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A Smart Agricultural Assistant for Crop Recommendation using Machine Learning

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***Abstract*— This paper presents a Smart Agriculture Assistant that uses data analytics and machine learning to assist farmers in making informed decisions about various farming practices. The assistant offers a holistic approach to enhance agricultural decision-making process by recommending crops based on soil attributes, climate, and local weather conditions, as well as providing precise fertilizer and pesticide guidance tailored to Indian contexts. Data is collected from various sources, such as weather forecasts, groundwater data, soil maps, and crop prices. Machine learning algorithms are trained on that data to generate optimal recommendations for farmers.**

The study demonstrates the effectiveness of smart agricultural techniques over conventional methods in improving crop selection accuracy and optimizing fertilizer application, thereby enhancing agricultural productivity. Furthermore, the integration of image analysis technology using computer vision enables the system to assess crop quality parameters, aiding in the detection of grade, size, colour, and disease presence. It also provides insights of estimated real-time crop prices by taking into account the fickle market dynamics. This offers valuable information to the farmers for increasing profit margins. The assistant is implemented as a web application that can be accessed by farmers from anywhere. This research provides a framework for the integration of data-driven technology to solve the unique issues encountered by Indian farmers. The Smart Agriculture Assistant presented here represents the power of data science and deep learning for a more prosperous and sustainable future for Indian agriculture.

***Index Terms*— Machine Learning, Artificial Intelligence, Computer Vision, Image Analysis, Smart Farming.**

I. INTRODUCTION

Agriculture is among the most important sectors of the global economy, as it provides food, feed, fibers, and fuel for billions of people. It also supports several industries that depend on agricultural produce for raw materials. Agriculture is the backbone of the Indian economy, employing about 50% of the workforce and contributing to 17% of the GDP. However, agricultural productivity and food security are facing serious challenges due to climate change, population growth, and resource constraints. As erratic weather patterns, diminishing groundwater resources, and unpredictable soil conditions become increasingly prevalent, there is a pressing need for innovative and technologically-driven solutions that can help farmers optimize their farming practices and increase their yields and incomes.

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Climate change is causing extreme weather events like droughts and floods at a higher frequency, which can damage crops and reduce yields. Population growth is putting pressure on the available land and water resources, making it difficult to increase agricultural production. Resource constraints, such as the shortage of water, fertilizers and pesticides, are also making it difficult for farmers to produce enough food. Throughout the world, farmers follow conventional methods of agriculture as stipulated by the traditions in their communities. However, many of those practices are becoming unsustainable, due to intensive labor, cost, time etc. Meeting the burgeoning demands of a burgeoning population while safeguarding environmental resources necessitates a paradigm shift in agricultural practices.

New strategies evolved to address these issues. Precision farming is one such development. In order to increase agricultural output sustainability, this farming management technique relies on monitoring, measuring, and reacting to temporal and spatial variability. It is employed in the production of both livestock as well as crops. It frequently uses technology to automate farming tasks, enhancing their performance, diagnosis, and decision-making [1]. One of the main elements of the third wave of the contemporary agricultural revolution is precision agriculture (Kumar et al, 2022). The rise of mechanized agriculture between 1900 and 1930 was the first agricultural revolution. During this period, each farmer produced enough food to serve roughly twenty-six people. With the introduction of new genetic modification techniques in the 1960s, the Green Revolution took off and each farmer was able to feed roughly 156 people. It is projected that by 2050, there will be approximately 9.6 billion people on the planet, meaning that food production will need to more than quadruple from its current levels to feed everyone. If new technical developments in the precision farming revolution are applied, it is predicted that each farmer will be able to feed 265 people on the same amount of land (Global E, 2017).

Precision farming involves the convergence of modern technology such as robots, sensors and electronic devices. This results in a decrease in workload, higher profitability and improved decision making. However, the usage of these technologies varies across countries and locations. The adoption of modern technology is low due to the high overhead costs of implementing them. The latest innovations in computer science and IT can result in further enhancement of precision farming techniques. Over the years, advancements in artificial intelligence, machine learning, computer vision, big data and the Internet of Things (IoT) have paved the way for the development of smart agricultural systems. These systems harness the power of data-driven technologies to assist farmers in critical facets of their profession. There are a number of existing smart agricultural systems that have been developed to address different challenges. For example, some systems use Artificial Intelligence to recommend crops that are best suited for a particular region's climate and soil conditions. This research paper embarks on introducing a transformative Smart Agriculture Assistant tailored specifically to the diverse ecological landscapes of India. This smart assistant utilizes cutting-edge data analytics and machine learning, designed to address the unique challenges faced by Indian farmers. It offers a multifaceted approach towards precision farming, encompassing functionalities like crop recommendation, fertilizer guidance, and quality assessment through image analysis. The system can provide farmers with recommendations on the best crops to grow, the most effective pesticides and fertilizers to use, and how to manage their crops to achieve the best possible yields. The crop recommendation module leverages a repository of soil data, groundwater levels, historical climate information, and real-time weather updates, offering tailored insights to aid farmers in making informed decisions about crop selection. In agriculture, machine learning can be applied to identify diseases and weeds in crops, recognize species, and quantify organic carbon, soil nutrients, and moisture content. It can also be used to estimate crop yield. Deep Learning builds on traditional machine learning by adding complexity to the model and altering the input with different functions that enable hierarchical data representation through several layers of abstraction. (Durai and Shamili, 2022). A significant benefit of Deep Learning is feature learning i.e. the automatic extraction of features from original data. Additionally, the precise fertilizer guidance system employs machine learning models trained on extensive Indian fertilizer-application datasets, ensuring optimal nutrient supplementation in accordance with the selected crops and prevailing soil conditions. Furthermore, the integration of image analysis with computer vision empowers it to evaluate critical crop quality parameters, including size, grade and colour. It can also be trained to detect the presence of diseases, weeds and pests. This serves as a crucial tool in bolstering the overall quality and market competitiveness of the produce, thereby contributing to the economic sustainability of agriculture. In view of the aforementioned, this paper endeavors to bridge the gap between traditional farming practices and modern data-driven precision agriculture. A sophisticated Smart Agricultural Assistant that we've presented intends to offer a comprehensive and integrated solution. It is designed to be inexpensive, user-friendly, and adaptable to different crops and regions. The system described herein aims to empower Indian farmers with the expertise and knowledge required to negotiate the complex agricultural terrain, ultimately guiding the agriculture sector towards a more sustainable and prosperous future.

The objective of the research paper is design, implement, and evaluate the proposed smart agricultural assistant. Additionally, we will compare the performance of the proposed system with existing farming methods in terms of accuracy, usability, and impact. It also strives to identify the factors that contribute to the success of smart agricultural systems and propose suggestions for their improvement.

II. Literature Survey

By 2050, the world's population will be close to 9 billion, driving up demand for agriculture but decreasing the number of farmers. Traditional agriculture is struggling with a labour shortage, rising energy costs, and excessive input use. By strengthening corporate control, seed manipulation disadvantages small and medium-scale farmers. However, small farms have a big impact on sustainability and food security. By combining technology like sensors and IoT, smart farming improves crop yields and sustainability [2]. Agriculture's transformation from 1.0 to 4.0 has significantly increased productivity. Agriculture in the past produced little and required manual labour. Agriculture 2.0 increased productivity by introducing energy and machinery. For more intelligent farming, Agriculture 3.0 combines connectivity, IoT, and renewable energy. The most recent generation of agriculture, 4.0, emphasizes organic farming and consumer needs while embracing big data, machine learning, IoT, and other technologies [3]. Doshi et al (2019) reported that Internet of Things (IoT) will be the future of Smart Computing, which is being used in various fields such as manufacturing, agriculture, transportation, and business management. The authors introduce a working product that allows farmers to access real-time data on their crops using sensors, microcontrollers, and other hardware items. They suggest that the product notifies farmers through visual alerts, a mobile app, and a buzzer. Future work can focus on improving the product. The ESP32s node MCU can be used in large farmlands with multiple prototypes connected through Bluetooth. The network can use artificial intelligence and data mining algorithms to make decisions. A three-dimensional (3D) mapping of farmlands can be done by connecting drones to the system [4]. Durai and Shamili (2022) studied smart farming using Machine Learning and Deep Learning techniques. A XGBoost regressor model that can analyse the soil conditions, predict weather, recommend the ideal crops for cultivation and determine the amount of fertilizers was developed [5]. The Agristack program in India is a novel initiative to promote intelligent agriculture practices. For small-scale farmers, the platform offers native digital solutions that include pre-harvest inputs, PHM, consulting services, e-market connections, and soil health information systems. This can result in a more effective use of already available resources, greatly enhance the agricultural value chain, raise farmer incomes, and improve socioeconomic conditions for farmers [6].

Tamil Nadu contributed 12% of India's total sugarcane production in 2020, which was 20% of the global total. Using RFLP, rDNA, and sequencing, Rao G. P. et al. identified and characterized photo plasmas related to sugarcane illnesses. For the high accuracy detection of sugarcane borer disease, a support vector machine-based approach was developed. Direct and nested PCR amplification performed better than traditional techniques for the detection of sugarcane grassy shoot disease, according to H. Yu et al. X. Liu used PCR methods to identify numerous sugarcane diseases and provided management recommendations. In Australia, researchers employed Spectral Vegetation Indices to accurately diagnose orange rust illness. Two methods were used to gather the input photos. The Indian Institute of Sugarcane Research, Sugarcane Breeding Institute, Tamil Nadu Agriculture University, and other research institutions were one source of the input photographs. These images served as training data for algorithms such as CBR (Case-Based Reasoning), Neuro-fuzzy, and ANNs (Artificial Neural Networks). Another approach to data collection was obtaining input photos from farms or other agricultural areas. These images served as ANN test data [7]. Deep learning methods such as Radial Basis Function Networks (RBFN) and Extreme Learning Machines (ELM) provide for improved model performance and rapid learning. Time series analysis methods such as Autoregressive Integrated Moving Average (ARIMA) and Recurrent Neural Networks (RNN) can be used to forecast crop yields. [8]. A study of the adoption and diffusion of new technologies in the production of plant and animal products over the previous few decades in agricultural economics led to the need to research and comprehend the role of actors/stakeholders with regard to policy making and marketing practices in Greece. Those who remained silent in response to specific queries did so systematically because they felt that individuals living in rural Greece did not require smart farming technologies. Instead of incorporating new processes into the food production process, they think that the groups involved should concentrate on social and economic revisions of the policies in place and modernizing the infrastructure already in place [9].

Jerhamre et al studied the hurdles when implementing Artificial Intelligence (AI) in agricultural businesses. The primary opportunities that have been identified include the significance of smart farming in the strategic agendas of various industry stakeholders, the widespread trend towards software technology being provided as a service through shared machinery, the abundance of data that is currently available, and the high level of interest that farmers have in new technologies. On the other hand, the study highlights the primary obstacles as being the absence of technical expertise in the industry at times, potential cybersecurity risks, technical and legal obstacles to data ownership, and the necessity for a strong economic case [10]. Fruit appearance plays a major role in consumer preferences and quality grading. Fruit quality is determined by its colour, texture, size, and form. For external quality control, existing computer vision systems have been used, with fruit grading and classification based on observations. [11]. An inventive use of smart farming technology is banana quality monitoring systems, which use sophisticated algorithms and sensors to assess the maturity and overall quality of bananas throughout their life cycle. Knowledge Embedded-Graph Convolutional Neural Networks (KEGCNNs) are used in this suggested system to score and classify banana fruit. By transforming banana photos into a knowledge graph, utilizing knowledge embedding to convert them into a continuous vector space, and employing Graph Convolution Neural Networks (GCNNs) to assess the graph structure and produce precise detections, the method seeks to evaluate the quality of banana fruit. An organized depiction of knowledge, known as a Knowledge Graph (KG), links entities (nodes) through relationships (edges) between them. A KG can be extremely helpful in organizing and displaying pertinent data about bananas and their attributes when employing Machine Learning (ML) to determine the quality grading of bananas [12]. Big data generation is made possible by advancements in and applications of cloud computing, IoT, and network technologies in smart farming. Big data is defined as data, both unstructured and structured, that exceeds the capacity of conventional data processing methods and tools. The five Vs—volume, velocity, variety, veracity, and value—define the "big" component of this phrase. In order to achieve this, raw data from many sources must first be digested, combined, and kept in a centralized storage location called a data lake. Second, in order to filter, aggregate, and otherwise prepare the data for analysis, big data solutions must be employed. These solutions must be based on both batch operations that operate in the background and real-time jobs. Providing insights from data through analysis and reporting chores is the final phase. Two fundamental prerequisites are typically present for big data systems. obtaining a vast real-time data stream from various sources in the first place, and then analysing this data to produce immediate results in the second place. Based on this, big data systems frequently employ three cutting-edge software architectures: Lambda, Kappa, and a hybrid of the two. [13]

Climate change is a critical factor affecting agriculture. While elevated CO2 levels can enhance plant growth through improved photosynthesis efficiency, it also results in higher temperatures that counteract these benefits by causing heat stress and water scarcity. Additionally, rising temperatures can harm soil microbial populations and worsen soil salinity, with up to 50 percent of agricultural land predicted to be affected by salinity by 2050. Furthermore, the current climate crisis has led to resource shortages, including macro and micronutrients such as phosphorus and nitrogen. Hence, smart indoor farming has been suggested. Here, sensors are used to measure parameters like PH, Electrical Conductivity, Ion Selective, and Temperature.

Vertical farming techniques like aeroponics are utilized. Also, IoT and AI are used to balance nutrients like water, nutrients, etc., based on plant parameters that affect plant growth. It was found that Vertical Farming provided better indicators with respect to land and water [14]. A study on the impact of climate change in Sub-Saharan Africa sheds light on a range of pressing issues, including the dwindling agricultural yields, the growing difficulty in accessing food, and the financial hardships faced by countries heavily reliant on farming, all exacerbated by climate change and underlying structural issues. The text suggests that to confront these complex challenges, a holistic approach is imperative. This approach should revolve around the promotion of sustainable intensification and the implementation of climate-smart agriculture (CSA) techniques [15]. Research on IoT and smart sensor-based smart farming conducted globally has yielded positive outcomes. Numerous small-scale agricultural fields have used IoT-based technology. The financial burden associated with the deployment and installation of IoT-tagged sensors and accessories across a sizable acreage of agricultural land is one of the main obstacles. Furthermore, there is uncertainty regarding the relationship between implementation costs and profit margins. The cost of purchasing hardware, installing software, and running the system are the main expenses associated with implementing IoT-enabled technology. Energy consumption, system maintenance, service registration, and labour costs related to running the integrated hardware devices and related software will all incur additional expenditures [16].

III. METHODOLOGY

The proposed smart farming assistant can be built as a multi-layered system, leveraging AI, ML, and other advanced techniques to process various data inputs and provide valuable insights to farmers described in figure 1. The main layers include:

1. Data Acquisition Layer

- Sensors are used across the farm to collect real-time data on soil parameters (moisture, pH, nutrient levels), weather conditions (temperature, precipitation, humidity), and aerial imagery from drones or satellites.
- Soil Map data is acquired from government databases, soil surveys, and on-field sensors.
- Weather data is retrieved from weather stations, satellites, and historical records.
- Remote Sensing Data from satellites, drones, and multispectral sensors.
- Crop Yield Data based on historical data from farms and agricultural organizations.
- Market prices and Minimum Support Price (MSP) data from Government sources.

2. Data Preprocessing Layer

- *Data Integration*: Combine data from various sources into a central repository, ensuring proper timestamping, location tracking, and data synchronization.
- *Data Cleaning*: Address missing values, outliers, and inconsistencies in the data using filtering, interpolation, and anomaly detection techniques.

3. Data Analysis and Decision Making Layer

Machine Learning Models

- o *Crop Yield Prediction*: Employ regression models (e.g., Random Forest, XGBoost) trained on historical yield data, soil and weather variables, and remote sensing images to predict future yields.
- o *Crop Quality and Price Forecasting*: Use time series analysis and market trend prediction models (e.g., ARIMA, LSTMs) to estimate crop quality based on environmental factors and predict market prices based on historical trends and current market conditions.
- o *Pest and Disease Prediction*: Train image recognition models (e.g., CNNs) on labelled datasets of diseased crops and aerial imagery to predict potential pest and disease outbreaks. Deep learning models can analyse plant images for early disease detection.

4. Output Layer

- *Predictive Insights*: Generate reports and actionable recommendations based on model predictions, including optimal irrigation schedules, fertilization needs, pest and disease control strategies, and harvest timing.

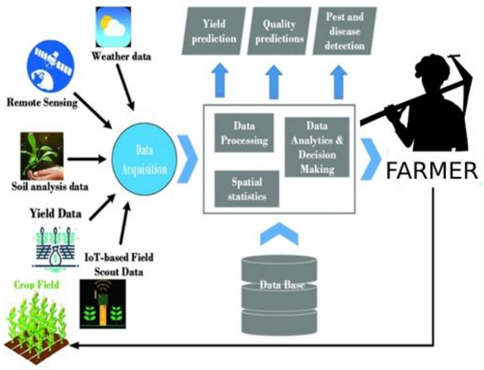


Figure 1. Architecture of the proposed Smart Farming assistant system

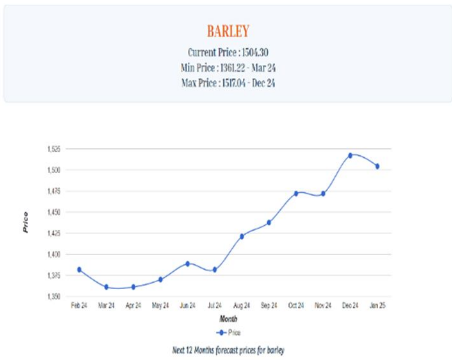


Figure 2. Crop price forecaster

IV. CROP RECOMMENDATION SYSTEM

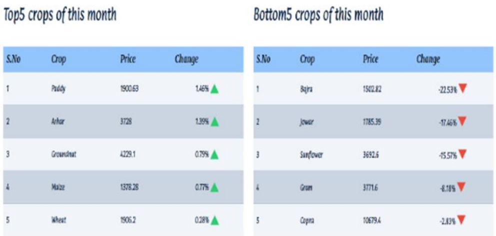
The project contains two modules namely crop recommendation and crop cost estimation. The proposed work is a Web application. For convenience of use, the website offers both a guest login and a user login page. Users must first register with their basic information and create their username and password, in order to access these modules.

Artificial Intelligence powered predictive analysis used for determining the crop health and its well-being and the various threats which may occur in our crops and this is done mainly with the help of processing pre-existing rainfall data, soil maps and by utilizing a range of machine learning algorithms, including Random Forest, AdaBoost, XGBoost, Decision Trees, Super Vector Machines, and Logistic Regression, to mention a few.
The crops are recommended based on the following parameters like Nitrogen level, Phosphorus level, Potassium level, temperature, humidity, PH value and rainfall.
The available Data fields includes:

- *N* - ratio of Nitrogen content present in soil
- *P* - ratio of Phosphorous content present in soil
- *K* - ratio of Potassium content present in soil
- *Temperature* – temperature in degree Celsius
- *Humidity*- relative humidity of the soil in percentage
- *PH* - PH value of the soil
- *Rainfall* - rainfall in mm
- *label* - name of the crop

The rainfall, temperature, and fertilizer data sets that are currently available for India were used to create this dataset. It was sourced from Kaggle and government websites such as mausam.imd.gov.in.
API calls to the backend are used for the following tasks:

- Provide optimum soil conditions for each crop.
- Predicting the ideal crop for the given soil parameters.
- Crop prediction based on locality and season.
- Provides the most and least in-demand crops of this month along with a price forecaster for selling their produce in the market when there is a demand for the product.
- Analytics of individual crop.



Top5 crops of this month

S.No	Crop	Price	Change
1	Paddy	1900.63	1.46%
2	Arhar	3728	1.39%
3	Groundnut	4229.1	0.79%
4	Maize	1378.28	0.77%
5	Wheat	1906.2	0.28%

Bottom5 crops of this month

S.No	Crop	Price	Change
1	Bajra	1502.82	-22.53%
2	Jowar	1785.39	-17.46%
3	Sunflower	3692.6	-15.57%
4	Gram	3771.6	-8.18%
5	Copra	10679.4	-2.83%

Figure 3. Predicting the best crops in terms of price

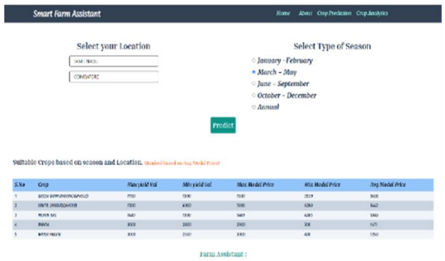


Figure 4. The interface of crop recommendation feature

V. Conclusion

The paper has explored the potential of machine learning, AI, and other modern tools to significantly improve farming practices. By integrating these technologies into various stages of crop production, we propose a system offering precise crop recommendations and accurate price forecasts, leading to enhanced productivity and sustainability due to better crop selection and resource management. With the price forecasting module, farmers can maximize profits. However, further research is necessary to develop robust and affordable tools and address challenges like data accessibility, cybersecurity, and farmer training. Collaborative efforts between researchers, developers, and agricultural stakeholders are crucial to bridge the digital divide and ensure equitable access to these technologies. In conclusion, the integration of machine learning, AI, and modern tools represents a transformative opportunity for the agricultural sector.

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