# KrishokBondhu: A Retrieval-Augmented Voice-Based Agricultural Advisory Call Center for Bengali Farmers

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Abstract-In Bangladesh, many farmers continue to face challenges in accessing timely, expert-level agricultural guidance. This paper presents KrishokBondhu, a voice-enabled, call-centreintegrated advisory platform built on a Retrieval-Augmented Generation (RAG) framework, designed specifically for Bengalispeaking farmers. The system aggregates authoritative agricultural handbooks, extension manuals, and NGO publications; applies Optical Character Recognition (OCR) and documentparsing pipelines to digitize and structure the content; and indexes this corpus in a vector database for efficient semantic retrieval. Through a simple phone-based interface, farmers can call the system to receive real-time, context-aware advice: speechto-text converts the Bengali query, the RAG module retrieves relevant content, a large language model (Gemma 3-4B) generates a context-grounded response, and text-to-speech delivers the answer in natural spoken Bengali. In a pilot evaluation, KrishokBondhu produced high-quality responses for 72.7% of diverse agricultural queries covering crop management, disease control, and cultivation practices. Compared to the KisanQRS benchmark, the system achieved a composite score of 4.53 (vs. 3.13) on a 5-point scale—a 44.7% improvement—with especially large gains in contextual richness (+367%) and completeness (+100.4%), while maintaining comparable relevance and technical specificity. Semantic-similarity analysis further revealed a strong correlation between retrieved context and answer quality, emphasizing the importance of grounding generative responses in curated documentation. KrishokBondhu demonstrates the feasibility of integrating call-centre accessibility, multilingual voice interaction, and modern RAG techniques to deliver expert-level agricultural guidance to remote Bangladeshi farmers, paying the way toward a fully AI-driven agricultural advisory ecosystem.

Index Terms—Retrieval-Augmented Generation, Agricultural Advisory System, Bengali NLP, Voice Interface, Large Language Models, Knowledge Dissemination

## I. INTRODUCTION

Agriculture continues to play a pivotal role in Bangladesh's economy. As reported in the 2022 Labour Force Survey, about 45.33% of employment was in the agricultural sector, a rise from 40.6% in 2016–17 [1]. Yet, more recent estimates based on ILO-modeled data suggest that the share has declined to around 35.27% [2], reflecting shifts in the labor structure. Despite its central importance, many farmers still lack reliable and timely guidance on crucial issues such as crop diseases, pest outbreaks, optimal cultivation techniques, and efficient

resource use. Traditional extension services, though invaluable, are stretched too thin to provide real-time, on-demand support to all communities, especially in remote or underserved areas.

Another barrier is language: much of the agricultural knowledge base is written in English or technical Bengali, making it less accessible to farmers who may not be comfortable with formal or specialized terminology. At the same time, advances in large language models (LLMs) and retrievalaugmented generation (RAG) create new opportunities to bring agricultural knowledge directly to farmers [3], [4]. But using a general-purpose LLM without domain grounding often yields vague or incorrect advice, because it may ignore local context—such as particular crop varieties, region-specific pest cycles, or soil conditions. Systems like AgAsk demonstrate how combining retrieval from scientific documents with conversational interfaces can yield more accurate, contextually relevant answers in the agriculture domain [4]. Yet in the Bengali context, building a system that understands users' spoken or written queries in natural language and delivers culturally appropriate guidance involves dealing with morphological complexity, dialect variation, and limited linguistic resources.

In this paper, we present KrishokBondhu, an agricultural advisory system that combines retrieval-augmented generation (RAG) with a spoken interface to offer farmers real-time, context-aware guidance in Bengali. The name KrishokBondhu translates to "farmer's friend," and reflects our mission to bring expert agricultural knowledge within reach. Our system is built to tackle three core challenges: anchoring advice in verified agricultural sources to reduce hallucinations or vague outputs; allowing users to interact via speech so literacy does not become a barrier; and adapting recommendations to Bangladesh's unique cropping systems, climate, and farmer practices. We make three primary contributions:

- A document processing pipeline that collects, OCRs, cleans, segments, and indexes Bengali agricultural texts into a vector retrieval store.
- 2) A full implementation of KrishokBondhu using RAG, LanceDB, the Gemma 3-4B model, and a speech interface to enable natural query and response in Bengali.

 An evaluation framework built around realistic farmer queries and a comparative benchmark with Kishan QRS, demonstrating measurable improvements in quality, contextual richness, and accuracy.

## II. RELATED WORK

Agricultural advisory systems have progressed from early rule-based and vocabulary-driven approaches toward neural and multimodal architectures. FAO's AGROVOC, a multilingual agricultural thesaurus, has long supported indexing and cross-lingual retrieval [5], but its controlled-vocabulary approach struggles with expressive, free-form farmer queries lacking flexibility or semantic inference.

More recently, neural QA systems tailored for agriculture have emerged. The KisanQRS system trains deep models over Kisan Call Centre logs to map farmer queries to responses [6]. However, dataset access is limited, and such systems often lack grounding in authoritative texts or visual evidence. Systems like AgroLLM extend this by integrating RAG to improve the relevance and correctness of responses using agricultural databases [7].

To overcome hallucination and data sparsity, Retrieval-Augmented Generation (RAG) has become a dominant paradigm. By retrieving supporting context before generation, RAG grounds outputs in factual sources [3], [8], [9]. While RAG is already adopted in legal, medical, and code domains, its application in agriculture—especially in low-resource language contexts—remains underexplored.

Voice-based advisory approaches have been studied to overcome literacy barriers. Surveys of voice assistants in agriculture summarize their promise and challenges in rural deployment [10]. In greenhouse trials, voice messaging systems combined with human-sensor inputs have been used to build agricultural knowledge over time [11]. However, most such systems rely on recording or message playback rather than interactive, context-aware conversational responses [12]

Multimodal AI is another emerging direction. AgriDoctor fuses image, text, and knowledge retrieval to build a multimodal assistant for crop disease diagnosis and domain-aware QA [13]. Similarly, spatial-vision systems using Earth Observation and retrieval-augmented methods enable conversational assessments of agricultural plots [14]. These systems point to the future of combining multiple modalities in agricultural advisory.

Nevertheless, gaps remain: (i) few systems fully integrate speech input, multimodal grounding, and localized domain knowledge; (ii) many are not evaluated in low-resource or local-language settings; (iii) adaptation to regional cropping systems and dialects is rare. Our work addresses these gaps by offering a voice-enabled RAG system tailored to Bangladeshi agriculture, combining text and voice modalities, and evaluating on domain-specific queries in Bengali.

## III. SYSTEM ARCHITECTURE AND METHODOLOGY

# A. Data Collection and Source Curation

KrishokBondhu's knowledge base is constructed from authoritative agricultural documentation published by governmental and non-governmental organizations in Bangladesh. Key sources include the Krishi Projukti Hatboi [15], Bangladesh Agricultural Research Council (BARC) handbooks, Department of Agricultural Extension (DAE) field manuals [16], Bengali agricultural science textbooks, and sector-specific publications from the WorldFish Digital Repository [17]. The curated corpus comprises approximately 2,500 pages encompassing major crops (rice, wheat, jute, vegetables, pulses, and oilseeds), as well as livestock management, fisheries, and integrated farming practices. Source materials vary from well-structured digital PDFs to low-quality scanned images, necessitating a robust and adaptive document processing pipeline capable of handling OCR-based text extraction, error correction, and content normalization.

TABLE I
KEY SOURCES FOR AGRICULTURAL KNOWLEDGE BASE

Source	Summary
Krishi Projukti Haatboi	Core Bengali handbook on crops and cultivation practices.
BARC Handbook	National reference on modern crop varieties, irrigation, and pest control.
DAE Field Manuals	Practical guides for pest, soil, and irrigation management.
Agriculture Textbooks	Basic school-level materials on crops, soil, and pests.
Agricultural Science Vol. 1	Advanced text on plant physiology and crop science.
Farmers' Guidebook	Covers aquaculture, horticulture, and integrated farming.
BARC Bulletins	Short crop-based manuals with recent updates.
West Bengal Agro Books	Regional references aligned with similar climate and soil.

# B. Document Processing and OCR Pipeline

All collected documents were processed through a Bengalicapable Optical Character Recognition (OCR) and cleaning pipeline to ensure accurate text extraction and normalization. The workflow included image enhancement, skew correction, and noise reduction prior to OCR to improve recognition accuracy. Post-processing corrected common Bengali character errors using rule-based and contextual validation methods. Extracted text then underwent normalization to handle inconsistent Unicode encoding, mixed scripts, and formatting artifacts. Finally, the cleaned text was segmented into semantically coherent sections (150–300 tokens), each enriched with metadata such as source, topic, and structural position. The standardized output was stored in Markdown format to facilitate efficient vectorization and retrieval in the RAG system.

## C. Vector Database and Retrieval System

The processed and segmented corpus was transformed into dense vector embeddings using a sentence-transformer model [18] optimized for semantic similarity. These embeddings capture contextual meaning between user queries and document content, enabling retrieval based on semantics rather than exact keywords. LanceDB [19] was employed as the vector storage backend for its efficiency and Python integration. Each text segment, along with metadata, was indexed for fast approximate nearest-neighbor (ANN) search using cosine similarity. During query time, user questions are embedded with the same model, and the top-k semantically relevant segments are retrieved to form the contextual input for generation. A lightweight re-ranking layer further improves relevance by considering metadata and keyword overlap, combining the precision of lexical matching with the contextual strength of embeddings.

## D. Language Model Integration and Response Generation

Gemma 3-4B [20], deployed through LM Studio [21], provides the generative component. The 4-billion parameter model balances response quality with computational requirements for local deployment while maintaining strong Bengali language performance.

Prompt engineering optimizes factual accuracy, relevance, and appropriate farmer interaction tone. Retrieved segments are incorporated as context, with instructions to generate responses based primarily on provided context, cite specific practices, and acknowledge uncertainty when information is insufficient. The prompt specifies accessible language, practical focus, and culturally appropriate communication. Conservative temperature and sampling parameters prioritize consistency and accuracy. Post-processing verifies coherence, checks for hallucinations against retrieved context, and formats responses for voice delivery.

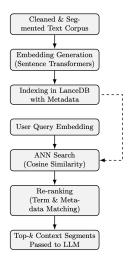


Fig. 1. Document Processing and OCR Pipeline

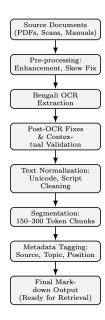


Fig. 2. Vector Database and Retrieval Workflow

# E. Voice Interface Integration with VAPI

The VAPI [22] module enables seamless voice interaction, extending KrishokBondhu's accessibility to farmers with limited literacy. It performs Bengali speech-to-text (STT) for incoming queries and text-to-speech (TTS) synthesis for system responses. Operating in a client–server configuration, VAPI handles audio capture, transcription, and synthesis, while the RAG server performs embedding, retrieval, and generation. The complete workflow begins with the farmer's spoken query, which is transcribed into text, processed by the RAG engine, and converted back into natural Bengali speech. To mitigate recognition errors—particularly with agricultural terms—the system applies fuzzy matching, ambiguity prompts, and contextual dialogue tracking, ensuring coherent multi-turn conversations.

## F. Evaluation Methodology

Due to the absence of a standard Bengali agricultural QA benchmark, KrishokBondhu was evaluated through a compar-

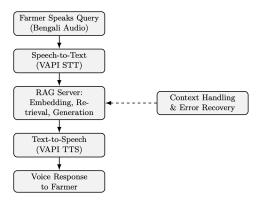


Fig. 3. Voice Interface Integration Workflow with VAPI

ative analysis with published examples from Kishan QRS [6]. A representative test set of Bengali farmer-style questions was manually curated from agricultural handbooks and extension guides, covering major topics such as crop diseases, pest control, fertilizer use, irrigation, and variety selection. Each system's responses were assessed by agricultural experts using three quality levels—high, moderate, and poor—based on accuracy, relevance, and practical usefulness. For Kishan QRS comparison, a 5-point scoring framework was applied across relevance, completeness, actionability, contextual richness, and specificity.

To complement human evaluation, semantic similarity between questions, retrieved segments, and generated responses was computed using cosine similarity. This quantified both retrieval precision and generation faithfulness, helping identify gaps and potential hallucinations in responses. Overall, the evaluation captures factual correctness, contextual grounding, and practical utility for Bengali-speaking farmers.

## IV. RESULTS AND DISCUSSION

## A. Overall System Performance

As shown in Figure 4, Krishokbondhu delivered highquality responses for 72.7% of test queries, indicating strong reliability in addressing farmers' information needs. Moderatequality answers (9.1%) typically arose when relevant context was partially retrieved or when queries required synthesizing dispersed information. Poor responses (18.2%) were mostly linked to under-represented topics or recent developments not yet present in the knowledge base. Table II presents representative responses from Krishokbondhu across diverse agricultural queries.

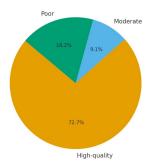


Fig. 4. Distribution of response quality categories across test questions, showing strong performance with 72.7% high-quality responses.

# B. Comparative Analysis with Kishan QRS

To contextualize Krishokbondhu's performance, we conducted a comparative analysis with responses published in the Kishan QRS paper. Table II presents matched query-response pairs from both systems, highlighting substantial differences in response characteristics. While Kishan QRS provides concise, technically focused answers averaging 87 characters, Krishokbondhu generates comprehensive responses averaging 692 characters, representing a 7.9-fold increase in detail.

Quantitative evaluation across five criteria reveals Krishokbondhu's superior performance, as presented in Table III. The system achieved an overall score of 4.53 out of 5.00, representing a 44.7% improvement over Kishan QRS's score of 3.13. The most substantial gains appear in contextual richness (4.67 vs 1.00, +367%) and completeness (4.67 vs 2.33, +100.4%), reflecting Krishokbondhu's comprehensive approach to agricultural advisory.

Figure 2 visualizes the comparative performance across evaluation criteria, highlighting Krishokbondhu's particular strengths in providing contextual understanding and comprehensive coverage. Both systems maintain equivalent relevance to queries and similar levels of specific technical details, but Krishokbondhu significantly enhances actionability through step-by-step guidance and completeness through multi-faceted responses.

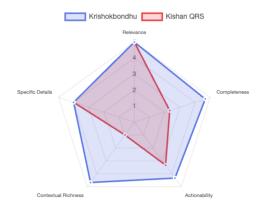


Fig. 5. Radar chart comparing Krishokbondhu and Kishan QRS across five evaluation criteria, showing Krishokbondhu's superior performance in contextual richness and completeness.

Information coverage analysis (Table IV) reveals distinct differences in response philosophy. Krishokbondhu consistently provides cause explanations (100% of responses), prevention measures (100%), and expert referrals (100%), features largely absent from Kishan QRS responses. This comprehensive approach addresses a critical gap in agricultural extension: farmers often lack understanding of underlying causes, leading to improper implementation of recommendations.

Figure 3 illustrates the percentage improvements across evaluation criteria, with contextual richness showing the most dramatic enhancement at 367%. These improvements validate several design decisions in Krishokbondhu, particularly the RAG architecture's effectiveness in grounding responses in comprehensive agricultural handbooks and the system's optimization for voice-based interaction where detailed explanations enhance farmer understanding.

## C. Semantic Similarity and Response Quality Correlation

Figure 7 illustrates a clear positive correlation between semantic similarity and response quality. Most high-quality responses had similarity scores above 0.85, indicating strong alignment between user queries and retrieved content. This

 $TABLE \; II \\ Sample \; Responses \; from \; Krishokbondhu \; System \; (Bengali)$ 

Query (Bengali)	Krishokbondhu Response (Bengali)
রসুনে ছত্রাকজনিত আক্রমণ কীভাবে নিয়ন্ত্রণ করবেন (How to control fungal at- tack in garlic)	সমস্যার কারণ: আপনার রোপানো গাছের উপর ছ্ত্রাকজনিত রোগ হয়েছে। এটি সাধারণত ভেজা আবহাওয়া এবং অতিরিক্ত আর্দ্রতার কারণে হয়ে থাকে। তাংক্ষণিক ব্যবস্থা: রোগা হওয়া পাতাগুলো দ্রুত সরিয়ে ফেলুন। খ্রিসারিন-এর সাথে সামান্য কদমেলে মিশিয়ে আক্রান্ত স্থানে লাগান। ছ্রাকনাশক (যেমন: Carbendazim) ব্যবহার করতে পারেন। ভবিষ্যাতে প্রতিরোধ: অতিরিক্ত জ্বল দেওমা থেকে বিরত থাকুন। গাছের চারপাশে পর্যাপ্ত বাতাস চলাচলের ব্যবস্থা রাখুন। পরামর্শ: স্থানীয় কৃষি অফিসার-এর সাথে যোগাযোগ করুন।
পেঁয়াজের আকার ও ফলন কীভাবে বাড়ানো যায় (How to increase onion size and production)	১. বীজ নির্বাচন: BARI থেকে উন্নত জাতের বীজ সংগ্রহ করুন (BARI Hybrid 322)। ২. জমি তৈরি: দোআশ মাটিতে পর্যাপ্ত জৈব সার বাবহার করুন। ৩. চারা রোপণ: সারি থেকে সারির দূরত্ব ৬০–৯০ সেমি রাখুন। ৪. সার প্রয়োগ: প্রথমবার ১ কেজি ইউরিয়া + ১০৫ গ্রাম TSP প্রতি হেক্টরে। দ্বিতীয়বার ৫০০ গ্রাম ইউরিয়া। ৫. সেচ: মাটি সবসময় ভেজা রাখুন, কিন্তু জলাবদ্ধ না হয়। বিশেষ পরামর্শ: কৃষি বিশেষজ্ঞের পরামর্শ নিন। (৪97 characters)
গমে ছ্ত্ৰাকজনিত আক্ৰমণ (Fungal attack in wheat)	<ol> <li>রোগ প্রতিরোধী জাত নির্বাচন: BARI Gom-30, BARI Gom-36 বেছে নিন।</li> <li>স্বাস্থ্যকর বীজ বপন করুন।</li> <li>ছুত্রাকনাশক: কার্বেভাজিম (Carbendazim), ম্যানকোজেব (Mancozeb) অথবা কপার অক্সিক্লোরাইড ব্যবহার করুন।</li> <li>স্বাচিক সময়ে চাঘাবাদ করুন।</li> <li>স্বাচীয় কৃষি অফিসের সহায়তা নিন।</li> <li>ছুক্তকুপূর্ণ: প্যাকেজের নির্দেশাবলী পড়ে সঠিক মাত্রায় ব্যবহার করুন।</li> <li>(612 characters)</li> </ol>

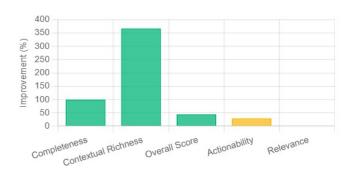


Fig. 6. Percentage improvement of Krishokbondhu over Kishan QRS baseline across evaluation criteria, demonstrating substantial gains in contextual richness and completeness.

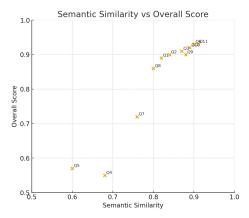


Fig. 7. Relationship between semantic similarity and overall quality scores, showing positive correlation between retrieval quality and response assessment.

TABLE III
COMPARISON BETWEEN KRISHOKBONDHU AND KISHAN QRS

Krishokbondhu (Bengali)	Kishan QRS (English)	
Retrieval-Augmented Generation (RAG) pipeline using Gemma-3-4B and LanceDB for context-grounded Bengali answers.	Rule-based and deep-learning models trained on historical Kisan Call Centre logs.	
Integrates OCR, ASR, and TTS modules for Bengali speech-based interaction.	Text-only interface; accepts English or transliterated Hindi input.	
Knowledge base built from BARC's Krishi Projukti Hatboi, DAE manu- als, WorldFish repository, and text- books.	Proprietary dataset from Kisan Call Centre logs; not publicly available or extensible.	
Generates detailed responses with explanations, preventive actions, and expert referral guidance.	Produces short prescription-style answers focused on chemical dosage.	
Retrieval layer expandable through new document ingestion.	Static dataset; cannot adapt or update post-training.	
Supports voice and text I/O for low- literacy farmers via mobile IVR.	Operated by call-centre agents; farmers interact indirectly.	
Evaluated on factuality, relevance, and fluency metrics.	Evaluated on text-mapping accuracy only.	

suggests that effective retrieval is a strong predictor of answer quality.

Interestingly, a few lower-similarity cases still produced good answers—often when information was scattered across multiple segments or required broader reasoning. On the other hand, some high-similarity matches led to weaker responses, underscoring that retrieval precision, not similarity alone, is critical for consistent quality.

# V. CONCLUSION

This paper presented Krishokbondhu, a voice-based agricultural advisory system built on a RAG architecture tailored

TABLE IV EVALUATION METRIC COMPARISON

Metric	Krishokbondhu	Kishan QRS	% Gain
Relevance	5.00	5.00	+0.0%
Completeness	4.67	2.33	+100%
Actionability	4.33	3.33	+30%
Contextual Info	4.67	1.00	+367%
Specific Detail	4.00	4.00	+0.0%
Avg. Score	4.53	3.13	+44.7%
Resp. Length	692 chars	87 chars	$7.9 \times$

TABLE V
INFORMATION COVERAGE ANALYSIS

Information Feature	Krishokbondhu	Kishan QRS
Cause Explanation	3/3 (100%)	0/3 (0%)
Immediate Actions	3/3 (100%)	3/3 (100%)
Prevention Measures	3/3 (100%)	0/3 (0%)
Specific Dosages	2/3 (67%)	3/3 (100%)
Variety Recommendations	2/3 (67%)	0/3 (0%)
Expert Referral	3/3 (100%)	1/3 (33%)
Average Coverage	83.3%	38.9%

for Bengali-speaking farmers. By integrating authoritative documentation, OCR-based digitization, semantic retrieval (via LanceDB), and the Gemma 3–4B language model, the system delivers context-aware, voice-enabled responses with 72.7% high-quality output across diverse agricultural queries. Compared to the Kishan QRS baseline, Krishokbondhu achieved a 44.7% improvement in overall quality, with substantial gains in contextual richness and completeness.

Despite these promising results, the current evaluation has limitations. Due to unavailability of public datasets, only a few matched queries from Kishan QRS were used, and manual assessments may introduce subjectivity. Broader evaluations, including automatic metrics aligned with domain-expert judgments, are needed. The knowledge base, while extensive, still lacks coverage of newly released crop varieties and evolving practices. Future work will focus on expanding content coverage, integrating real-time data (e.g., weather, market prices), and optimizing response length for voice delivery.

Further improvements may involve domain-specific finetuning of LLMs, incorporating structured knowledge graphs alongside vector retrieval, and introducing adaptive response modes (e.g., quick-reference vs. detailed guidance) based on farmer profiles. Krishokbondhu marks an important step toward democratizing expert agricultural advice and highlights the potential of retrieval-augmented NLP systems to enhance knowledge access in low-resource rural settings.

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