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Agri Pulse: A Comprehensive Tool for Smart Agriculture Management: A Review

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Abstract: Agriculture is the pillar of world food security, but it is confronted with challenges like climate fluctuation, soil erosion, pest attacks, water shortages, and unstable market prices. AgriPulse is a smart agriculture platform powered by AI that combines Crop Recommendation, Yield Forecasting, Plant Disease Detection, Soil Health Monitoring, Weather Forecasting, Market Connectivity, and AI-based Decision Support to improve agricultural productivity and sustainability. This system utilizes Machine Learning (ML), Deep Learning (DL), Internet of Things (IoT), and Explainable AI (XAI) to offer real-time insights as well as predictive analytics. AgriPulse uses Random Forest, Genetic Algorithms, and Support Vector Machines (SVMs) for classification of crops as well as the prediction of yields with high accuracy in suggesting the most appropriate crops according to soil and weather factors. Plant disease detection system based on deep learning using CNNs, GANs, and Self-Supervised Learning (SSL) guarantees early detection of plant infections, minimizing losses from pests and diseases. IoT-based soil health monitoring system continuously monitors moisture, pH, and nutrients, maximizing fertilizer usage and irrigation management. Agri Pulse also has an AI-based market prediction module, with Time Series Forecasting (ARIMA) and Regression models, to forecast crop prices and enable farmers to make informed sales decisions. In addition, weather prediction algorithms examine meteorological data to offer early warnings of unfavourable conditions to help farmers manage risks. The platform is accompanied by an AI chatbot that provides localized, personalized recommendations in local languages for ease of access and use. By combining precision agriculture technology, Agri Pulse seeks to optimize crop production, improve resource management, lower environmental footprint, and enhance farmers' connectivity with markets. Through this integrative strategy, stakeholders are empowered with data-driven decision-making, leading to a sustainable and resilient food industry future.

Keywords: Machine Learning (ML) in Agriculture, Deep Learning (DL) for Crop & Disease Prediction, Crop Recommendation System, Yield Prediction, Soil Health Monitoring, Precision Farming, AI for Plant Disease Diagnosis, Pest Detection using Computer Vision, AI-powered Market Intelligence, Crop Price Forecasting, Time Series Forecasting (ARIMA, LSTM), Remote Sensing in Agriculture, AI-based Weather Prediction, Climate-Smart Agriculture, Self-Supervised Learning (SSL) for Pest & Disease Identification, Automated Decision Support Systems, AI-powered Agricultural Chatbots.

I. INTRODUCTION

Agriculture is a basic building block of global food security, economic stability, and rural development. The industry, however, is plagued with recurring challenges that include climate change, soil erosion, water stress, pest attack, and unpredictable market prices, all of which have a very significant effect on agricultural productivity. Conventional agricultural practices tend to be based on manual labor and experiential decision-making, resulting in inefficiencies in the choice of crops, irrigation scheduling, pest control, and post-harvest handling. In order to meet these challenges, data-driven, AI-based solutions have become revolutionizing tools for contemporary agriculture.

Recent developments in Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), and the Internet of Things (IoT) have transformed the sector of agriculture by bringing precision farming, real-time observation, and automated decision-making. AI-based agricultural systems utilize big data analysis, predictive modeling, and intelligent automation to maximize farm operations. Machine learning algorithms like Random Forest, Support Vector Machines (SVM), and Neural Networks are most commonly used to recommend crops [2] and predict yields [10] based on soil quality, weather, and past year yields, which enable farmers to make informed choices regarding soil, climate, and past year trends. IoT-enabled soil health management systems also obtain and analyze in real-time measurements of moisture content, nutrient, and environmental condition, enabling targeted fertilizer application and optimal irrigation approaches.

An important aspect of farm productivity is the detection of diseases and pests at an early stage. Manual inspection is a traditional method used for disease identification, which takes time and may be error-prone.

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AI-based methods employing Convolutional Neural Networks (CNNs), Generative Adversarial Networks (GANs), and Self-Supervised Learning (SSL) have dramatically improved the efficiency and accuracy of plant disease identification. AI-driven pest management systems ensure early detection and suggest site-specific interventions, curtailing overuse of pesticides and lowering crop loss. Additionally, AI-driven smart irrigation systems continuously optimize water supply according to current soil water status, crop water needs, and weather patterns, promoting sustainable use of water.

Outside of farm-level activities, AI-based market projection and supply chain management are also essential for improving farmers' profitability [3]. ARIMA and LSTM-based time series forecasting models make it possible for farmers to forecast price changes, schedule harvesting for optimal timing, and decide on optimal selling strategies. AI-based bidding and trading platforms also help establish direct farmer-to-market channels, mitigating reliance on middlemen and providing fair prices.

This literature survey discusses current development in AI-enabled agriculture across topics such as crop choice, yield estimation, monitoring of soil quality, disease identification in plants, water management of resources, climate forecasting, and market intelligence. The work endeavours to compare and evaluate current approaches to identify the areas of gaps. Technologies such as AgriPulse are based on a variety of these and combine them under one large-scale, data-led, data-backed agricultural paradigm for farmers with automated real-time input, and precision-based solutions leading to higher productivity and sustainability.

II. TECHNOLOGIES

Advanced technologies have fundamentally changed conventional farm practices to adopt more efficient and sustainable solutions in crop management, soil health, disease detection, irrigation optimization, and market prediction. AI agricultural systems depend on a mix of machine learning models, IoT-capable smart sensors, remote sensing, and predictive analytics to feed real-time intelligence and automation. These technologies enhance decision-making based on data, minimizing wastage of resources while improving productivity and resilience to environmental pressures.

Machine Learning (ML) and Deep Learning (DL) are critical in precision agriculture since they support informed crop suggestion and yield forecasting. Algorithms like Random Forest, Support Vector Machines (SVM), Decision Trees, and Artificial Neural Networks (ANN) evaluate soil content, climatic factors, and past crop yields to recommend the most appropriate crops and forecast yields. Besides this, sophisticated Deep Learning methods like Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) are utilized for disease detection in plants, enabling them to detect diseases early and classify them, followed by intervention and mitigation actions.

The Internet of Things (IoT) further augmented agricultural smarts by providing real-time measurement of soil and environmental conditions. IoT sensor devices gather datasets on temperature, NPK content, nitrogen, phosphorus, pH, and moisture levels to enable farmers to maximize fertilizer usage and irrigation processes. These data are pulled from sensor networks, remote field stations, and agriculture monitoring systems and are of high accuracy and reliability. Intelligent irrigation systems, driven by AI algorithms that analyse real-time weather patterns and soil moisture content, regulate water supply to maximize resource efficiency and avoid over-irrigation.

Remote sensing technologies such as drone monitoring and satellite imaging have transformed large-scale agricultural analysis. AI-driven drones with multispectral and hyperspectral cameras take high-resolution images of agricultural land, helping in crop health evaluation, pest identification, and yield prediction. In parallel, Satellite imaging and Geographic Information Systems (GIS) offer useful datasets regarding vegetation condition, soil wetness, and weather conditions that are combined with AI models for agricultural planning on a large scale. Remote sensing datasets are obtained from satellite imagery databases, government agricultural surveillance initiatives, and bespoke drone monitoring systems.

Predictive analytics and time series forecasting are of great importance to market intelligence and risk management for farmers. Artificial intelligence-based models like ARIMA, LSTM, and Regression analysis use past pricing data to forecast crop prices in the future to help farmers maximize harvesting and selling plans. Additionally, weather prediction models combine climate data, meteorological sensors, and satellite images to give early indications for temperature changes, rainfall differences, and extreme weather, and farmers can take precautionary steps against climatic risks.

Apart from automation and data analytics, AI-based chatbots and decision support systems help farmers by offering real-time agricultural recommendations on weather, crop diseases, and market conditions. Using Natural Language Processing (NLP) and AI-based automation, such chatbots make agronomists' and market analysts' expertise available to farmers, especially those in rural pockets who have limited access to these experts.

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Advisory platforms using AI examine farm-specific data to suggest best planting schedules, irrigation plans, and pest management techniques, increasing precision farming potential even further.

Combining these latest technologies, AI-powered smart agriculture platforms like Agri Pulse equip farmers with data-driven insights, automation, and predictive intelligence, culminating in enhanced efficiency, sustainable resource utilization, and better agricultural productivity.

III. STUDY OF RELATED WORK

The review of related work presents a summary of current developments in AI-based agriculture, discussing several methodologies and technologies employed to solve problems in crop management, monitoring soil health, detecting diseases, optimizing irrigation, and market prediction. Researchers have undertaken various methods combining Machine Learning (ML), Deep Learning (DL), Internet of Things (IoT), Remote Sensing, and Predictive Analytics to improve agricultural productivity and sustainability.

In recent years, machine learning and artificial intelligence have played an important role in precision agriculture by helping in crop choice, predicting the yield, and detecting disease.

Geethajali et al. [1] presented an AI-based chatbot for precision agriculture, offering farmers crop suggestions, yield optimization methods, and disease control methods. Their work highlights the potential of AI-based conversational agents in filling the knowledge gap in farming. In the same vein, Chandolikar et al. [6] and Maduri et al. [7] proposed chatbot-based agricultural support systems with artificial neural networks, which further improved automated advisory systems for farmers.

Mahmud et al. [2] introduced a hybrid machine learning model that incorporates genetic algorithms to enhance crop prediction accuracy. Their method optimizes the hyperparameters of the model, which has an impressive accuracy rate of 99.3%. Likewise, Nigam et al. [9] and Reddy et al. [10] investigated several machine learning algorithms, such as Random Forest and Support Vector Machines, to improve crop yield predictions, while Krishna et al. [12] concentrated on the comparison of multiple models for predictive performance.

Badshah et al. [5] explored strong machine learning models for crop classification and yield prediction, utilizing Explainable AI (XAI) methods like LIME and SHAP for interpretability. Their results are consistent with Elbasi et al. [3], who performed a systematic review of the literature on AI in agriculture, emphasizing the efficacy of deep learning and IoT-based solutions.

Varsha et al. [4] discussed Streamlit-based AI-powered farm management systems, which provided real-time monitoring and decision-making functionalities. Devan et al. [14] also suggested a hybrid machine learning framework for fertilizer recommendation and crop yield prediction using several predictive models to improve accuracy.

Vaishnavi et al. [13] and Pande et al. [15] proposed machine learning-based crop recommendation systems, taking into account seasonal fluctuations and productivity indicators for effective crop selection. Their work is in line with Reddy et al. [11], who emphasized crop price forecasting using AI methods to aid farmers in market-oriented decision-making. AI and machine learning are revolutionizing agriculture by improving crop forecasting, farm management, and advisory systems. Chatbot-based solutions (Geethajali et al. [1], Chandolikar et al. [6]) offer real-time advice, while predictive models (Mahmud et al. [2], Badshah et al. [5]) enhance crop classification and yield prediction. AI-based farm management (Varsha et al. [4]) and hybrid models (Elbasi et al. [3], Devan et al. [14]) maximize resource allocation and decision-making. These innovations push smart, data-driven agriculture toward improved sustainability and profitability.

These works together emphasize the progress in AI-based agricultural decision support systems, which serve as the basis for precision farming solutions such as AgriPulse. Decision support systems powered by artificial intelligence have also been used to fill the knowledge gap in agriculture. Research on Natural Language Processing (NLP)-based chatbots has proven their worth in delivering real-time agricultural counsel, disease diagnosis, weather conditions, and market prices. The AI-based advisory tools provide individualized suggestions and improve decision-making among farmers, especially those from rural areas who have limited exposure to expert advice. This comparison of related work highlights the advancements in AI-powered intelligent agriculture, underscoring the contributions made by machine learning, IoT, deep learning, and predictive analytics in addressing problems of modern-day agriculture.

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The ensuing sections compare methodologies and report research gaps and potential future directions for the use of AI in agriculture. The scalability of IoT-based smart farming systems has enabled accurate monitoring and adaptive management of agricultural inputs, maximizing efficiency and sustainability. In addition, AI-driven market intelligence solutions have allowed farmers to make informed decisions about harvest schedules and price plans to achieve greater profitability. With these innovations, however, comes the hindrance of challenges such as poor data availability, exorbitant implementation costs, and the demand for more interpretable AI models, which calls for more research and development. Current research points to the large contribution of AI and machine learning in precision agriculture, enhancing crop forecasting, farm management, and decision-making. Despite this, data constraints, climate uncertainty, and accessibility limitations point to the necessity for more adaptable, scalable, and farmer-centric AI solutions.

TABLE I
COMPARATIVE ANALYSIS OF AI-BASED METHODOLOGIES IN SMART AGRICULTURE

Feature	**Crop Recommendation & Yield Prediction**	**Soil Health Monitoring**	**Plant Disease Detection**	**Water Management**	**Market Forecasting**
AI Models Used	Random Forest, SVM, ANN, Genetic Algorithms	IoT with ML	CNNs, GANs, SSL	ML-based Smart Irrigation	ARIMA, LSTM, Regression
Data Sources	Soil composition, climate, historical yield	Sensor data (pH, NPK, moisture)	Image-based disease recognition	Soil moisture, climate data	Market trends, economic indicators
Accuracy	95%-99%	High Precision	90%-98%	85%-95%	80%-95%
Implementation	AI-based recommendation systems	AI-enabled soil monitoring	AI-powered pest detection	IoT-based irrigation control	AI-driven price prediction models
Limitations	Requires large datasets for high accuracy	Sensor dependency, real-time data challenges	Need for large labeled datasets	High infrastructure costs	Market uncertainties affecting predictions

Table I presents a comparative overview of the different AI-based approaches employed in crop recommendation, soil health assessment, plant disease identification, water management, and market prediction. The AI algorithms applied in these fields vary from machine learning methods like Random Forest, Support Vector Machines (SVM), and Artificial Neural Networks (ANN) for crop suggestion to deep learning algorithms like Convolutional Neural Networks (CNNs) and Generative Adversarial Networks (GANs) for plant disease identification. The sources of data also differ extensively, with crop suggestion based on soil and weather data and plant disease identification based on image recognition methods. Market forecasting models take into account historical market trends and economic indicators that are subject to unpredictable external effects.

On the accuracy front, AI-based models tend to offer high performance, ranging from 95%-99% for crop recommendation models to up to 98% for plant disease detection models. The implementation challenges and constraints of each category, however, vary. Soil health monitoring is based on real-time IoT sensor data, which is prone to sensor failures and data inconsistencies, while AI-based irrigation control demands high infrastructure investment, hence restricted in rural regions. Moreover, market forecasting models are plagued by uncertainties resulting from demand variability and price volatility. Overcoming these constraints needs improved data integration, more interpretable AI models, and scalable solutions to drive AI adoption in smart agriculture.

IV. CHALLENGES IN EXISTEM SYSTEM

Despite significant advancements in AI-driven agriculture, several challenges hinder the widespread adoption and efficiency of these technologies. The key challenges include data availability, computational requirements, model interpretability, infrastructure constraints, cost limitations, and real-world adaptability. By analyzing related research, we can identify the primary obstacles affecting AI implementation in precision agriculture.

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Constrained Real-Time Decision Support – Although chatbot-based advisory systems (Geethajali et al. [1], Chandolikar et al. [6]) are useful in presenting insights, they are not necessarily adaptable in real time to unforeseen environmental or market updates, which constrains them for responding effectively under dynamic farming scenarios.

Accuracy and Generalization Problems – Crop prediction and yield forecasting machine learning models (Mahmud et al. [2], Badshah et al. [5]) are hampered by accuracy as a result of data scarcity, local conditions, and unpredictable weather conditions, making them less reliable in varying agricultural environments.

Convergence of AI and IoT – AI-based farm management software (Varsha et al. [4], Elbasi et al. [3]) demands transparent IoT sensor integration, cloud computing, and AI algorithms, but issues such as lack of data connectivity, infrastructural expense, and technical knowledge slow down the adoption process.

Scalability and Computational Intensity – Hybrid AI algorithms (Devan et al. [14], Pande et al. [15]) yield improved prediction efficiency but tend to involve high levels of computational effort and large quantities of data and therefore are impractical to apply to resource-constrained devices being employed by small farmers.

Market and Economic Factors – AI-driven crop price and market forecasting models (Reddy et al. [11]) are not robust in managing volatile economic patterns, trade policies, and unexpected disruptions, resulting in inconsistent advice to farmers.

User Adoption and Accessibility – Most AI-based solutions have technical expertise needs (Nigam et al. [9], Reddy et al. [10]) and hence would be less available to conventional farmers, which suggests the importance of user-friendly interfaces, local language support, and training programs.

Explainability and Trustworthiness in AI-driven Decisions – AI systems (Badshah et al. [5]) lack transparency and interpretability, hindering trust among farmers toward computer-issued suggestions since their decisions would remain obscure to explain. Privacy and Security in the Data – AI technologies compile agribusiness confidential information (Elbasi et al. [3]) leading to concern regarding privacy and protection of that information and lack of proper rights.

Cost is yet another significant constraint. Although AI-driven advisory systems, drones, and IoT devices can increase efficiency, their steep initial cost and maintenance expenses render them inaccessible to most farmers (Machine Learning-Driven Forecasting and Marketing Optimization Platform for Sustainable Agriculture. Moreover, small farmers also incur financial risks in using AI solutions because their success relies on data quality, model precision, and fluctuating environmental conditions.

Finally, AI agricultural models tend not to generalize across regions and climatic conditions. For example, an AI model that has been trained on North American climate data will not work well in African or Asian agricultural environments, where soil types and weather patterns are quite different (E-Xpert Bot - Guidance and Pest Detection for Smart Agriculture Using AI). Likewise, pest and disease detection models learned on a small number of plant species have difficulty detecting new crop diseases and pests beyond their training set. Overcoming the challenges in current AI-based agricultural systems is essential for the successful implementation of smart farming technologies. Data scarcity, high computational expense, infrastructure constraints, and model interpretability remain major bottlenecks for large-scale deployment. Farmers struggle to access credible AI-driven insights because of low digital literacy and IoT deployment costs. Breaking these hurdles calls for cheap AI solutions, enhanced data collection methods, and enhanced infrastructure support. Addressing these challenges can make AI fundamentally transform agriculture into a more efficient, accessible, and sustainable profession for farmers across the globe. Combining machine learning, IoT, and remote sensing through hybrid AI models can aid in overcoming limitations in smart agriculture. Standardizing data and making it accessible will enhance the accuracy and responsiveness of AI models across various regions. Governments and private enterprises need to fund digital infrastructure as well as low-cost AI-powered tools to benefit small-scale farmers. Augmenting explainable AI (XAI) methods will also develop trust among farmers, leading to greater adoption. An intersectoral collaborative effort between policymakers, researchers, and agritech firms is critical to propel the future of AI in agriculture.

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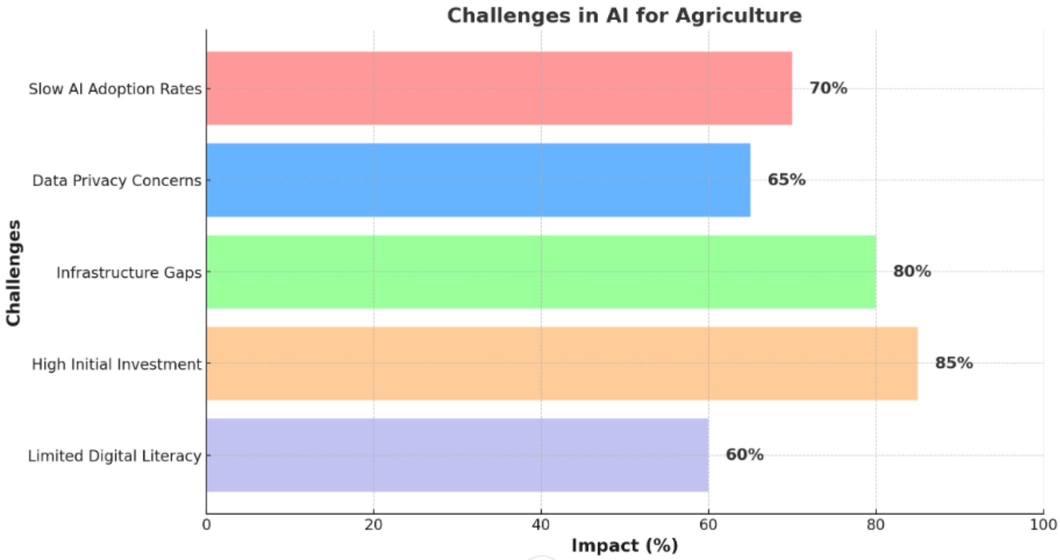

Fig 1. Key Challenges in AI-Based Agriculture and Their Impact

The graph also emphasizes the major challenges to implementing AI-based technologies in agriculture, with financial expenditure high upfront (85%) and infrastructure shortages (80%) being top of the list. Implementing IoT-based precision farming, AI-based drones, and automated irrigation systems is too expensive for small and medium-scale farmers to adopt en masse. Furthermore, limited internet connectivity and inconsistent power supply in rural settings hinder the installation of real-time AI solutions, limiting access to data-driven decision-making and farm automation.

Slow rates of AI adoption (70%), data privacy issues (65%), and limited digital literacy (60%) are other key challenges. Farmers are skeptical about AI recommendations and would rather use conventional farming practices because of low awareness and resistance to change. Data privacy issues further complicate AI adoption because farmers are not willing to provide farm data to AI systems owing to ambiguous policies. Moreover, limited digital literacy among rural farmers prevents them from effectively utilizing AI-driven advisory platforms and predictive analytics tools. The solutions to these challenges include affordable AI solutions, better infrastructure, transparent data policies, and farmer training programs to bridge the technology divide in agriculture.

V. CONCLUSION

Artificial Intelligence and machine learning have transformed the agricultural industry by improving crop forecasting, disease identification, market prediction, and farm management. Research has shown the efficiency of AI-powered chatbots, predictive analytics, and IoT-based monitoring systems in raising productivity and efficiency. Yet, there are serious challenges such as data quality issues, climate variability, absence of real-time adaptability, high cost of implementation, and low accessibility for small farmers. Furthermore, AI models tend to be plagued by interpretability issues, integration challenges, and scalability limitations based on infrastructure availability in rural settings. Resolving these problems is crucial to making AI-based agricultural solutions reliable, inclusive, and sustainable for all farmers.

Future studies must concentrate on creating more resilient, interpretable, and adaptive AI models that can cope with real-time climate uncertainties and local soil heterogeneities. The convergence of edge computing and power-efficient AI infrastructure can facilitate wider adoption of such technologies in low-resource rural and farming contexts. Moreover, the enhancement of multilingual and culturally sensitive AI-powered advisory systems will promote their usage among more heterogeneous farming groups. More enhanced AI-based detection of pests and diseases using high-resolution imaging and deep learning capabilities will further bolster early intervention options to minimize losses of crops. Implementation of blockchain for safe and transparent sharing of data and AI-powered market forecasting systems can empower farmers with improved pricing models and supply chain management.

Financial incentives, infrastructure development, and training programs to facilitate AI adoption among farmers can be provided through collaboration between policymakers and stakeholders. Promoting open-source AI models and standardization initiatives will help improve interoperability across various agricultural ecosystems. Finally, cross-disciplinary studies integrating AI, remote sensing, climate sciences, and regenerative farming systems will be vital in

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creating overall, future-fit agricultural solutions. Through the handling of these problems and the diversification of AI functions, future precision agriculture holds the potential for greater productivity, minimized wastage of resources, and enhanced food security worldwide.

REFERENCES

[1]. T. M. Geetanjali, P. B. Prithvi raj, P. K. M. Prajwal, P. G. C. M. Prajwal, and Priyanka., "Agroinsights Chatbot: AI-Driven Precision Farming for Optimal Yields, Crop Selection, And Disease-Free Harvests," in 2024 IEEE North Karnataka Subsection Flagship International Conference (NKCon), 2024.

[2]. T. Mahmud, N. Datta, R. Chakma, U. K. Das, M. T. Aziz, M. Islam, A. H. M. Salimullah, M. S. Hossain, and K. Andersson, "An Approach for Crop Prediction in Agriculture: Integrating Genetic Algorithms and Machine Learning," IEEE Access, vol. 12, pp. 173583, 2024.

[3]. E. Elbasi, N. Mostafa, Z. Alarnaout, A. I. Zreikat, E. Cina, G. Varghese, A. Shdefat, A. E. Topcu, W. Abdelbaki, S. Mathew, and C. Zaki, "Artificial Intelligence Technology in the Agricultural Sector: A Systematic Literature Review," IEEE Access, vol. 11, pp. 171-202, 2023.

[4]. L. Varsha, S. Ankith, M. Deeksha, and S. J., "AI-Driven Farm Management System using Streamlit," in 2024 IEEE 15th International Conference on Computing Communication and Networking Technologies (ICCCNT), 2024.

[5]. A. Badshah, B. Y. Alkazemi, F. Din, K. Z. Zamli, and M. Haris, "Crop Classification and Yield Prediction Using Robust Machine Learning Models for Agricultural Sustainability," IEEE Access, vol. 12, pp. 3486653, 2024.

[6]. N. Chandolikar, C. Dale, T. Koli, M. Singh, and T. Narkhede, "Agriculture Assistant Chatbot Using Artificial Neural Network," in 2022 International Conference on Advanced Computing Technologies and Applications (ICACTA), Coimbatore, India, 2022, pp. 1-5

[7]. P. K. Maduri, P. Dhiman, M. R. Shukla, S. Anand, and S. P. Singh, "Farmers Agriculture Assistance Chatbot," in 2021 3rd International Conference on Advances in Computing, Communication Control and Networking (ICAC3N), Greater Noida, India, 2021, pp. 1884-1889.

[8]. M. Momaya, A. Khanna, J. Sadavarte, and M. Sankhe, "Krushi – The Farmer Chatbot," in 2021 International Conference on Communication Information and Computing Technology (ICCICT), Mumbai, India, 2021, pp. 1-6.

[9]. A. Nigam, S. Garg, A. Agrawal, and P. Agrawal, "Crop Yield Prediction Using Machine Learning Algorithms," in 2019 Fifth International Conference on Image Information Processing (ICIIP), Shimla, India, 2019, pp. 125-130.

[10]. D. J. Reddy and M. R. Kumar, "Crop Yield Prediction Using Machine Learning Algorithms," in 2021 5th International Conference on Intelligent Computing and Control Systems (ICICCS), Madurai, India, 2021, pp. 1466-1470.

[11]. H. K. Reddy and M. R. Kumar, "Crop Price Prediction Using Machine Learning Algorithms," in 2021 4th International Conference on Computing and Communications Technologies (ICCCT), Chennai, India, 2021, pp. 611-616.

[12]. V. Krishna, T. Reddy, S. Harsha, K. Ramar, S. Hariharan, and B. A, "Analysis of Crop Yield Prediction using Machine Learning algorithms," in 2022 2nd International Conference on Innovative Sustainable Computational Technologies (CISCT), Dehradun, India, 2022, pp. 1-4.

[13]. S. Vaishnavi, M. Shobana, R. Sabitha, and S. Karthik, "Agricultural Crop Recommendations based on Productivity and Season," in 2021 7th International Conference on Advanced Computing and Communication Systems (ICACCS), Coimbatore, India, 2021, pp. 883-886.

[14]. K. P. K. Devan, B. Swetha, P. Uma Sruthi, and S. Varshini, "Crop Yield Prediction and Fertilizer Recommendation System Using Hybrid Machine Learning Algorithms," in 2023 IEEE 12th International Conference on Communication Systems and Network Technologies (CSNT), Bhopal, India, 2023, pp. 171-175.

[15]. S. M. PANDE, P. K. RAMESH, A. ANMOL, B. R. AISHWARYA, K. ROHILLA, and K. SHAURYA, "Crop Recommender System Using Machine Learning Approach," in 2021 5th International Conference on Computing Methodologies and Communication (ICCMC), Erode, India, 2021, pp. 1066