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A Framework for Offline Artificial Intelligence Based Assistant for Small and Marginal Farmers

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Abstract

Applications of artificial intelligence (AI) to agri-culture include crop monitoring, detection of plant diseases, irrigation scheduling, yield prediction, and agricultural decision support. Advances in conversational AI, large language models (LLMs), mobile computing, and edge AI have made it possible to offer farmers agricultural advice using AI that is convenient and contextualized. Nevertheless, most of the current advisory systems are Internet-based and use cloud computing services that are not available to farmers in rural settings. The other challenges facing such advisory systems are inadequate regional language capabilities, incomplete localization of agricultural expertise, and the credibility of the AI-based recommendations. This paper provides a review of current research on agricultural advisory systems using AI, conversational agents, lightweight machine learning algorithms, and on-device AI. From the reviewed liter-ature, the paper has identified five main research gaps: internet dependence, computational cost, specific task capabilities, lack of localization and language capabilities, and recommendation cred-ibility. The proposed solution involves developing a conceptual framework for an offline agricultural assistant based on local on-device computation, locally stored agricultural knowledge, regional languages, and simple user interface. This approach is designed to offer appropriate farming advice while avoiding the need for constant internet access. The paper highlights several issues of implementation, maintenance based on knowledge and research needs. It will be necessary to develop a prototype and test it in order to evaluate its real applicability and efficiency.

Keywords: Agricultural Advisory Systems, Artificial Intelli-gence, Edge AI, Lightweight AI, Localized Agriculture, Offline AI, On-Device AI, Smallholder Farmers, Smart Agriculture.

I. Introduction

Artificial intelligence (AI) has been used increasingly of-ten in agriculture to help with crop monitoring, disease de-tection in plants, irrigation control, forecasting yields, and other decision-making tasks related to farming. With recent advances in conversational artificial intelligence and large language models (LLMs), there are more opportunities for the use of AI in giving guidance in agriculture through natural-language interaction. It means that farmers will be able to ask questions and get answers in the form of conversations. Even though it is possible to use new tools and technologies to give agricultural guidance, many AI-based systems of such type require access to the Internet and computing resources available in the cloud. This fact can make such systems hard to access for people living in rural areas where there is no stable Internet coverage and affordable computing devices with enough capacity of memory and

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computing power. There is an option in the form of edge AI and on-device machine learning, which can allow selected tasks related to AI to be performed locally on smartphones or any other devices with limited resources. Voice-based and regional-language interac-tion could add further accessibility to the farmers who have trouble using traditional text-based applications. Nevertheless, the current approaches to agricultural AI tackle various parts of this issue. Conversational advisory systems concentrate more on answering questions and information retrieval, while the lightweight mobile applications usually target some particular tasks such as crop and disease recognition. Offline processing, localized agricultural knowledge, resource-efficient comput-ing, and accessible interaction deserve more consideration thus. This paper provides a literature review on conversational agricultural AI, agricultural language models, mobile and edge AI, and lightweight machine learning. It pinpoints recurrent research gaps and suggests a conceptual framework for an offline, lightweight, and localized agricultural assistant for small and marginal farmers. The challenges that come along with the recommendation accuracy, knowledge-based updates, device limitations, and real-world evaluation are considered. The rest of this paper is structured as follows. Background and motivation are discussed in Section II. Related works are reviewed in Section III, and the comparative analysis of the approaches is provided. The research gaps are outlined in Section IV. The proposed scope, objectives, and conceptual framework are described in Section V. challenges and lim-itations. Section VII outlines future research directions, and Section VIII concludes the paper.

II. Background and Motivation

Small and marginal farmers form a very large percentage of the total number of farmers in many developing regions. Also, they work on very small plots on very thin margins, leaving no room for any mistakes. If applied using the wrong water, the price is loss of income, and the same goes with fertilizer application. These are times when expert advice is required. They are also the times when you are most unlikely to find one. This advisory service gap was supposed to be bridged using digital means over the years. Early systems were created using static content: Static FAQ, SMS tips, menu based apps. They were practical but inflexible; an answer would be provided only if someone had thought of it. Conversational AI (CAI) and Large Language models (LLMs) do just that. The farmer can now ask a question in their own language and get a suitable response to it. This is why recent studies are optimistic about the capability of AI to provide guidance. And why should you even worry about creating an offline assistant? Because of the distance between the two locations. You need to have reliable Internet connection and bandwidth for cloud models, while rural areas often cannot provide that. Inclusivity comes first and foremost, using “intelligence” in favor of farmers, who lack a modern phone or even decent signal—those are the people who get left behind and who could benefit from it.That is a pragmatic approach to the matter. The cell phones that rural farmers use will most likely be affordable, with minimum memory and processing power, and if they use a pay-as-you-go data plan, it will be very limited, or they might lack Internet connection. Doesn’t add another layer of functionality that would make design unnecessarily big or drain batteries or require Internet connection. That should be the primary requirement, and it will affect the rest of the features within the system. That is the difference between a lot of directions for agriculture AI, where resources are presumed by the people, for whom those tools are supposed to be used.

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III. Related Work

The data that has been collected in the study shows in-creased use of AI in farm consultancy. In response to farmer's questions, there are some systems. There are some that provide information on the decisions to make, detect plant disease, monitor the state of the crop or provide information in a chat interface. Generally speaking, these systems can be classified into two groups that complete each other. The other group is interested in answering and understanding the farmer's queries with the help of conversational AI or language models. The second one is effective performance of the application on a mobile or embedded device. Please note that if one group is doing something good, the other will not do that, normally. Language based systems are flexible, user friendly, costly and cloud based. On-device applications are highly limited in their capabilities and are offline based. A really important case study is the combination of the two.

A. Conversational AI and Language Models for Answering Questions from Farmers.

Conversational AI and Language Models for providing an-swers to farmers' questions. Farmer.Specific examples of how this was done include the following: Chat [1] and AgriLLM [2] are proof that AI and Language Models have capabilities to comprehend and translate a question from a farmer into relevant suggestions. Farmer.Chat is an example of scale, i.e., the ability to reach numerous smallholder farmers through chat. Nevertheless, it is the use of transformer-based language models for providing answers to farmers' questions with high accuracy that is novel and demonstrated in AgriLLM. As such, it would be beneficial to briefly review the study of Kuska et al. [3] by including some kind of filter that would help to distinguish crop-production decisions that can be used by LLM models and those that cannot.

B. Conversational search and domain-specific agents.

The importance of employing natural language and effective retrieval in order to assist farmers is considered in AgAsk [4] as well as in a comparison of the various technologies of conversational agents [5]. The matching between answers and agriculture-related questions is greatly improved by employing AgAsk. Meanwhile, the banana study investigates the most appropriate agent technologies for one crop and one farming scenario. All that they have in common is that the knowledge of words is not sufficient, the way of retrieving the information and linking it to a reliable source will affect the quality of the advice given.

C. Mobile and Edge AI for agricultural Tasks.

There is yet another aspect of mobile/edge AI, and it is clear that AI models may be physically located in a phone or a board. It is about 'lightweight on-device AI' as clearly illustrated by P2OP [6], RTSD-Net [7] and mobile cassava disease diagnosis applications [8]. They all point at the issues encountered by farming and only the light and nearby AI can help address them. P2OP can be applied in the field in order to determine whether or not there is a disease on a plant using the mobile device. RTSD-Net is an example of a real-time crop de-tection system, which uses low-power embedded devices. Off-line diagnosis system of cassava disease using mobilecamera. In conclusion, it is necessary to say that effective agricultural AI applications do not necessarily need the cloud technology.

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D. This is one way to look into the literature.

But it is also true that the literature is very transparent regarding its limitations. Many dialogue systems, as well as advisory systems, still depend on the Internet or some other external infrastructure in order to function. Normally, lightweight versions are used to perform certain functions, such as disease or crop detection rather than advice-giving on the farm. However, the question remains unanswered by all these studies– is the advice really effective in the field? Literature Survey Matrix, appropriately named, is used to present the studied papers as seen in Table I.

Research Novelty and Original Contributions

In the case of the already existing AI-based farm advisor systems, it is clear that they prove the capability of conver-sational AI, large language models, information retrieval, and mobile-based deep learning for making agricultural decisions. Nevertheless, such solutions typically take into account only one aspect of the issue. Conversational solutions are intended for handling farmers' questions, while mobile and edge AI applications pay much attention to some particular problems (crop recognition or plant disease recognition). Thus, there is still room left for research, concerning the integration of offline mode, localized agriculture knowledge, lightweight AI and farmers' easy access. What makes this paper unique is its conceptual framework for developing an offline, lightweight, and localized agricultural assistant. In this way, instead of using a huge cloud-based language model, the authors pay more attention to local processing, which is complemented with a knowledge base, containing information about crops, typical plant diseases, irrigation, fertilizer use and farming techniques in the particular area.

TABLE I
LITERATURE SURVEY MATRIX

Sr.	Paper Title	Year & Author	Methodology	Key Findings	Research Gap
1	Farmer.Chat: Scaling AI-Powered Agricultural Services for Smallholder Farmers	N. Singh et al. (2024)	Conversational AI, field-scale deployment	Demonstrates a scalable, AI-powered advisory service reaching a large number of smallholder farmers through a chat-based interface	Continued reliance on connectiv-ity and cloud infrastructure lim-its scaling to low-connectivity re-gions.
2	AgriLLM: Harnessing Trans-formers for Farmer Queries	K. Didwania, P. Seth, A. Kasliwal & A. Agarwal (2024)	Transformer-based NLP model	Shows that transformer-based lan-guage models can accurately inter-pret and answer farmer queries	High computational requirements limit deployment on low-resource or offline devices.

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3	AI for Crop Production – Where Can Large Language Models (LLMs) Provide Sub-stantial Value?	M. T. Kuska, M. Wahabzada & S. Paulus (2024)	Review and analysis	Identifies specific crop-production decisions where LLMs can add measurable value	Lightweight, practical implemen-tation for real-on-farm conditions remains underexplored.
4	AgAsk: A Conversational Search Agent for Answering Agricultural Questions	H. Li, B. Koopman, A. Mourad & G. Zuccon (2023)	Conversational search agent, information retrieval	Improves retrieval and relevance of agricultural answers through con-versational search	Depends on external question-answer repositories and internet access to function.
5	A Study of Conversational Agent Solution Technologies for Banana Farmer Assistance	L.-A. Calvo-Valverde et al. (2023)	Comparative study of agent technologies	Evaluates conversational agent technologies suited to banana farmer assistance	Localized language support and domain-specific knowledge inte-gration remain limited.
6	P2OP – Plant Pathology on Palms: A Deep Learning-Based Mobile Solution for In-Field Plant Disease Detection	S. Janarthan et al. (2022)	Deep learning, mo-bile application	Enables in-field plant disease de-tection directly on a mobile device	Task-specific (disease detection only); not designed for broader agricultural advisory.
7	Real-Time Strawberry Detec-tion Using Deep Neural Net-works on Embedded System (RTSD-Net)	Y. Zhang et al. (2022)	Embedded deep neural network	Demonstrates real-time crop detec-tion is feasible on low-power em-bedded hardware	Narrow task scope; generaliza-tion to other crops and tasks is limited.
8	A Mobile-Based Deep Learn-ing Model for Cassava Dis-ease Diagnosis	A. Ramcharan et al. (2019)	CNN-based mobile diagnosis tool	Provides accurate, offline diagnosis of cassava disease using a smart-phone camera	Limited to a single crop and dis-ease type; lacks broader farming guidance.

The principal contributions of this study are as follows:

1) Integrated offline advisory framework: The proposed concept includes an architectural design in which AI algorithms are run locally and use a knowledge base containing regional agriculture information in order to provide recommendations in an offline manner.

2) Localized agricultural knowledge: The concept focuses on the need for organizing and structuring region-specific information regarding crop, disease, irrigation, fertilizer, and farming practices.

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3) Accessibility in farmer interaction: Supporting the lan-guage used in the specific region, voice-based interac-tion, and simplifying the user interface are considered important aspects to increase accessibility for the farm-ers.

4) Efficient computing with low resource consumption: The paper evaluates the possibility of using light-weight AI algorithms and edge computing to minimize the dependence on cloud computing infrastructure.

Comparison of gaps in existing works: The comparison of existing works with the conversational advisory systems and mobile AI systems is done to identify the gaps that exist in the areas of offline availability, computation requirements, localization, task handling, and recommendation reliability.

Comparative Analysis of Research Coverage

Each study focuses on a particular aspect of AI-based agri-cultural assistance such as conversational advisory systems, identification of crop diseases, and lightweight AI models. However, there is a difference in the aspects of offline func-tionality, localized knowledge in agriculture, regional language interface, and comprehensive farming advisory services that have been covered by each study. Fig. 2 provides a compara-tive summary of these research dimensions to show how the research gaps identified in the proposed framework have been addressed.

IV. Research Gaps

By analyzing the literature review, there are five gaps that keep appearing. The gaps are presented below.

1) Internet dependency. Many conversational and advisory systems require internet access to function properly [1] and conversational search agents [4], which is difficult for farmers in areas with a poor signal.

2) Computational cost. Transformer-based and other large models [2] use more computational power and memory, making it harder to implement them on an affordable smartphone.

TABLE II
COMPARATIVE ANALYSIS OF EXISTING AGRICULTURAL AI APPROACHES

Approach	**Representative stud-ies**	**Major capability**	**Important limitation**	**Research opportunity**
Conversational agricul-tural advisory	Farmer.Chat [1]	Provides agricultural guidance through conversational interac-tion	Connectivity and cloud infrastruc-ture requirements may limit access in poorly connected areas	Investigate offline advisory ca-pabilities

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Transformer-based agri-cultural language mod-els	AgriLLM [2]	Interprets and responds to farm-ers' queries	Computational and memory require-ments may restrict deployment on low-resource devices	Explore lightweight models and local knowledge retrieval
Agricultural conversa-tional search	AgAsk [4]	Improves relevan retrieval of t agricultural informatio n	Depends on access to information sources and supporting infrastructure	Investigate locally available agricultural information
Mobile plan diseas detectio t e n	P2OP [6]; Ramcharan et al. [8]	Supports crop or disease identifi-cation on mobile devices	Primarily addresses specific diagnos-tic tasks rather than broad agricul-tural advice	Combine task-specific AI with wider advisory knowledge
Embedded crop detec-tion	RTSD-Net [7]	Supports crop detection using embedded computing	Limited task scope may restrict broader agricultural decision support	Explore with a integration advisor wider y agricult ural framework
Offline, localized agri-cultural assistant (pro-posed concept)	This study	Combines offline operation, local agricultural knowledge, lightweight AI, and accessible interaction	Requires implementation , knowl-edge validation, and field testing	Evaluate usability, reliability, resource consumption, and of-fline functionality

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Research Paper	Offline Operation	Lightweight AI	Localized Knowledge	Regional-language & Voice Interaction	Broad Farming Advisory
Farmer.Chat [1]	Yes	Yes	Yes	Yes	Yes
AgriLLM [2]	Yes	Yes	Yes	Yes	Yes
AgAsk [4]	Yes	Yes	Yes	Yes	Yes
P2OP [6]	Yes	Yes	Yes	Yes	Yes
Cassava Disease Diagnosis [8]	Yes	Yes	Yes	Yes	Yes
Proposed Framework	Proposed	Proposed	Proposed	Proposed	Proposed

Yes (explicitly supported by the paper) **Partial** (supported to a limited extent) **Not reported** (not established in the paper) **Proposed** (part of our conceptual framework)

Fig. 1. Comparative coverage of key research dimensions across existing agricultural AI studies and the proposed framework.

3) Task-specific scope. Lightweight and task-specific mod-els are designed for one job, such as detection of diseases or recognition of plants [6] [8], which is not very useful in larger farming contexts.

4) Localized knowledge and language. Models support for regional languages and localized knowledge about the farming process is limited [5], which is a drawback in terms of local practices.

5) Reliability of recommendations. Ensuring the usefulness of the advice generated by AI in different contexts and real-world farming conditions is a major challenge [3].

V. Proposed Scope and Objectives

This research is helpful to study the AI technologies that will be useful for the farming sector and which will provide solutions to the problems of small and marginal farmers. The scope of the project is to develop the AI which will help in answering the queries of the farmers, conversational agri-culture, plant disease diagnosis, crop monitoring and farming decision support. The emphasis is on the previous done work on conversational AI, edge AI, on-device AI and lightweight deep learning technologies that would enable the development of AI which runs on the phone or some other device without depending upon the cloud. What it means is the development of an offline, lightweight and localized AI agricultural assistant which would provide useful advice to the farmers without the need of continuous internet connection and AI which runs locally on the information pertaining to the region. What we mean is to integrate the different aspects together to make a single AI assistant which will serve as natural-language interface, on-device inference and local knowledge base.

A. Objectives

The following are the objectives that help us attain the above solution:

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1) Studying and designing an offline AI-based farming assistant that can offer guidance without requiring a continuous internet connection.

2) To design a local farming knowledge base which con-tains information about crops, diseases, irrigation prac-tices, fertilizers, and general farming methods.

3) To incorporate regional language support and voice interaction so that the farmers can communicate in a language they are familiar with

4) To design a very simple interface which the farmers can easily figure out how to use.

B. Localized Knowledge Base

The major concern in this topic is having a local farming knowledge base stored in the device itself. Rather than relying on a single large model which can answer all the questions, the assistant integrates a relatively small model along with a basic store of region-specific knowledge regarding the crops that are grown locally, the diseases and pests affecting those crops, general irrigation practice, the fertilizers that can be used, and the farming practices in the region. Having it on the device means that we get two advantages. First, there is no need for a remote server to contact in order for the software to do its job. Second, the solution provided by the software will be localized, which means that the local knowledge gap which keeps creating difficulty in the reviewed paper [3] [5] will be closed. In case of connection detection, even partial, optional synchronization can supplement or enrich the knowledge base, so the system will always be working without any signal needed to respond.

C. Interaction Design

In order to help the farmers in question, the assistant needs to be user-friendly. Regional language support and voice input makesit possible to avoid the barrier of illiteracy that would otherwise become an issue for those who don't know how to read and type; the farmer will simply ask and receive the answer from the system. Simplify the interface, reduce the number of steps and prompt and delete the training necessary prior to its use. This approach stems from the goals and from their findings in the literature natural-language interaction assistances for accessing advice [1], [2], [4]. In this case, we should transfer this advantage to an offline and low-resources environment.

D. Conceptual System Architecture

Figure 1 presents a usual system flowchart. The farmer either says or types a question in the language which is convenient to him. All operations occur on the device level: the voice is converted to the text; a lightweight language or small model analyzes the question, and the answer is retrieved from the local knowledge base about farming which is stored on the phone. Then the result goes back as either text or voice output. As the inference and the retrieval of operations happen on the device level, the assistant receives the answer without any network connection, and when the connection occurs, the system can update the knowledge base.

Working of the Proposed System

The proposed offline agricultural assistant follows a se-quence of operations to provide localized farming guidance. First, the farmer enters a question through text or voice input in a supported language. If voice input is used, speech-to-text processing converts the query into text. The input is then processed

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by a lightweight on-device AI model, which works with a locally stored agricultural knowledge base to identify relevant information. The system prepares a response and presents it to the farmer as text or voice output. Since the primary processing and knowledge retrieval occur locally, the system is intended to provide basic agricultural guidance without continuous internet connectivity. When connectivity becomes available, the knowledge base may be updated to improve the relevance of future recommendations.

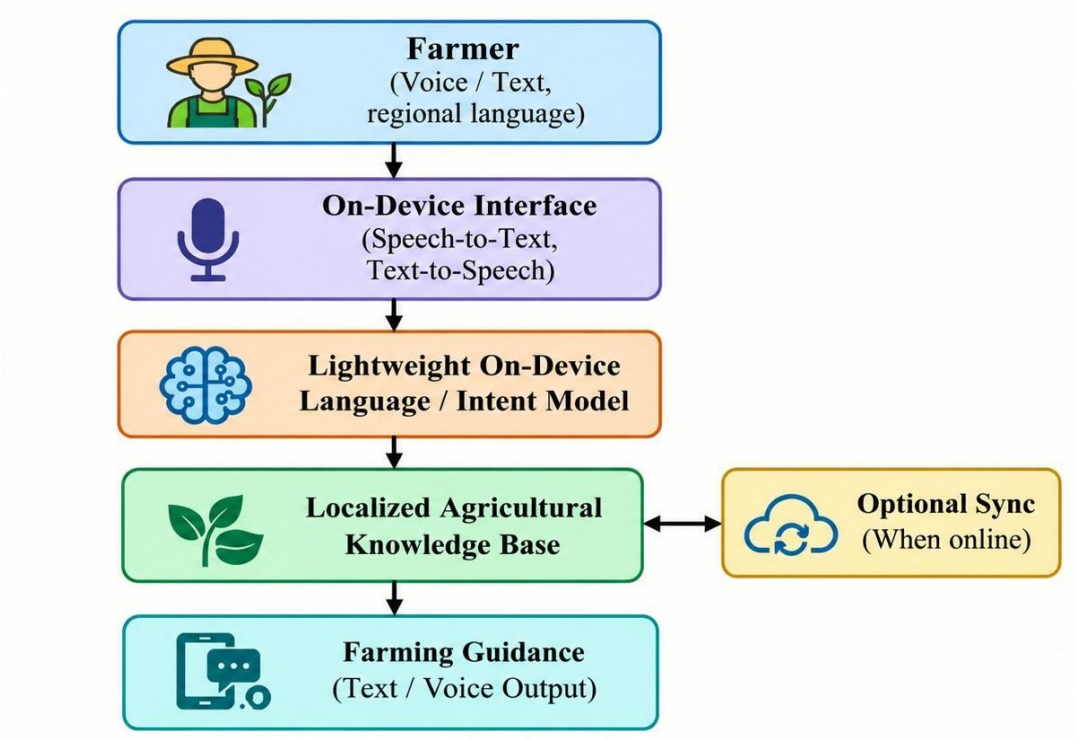


Fig. 2. Conceptual architecture of an offline, localized agricultural assistant.

VI. Discussion: Challenges and Limitations

There is a number of limitations associated with the subject under discussion, which should be highlighted. An offline system, in turn, will not be as resource intensive as a cloud system. That is one of the key solutions; in other words, the limit to the number of resources available to fit a low-cost device limits the level of reasoning of the assistant. Another challenge is keeping the information up-to-date and ensuring the accuracy of solutions when dealing with crops and specific areas. Conditions may vary from one district to another; there-fore, advice working well for a particular area can be utterly wrong in the next one. Those are the gaps in literature. Specific task-oriented models [6] [8] will be accurate enough because of being limited to a single task, and the idea to transform them into generalized assistants while saving resources is rather difficult. Going off-cloud [1], [4] has another limitation; you and will have to give up the convenience of centrally updated models, while The way in which the system stays updated is dependent on the design of the offline systems. This should be made clear to the user so that they know the capabilities of the assistant. This list of challenges is interconnected as well. For example, the low-cost device cannot accommodate a huge size of the model; small models may not understand the complex language and respond to complicated questions. This is why a light-weighted

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AI model which operates due to the organized knowledge base is necessary for this task. In such a way, most of the valuable information will come from the knowledge base rather than from the model itself. The value of the information becomes critical. The local farming knowledge and relevant recommendations are tightly interrelated since both pieces are necessary for giving advice to the farmer. Another challenge concerns information updates. If there is no continuous Internet connection, then the information can be outdated and take some time before the solution appears. Therefore, the assistant should continue giving valuable infor-mation regardless of the lack of accuracy of its knowledge base. Despite these challenges, an offline agricultural assistant is not a bad idea. These challenges give some ideas about the development of such a system.

VII. Future Work

Many things need to be done to improve this project. Lightweight AI models can be enhanced to give better output while operating under the constraints of low-end devices. Moreover, local knowledge bases can be augmented by in-creasing the number of crops and farm crops covered, and regional considerations incorporated. Language support can be extended to include other regional languages and enhance voice interaction to make the assistant easily accessible to farmers facing difficulties in reading. In addition to this, accu-racy in giving farming advice can also be enhanced. All these improvements would make the assistant practical and useful for the farmers having poor connectivity to the internet. Some possible improvements are of particular significance. First, various approaches like model compression, quantization, and knowledge distillation may contribute to reducing the size of AI models to fit into low cost and simple smartphones. In this way, the potential of on-device abilities shown by task specific models may become extended to more universal assistance for farming [6] [8]. Second, there is a need to enrich local knowledge bases, and keep them up to date. At the same time, simple approaches for validating the recommendations of local knowledge bases can be useful in solving the problems of reliability and localization found in previous works [3], [5]. Third, the introduction of additional languages and improve-ment of voice communication will make the assistant available for wider range of farmers. Finally, testing with real farmers in real conditions and local languages should be conducted. Previous experience [1] shows the necessity of understanding the needs of users in practice. The successful work of the offline assistant will depend not only on technology itself, but also on its practical applicability.

VIII. Conclusion

This research article presents a review of current studies about AI agricultural advice system, conversational AI, large language models, edge computing, and lightweight ML. The reviewed literature highlights the prospects of using AI for agriculture-related decision making via conversational advice, information search, and mobile crop analysis. Yet, there are several key challenges to be solved: dependency on internet connection, computer power needs, scope of tasks, insufficient regional language support, localization of agricultural knowl-edge base, and accuracy of advice. In order to solve these problems, the paper presents a conceptual offline agricultural assistant design that includes lightweight on-device compu-tation, local storage of agricultural knowledge base, regional language conversation, and user interface. Accessibility and localized support are key concepts within the framework for the farmers that may have limited connectivity or access to devices with high performance. The proposed framework can be seen as a concept for future research rather than an imple-mented solution. The areas for further investigation include creating a prototype and studying its resource consumption and offline

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abilities, verifying the recommendations made by the system and testing it in the real world with actual farmers. Such research will clarify whether the proposed approach will work.

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