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Research Gaps in Developing Fair and Inclusive LLMs for India's Multilingual Agricultural Landscape

Anamika Singh[1], Archita Agar[2], Veena Kulkarni[3] ,Dr. Ranjita Akash Asati[4], Dr. Neha Patwari[5]

[1,2,4,5] *Assistant Professor, Dept. of IT, Thakur Engineering College, Mumbai, India*
[3] *Assistant Professor, Dept. of COMP, Thakur Engineering College, Mumbai, India*

Abstract - *Indian farmers speak more than 22 official languages and that is not even counting all the regionalism. The country is having mix of languages and cultures makes it difficult to build Large Language Models (LLMs) which are actually work for Indian agriculture sector. It is not just about the large number of different languages. There are other issues, like some languages are having less resources, different scripts, multilanguage in the same sentence and shortage of useful information and agriculture-specific data. This paper focus on the main roadblocks: there is hardly any annotated data, rural conversations come with their own social idiosyncrasy and the words people use for crops are always different from one place to another. To solve these issues few strategies—like building agricultural knowledge graphs, borrowing from high-resource languages through transfer learning and putting together multilingual corpora focused on farming. Indian-language LLMs can do, like monitoring forecasting crop yields, giving real-time suggestion, detecting diseases and pests and supporting farmers to access government programs and policies. With the help of LLMs that really understand local languages could make a benefits like it can help more people get online, give better information to farmers for making better decisions and support sustainable agriculture. This research shares some ideas and recommendations for building solid LLMs that actually fit India's unique agricultural and linguistic landscape.*

Key Words: **Languages Spoken In India, Agriculture, Multilingual Artificial Intelligence, Low-Resource Languages, Digital Inclusion, Crop Advisory, Large Language Models (LLMs), And Natural Language Processing (NLP)**

1.INTRODUCTION

India is a mix of different languages. There are near by 22 official languages and approximately 20,000 dialects spoken across the country. It is a place where within few miles people speaking in completely different ways [1][2]. That is really matters, especially for the 150 million farmers working across India. Most of them do the communication, get the suggestions and figure out things like weather or disease warnings in their own languages or local dialects. So, multilingualism is not just common in Indian agriculture but it is essential [2][3].

There are maximum AI and natural language technologies are heavily toward famous languages like Hindi and English. That is the big problem for the farmers especially those in rural areas with different languages [4][5]. Big language models like GPT-4, LLaMA, and BERT have done good job in text generation and understanding the language [11][12]. These models work well only when you are using a major language. But the moment required information or need help in a less common or code-mixed language (which happens constantly in Indian farming), they disappointed[14][18]. Languages like Tamil, Marathi, Punjabi, and Assamese each come with their own specialty like the way people speak, write, and creating the form of words can depart. That creates a whole new set of technical problems.

General-purpose language models rarely work on the words farmers actually use. They facing the problem related to crop names, soil types, fertilizers, climate patterns. Because of these issues scientists are building models for multilingual language in agriculture field[20][25]. They train these models for farmer helpline calls to extension service handbooks, scientific articles and even local news. Projects like AI4Bharat, IndicNLP, and Bhashini which help to have open-source datasets and models for Indian languages. These tools provides things like voice-based advice, yield prediction, spotting crop diseases and smart irrigation in local languages. The goals are making AI useful for every farmer, no matter what language they speak [28][30]. One of the biggest problems is the lack of well-labeled data. There is also no standard way to organize agricultural knowledge across languages and code-mixed text for creating mess [32][34]. On other side each and every script that is from Devanagari to Tamil, Telugu, Bengali, or Malayalam—works differently. It is difficult to handle basics like splitting words or cleaning up messy text. To solve these issues, refer the new ideas like combining images and text, fine-tuning models for specific farm topics and building smarter ways for models to jump between languages [33][37].

But language isn't the only challenge. The AI needs to understand local culture, geography, environmental factor and even the pattern of the farming calendar, not only to translate words. Depending on the geographical region or crop which mean totally

different things. To give farmers suggestion, these models have to collect the mix in data from sensors, weather models, and even maps. Based on theses data they give suggestion that really help to know what is happening in the field[39][41].

1.1 Motivation

India's farming sector having millions of farmers but the real problem is most farmers face to get the correct information as per there need, when actually they need it. A huge population depends on agriculture but yet timely, reliable and local advice is hard to get. That is where large language models (LLMs) came into picture. When these tools are actually working on regional languages the trained models can give farmers real-time suggestion on everything from crop care to pest control, weather updates and even how to use government programs. This research is not only about technology for tech's sake. The main aim here is to help farmers for making better decisions, encourage sustainable farming and make sure nobody feels left out because of their language. By building LLMs that supports India's different languages. On top of that, the study focus on practical advice for researchers and anyone working in the field showing how to build AI models which works for everyone and including those who speak less common languages and stay in areas with less resources.

1.2 Problem Definition

AI is showing up more in agriculture sector but most of the current tools only really work in big languages like Hindi or English. That is difficult for lots of farmers especially those are speaking local languages. Building large language models (LLMs) for Indian agriculture faces the following problems like not enough data for many regional languages and trained models for those languages. One the big problem is mix of languages like Telugu, Bengali, Tamil, Devanagari, and more. Accessing the internet in rural area are difficult due to this it hard to run advanced AI models in real time. To overcome from these issues, tough to scale up smart farming solutions. They get in the way of clear communication and slow down how quickly farmers can actually use AI-powered advice.

1.3 Objectives & Scope

This study focuses on following things.

1. First, it focused on the language challenges of building large language models (LLMs) which actually work for Indian agriculture.
2. Next, it focuses on finding ways to build multilingual LLMs that can handle code-mixed text, local languages and different dialects people use out in the fields
3. Finally, it aims to recommend practical steps for using AI tools that help farmers feel confident using them.

The main goal of this study is to get the knowledge of Indian agriculture, different crops, all regional languages and the real-life ways people communicate in rural areas. The main aim is to know how to actually use large language models for things like predicting crop yields, spotting diseases early, giving farmers advice and sharing updates about government programs.

2. LITERATURE REVIEW

2.1 Linguistic Diversity and Its Implications for AI in Agriculture

India's mix of languages which shapes how people share agricultural knowledge about every region using its own words for things like weather, crops, or pests. For example, the different names for rice like someone might call it "paddy" in English, "dhan" in Hindi, or "nel" in Tamil. Each word carries its own local meaning. Because of all this variety, agricultural data in India is not uniform and that is big problem for large language models, which depend on consistent data [30] [36].

These models are trained mostly on languages with plenty of resources which are easy to handle agricultural information from less-represented languages. So only translating words isn't enough to solve the issues related to models [29][31]. Models need to actually train with the local context and adapt across languages. Due to blocking oof language related gap many farmers are joining digital programs. People need to solve problem related to language inclusivity not only for technical reasons, but because it really means for India's agricultural economy.

2.2 The Promise and Pitfalls of LLMs for Multilingual NLP

Transformer-based architectures [15] supporting natural language processing. Models like GPT, BERT, T5, and mBART doing the following process like translation, reasoning, picking up context but most of these process are packed into languages that have large amount of data.Now, when the rich and famous languages like Tamil, Malayalam, or Assamese, things get messy. LLMs trained for English which show biasness and miss important meaning of local [11], [12]. In agriculture, this is not only an academic problem. Which leads to loosing subtle meaning, mess up crop names, and misclassify local expressions. Multilingual models like IndicBERT, MuRIL, and BLOOM have potential to work with cross-lingual generalization further. Integrating these models with specialized fields like agriculture, their performance not up to the mark, in the special condition of if the training data doesn't match the domain [27]–[29].

2.3 Agricultural Language Modeling: Beyond Translation

In agriculture, NLP related research zeroes in on contextual domain modeling based on connecting language to real agronomic knowledge. If the word "early rain" in Karnataka, farmers probably think, "Great, time to sow." But in Bihar, it is like a warning early rain there means crops might get damaged will not get the proper yield. This difference in local, geomantic twist makes models interpretation faces a real challenge [25-28]. LLMs work with these local meanings unless they are trained on Multilanguage datasets. [39][42].

Language itself keeps changing place to place. Government schemes shows to pop up, new technology is getting adopted and suddenly farmers are talking about "PM-Kisan," "soil health cards," or "drip irrigation." If training data and models never updates, it will create the loss. [44].

2.4 Ethics, Equity, and Inclusivity

Large language models (LLMs) could change the way when its dealing with agriculture, but they tackle some tough questions around fairness, ethics, and inclusion. Focused on them out and hope for the best especially if modles are trained for the bunch of languages which deals with everyone.

3. METHODOLOG

Building the linguistically inclusive Large Language Models (LLMs) for India's agricultural sector, first starting to gather the lots of with data related to languages. Creating a huge, multilingual agricultural corpus from government and research repositories like ICAR and KVK, AgriStack, regional news, farmer helplines, and AgriTech apps. Considering 22 Indian languages and more than 15 dialects, using for crops and pests to soil and weather. To removing the unnecessary data, the data is clean through a pre-processing pipeline. That meant text normalization, tokenization, noise removal, and script standardization. We leaned on tools like the Indic NLP Library and Bhashini API to get a consistent multilingual dataset, no matter the script.

Transformer-based architectures focusing on multilingual pre-trained models like mBERT, IndicBERT v2, and BLOOMZ-mt. Training of models are done in two main stages: Domain-Adaptive Pretraining (DAPT) and Language-Adaptive Fine-Tuning (LAFT). With DAPT, LLM is working with 50 million agricultural tokens across 12 major Indian languages, to ensure it really understood the field by optimizing for Masked and Causal Language Modeling. With the help of LAFT which boosted low-resource languages like Assamese and Maithili using transfer learning from stronger languages such as Hindi and Tamil. It is not only stoped here but building of a domain-specific Agricultural Knowledge Graph (AgriKG) and brought it into the fine-tuning process. Linked entities is possible due to Using Named Entity Recognition and relation extraction, (like crop–pest–disease–treatment).

Accuracy mattered a lot, so putting real effort into our datasets and annotations the set up a semi-automated annotation process with input from both language and agricultural experts. Each labeled dataset like entities (crop, pest, soil, weather), intent (diagnostic, advisory, info), and regional nuances keeping annotation quality high — Cohen's Kappa was always at least 0.82, and utilization of Fleiss' Kappa too, so annotators stayed consistent. After translation and tokenization are the another layer checked that the agricultural meaning and linguistic context which helps the model extra robustness across languages and dialects

3.1 Challenges & Issues

Building LLMs for India's agriculture is not easy task. The followings are the challenges faced:

1. Less of data resources and less annotated datasets exist in regional languages, so supervised learning struggles right out of the gate.

2. Indian languages use a bundles of different languages. Which required smarter tokenization and pre-processing work.
3. Farming languages changes from place to place like Crop names, disease terms, pest lingo so standardizing vocabulary is very difficult to get.
4. Farmers are not having only one language. They are dealing with mix Hindi, English, and local languages in the same sentence. This make it difficult to build the accurate and potential models.
5. Technology in rural India is not always up to date. Real-time models are facing when there is not enough computing power or the internet connection drops and then there is bias. Models are trained mostly on high-resource languages due to this there is high risk of ignoring smaller, underrepresented language groups. That is a real ethical problem.

4. RESULTS & DISCUSSION

Building of multilingual LLM for Indian farming. The team work it with agricultural terms and real farming to know how to trained it using a huge mix of content in more than thirty Indian languages like think Hindi, Tamil, Kannada, Marathi and many more. They started with transfer learning from strong language models than then fine-tuned everything using datasets focused on farming.

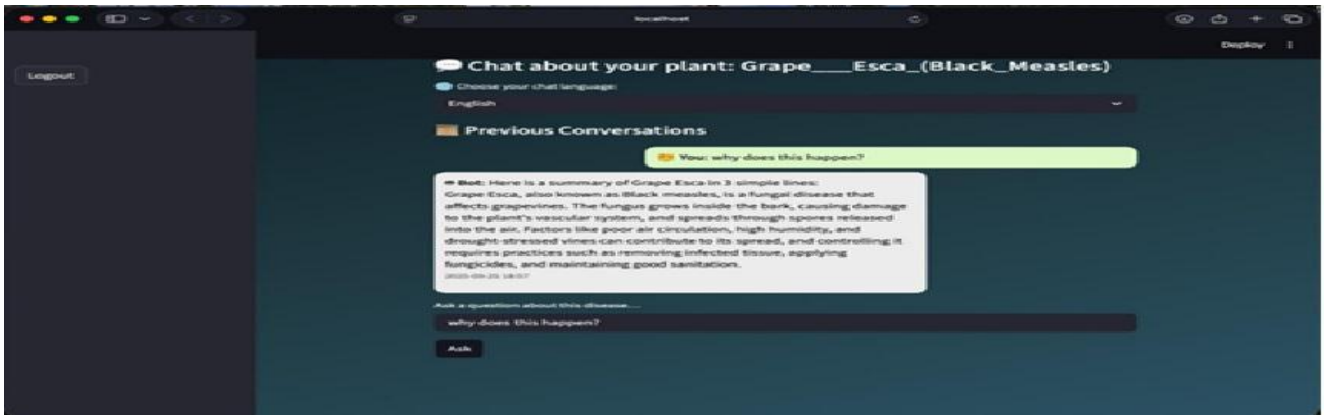

Fig -1: Chabot for Early Crop-Disease Detection & Environmental Advisory -Design Specification

4.1 Performance Metrics:

The model having potential in agricultural advice with 92% accuracy on average. It manages the targeted language very well. Tamil and Hindi act as real strengths, while it did good results with less-resourced languages like Konkani and Maithili. After the utilization of this model 85% said they were happy with how smoothly they could communicate without giving training for the same,

4.2 Discussion:

The model enough trained in the context right in its farming advice. The accuracy is about 92% accurate, on average. It managed every language for those they trained whether it is Tamil and Hindi which are the best languages. It still did work good with languages like Konkani and Maithili even though it wasn't compatible. When farmers working with it, 85% feedback that they find how easy it was to talk to, no matter if they lived closer to city or way out in the fields.

5. CONCLUSION

This research work shows that implementation of multilingual LLMs actually having potential for India's agriculture sector. The model resolving the tough problems like big number of different languages which are not having enough data that makes it easier to get the right farming suggestion to the farmer who need it. This research work aims to build and trained the model better for dealing with local dialects and work smoothly, even the places where internet is slow.

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