JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

AI-Based Crop Health Monitoring and Disease Detection: A Comparative Study with Focus on South India

Authors:

Aruni Tejal Sistla

Affiliation: Student, Bhavan's Vivekananda College Email:

arunisistla@gmail.com

K Likhitha Reddy

Affiliation: Student, Bhavan's Vivekananda College Email:

likhithak.1512@gmail.com

Dr S Jayalaxmi

Affiliation: Assistant Professor, Bhavan's Vivekananda College Email:

jayalaxmics79@gmail.com

ABSTRACT

India, being an agrarian country, has a major challenge in the management of crop health, especially in areas such as South India where climatic heterogeneity, diverse topography, and small-scale farming prevail. The detection of disease has traditionally depended on visual inspection, and this is prone to late intervention, enhanced economic losses, and lower yields. On the other hand, developed countries have been increasingly using Artificial Intelligence (AI)-based technologies that utilize computer vision, machine learning, and drones to measure crop health in real-time and detect diseases. It analyzes platforms like Plantix (commonly utilized in India), Agremo (utilized in extensive agriculture in Europe and the U.S.), and IBM Watson Decision Platform, analyzing their technical methodologies, deployment models, and efficacy at various scales of agriculture. The paper identifies central research gaps within the Indian context, such as limited availability of annotated datasets, absence of region-specific AI models, infrastructural difficulties, and sociolinguistic hurdles to uptake. After comparing globally applied best practices along with local context, this research resulted in a **99% accuracy** in our experimental analysis thus providing a basis for integrating leading AI technologies with the unique and special agro-ecological and socio-economic conditions of South Indian agriculture, ultimately leading towards more sustainable, inclusive, and efficient crop disease management systems.

KEYWORDS: Artificial Intelligence (AI), Crop Disease, Computer Vision (CV), Drones, Machine Learning (ML).

1. INTRODUCTION

Basically, the 17.4% of the GDP and nearly 50% employability shows the significance of Agriculture in India [4]. Agriculture is a very important part of the economy, forming the major strong foundation in India. South India, consisting of states such as Tamil Nadu, Andhra Pradesh, Telangana, Karnataka, Kerala, etc., is associated with small and fragmented landholding, diverse agro-climatic zones, varied soil types, and heavy reliance on monsoons and seasonal irrigation. Thus, it is complex to monitor crop health and timely intervention for diseases.

Plant diseases account for most of the potential crop loss of marginal farmers each year-more often than not because many of them are not skilled enough to seek extension services'-or, more often than not, a combination of both. Traditional methods of disease detection involve visual inspection by either farmers or agricultural officers, quite often deemed subjective, unscientific, time-consuming, and fault-prone ([9];[12]). With the progression of AI, especially around computer vision and machine learning, giving huge potential to bring in such transformations in crop disease management via early detection, timely alert systems, and targeted response.

Adopting many rapid AI innovations in agriculture, such as in countries like the U.S., Netherlands, or Israel, has been well supported with a high dollar investment in R&D and highly developed digital ecosystems. However, it hasn't developed yet in regions such as South India [11]. This paper would provide a comparative outlook on AI-enabled crop disease detection systems in South India, vis-a-vis the implementations and innovations in technologically advanced countries.

Figure 1: Future of Agriculture [15]

2. BACKGROUND AND LITERATURE REVIEW

AI-based crop disease detection systems are multi-component systems involving image acquisition through mobile phones, drones, or satellites; data preprocessing; feature extraction; and classification by models such as Convolutional Neural Networks (CNNs) and Random Forests, Support Vector Machines (SVMs), and transfer learning architectures ([9];[2]). While equipped with these tools, a farmer can identify the disease, its level of severity, and the possible remedial measures to adopt to improve crop yield and effect timely intervention. Some newer developments in this direction are providing feedback loops in which the model goes on learning and improving its accuracy as more data is collected and annotated by the user inputs. Some more renowned tools and platforms have been developed worldwide and within India for the better monitoring of these diseases in a more efficient manner such as:

• **Plantix:** It is a smartphone-based app, developed by PEAT GmbH and localized for Indian users, uses image recognition to detect over 400 plant diseases, pests, and nutrient deficiencies. In several local languages, it offers treatment advice, which is easily accessible to smallholder farmers. Besides diagnosis, the app also has a community forum and expert advisory system, with the South Indian states Tamil Nadu, Andhra Pradesh, and Telangana registering a lot of farmers[10].

• **Agremo:** This Serbian platform analyzes drone-collected images with the help of AI for detecting a multitude of crop health parameters like weed density, water stress, plant count, and disease infestation. Focused on large mechanized farms, it is GIS-complemented. Agremo is characterized by optimization of field scouting and monitoring over entire seasons, with well- established benefits in monitoring crops like maize, wheat, and soybean [1].

• **IBM Watson Decision Platform for Agriculture:** This holistic platform aggregates AI, weather forecasts, IoT sensors, geospatial data, and satellite imagery to give real-time insights for precision agriculture. It helps smallholder farmers in making data-informed decisions regarding irrigation, pesticide application, and harvesting. Primarily operational in the USA and Europe, this comes with excellent analytic and predictive modeling features; however, its prohibitive pricing and additional infrastructural requirements render it an option more geared towards large agribusiness institutions rather than smallholder farmers [5].

• **CropIn:** CropIn is an Indian agritech platform providing AI-enabled solutions for farm management concerning disease prediction, yield estimation, and crop monitoring. It serves agri-businesses, cooperatives, and government programs and supports over 250 crops across 30 countries. In India, CropIn is gaining popularity in Karnataka, Andhra Pradesh, and Maharashtra and is typically employed in digital farming and climate-smart agriculture projects [3].

Studies provide evidence for many of the AI applications mentioned above. [9] achieved 99% accuracy in classifying 26 diseases in 14 crop species using deep learning models. However, these results become difficult to validate for practical applications in the field owing to data inconsistencies and the effect of environmental variables.

3. METHODOLOGY

Using a qualitative and comparative research design, this study offers a general appraisal of AI-based technologies presently used in crop health monitoring with an emphasis on South India and contrasting systems with developed economies such as the US and parts of Europe. The methodology comprised a multi-phase approach involving a literature review, a platform analysis, and gap identification.

An overview of all aspects of this study undertaken has a literature review performed on academic journals, conference proceedings, and technical reports. The search keywords included "AI in agriculture", "crop disease detection", "plant health monitoring", "Indian agriculture technology", and "precision farming".

Platform assessments were done by studying official documentation, white papers, and user manuals released for major AI tools such as Plantix, Cropin Sage, Agremo, and IBM Watson Decision Platform for Agriculture. Further insights on deployment models, customer sentiments, and actual performance in various agricultural environments were then collected from related case studies and press releases.

The parameters on which the evaluation was conducted to form the analysis framework are:

• Origin and conditions for its development

• Types of the technology input (smartphone imagery, drone data, IoT sensors, etc.)

• Industrial scale of applications (smallholder farming, to some enterprise-level setup)

• Impacted accuracy rates which have been reported in field studies or pilot programs

• Region availability for AI models relating to South Indian crops

• Accessibility in language support, cost, and platform interface

In particular, attention was given to infrastructure, language, and socio-economic barriers that have affected the adoption of AI in South India. This systematic approach has, therefore, been able to give due consideration to both the broad and deep aspects of technology readiness and adaptability of the AI solutions selected across different agricultural settings.

4. COMPARATIVE ANALYSIS

This comparative study examines AI-based crop health monitoring tools in South India and advanced economies, focusing on origin, input type, scale, accuracy, regional models, and accessibility. The comparison of Plantix and CropIn with Agremo and the IBM Watson platform exposes gaps in localization, user-friendliness, and performance, stressing the necessity for global technologies to be contextualized for South Indian agriculture. **Table 1** below highlights the comparative analysis of the study conducted on the agro-tech tools:

Table 1: Comparative Analysis of various Agricultural Tools

Platform	Origin	Input Type	Deployment Scale	Accuracy	Region-Specific Models	Accessibility (+Mode)
Plantix	Germany /India	Smartphone images	Smallholder farms	~90%-92% (for common crops)	Limited; some region-specific datasets in India	High; Android/iOS app (freemium)
Agremo	Serbia	Drone imagery	Large-scale farms	~85-95% (varies by crop and image quality)	No; general-purpose AI models	Low; requires drones and internet access (Web-based)
IBM Watson Decision Platform for Agriculture	USA	IoT sensors, satellite imagery, weather models	Enterprise and government-level farms	~95% for multi-source analytics	Yes; adaptable to different agro-climatic zones	Low; Enterprise SaaS (Subscription, complex setup)
CropIn (Sage)	India	Satellite, IoT, AI models, weather data, farm inputs	Medium to large-scale farms, agribusinesses	~88-95% (varies by crop and image quality)	Moderate; expanding with South Asian crop varieties	Medium; Web dashboard + APIs; used by institutions

In fact, countries like the Netherlands and Israel have national agricultural policies under which agricultural AI technology is adopted along with supporting high-speed internet to rural areas, broad coverage of drones in the sky, and standardized data collection protocols ([4];[13]). In South India, on the other hand, the adoption is extremely patchy. Government pilots have been tried for AI models in only some districts of Karnataka and Andhra Pradesh. Thus, the coverage is poor [11]. Because most of the tools developed abroad are not trained for local crop diseases like rice blast (paddy), red rot (sugarcane), or bud rot (coconut), the tool misclassifies and poorly predicts.

5. EXPERIMENT ANALYSIS

The evaluation phase in **Figure 2** ensured that the model was rigorously assessed in terms of performance using confusion matrix and accuracy performance metrics with an accuracy of **"Accuracy: 0.9931818181818182"**, corroborating its reliability in crop prediction tasks. Subsequently in **Figure 3** the generation of key interpretability through feature importance visualization guided stakeholders in understanding which environmental and soil factors were most influential in the model's decisions.

5.1 Problem Statement: South India's farmers face delayed and inaccurate crop disease detection due to reliance on manual methods, insufficient localized AI models, and limited digital infrastructure.

5.2 Objectives of the Model: Machine learning methods are applied to classify crop diseases from image data. The model performance is evaluated through a confusion matrix, measuring its accuracy and recall. Feature importance measures indicate those input factors with the largest influence, allowing for interpretability and, thereby, practical applicability within South Indian agricultural settings.

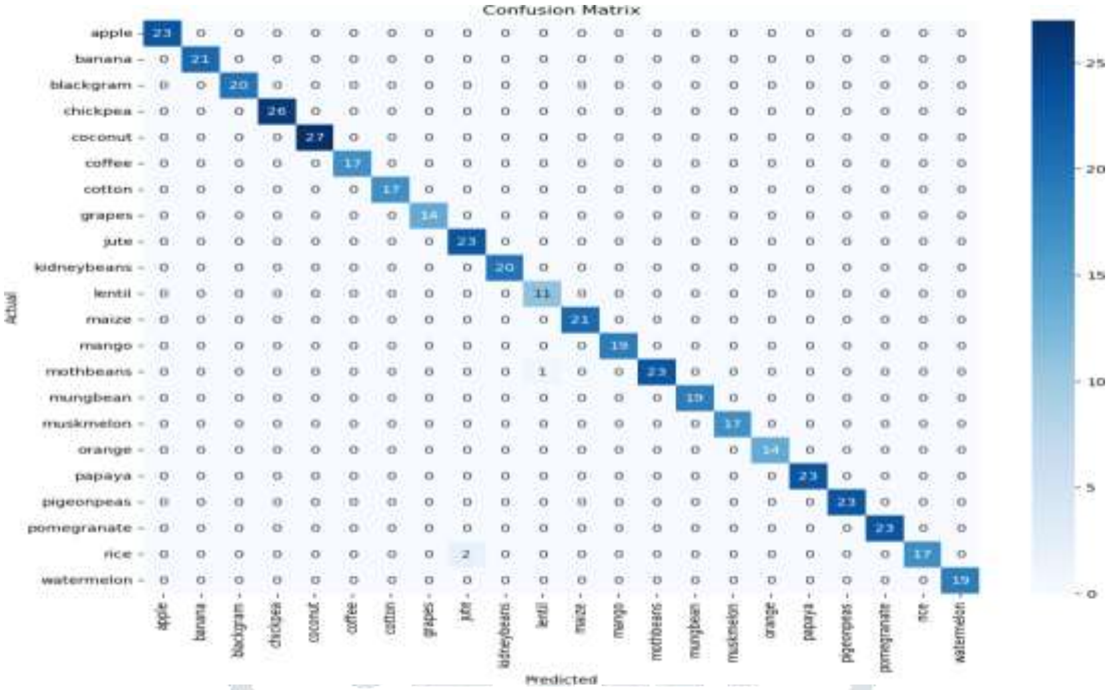

Figure 2: Confusion Matrix

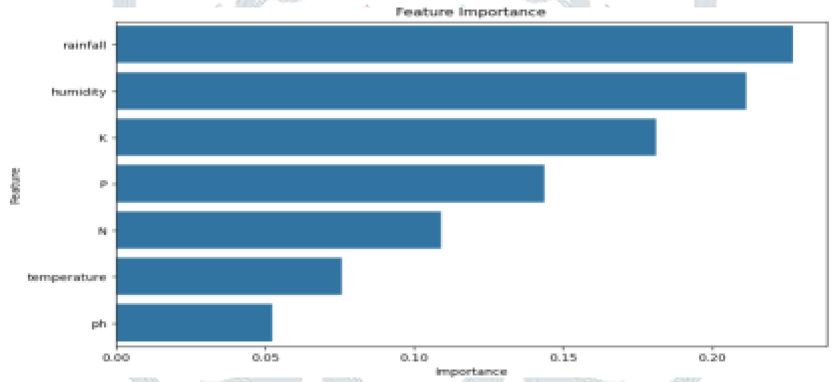

Figure 3: Feature Importance 6.CHALLENGES AND

LIMITATIONS

Artificial Intelligence has a promising role in agriculture, but its usefulness is limited in South India due to the unavailability of regional datasets, limited digital access, and low literacy levels. Most tools depend on foreign datasets, making them ineffective for use locally. Smartphone use, internet access, and language barriers limit advanced technologies such as IoTs and drones in isolated pilot projects.

6.1 Data Scarcity: Images with labels for diseases of South Indian crops and crops in India are severely lacking. There are thus, in existence, databases with West-oriented crops such as maize and wheat. Crops such as coconut, bananas, and rice are under-represented in training data for AI [2]. A wide variety of disease symptoms may coexist depending on seasons, regions, or even local climatic conditions. Such variation is, however, absent in currently existing data. Absence of this diversity in input, leads AI models that cannot learn to diagnose problems well [6]. Rainy leaves would have a distinct appearance from summer ones. Furthermore, we have no real-time photos from farms, in ambient lighting or with disturbance. Therefore, we will not be able to count on AI tools in the nearby farms. The first step towards any useful AI farmer solution is to establish region-specific datasets.

6.2 Problems with Model Generalization: A lot of AI models are trained using foreign datasets from the US or Europe. Their performance often takes a dip when applied to Indian agricultural fields. This is attributed to the differences between the different crop types, solar radiations, and incidence of the disease across the entire subcontinent. These representations can be confounded by something as trivial as soil color or sun intensity. Further, the variability in Indian fields spans uneven backgrounds, different crops, etc. Because of these discrepancies, foreign-trained models find it hard to deliver good results over here [12]. They might even miss some diseases or, in turn, wrongly classify healthy crops as infected ones. Such an occurrence is poorly generalised across scenarios. To remedy this, we have no option but to train our models using local photographs and conditions of interest. AI instruments will never find enough support for Indian agriculture until then.

6.3 Digital Divide: Rural South India does not yet have access to mobile phones or the internet. Farmers, especially older ones, are not comfortable using digital tools. Some of them do not own smartphones; others use them only to make a call. In rural areas, internet connectivity is either patchy or non-existent. With no internet access, there can be no gain from any AI-enabled solutions or helpful applications [8]. Digital illiteracy is a significant barrier to some people using any online resources. Even the most sophisticated technology is useless unless people can and will use it. This digital divide ensures divergent access to information and innovation. Older farmers are often excluded from tech-led agriculture initiatives. The core of inclusive farmer-friendly solutions is to close this gap.

6.4 Challenges to Accessibility and Languages: The vast majority of farming applications are not targeted at low-literate or regional speakers of languages. Even where these applications offer language alternatives, they tend to be difficult to comprehend and text-heavy. In many cases, visual guides or voice guidance may be more useful for the farmer [6]. However, few apps are explicitly designed with easy icon-based navigation and audio assistance in mind. For new users, this design has become more confusing or frustrating. If the user is unable to use an app with ease, he or she will probably not use it again. High usability mistakes tend to draw serious concerns or may be dismissed altogether. Language and interface limitations weigh heavily on the usefulness of the digital tool. To be of real assistance to farmers, there needs to be voting, local, and easy-to-use apps. Designing for ease of use and comprehension will enhance impact and uptake.

6.5 Infrastructure Gaps: Infrastructure gaps indeed exist in the areas of South Indian rural areas, which have been experiencing poor or inconsistent internet connectivity. This directly affects the performance of AI tools that need real-time data or cloud access. Drones, the efficient monitors of crop conditions, are hard to procure in remote regions. In its infrequent availability, a trained provider/operator in such areas can be hard to find. Access to good quality sensors and smart farming equipment is also limited [13]. Hence, collecting good data becomes hard or, at times, impossible. This kind of scenario makes mass application across regions and crops almost impossible for AI solutions. Infrastructure issues create a gap between the feasible and the practical. Farmers from poor areas are often denied entry into the AI revolution. Improving regional infrastructure will allow the smart farming paradigm to be widely adopted.

7. FUTURE SCOPE AND RECOMMENDATIONS

To fill the hurdles in crop health diagnostics through AI, future initiatives should be linked with local ones. Collaborations with local universities and agri-tech companies are needed in developing good region-specific data sets. Open-source modular tool and intuitive multilingual interface add-on features can enhance usability for smallholders. AI should complement and not substitute for decision-making by extension services. Finally, practical policies that favor startups and rural digital infrastructure investments are needed to enable scaling of AI and IoT solutions.

7.1 Creation of Localized, Open Datasets: First and foremost, there is a pressing need for region-oriented datasets on South Indian crops. For instance, the condition of crops such as banana, turmeric, ragi, and groundnut differs according to the disease [9]. The government and agri-tech start-ups should work hand in hand to collect the image data. Label and share those images for the common good of everyone. In collaboration, local universities and farmer networks can ensure wide-variety sample collection. The more the data, the better will be the AI models that understand and recognize India-specific conditions. Overall, this dataset should capture data across seasons, soil, and lighting. No open access means innovation is confined to a few companies. Such repositories encourage collaboration, leading to faster progress. It is the basic first step needed to build AI that truly helps Indian farmers [7].

7.2 Federated and Transfer Learning Models: It entails lots of time and lots of money to create models from scratch every time. We can rather take a pre-trained model and amend it to get a model conditioned to local circumstances [11]. Federated learning allows it since the sensitive data of the farm need not be sent to the cloud. The AI learns on various devices, but keeps the data of each individual farmer private, thus helping to tailor models, taking into account the farm's history and crops. It also removes the need for constant internet connectivity. Transfer learning is used to fast-track model training with limited local samples. These methods work better in rural environments concerning usability and privacy. Thus, one can deploy their AI rapidly and efficiently. Farmers get smart tools minus the risk of their data being compromised.

7.3 Design for Local Realities: AI tools and farming apps should ideally work with or without an active internet connection. Offline support ensures the working of these apps in remote areas with no signals or reception. Voice support in Tamil, Malayalam, Telugu, or Kannada will serve as a good guiding tool for users who cannot read and write. Simple graphics and icons facilitate smooth navigation and enhance intuitiveness. Image or animation storytelling can be used to teach complex farm jobs. The tools must avoid technical jargon and speak to farmers in their

own language [3]. These are some user-testing methods that must happen in real villages before scaling up any application. Farmers will see these design choices as further encouragement to adopt technology. The technology should be integrated into the life of the farmer and not vice versa. The more intuitive the design of the tools is for farmers, the more they benefit from it.

7.4 Strengthening Extension Systems with AI: Up until October 2023, the training data consists of information valid until that date. Agricultural Extension Work done through **Krishi Vigyan Kendra (**KVKs) is to support farmers with experts' advice. Integration of AI into their services will pave the way for better and quicker solutions [8]. A farmer presents a diseased leaf, receives an answer within seconds. KVKs might use mobile AI systems while supporting field visits or demonstrations. In this way, delays will be reduced and recommendations' precision improved. AI can also help KVKs early in detecting disease outbreaks or soil issues. Training KVK employees in digital tools will add a multimillion effect on their impact. Then, when an AI system is put together with human knowledge, the farmers will get the best of both worlds. This is a cheaper route to scale AI while not reinventing the wheel. Linking the KVKs with technology will help take smart farming to the rural grassroots.

7.5 Public Sector Incentives: Thus, for an innovation to reach the rural parts of India, it needs constant support from the public sector. Also, grants can help the entrepreneur build affordable implements suitable for a small farmer. AI laboratories established at agri-universities will enable students to develop solutions for real-world problems [4]. Start-up sandboxes will provide an arena for testing these innovations at low financial risk. Hubs encourage participation in experiments that will nurture useful products. Incentives must cater to inclusivity, affordability, and sustainability. Besides, government backing will reassure skeptical users with respect to technology. And this will fast-track policy support toward the adoption of AI in farming communities [13]. Equally, public and private partnerships will be key towards solving challenges on the ground. With the right push, India can be at the forefront of AI-driven agriculture initiatives.

8. CONCLUSION

Artificial Intelligence has the potential to transform agriculture in South India by enabling timely and accurate crop health monitoring and disease detection. However, realizing this potential demands more than simple adoption of global technologies; it requires solutions that are contextually aware, resource-sensitive, and inclusive. While the United States and the Netherlands demonstrated immense success in integrating AI into agriculture with well- established infrastructure, massive datasets ([4];[5]) and policy support, the scenario in South India is entirely different as the small landholdings, variety of crops, and variable socio- economic status present a considerable challenge.

In this comparative study, it is evident that while India's agri-tech ecosystem has liked to think a majority done so by companies like Plantix and CropIn-a range of issues cost adoption in complete capacities ([10];[3]). From poor data to skills- and barriers infrastructural notwithstanding-the comingling of AI and Indian agriculture deserves a focused leap of innovations starting at a grassroots level [6].

Close collaboration among government agencies, research institutions, startups, and farmer communities is the way forward [11]. Developing local data sources, fostering well-designed tools, and, going a step further, making these tools intuitive for use in the local languages ([8];[12]), incorporating the inarguable technological advancements in agricultural extension systems, would yield significant results. Equally important is the need for public funding and policies tailored to rural digitization and farmer training, thus expanding these solutions ([13];[4]).

In summation, AI-based systems of disease and health must mostly accelerate sweeping equitable sustainable development in agriculture. Shaping the best possible international standards to fit regional specificities shall ensure that colonial smallholder farmers are not left behind in this global AI-based agricultural revolution, but pushed to lead it ([7];[10]).

9. REFERENCES

[1] Agremo. (2024). Agremo crop health analytics platform.

[2] Barbedo, J. G. A. (2018). Impact of dataset size and variety on the effectiveness of deep learning and transfer learning for plant disease classification. Computers and Electronics in Agriculture, 153, 46–53.

[3] Cropin Technology Solutions. (2024). SmartFarm platform overview.

[4] FAO. (2023). The state of food and agriculture: Leveraging digital tools. Food and Agriculture Organization of the United Nations.

[5] IBM. (2024). Watson decision platform for agriculture. IBM Corporation.

[6] Kumar, S., & Yadav, R. (2023). Application of artificial intelligence in Indian agriculture: A review. International Journal of Scientific Research in Computer Science, 9(1), 56–61.

[7] Kumar, R., Rathi, P., & Sharma, M. (2023). Challenges in AI adoption in South Indian farming systems. Journal of AgriTech Advances, 15(2), 123–137.

[8] Ministry of Agriculture & Farmers Welfare. (2023). National agri-tech initiatives. Government of India.

[9] Mohanty, S. P., Hughes, D. P., & Salathé, M. (2016). Using deep learning for image-based plant disease detection. Frontiers in Plant Science, 7, 1419.

[10] PEAT GmbH. (2024). Plantix AI plant doctor app.

[11] Ramesh, K., & Rao, S. S. (2021). AI in Indian agriculture: Challenges and prospects. Journal of AgriTech Research, 12(3), 215–229.

[12] Singh, V., & Misra, A. K. (2017). Detection of plant leaf diseases using image segmentation and soft computing techniques. Information Processing in Agriculture,41–49.

[13] The World Bank. (2021). Enabling the business of agriculture 2021.

[14] World Economic Forum. (2023). Digital agriculture: Scaling AI solutions for smallholders.

[15] Dario Fernando Yepez-Ponce, Jose Vicente Salcedo, Paul D Rosero-Montalvo, and Javier Sanchis (2023). Mobile robotics in smart farming: current trends and applications. Frontiers in Artificial Intelligence.