops, as it works based on images and processing agricultural image data to identify diseases, crop quality, pest infestations, and fruit ripening in real time.

YOLOv8, in turn, generates high detection accuracy and fast performance based on deep learning and computer vision techniques, although with greater computational and implementation complexity compared to other models.

In short, Random Forest specializes in forecasting large-scale structured data, while Prophet, in a dedicated and collaborative manner, acts as the largest hub for temporal forecasting, and YOLOv8 provide intelligent visual analysis that generates permission for the farmer support system to trigger comprehensive and accurate data-driven support, leading to better and more efficient agricultural decision-making.

IV. RESULT AND DISCUSSIONS

A. Market Insights

This module works based on the random forest and prophet models, which are ML algorithms that assist in predicting statistical data related to occurrences and facts. These algorithms work on the classification and regression of trees, classifying them as majorities when related to classification and averaging for regression, since prophet is an algorithm that works in cadence with time series where trends, holiday effects, errors, and seasonality are the behavioral patterns of this algorithm, working especially for long-term or longer-term forecasts, while Random Forest is for short-term forecasts.

This module helps farmers to have an understanding of the normal functioning of the agricultural market as well as the various exchange markets, since the module provides price data for various products in various markets based on product type, year, and month, thus ensuring that farmers do not face difficulties in knowing about possible price fluctuations in different cities or markets. Based on accurate data, the farmer has an understanding and vision related to their production and can even predict where and how to market their products, thus preventing product deterioration. It is also highly relevant in assisting with product storage and control, predicting, monitoring, and choosing the best month, year, and market to sell their products.

With this module, farmers are strengthened since they have the technological means to know how the commercial market is doing from their own premises, leading many farmers to invest in more profitable products that can provide a higher and better profit based on market statistics and product type. On this basis, monitoring must be constant and permanent so that stored products do not decrease in value in the purchase market.

This module combines value, attention, and the ability to engage farmers in using a feature that, operating simply and effectively, provides advanced solutions to mitigate many of the problems farmers face related to marketing their products.

Fig.2 Market Insights

B. Smart Advisory

The Smart Advisory Module is a module of our application that works on top of the Market Insight module, operating with YOLO (You Only See Once), which is from the deep learning family.

It's a model that works in real time for object detection and classification, as well as segmentation. It has great relevance and utility in our system since, through neural networks and computer vision, this algorithm is able to detect foreign objects on a given surface.

It is used to identify diseases and fungi in a given plant, thus guaranteeing accurate and timed information on the plant's condition. In the Farmer Support Application, YOLO works as a farmer's helper, avoiding the need for blind-eye analysis.

YOLO, with its high performance and relevance, acts precisely in this chain so that farmers have at their disposal a technological resource capable of addressing doubts and omissions related to their crops. In this order, through the upload of a leaflet from their crop, YOLO uses all the developed tools and models that compose it to identify the state of the farmer's plantation or crop, providing even details of the data associated with the type of disease affecting the plantation, the type of plant, the relevance of the percentage that this plant is being affected by this disease, and a brief recommendation of the type of product to be used to solve the problem affecting production.

This mechanism provides reliability and credibility to farmers with the utmost certainty that the technology related to the analysis and detection of objects in plants is reliable, thus assisting in better production and guaranteeing higher quality, disease-free products for end consumers.

This technology, in a way, avoids gross losses that were long recorded in the production of various cereals and provides a very quick response in terms of mechanized and paced production with support for new technologies.

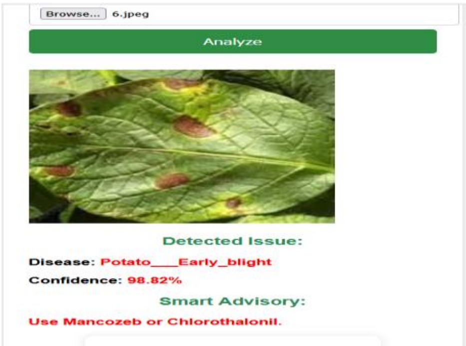

Fig.3 Smart Advisory

V. CONCLUSIONS

This study presented a comparative approach by using an intelligent system of three advanced ML and artificial intelligence models such as Random Forest, Prophet and YOLOv8 each model contributing significantly and uniquely to improving agricultural decision-making through predictive analysis and time series forecasting and computer vision technologies.

Random Forest demonstrated solid performance in forecasting crop prices using structured agricultural data such as crop type, market location, month and year, while prophet efficiently predicted future market trends by analyzing seasonal patterns and historical price movements, thus making it highly suitable for agricultural time series analysis. YOLOv8, with its features, improved the system through real-time crop monitoring, disease detection, quality assessment and visual analysis of agricultural images.

Feature	**Random Forest**	**Prophet**	**YOLOv8**
Function	Predictio n	Forecastin g	Detection

Data Type	Structure d	Time-Series	Image
Accuracy	High	High	Very High
Speed	Moderate	Fast	Fast
Complexity	Medium	Low	High

The study aims to show that each model operates with different types of data and techniques, since the integration of each model is unique and independent, using comparative methods, thus creating a robust and comprehensive farmer support system.

Based on intelligent phenomena, because in the highest combinations, predictive models for detecting and predicting are usually functional, based on images that allow farmers to make informed decisions about crop management, ensuring market planning and disease control and market strategies.

This in-depth study demonstrates the great potential of machine learning and the technological aspect that intelligently improves productivity based on artificial intelligence, reducing the uncertainty of farmers having effective production and increasing predictions and support for agricultural practices based on reliable and credible real data. The integration of Random Forest, Prophet and YOLOV8 provides a scalable and efficient framework for the development of smart agricultural solutions capable of addressing the challenges of agriculture and promoting sustainable agricultural development.

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