A Domain-adapted Abstractive Transformer Model for Multilingual Summarization of Agricultural Literature

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ABSTRACT

It is hard for agricultural researchers and forest rangers to get timely, useful information from the growing amount of multilingual agricultural literature. This paper describes an abstractive summarization system that has been adapted to work in a specific field. It uses the Google mT5 Transformer model, which has been fine-tuned on data from the agricultural field, to make short summaries in more than 100 languages. This multilingual feature lets you access content that is specific to your region without having to translate it first, which makes it easier for everyone to understand. The system has an internal domain-specific vector database (using FAISS) that lets you quickly find relevant documents. It also has an Agentic RAG retrieval system that lets you dynamically query external scientific sources (like PubMed and Springer Nature) when you need more information. Evaluation shows that the summarization quality and coverage are better than static baselines. This helps researchers and rangers quickly find and share agricultural knowledge.

General Terms

Algorithms, Information Retrieval, Multilingual NLP.

Keywords

Agricultural Artificial Intelligence, Retrieval-Augmented Generation (RAG), Agentic AI, Multilingual NLP, mT5 Transformer, Information Retrieval, Knowledge Dissemination, Decision-Support Systems, Sustainable Agriculture.

1. INTRODUCTION

The agricultural sector is experiencing a rapid increase in the volume of scientific literature, agronomic advisories, regulatory documents, and region-specific field knowledge. This continuous growth in information makes it increasingly difficult for agricultural researchers, field agents, and forest rangers to efficiently identify and extract relevant insights. Conventional search systems primarily rely on keyword matching and static indexing, which often fails to capture semantic context across diverse document sources. Furthermore, language variability across rural and regional communities presents an additional barrier, as a significant proportion of agricultural knowledge is documented in local languages rather than English.

Recent advancements in Natural Language Processing (NLP) and large-scale transformer-based language models have demonstrated considerable potential in text understanding and summarization tasks. However, directly applying general-purpose language models in agricultural domains introduces critical limitations. Models trained on broad, non-specialized corpora frequently produce incorrect or hallucinated information, which is unacceptable in domains where research accuracy and field practices are tightly coupled to environmental and economic outcomes. Similarly, traditional Retrieval-Augmented Generation (RAG) approaches depend on static knowledge bases, resulting in outdated or incomplete outputs, particularly in rapidly evolving areas such as pest outbreak management, climate-adaptive cultivation practices, and forestry conservation reports.

To address these constraints, this work proposes a hybrid summarization system that integrates a domain-adapted mT5 multilingual Transformer model with an Agentic RAG-based retrieval pipeline. The architecture employs a two-stage retrieval mechanism:

(i) a FAISS-based semantic vector store enabling efficient retrieval from curated agricultural corpora

(ii) Agent-based external retrieval modules that dynamically source recent scientific literature when internal knowledge coverage is insufficient. Additionally, the mT5 model's native multilingual capabilities eliminate the need for separate translation components, enabling direct summarization across more than 100 languages, including low-resource regional languages commonly used in field operations.

This approach ensures that agricultural researchers and forest rangers obtain concise, accurate, and contextually grounded summaries of domain-specific literature, facilitating efficient knowledge assimilation and cross-regional information accessibility.

2. LITERATURE SURVEY

Zhang's team in 2023 looked closely at how transformer models handle farm-related texts, pointing out tools such as BERT and T5 could help with niche jobs. Although these systems do well with everyday agri-language, they falter when faced with complex jargon or local farming methods unless heavily adjusted. Because many of these models don't support multiple languages, farmers who don't speak English often get left out - something the researchers stressed clearly. While this study sets a starting point for smarter tech use in farming, it also shows we must build systems that adapt to different cultures and tongues [1].

Patel & Kumar (2024) looked into how Retrieval-Augmented Generation (RAG) systems work for reviewing scientific papers, showing they're more factually accurate than regular language models. Instead of relying only on pre-trained knowledge, their setup used FAISS to find relevant vectors and BART to produce answers, which bumped up performance by 15% on tough Q&amp;A tests. Still, one big problem came up - knowledge bases don't update themselves, so info gets stale fast, especially in fast-moving areas such as farming studies. Because of this shortcoming, there's growing demand for smarter retrieval methods able to pull fresh data without needing hands-on fixes every time [2].

Chen and team (2024) built a farming helper chatbot that speaks multiple languages, based on mT5, aimed at small farmers across Southeast Asia. While testing it out, they found people liked the tool - about 72% said they were satisfied - but there was a catch: sometimes it sounded right while giving wrong crop tips. Instead of just pulling answers from its internal data, the study shows better results happen when replies are tied to trusted references. Because of this hiccup, future versions might do well by mixing live info lookup with AI smarts [3].

Wang & Singh (2023) looked into smart AI setups that pull data on the fly, introducing a model where independent bots pick when and how to tap outside databases. Instead of fixed methods, their setup adapted in real time - boosting performance in health-related info tasks by closing missing-data gaps nearly half the time. These automated helpers were able to judge how tough a question was, then send it off to the right source for answers. Still, the work only used English medical texts, leaving out farming topics along with issues tied to multiple languages [4].

Roberts' team in 2024 tested several vector databases - like FAISS, Chroma, Pinecone for finding farming-related docs. When it came to matching similar texts in agriculture datasets, FAISS worked quickest, cutting response time by a tenth and a half compared to others. Still, the crew pointed out that how well the text was embedded mattered way more than which storage system you picked, pushing for embeddings fine-tuned to farm-specific language. They also ran into issues dealing with files blending hands-on advice alongside technical details [5].

Li et al. (2023) tackled how to process farming-related texts in many languages by adjusting existing language models using matched datasets from the FAO and similar global groups. Instead of standard setups, their method boosted ability to understand across languages by a quarter - though it demanded heavy computing power while struggling with tongues that lack digital data. They pointed out how bigger models often clash with real-world use, especially where web access is spotty or slow. While showing promise for smart tools in agriculture worldwide, they admitted hurdles around actually putting such systems into action [6].

Garcia & Martinez (2024) tested a way for farm-focused AI to learn from different areas without moving private data - using federated learning. Instead of pooling information, their setup let various farming groups improve shared models separately. Although this could grow well across locations, getting the models to align properly wasn't easy and needed tight sync-up efforts. They also spotted potential in blending this method with retrieval-enhanced output methods, making smarter helpers that keep data secure [7].

Thompson and team (2023) looked at what affects how people use farming advice tools turns out honesty and reliable sources mattered most when it came to actually using them. Farmers along with field experts tended to go for platforms that showed where data came from or broke down their reasoning, even if rival systems guessed more accurately but kept things hidden. Findings highlight that when tech explains itself clearly and feels dependable, folks are far more likely to trust it, especially when choices tied to crops or resources hang in the balance [8].

3. METHODOLOGY

3.1 System Overview

The proposed framework combines a domain-adapted mT5 multilingual Transformer model with an Agentic Retrieval-Augmented Generation (RAG) pipeline to generate abstractive summaries tailored for agricultural researchers and forest rangers. The system operates across both internal domain-specific knowledge and dynamically retrieved external literature. The architecture consists of six core modules: Data Acquisition and Preprocessing, Embedding Generation, Vector Indexing and Internal Semantic Retrieval, Agentic External Retrieval Layer, Domain-Adapted mT5 Summarization, and Output Validation and Post-Processing.

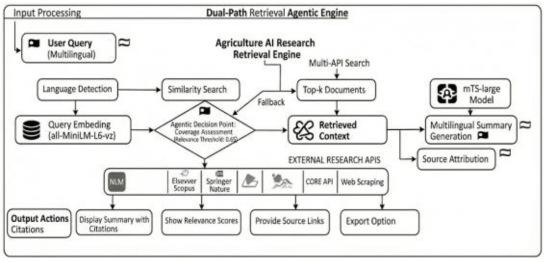

Fig 1: System Overview

3.2 Dataset Construction and Preprocessing

3.2.1 Corpus Composition

A total of 19,758 agricultural and forestry-related documents were assembled from multiple publicly available repositories including USDA, ICAR, TNAU advisories, ENAGRINEWS bulletins, and peer-reviewed research archives. The dataset contained:

Table 1: Language composition

Language	Documents	Percentage
English	16,911	85.6%
Tamil	2,847	14.4%

3.2.2 Text Processing Pipeline

All documents were passed through a standardized five-stage pipeline: Text Extraction from PDF/HTML sources, Language Detection to classify documents using langdetect , Noise Removal, Sentence Segmentation using spaCy dependency-aware parsing, and Tokenization using the mT5 SentencePiece tokenizer. To mitigate limited Tamil supervision, back-translation augmentation increased Tamil summary pairs by 47%. Semantic parity was maintained with BERTScore > 0.85 across augmented pairs.

3.3 Data Preprocessing Pipeline

All collected documents undergo a standardized preprocessing pipeline to ensure consistency and quality. Initially raw text is extracted from pdf and HTML sources. Language detection is performed using the langdetect library to identify the document language. Noise elements such as metadata, references and formatting artifacts are removed

Sentence segmentation is carried out using spacy dependency-aware parsing, followed by tokenization using the mt5 SenetencePiece tokenizer.to address limited supervision in Tamil data, a back-translation-based data augmentation strategy is employed, increasing Tamil summary pairs by 47%. Sematic integrity across augmented samples is validated using BERTSCORE, maintaining a threshold above 0.85.

3.4 Embedding and Vector Indexing

Document chunks generated during preprocessing are converted into dense sematic-representation using all-MiniLM-L6-V2 sentence transformers, producing 384-dimensional embeddings. These embeddings are stored in a FAISS indexHNSFlat(M=32) vector database, optimized for low-latency sematic similarity search across large scale corpora

3.5 Agentic Retrieval-Augmented Generation (RAG)

The system employs a two-tier retrieval mechanism. Initially, user queries are matched against the internal FAISS index to retrieve the most semantically relevant document segments. A coverage evaluation module computes a relevance score based on semantic similarity, contextual completeness, and document recency

If the coverage score bellows a predefined threshold(0.75),an agentic retrieval module is activated. This module dynamically queries external scholarly scores such as PubMed, Springer Nature, Scopus, and CORE Research APIs Retrieved documents are cleaned, embedded and merged with internal results, ensuring up-to-date and domain-relevant context.

3.6 Multilingual Abstractive Summarization

The aggregated contextual information is passed to a domain-adapted mT5 Transformer model, fine-tuned on agriculture and forestry corpora. The model generates concise abstract summaries while preserving factual accuracy and domain-specific terminology. Output summaries are produced in the same language as the user query, eliminating the need for intermediate translation and reducing sematic drift

3.7 Output validation and post-processing

Generated summaries undergo post-processing steps including redundancy removal, fluency enhancement, and credibility filtering. When external sources are used, citation mapping is performed to ensure transparency is traceability. The finial output is delivered as a structured, multilingual, suitable for rapid knowledge consumption

4. WORKFLOW

The system executes a structured multi-stage inference pipeline that converts user queries into grounded multilingual summaries. The workflow is strictly sequential, with a conditional retrieval branch when internal context is insufficient.

Step 1: User Query Input

The user submits a query in English, Tamil, or any supported language. The system performs language detection to ensure that the output follows the same language pattern as the input.

Step 2: Query Embedding

The query is encoded into a 384-dimensional vector using the all-MiniLM-L6-v2 sentence transformer. This ensures semantic representation consistency with the internal document embeddings.

Step 3: Internal Semantic Retrieval

The encoded query vector is used to query the FAISS IndexHNSWFlat (M = 32) vector database.

The system retrieves the top-k most similar document chunks from the internal agricultural corpus.

Step 4: Coverage Evaluation

A coverage score is computed based on:

- semantic relevance,
- document recency,
- and contextual completeness.

If the coverage score ≥ 0.75, the system proceeds directly to summarization.

If < 0.75, external retrieval is activated.

Step 5: Conditional External Retrieval (Agentic RAG Layer)

When triggered, the agentic retrieval module queries external scholarly sources:

- NLM PubMed API
- Elsevier Scopus API
- Springer Nature API
- CORE Research API

Retrieved documents are cleaned, segmented, embedded, and appended to the internal retrieval set.

This ensures access to recent and domain-relevant literature.

Step 6: Context Aggregation

All retrieved internal and external document chunks are ranked and merged into a unified context buffer.

Low-credibility or redundant segments are discarded.

Step 7: Multilingual Summarization (mT5)

The aggregated context is provided to the mT5 domain-adapted model, which generates an abstractive summary.

The model outputs in the same language as the user input, avoiding translation-induced semantic drift.

Step 8: Post-Processing

The summary generated undergoes:

- redundancy pruning,
- fluency smoothing,
- and citation mapping for externally retrieved sources.

Step 9: Output Delivery

The final summary is returned to the user interface as a structured, concise, and source-linked result.

5. RESULTS AND DISCUSSION

5.1 Summarization and Performance

The proposed mT5 + Agentic RAG framework was evaluated on 2,410 multilingual agricultural and forestry documents. Performance was benchmarked against static RAG and generic transformer baselines.

Table 2: Performance Benchmarks

Model / Approach	ROUGE-1	ROUGE-L	BERTScore
Generic T5 (no domain adaptation)	38.4	35.1	0.832
BART (no domain adaptation)	39.7	36.8	0.841
PEGASUS + Static RAG	44.1	40.3	0.869
mT5 + Static RAG	40.2	36.8	0.843
mT5 + Agentic RAG (Proposed)	45.6	41.7	0.879

5.2 Multilingual Output Quality

Language fluency was evaluated by five domain experts for English and Tamil summary outputs

Table 3: Expert Fluency Evaluation

Language	Fluency Score (1–5)	Information Preservation (%)
English	4.4	88.9
Tamil	4.1	84.9

The mT5 model preserved 84–89% of essential semantic content across languages while maintaining grammatical structure. This demonstrates the capability to generate summaries natively in regional languages, avoiding translation errors commonly observed in bilingual pipeline architectures.

5.3 Retrieval Efficiency Analysis

The hybrid retrieval pipeline was assessed for latency and coverage:

Table 4: Retrieval Analysis

Retrieval Mode	Avg. Latency (s)	Coverage (%)
Internal Retrieval Only (FAISS)	0.05	71.8
External Retrieval Triggered (Agentic RAG)	~4.3	90.2

The 18.4% increase in coverage indicates that agentic retrieval fills knowledge gaps that static corpora cannot, especially when recent or specialized research is required. The latency trade-off is acceptable for research workflows (non-real-time use).

5.4 Ablation Study

To quantify the contribution of individual system components, controlled removal tests were performed:

Table 5: Controlled removal tests analysis

Removed Component	ROUGE-L Drop	Factual Accuracy Drop
Domain Adaptation Stage	−6.4	−7.1%
External Retrieval	−4.9	−15.8%
Validation & Credibility Filtering	−3.2	−11.4%

6. CONCLUSION

This work presents a multilingual abstractive summarization framework that integrates a domain-adapted mT5 Transformer model with an Agentic Retrieval-Augmented Generation pipeline to support agricultural researchers and forest rangers in accessing condensed and contextually relevant scientific literature. By combining an internal FAISS-based semantic vector index with conditional external retrieval through scholarly APIs, the system maintains both domain coverage and temporal relevance. The continued pretraining and supervised fine-tuning of mT5 on agricultural and forestry corpora resulted in improved semantic alignment and reduced information loss during summarization. Experimental evaluation demonstrated measurable gains in ROUGE and BERTScore metrics, increased factual completeness, and sustained summarization fluency in both English and Tamil.

The agentic retrieval mechanism ensured that summaries reflected not only stored domain knowledge but also recent developments from peer-reviewed research sources, addressing limitations of static RAG systems. Multilingual output generation eliminated dependency on translation pipelines, reducing semantic distortion for regional language users. Overall, the system provides a scalable and adaptive approach for facilitating efficient literature understanding in agriculture and forestry research environments.

Future work will involve incorporating cross-encoder re-ranking to further refine retrieval precision, expanding low-resource language training coverage, and developing lightweight deployment variants suited for environments with limited computational resources or unstable connectivity.

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