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Hyperlocal Precision Agriculture in Deltaic Ecosystems: A Critical Survey of AI, Machine Learning, and Data-Driven Approaches for Crop Intelligence and Decision Support

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ABSTRACT

Deltaic agricultural systems are facing more and more stress because of changes in the weather, a lack of water, and more crop diseases. This problem is especially clear in the Cauvery Delta region of Tamil Nadu, India, where limited resources are making it harder and harder for farmers to grow crops. Recent improvements in artificial intelligence (AI), machine learning (ML), and deep learning (DL) have made it possible to create intelligent decision support systems for important agricultural tasks like finding crop diseases, predicting yields, managing irrigation, and giving farmers advice. Even though there has been a lot of progress, current research is still broken up, and there hasn't been much work done to bring it all together through comparative evaluation, systematic taxonomy construction, and finding research gaps across domains. To mitigate this limitation, this survey offers an extensive examination of AI-driven methodologies utilized in deltaic agricultural systems. The research encompasses machine learning (ML), deep learning (DL), and hybrid methodologies within essential agricultural sectors, offering a systematic comparative assessment based on performance, scalability, cost, and practical applicability. Also, a hierarchical taxonomy is created to sort existing systems by methodology, data dependency, and deployment context. This gives a clear picture of the current research trends. The survey also points out important structural problems that make it hard for people to use the technology in the real world. These problems include the lack of decision frameworks that consider the source of water, the difference between controlled experimental datasets and real-world conditions, the lack of region-specific (Tamil-language) advisory systems, and the reliance on hardware-intensive infrastructures. Finally, the paper talks about future research directions that will lead to AI solutions that are integrated, easy to understand, light, and focused on farmers. These directions stress the need for hyperlocal, easy-to-use, and scalable systems to help sustainable precision agriculture in deltaic areas with limited resources.

Keywords: Precision Agriculture; Crop Disease Detection; Yield Prediction; Irrigation Management; Farmer Advisory Systems; Deep Learning; Explainable AI; Internet of Things (IoT); Hyperlocal AI; Deltaic Agro-Ecosystem.

1. Introduction

Agriculture is the focus of a clashing set of interests, between food production and the effects of agriculture on the environment (i.e. ecosystem stress) and deltaic agro ecosystems have the highest imbalance between absolute potential productivity and risk of agricultural disturbance because of their relative scale and the availability of large quantities of water [1]. For example, the Cauvery Delta in Tamil Nadu has been considered the "Rice Bowl of South India" due to its very rich alluvial soils with a wide variety of crops (such as rice, sugarcane, bananas, coconut, legumes, oilseeds, vegetables) that can be grown more than once a year [1],[2]. These production abilities are however, increasingly being compromised by various environmental pressures, which include: (1) change in climatic conditions (temperature, precipitation, humidity) due to climate change; (2) inter-state tensions among states in terms of more water coming out of the river; and (3) high humidity, which supports the growth of fungi, bacteria and viruses on crops .

Government agency seasonal bulletins, crop calendars and traditional extensions relying on experience are very common as a source of agricultural advisory frames [10]. They are, however, not detailed enough to give information that can be specific to deltaic areas that are highly spatially variable. It cannot identify hyper-local differences in soil type, real time changes in weather, or the fact that there are several sources that the farmer may use to irrigate at various levels to provide varying amounts of water; they end up giving the farmer useless guidance. As a result, farmers cannot make sound decisions leading to less resilient operations.

The development of AI, ML, and DL has allowed developing data-oriented decision support systems in the sphere of agriculture. This has influenced several aspects such as detection of disease in crops, prediction of crop yield and control of irrigation and giving guidance to farmers among others [2],[13],[14]. Some studies have shown how we can move from a traditional, empirical model for disease forecasting to more integrated and complete models based on AI technology, utilizing IoT technologies and data analytics [1],[18]. Additionally, deep learning models, such as CNN's, have been shown to have high accuracy in classifying benchmark datasets of disease in plants; however, the same research has also exposed some limitations of these models when applied to the real-world setting and their ability to generalize beyond the data they were trained on.

In spite of numerous improvements in the field of research, the existing literature remains quite fragmented. Most of the already existing studies are related to a particular domain of problems (individual problems in various areas) and do not present a complete picture of the research itself. No serious synthesis of existing approaches that classifies the approaches, compares the relative performance of the approaches, and reveals limitations under various areas that will prevent a viable use of the approaches exists at the moment [2],[15]. This survey tries to address this gap in the literature by transcending the descriptive analysis and providing systematic and evidence-based synthesis.

The present paper is the initial step towards developing a holistic view of the application of Artificial Intelligence (AI) and Machine Learning (ML) to agricultural systems. The research paper discusses three key contributions of AI in agriculture as a framework, a comparative review of the use of AI systems in agriculture, and a synthesis of the literature on the research in different fields of AI application, all three of which will form the foundation of future research endeavours in precision agriculture that will integrate all of these disciplines. In addition, the paper provides opportunities where future research can be conducted to further develop the practical uses of precision agriculture, such as the necessity to have a better system in data management and sharing, the necessity to have open-source software to predict crop yield, and the necessity to have reliable means of gauging market demand of agricultural products.

1.1. Study Objectives

The main aims of this survey are the following:

- To examine and evaluate contemporary AI, Machine Learning, and Deep Learning-based systems in agriculture for the detection of crop diseases, yield forecasting, irrigation management, and providing guidance to farmers.
- To assess and contrast agricultural AI models to ascertain their relative performance in terms of efficiency, scalability, cost-effectiveness, interpretability, and practical applicability in real-world scenarios.
- To make a structured hierarchy of agricultural AI models that sorts them by the method used to solve the problem, how much data they need, and the situation in which they are being used or deployed.
- To find important areas where more research is needed, such as the need to create water-source-aware decision systems, controlled-to-field datasets, an advisory system that gives instructions in Tamil, and the fact that AI needs hardware to work.

➢ To pinpoint the challenges in employing current AI systems to aid farmers in delta ecosystems, characterized by fluctuating elevations, such as the Cauvery Delta.

➢ To propose avenues for future research aimed at creating hyperlocal, transparent, lightweight, and farmer-centric precision agriculture systems that facilitate sustainable agricultural practices.

2. Literature Survey

Artificial Intelligence (AI) and Machine Learning (ML) techniques have been successfully employed for Decision Support Systems in agriculture. I have organized this review to use a structured view of Methodological Approaches from Classical ML to Advanced Deep Learning, Hybrid & Advisory Systems like the existing Medical AI Studies frameworks.

Agricultural AI is largely based on traditional ML techniques. These methods have produced reliable results on structured data including soil and weather, as well as offering interpretable outputs. Applications of ML in precision agriculture have been reviewed by Sharma et al. [13]. The applications range from yield prediction for several crops (wheat, maize, corn, rice, barley) to different methods of machine learning (SVM, Random Forest, Neural Networks). Kamir et al. [14] constructed yield gap maps for wheat production using several variables to predict yield using ML models such as NDVI time series, rainfall, and temperature. Gümüşçü et al. [33] found that KNN, SVM and Decision Trees successfully predicted wheat planting using 300-day mean of meteorological variables with the most accurate prediction produced by the KNN model.

Disease detection has been successfully achieved through use of machine learning techniques. Pallathadka et al. [3] developed an automated system for detecting rice foliar disease using support vector machines (SVM), naive Bayes classifiers, and convolutional neural networks (CNNs); feature extraction via PCA and histogram equalization preprocessing were also utilized. Sujatha et al. [4] contrasted deep learning versus traditional ML techniques for detecting plant leaf diseases. Ramesh and Vydeki [27] utilized deep neural networks combined with the Jaya algorithm to identify and classify rice diseases (bacterial blight, brown spot, sheath rot, blast) accurately and efficiently. Wang et al. [28] built models based on SVM, backward propagation neural networks (BPNN), random forest, etc., for identifying wheat stripe and leaf rusts in both field and laboratory settings; they noted discrepancies in performance based upon wheat varietal differences and environmental factors.

Delfani et al. [1] documented the 1978 inception of the EPIPRE model as a pioneering farm-sample-based simulation tool designed to predict disease throughout a given growing season, utilizing data provided by the farmer on soil characteristics, stage of crop development, the presence of disease, and the approach to applying nitrogen fertiliser, as well as to determine optimal timing for fungicide use when crop damage was predicted. Similarly, from the information above, Beyer et al. [10] developed the SHIFT model, which had a mean deviation of 0.62±2.4 days from the respective actual vs predicted outbreak dates, thus providing users with the timing of fungicide application (without requiring the user to interpret epidemiological data), which was estimated to be 84.6% accurate. Many empirical models generated through the use of data sharing demonstrate on an aggregate basis that ML techniques are interpretable and computationally sufficient, but all face the significant challenge of having to use historical averages for modelling data, and thus all fail to provide a mechanism for modelling or generating new real-time deviations from historical averages [1],[32].

Agriculture AI Trends in Deep Learning – The Impact of Recent Developments in AI on Precision Agriculture – Deep Learning has led to remarkable advances in Agricultural AI. One of the key developments in this area has been the application of CNN architectures to crop disease identification from image data, which makes up 49 of 150 studies reviewed by Majdalawieh et al [2]. using a PRISMA approach. More than half of these studies reported greater than 99% accuracy with CNN architectures, and nearly all Vision Transformer models achieved 100% accuracy in some studies. In addition, one of the significant trends observed in the research literature was the movement from binary classification of diseased or healthy crops to multi-class classification of diseases. The use of Res Net, Dense Net, Efficient Net, and Mobile Net architecture has provided significant transfer learning capabilities with respect to the Agricultural dataset.

Haridasan et al [5]. used DL techniques (i.e., combining image processing, ML, and DL) to automate accurate disease detection for rice and paddy (which are the primary crops in the Cauvery Delta) thus allowing timely intervention and increased crop health. Waheed et al [29]. implemented Dense Net (dense CNN architecture) that can detect diseases in the leaves of corn. Kulkarni et al [15]. demonstrated that RNN architectures using a combination of soil properties, rainfall, and measurements of nutrients collected over a 31-year period have produced extremely accurate forecasts of rice yield. Chu and Yu [16] developed an end-to-end DL model to predict yield of rice grown in the summer and winter seasons in China. Cai et al. has developed a wheat yield prediction model based on SVM, RF and Neural Network methods, integrating 14 years of historical satellite and climate related information, finding that while both climate and satellite information were useful, the data provided by climate sources provided specific information not available via data from satellite sources.

Vision Transformers (ViT) have emerged as cutting-edge models. Hemalatha and Jayachandran [7] created a ViT for multi-task learning to localize and classify plant diseases while Kunduracioglu and Pacal [8] showed that grape leaf diseases can be classified using a ViT network. According to Majdalawieh et al. [2], traditionally trained CNNs perform comparably to VITs in terms of accuracy but require a fraction of the computation power compared to VITs; therefore, they present a better option for deploying AG-tech solutions into resource constrained (agricultural) environments (i.e., in the real-world). In addition, Majdalawieh et al. [2] determined that models trained on RGB images achieved 96.94% accuracy and models trained on hyperspectral images achieved 95.81% accuracy which confirms that costly image generating equipment does not necessarily produce the "best" image for certain classification tasks.

Programs based on a process and deep learning to forecast disease include the EWS model documented by Delfani et al. [1], that was developed for use in wheat rust (due to the efforts of Allen-Sader et al. [9]), including real-time field surveys, numerical weather predictions, spore dispersal forecasts, and model predicting environmental suitability, all to send alerts through 7 -14 days prior to human symptom appearance. Another program, the EPIWHEAT model (Savary et al. [17]), utilized only physical environmental conditions and was able to predict the occurrence of wheat disease by determining the potential epidemic at scales from the level of an individual field to

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a national epidemic at different levels of prediction accuracy. Thirdly, RUSTDEP (Rossi et al. [41]) was able to predict with high accuracy with a value of 80% within 95% confidence interval limitations over the mechanistic modelling; therefore, providing substantial justification for their use [1].

Deep learning methods, specifically convolutional neural networks (CNNs) and Vision Transform Network (ViT), provide excellent performance for detecting crop diseases as indicated in Table 2. Nonetheless, considerable weaknesses can be found in the studies examined. To begin with, most training datasets are from controlled sources such as Plant Village, which do not mirror actual conditions in the field and will limit the generalization of the algorithms. Secondly, most deep learning systems for crop disease detection utilise images after observable symptoms have occurred, meaning they are frequently used reactively rather than proactively. Thirdly, current systems typically don't factor in environmental factors such as water availability or how the source of irrigation will affect these diseases. Although process-based modelling systems, such as EWS and EPIWHEAT, are being developed to meet the need for early crop disease prediction by including environmental and climate parameters, they are primarily developed and validated for the temperate crop-based systems (specifically wheat); therefore, they are not easily transferred to tropical/delta crop systems.

Agricultural applications have experienced success as a result of hybrid AI methods incorporating the best of both worlds (multiple methods). Combining CNN and conventional ML methods gives rise to a hybrid technique to identify rice crop diseases in Agriculture IoT Systems developed by Wang et al [11]. Hybrid disease forecasting models were documented by Delfani et al [1], consisting of plant disease models, plant growth models, and fungicide models in a multi-model framework. Compared with single-method approaches, this hybrid approach yields more robust decision-support systems. An example of a hybrid EWS model for wheat rust is provided by [9] and [1], which integrates field survey results, weather predictions, spore dispersion models, and expert review; thereby validating that multi-source data fusion creates superior agricultural advisory information.

Farmers are becoming more aware of explainability as a vital factor for them to adopt artificial intelligence (AI) suggestions as they have greater choice than ever before. Delfani et al [1]. identified transparent, interpretable, and open-source AI development as a top-priority research area and found that most support vector machine (SVM) and artificial neural network (ANN) models currently in use are "black-box" models as it is usually very difficult to identify the relationship between input and output data through any systematic process. Also confirming the importance of cost-effectiveness analysis (CEA) as an alternative way to measure AI-based explainability, Majdalawieh et al [2]. determined that there were no CEA reports provided in their review of most studies examining the disease diagnosis/detection of plants. Accordingly, Gonzalez-Dominguez et al [40]. have stated that the disease models being developed for future agricultural systems will need to be flexible, transparent and integrated into decision support systems (DSS) that offer accurate and timely decision-making information to growers while considering economic factors in addition to technical support.

According to Garrett et al. [39], artificial intelligence (AI) aids big data translation for plant disease control and adapting to climate change. Examples include satellite-based systems (e.g. CHIME and NASA SBG) that provide high-resolution, "hyperspectral" images of plant health. Leal Filho et al. [38] documented AI's applications in the areas of water management and agriculture, and wildfire control. One of the key results of this study is that AI has forecasting capabilities to assess vulnerability within various regions. The diversified AI applications lead to creating integrated advisory systems that combine various types of data to provide clear and accessible recommendations to farmers based on region-specific languages.

Irrigation management has been mostly based on IoT sensor systems. According to Delfani, et al. [1], IoT system uses WSN & sensors for irrigation management of precision agriculture to collect and monitor the soil moisture, temperature, and crop yield. They send this information to the IoT cloud for future analysis. Misra, et al. [35], provide a review of imagery systems, big data and AI with respect to agriculture and food. Qazi et al. [37] do a narrative review of next generation smart agriculture using IoT enabled and AI based system with a discussion of communication technology (LoRa, ZIGBEE, WiFi, WiMax, and cellular technology) used to connect sensors. Variable rate technology has also been included as one of the important opportunities for precision agriculture to enable site specific resource management by Roy and George [36].

Since their inception, Farmer advisory systems have transitioned from being simple, printed bulletins to an advanced form of agronomist-based assistance; Shepherd et al. [23] indicate that farmers have an enhanced level of engagement with wide use of an LLM powered virtual assistant compared to the traditional way of communicating with an agronomist and use of an extension system. When analysing disease detection tools available on mobile platforms like Plantix, Majdalawieh et al. [2] conclude that they offer disease detection services but rely heavily on static knowledge bases. Kakwani et al. [25] show that having a dedicated Indian language pre-training of LLM exhibits much stronger Tamil natural language processing abilities, while Devlin et al. [26] provide evidence that BERT and the associated LLM will be able to use more than 100 different languages; the issue of adapting agricultural data in Tamil is currently not discussed in literature.

2.1. Problem Statement

➢ The Cauvery Delta is one of many Deltaic farming areas that are having major problems because of climate change, less water for farming, unpredictable rainfall patterns, and the spread of more crop diseases.

➢ There are already agricultural systems that use Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) to find crop diseases, guess yields, manage irrigation systems, and give farmers advice. However, these systems don't work well for Delta Agricultural Farm Operations.

➢ Most current AI, ML, and DL systems have been created and tested with controlled laboratory datasets. Because of this, they can't give Delta Agricultural farm operations the help they need.

➢ There are no AI, ML, or DL models that take into account the differences between irrigation sources, such as tanks, canals, borewells, and systems that get water from rain. But all farming operations in a Deltaic region must take into account all possible sources of irrigation.

➢ There aren't many ways to predict disease in deltaic crops using prevention methods. Most models that are currently in use only let you find diseases after they have already shown up, with symptoms already visible.

- Farmers in these areas can't use the agriculture advisory systems in Tamil (and other regional dialects), the real estate advisory systems, and so on. This makes it much harder for them to use these resources. Smallholders can't use precision agriculture very well because it needs expensive IoT (internet of things) hardware and software.

- There are no definitive surveys that directly compare precision agriculture (to provide information that would identify practice constraints as well as gaps) in deltaic agro ecosystems.

- Therefore, a systematic review is necessary to facilitate the development of hyper-local, explainable, lightweight, farmer-friendly AI technology for precision agriculture that promotes sustainability.

- A structured review is necessary to facilitate the creation of hyperlocal, transparent, efficient, and agriculturist-friendly AI solutions for sustainable precision agriculture.

3. Conclusion

This survey critically and systematically reviews Artificial Intelligence (AI) and Machine Learning (ML) approaches to smart agriculture in four key domains: crop disease detection, yield prediction, irrigation management and farmer advisory systems. The work is a synthesis of other peer-reviewed studies and an extension of the old machine learning methodology to deep learning, hybrid systems, and advisory systems. It also contains comparisons, summary of the results, list of gaps in the research and future research recommendations. The discussion indicates that even though there have been remarkable advancements in algorithms, such as CNN-based disease detection models with high accuracy and process-based forecasting models capable of offering early warnings of disease are not feasible in deltaic agro-ecosystems. These constraints are primarily due to structural issues. They are ineffective integration of decision models that are water-source-aware, disjunction between controlled experimental data and reality, slow progress to Tamil-language agricultural AI systems, and reliance on expensive hardware infrastructure. In order to move towards accessible, understandable, and climate-resilient precision agriculture, we need to resolve the problems identified in this survey. The research of the future must be aimed at the development of integrated solutions that are farmer-centred and consider local issues and language barriers. This strategy will assist in enhancing decision-making in support of smallholder farmers in deltaic regions.

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Competing Interests Statement

The authors have not declared any conflict of interest.

Consent for publication

The authors declare that they consented to the publication of this study.

Authors' contributions

All the authors equally contributed to this study.

Informed Consent

Not applicable for this study.

Institutional Review Board Statement

Not applicable for this study.

Ethical Approval

Not applicable for this study.

Declaration of Artificial Intelligence

The authors declare that no artificial intelligence (AI) tools or AI-assisted technologies were used in preparing this manuscript.

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