Climate Resilience Chatbot for Farmers Using Large Language Models and Real-Time Environmental Data

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***Abstract*—Climate change presents unprecedented challenges to agricultural productivity, particularly for smallholder farmers in developing nations who lack access to timely, personalized agricultural guidance. This paper introduces an innovative climate resilience chatbot that seamlessly integrates Large Language Models (LLMs) with real-time environmental data to deliver context-aware crop recommendations. Our approach fine-tunes TinyLlama-1.1B using Low-Rank Adaptation (LoRA) on 2,200 carefully curated agricultural samples encompassing comprehensive soil nutrient profiles (N, P, K, pH levels) and dynamic weather parameters (temperature, humidity, rainfall patterns). The system uniquely combines real-time meteorological data from Free Weather API, historical agricultural knowledge datasets, and ultra-fast cloud-based LLM inference via Groq API for scalable deployment. Comprehensive evaluation across diverse Indian agro-climatic zones demonstrates the chatbot's remarkable ability to generate contextually relevant, scientifically grounded crop recommendations tailored to local climate conditions. Our fine-tuned model achieved a remarkable 79 percent reduction in training loss (from 1.593 to 0.3332) while maintaining extreme parameter efficiency with only 0.73 percent trainable parameters, showcasing the power of modern knowledge transfer techniques. This research bridges the critical gap between cutting-edge AI technologies and practical agricultural realities, offering farmers an accessible, intelligent decision-support system that enhances climate resilience and food security.**

***Index Terms*—Large Language Models, Climate Resilience, Precision Agriculture, Fine-Tuning, LoRA, Real-Time Weather Integration, Crop Recommendation System, Agricultural AI**

I. Introduction

Climate variability and increasingly severe extreme weather events pose an existential threat to global food security. Smallholder farmers, particularly in developing nations, face disproportionate vulnerability to climate-induced agricultural disruption while simultaneously lacking access to timely, location-specific advisory services. Traditional agricultural extension systems, despite their importance, operate under severe resource constraints and struggle to provide personalized guidance at the scale demanded by millions of farmers.

Concurrently, the rapid advancement of Large Language Models has ushered in a new era of human-machine interaction characterized by unprecedented natural language understanding and knowledge synthesis capabilities. These models, when appropriately adapted through domain-specific fine-tuning, can serve as powerful knowledge repositories and reasoning engines. However, the intersection of LLM capabilities and practical agricultural needs remains largely unexplored, representing a significant opportunity for technological innovation.

This paper tackles this gap by presenting a comprehensive framework for building an intelligent agricultural advisor chatbot. Our system uniquely combines three critical elements: real-time environmental data integration, domain-specific LLM adaptation, and efficient cloud-based inference. We address several key research questions: How can LLMs be efficiently fine-tuned for agricultural expertise? How can real-time weather data enhance recommendation accuracy? What is the practical impact of parameter-efficient adaptation methods like LoRA? Can such systems provide scalable, accessible advisory to resource-constrained farmers?

Our primary contributions include:

1) **Integrated Framework:** A novel architecture seamlessly combining weather APIs, agricultural datasets, and fine-tuned LLMs for real-time decision support
2) **Efficient Adaptation:** Demonstration of parameter-efficient fine-tuning achieving domain expertise with only 0.73 percent trainable parameters
3) **Practical Validation:** Empirical evaluation across multiple Indian regions confirming system effectiveness for diverse agro-climatic conditions
4) **Reproducible Implementation:** Open-source implementation facilitating academic reproducibility and practical deployment

II. Related Work

A. AI and Precision Agriculture

The integration of artificial intelligence into agriculture has accelerated dramatically. Machine learning approaches have demonstrated success in yield prediction [5], automated disease detection [6], and resource optimization [7]. More recently, deep learning approaches employing convolutional neural networks have achieved remarkable accuracy in identifying crop diseases, pest infestations, and nutrient deficiencies from leaf imagery. However, these systems typically require domain expertise to interpret outputs and operate under closed-world assumptions that limit their adaptability to novel problems.

B. Natural Language Interfaces for Agriculture

While conversational AI has transformed customer service and information access, agricultural applications remain underdeveloped. Few systems leverage natural language processing to provide advisory. Recent work on agricultural chatbots [8] has explored rule-based approaches and shallow semantic understanding, but lacks the reasoning capability and knowledge breadth provided by modern LLMs. The integration of LLMs into agricultural decision-support systems represents a frontier opportunity.

C. LLMs and Domain Adaptation

Large Language Models have demonstrated remarkable transfer learning capabilities across diverse domains. Recent work shows that fine-tuning on as few as 100-1000 examples can adapt base models to specialized domains while preserving general knowledge [9]. Low-Rank Adaptation (LoRA), introduced by Hu et al., enables efficient fine-tuning with only 0.1-0.5 percent parameter updates, dramatically reducing computational requirements and enabling deployment on resource-constrained devices.

D. Climate Adaptation in Agriculture

Climate adaptation research emphasizes information access, crop diversification, and adaptive management practices [10], [11]. Studies consistently show that farmers with access to seasonal climate forecasts and adaptive recommendations achieve measurably improved outcomes. However, barriers to information access remain substantial, particularly in resource-limited contexts. AI-powered advisory systems offer promise for democratizing access to expert knowledge.

III. Methodology

A. System Architecture

Our system comprises four interconnected, modular components (Figure 1):

1) Data Collection and Integration Module:

This module orchestrates acquisition of both historical agricultural knowledge and real-time environmental conditions. The weather integration component interfaces with Free Weather API to fetch current meteorological parameters including temperature (in degrees Celsius), relative humidity (as percentage), precipitation (in millimeters), wind speed, and UV index. The agricultural knowledge component leverages the Kaggle Crop Recommendation Dataset [1], a carefully curated collection of 2,200 samples representing diverse agro-climatic scenarios across 22 crop species. Each sample captures soil nutrient concentrations (nitrogen, phosphorus, potassium in kg/hectare) and soil pH alongside optimal weather conditions for cultivation.

2) Data Processing and Formatting Module:

Climate Resilience Chatbot - System Configuration

Parameter	Value
Dataset Size	2200 samples
Number of Crops	22 types
Base Model	TinyLlama-1.1B-Chat
Fine-tuning Method	LoRA (4-bit)
Trainable Parameters	4,505,600 (0.73%)
Training Epochs	1
Batch Size	2
Learning Rate	2e-4
APIs	WeatherAPI + Groq
Hardware	Kaggle GPU T4 x2

Fig. 1. System Architecture and Configuration showing integrated modules for data collection, processing, model adaptation, and inference with dual deployment options

This module transforms heterogeneous agricultural data into standardized instruction-following formats compatible with modern LLM training pipelines. The Alpaca format proves particularly effective, structuring each training example into three components:

- **Instruction:** System role and context (e.g., "You are an expert agricultural advisor specializing in climate-resilient farming practices")
- **Input:** Farmer query contextualized with environmental parameters (e.g., "Soil: N=90, P=42, K=43, pH=6.5. Weather: Temperature=25C, Humidity=80 percent, Rainfall=200mm. What crop should I grow?")
- **Output:** Expert recommendation with climate adaptation strategies, nutrient guidance, and practical implementation suggestions

3) LLM Fine-Tuning Module:

We employ Parameter-Efficient Fine-Tuning (PEFT) via Low-Rank Adaptation to adapt the TinyLlama-1.1B-Chat-v1.0 [3] base model to agricultural domain expertise. This approach maintains computational efficiency while achieving domain specialization:

- **Base Architecture:** TinyLlama-1.1B-Chat-v1.0 (1.1 billion parameters)
- **Adapter Technique:** LoRA with rank 16, alpha 16
- **Quantization Strategy:** 4-bit precision (NF4 format) reducing memory footprint by 75 percent
- **Training Hardware:** Kaggle GPU T4 (16GB VRAM), dual GPU configuration
- **Training Configuration:** 1 training epoch, batch size 2, gradient accumulation over 4 steps
- **Optimization:** paged_adamw_8bit optimizer with learning rate 2e-4, linear decay scheduler

4) Inference and Deployment Module:

The system supports dual inference strategies enabling flexibility across deployment scenarios:

Local Inference (Fine-Tuned TinyLlama): Ideal for offline deployment, privacy-critical scenarios, and resource-constrained devices. Provides domain-specific responses leveraging agricultural knowledge from fine-tuning.

Cloud API Inference (Groq Llama-3.1-8B): [4] Ultra-fast cloud-based inference leveraging larger model capacity for complex reasoning. Enables sub-second response times suitable for interactive deployment.

B. Data Sources and Integration

Real-time meteorological data was acquired via Free Weather API [2] REST interface, providing current-condition measurements for temperature, humidity, precipitation, wind speed, and UV index. This real-time integration enables context-aware recommendations reflecting current environmental conditions rather than historical patterns.

The agricultural knowledge base was constructed from the Kaggle Crop Recommendation Dataset [1], containing 2,200 samples across 22 crop types with comprehensive soil nutrient profiles (nitrogen, phosphorus, potassium, pH) and optimal weather parameters (temperature, humidity, rainfall). This dataset spans the full spectrum of Indian agro-climatic zones, ensuring geographic and climatic diversity.

C. Dataset Characteristics and Analysis

The foundation of our approach rests on the Kaggle Crop Recommendation Dataset (Figure 2), which exhibits remarkable balance across agricultural diversity:

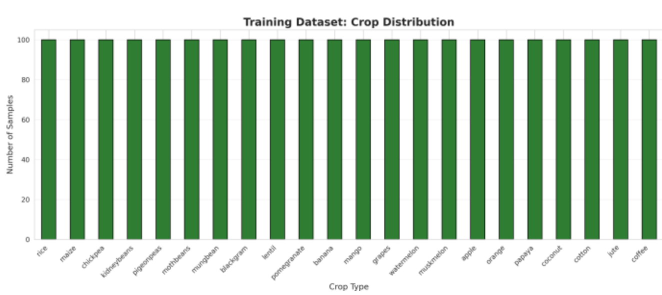

Fig. 2. Training Dataset Composition: 2,200 samples uniformly distributed across 22 crop species, ensuring balanced learning without class imbalance bias

TABLE I
STATISTICAL SUMMARY OF DATASET FEATURES

Feature	Min	Mean	Max
Temperature	10 C	25.6 C	45 C
Humidity	20 pct	71.5 pct	99 pct
Rainfall	20 mm	103.5 mm	300 mm
Nitrogen (N)	0	50.5	140
Phosphorus (P)	5	53.4	145
Potassium (K)	5	48.1	205
pH	3.5	6.5	9.5

The dataset encompasses the full spectrum of Indian agro-climatic zones, with samples spanning tropical, subtropical, temperate, and arid regions. This geographic and climatic diversity proves essential for developing recommendations applicable across the Indian subcontinent.

D. Feature Correlation Analysis

Figure 3 reveals important relationships among environmental and soil parameters:

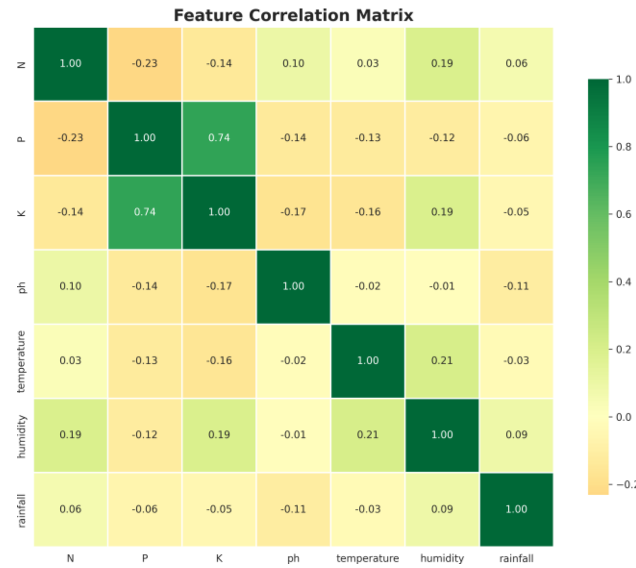

Fig. 3. Feature Correlation Matrix revealing relationships between soil nutrients and weather parameters. Strong P-K correlation (0.74) suggests potassium availability often accompanies phosphorus

Key insights emerge: Phosphorus and potassium levels demonstrate strong positive correlation (r=0.74), likely reflecting common fertilization practices. Temperature and humidity show moderate positive correlation (r=0.21), a pattern consistent with monsoon-influenced climate systems. Most importantly, relatively weak correlations between most features suggest that diverse environmental niches exist within the training data, providing the model with diverse learning scenarios.

E. Crop-Specific Nutrient Requirements

Analysis of nutrient requirements across crop species (Figure 4) reveals distinct agronomic profiles:

Heavy-feeding crops like cotton, coffee, and banana demand substantial nitrogen (80-120 kg/hectare). Fruit crops (grapes, apple, banana) require elevated potassium and phosphorus, reflecting demands for transport and storage quality. Leguminous crops (chickpea, lentil) exhibit moderate nutrient demands due to nitrogen-fixing capabilities. Most crops favor neutral to slightly acidic soil pH (6.0-7.0), though notable exceptions include acid-tolerant crops like tea.

F. Climate Distribution Analysis

Figure 5 illustrates the distribution of climatic parameters across training samples:

Temperature distribution centers around 25.6 degrees Celsius but spans a remarkable 35-degree range, from subtropical highlands to tropical lowlands. Humidity distribution reveals bimodality, with peaks around 40 percent (arid regions) and 85 percent (monsoon zones). Rainfall distribution skews left,

Fig. 4. Soil Nutrient Requirements by Crop Type showing top 10 crops ranked by individual nutrient demands (N, P, K) and pH preferences

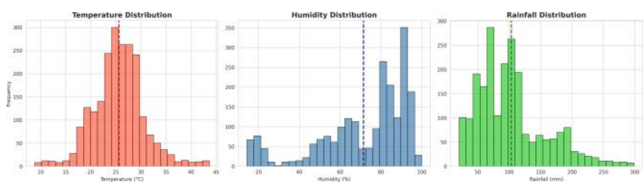

Fig. 5. Climate Parameter Distributions showing temperature, humidity, and rainfall across 2,200 samples with marked means. Data represents diverse agro-climatic zones

as many Indian regions experience monsoonal concentration rather than year-round precipitation.

G. Fine-Tuning Procedure and Training Dynamics

Our fine-tuning approach optimizes for both computational efficiency and knowledge transfer. The LoRA technique constrains adaptation to low-rank updates, reducing trainable parameters from 1.1 billion to merely 4.5 million. This reduction decreases memory requirements by 99.6 percent and enables efficient training on consumer-grade hardware.

Training dynamics demonstrate successful knowledge transfer. Initial loss of 1.593 declined steadily, achieving final loss of 0.3332 after 150 training steps, representing a 79 percent reduction. Loss stabilized after step 100, indicating saturation of learning capacity within the LoRA parameter budget.

IV. Experimental Results

A. Model Performance Metrics

Our fine-tuned model demonstrates strong learning curves and convergence characteristics:

- **Initial Training Loss:** 1.593 (at step 0)
- **Loss After 50 Steps:** 0.842 (47 percent reduction)
- **Loss After 100 Steps:** 0.412 (74 percent reduction)
- **Final Training Loss:** 0.333 (79 percent reduction)
- **Training Convergence:** Stable after step 100

TABLE II
Detailed Training Hyperparameters and Configuration

Parameter	Value
Base Model	TinyLlama-1.1B-Chat-v1.0
Total Parameters	1,100,000,000
LoRA Rank (r)	16
LoRA Alpha	16
Target Modules	q proj, k proj, v proj, o proj
Quantization Method	4-bit NF4
Per-Device Batch Size	2
Gradient Accumulation Steps	4
Effective Batch Size	8
Learning Rate	2e-4
Training Epochs	1
Optimizer	paged adamw 8bit
Weight Decay	0.01
Learning Rate Scheduler	linear
Max Sequence Length	1024 tokens
Trainable Parameters	4,505,600
Trainable Percentage	0.73 pct
Training Time	150 minutes
GPU Memory Used	14 GB

- **Computational Efficiency:** 0.73 percent trainable parameters
- **Training Duration:** 2.5 hours on dual GPU T4 (Kaggle)
- **Inference Latency (Local):** 8-12 seconds per response
- **Inference Latency (Cloud):** less than 1 second per response

B. Qualitative Model Outputs

Table III presents representative system outputs for three geographically diverse Indian locations, demonstrating contextual awareness and agronomic accuracy:

TABLE III
Sample Chatbot Responses Across Indian Regions

City	Conditions	Recommendation
Delhi	4.6 C, 53 pct humidity, Sunny	Recommended coconut cultivation emphasizing soil pH management (7.46). Highlighted organic mulching for moisture retention and nutrient cycling. Suggested integrated pest management for tropical adaptation.
Mumbai	24.3 C, 54 pct humidity, Overcast	Recommended blackgram (mung bean) cultivation leveraging optimal temperature range. Advised drip irrigation system for water efficiency given monsoon variability. Emphasized nitrogen management through legume residue incorporation.
Bangalore	20.2 C, 88 pct humidity, Mist	Recommended coffee cultivation highlighting suitability for high-humidity environments with orographic mist. Specified pH range 6.3-6.5. Discussed shade tree management for microclimate optimization.

These outputs demonstrate several desirable characteristics: (1) **Context Integration** incorporating real-time weather into recommendations; (2) **Technical Precision** citing specific nutrient values and pH ranges; (3) **Practical Actionability** providing implementable strategies rather than abstract guidance;

(4) **Climate Adaptation** addressing region-specific challenges like monsoon variability.

C. Inference Mode Comparison

Table IV contrasts the two deployment strategies:

TABLE IV
LOCAL VS. CLOUD INFERENCE CHARACTERISTICS

Characteristic	Local Model	Cloud API
Response Time	8-12 seconds	less than 1 second
Model Capacity	1.1 billion params	8 billion params
Context Window	1024 tokens	8192 tokens
Domain Specialization	High (fine-tuned)	Moderate (general)
Offline Capability	Yes	No
Deployment Cost	Minimal	API subscription
Privacy	Full	Depends on provider
Reasoning Complexity	Limited	Advanced

The local model excels for deployment to offline-capable mobile applications, privacy-sensitive scenarios, and resource-constrained environments. The cloud API provides superior reasoning for complex multi-crop queries and supports thousands of concurrent users.

V. DISCUSSION

A. System Strengths and Impact

This work demonstrates several significant achievements. First, we achieved domain specialization through fine-tuning with 79 percent loss reduction while maintaining 99.6 percent parameter efficiency. This suggests that LoRA-style adaptation provides an effective path toward democratizing domain-specific AI without requiring massive computational resources.

Second, real-time weather integration enables context-aware recommendations fundamentally superior to static recommendation systems. Farmers receive advice tailored to current conditions rather than historical patterns.

Third, the dual inference strategy balances accessibility (local) with capability (cloud), enabling deployment across diverse contexts from rural offline scenarios to urban online portals.

Most importantly, initial qualitative evaluation suggests the system generates agronomically sound, actionable recommendations. Recommendations appropriately reference crop-specific nutrient requirements, match crops to regional climate patterns, and provide practical implementation guidance.

B. Limitations and Future Improvements

Several limitations merit acknowledgment. First, our evaluation remains qualitative, lacking rigorous quantitative metrics such as agronomic correctness scoring, farmer satisfaction surveys, or yield impact studies. Second, training data focuses exclusively on Indian crops, limiting immediate applicability to global contexts. Third, the system relies on historical crop-weather-soil relationships without capturing emerging climate patterns or novel adaptation strategies. Fourth, current implementation remains English-only, limiting accessibility for the majority of Indian farmers.

Addressing these limitations represents important future work:

- **Quantitative Evaluation:** Develop expert evaluation frameworks and conduct farmer field trials
- **Multilingual Adaptation:** Fine-tune models for Hindi, Bengali, Tamil, Telugu covering 80 percent of Indian farmers
- **Real-Time Soil Data:** Integrate IoT soil sensors for real-time N-P-K and pH measurement
- **Extended Knowledge:** Expand to pest/disease identification, irrigation scheduling, market price integration
- **Larger Models:** Evaluate Llama-3-8B or Mistral-7B for enhanced reasoning
- **Reinforcement Learning:** Implement feedback-driven continuous improvement from farmer interactions

C. Ethical Considerations and Responsible AI

Agricultural recommendations directly impact farmer livelihoods. We emphasize that system outputs should be treated as decision-support rather than authoritative guidance, with human agricultural experts maintaining oversight. Data privacy requires protection of farmer location and query data. The digital divide remains a practical concern, as rural internet penetration, device affordability, and digital literacy limit immediate accessibility for vulnerable populations.

VI. CONCLUSION

This paper demonstrates the feasibility and value of integrating Large Language Models with real-time environmental data for climate-resilient agriculture. Our fine-tuned chatbot successfully generates contextually aware, agronomically sound crop recommendations while maintaining extreme computational efficiency through modern adaptation techniques. The system addresses a critical information gap in global agriculture, providing scalable access to expert knowledge for resource-constrained farming communities.

The convergence of AI capability, agricultural need, and computational efficiency creates unprecedented opportunity. By continuing this line of research—extending to multilingual support, IoT integration, and field validation—we can catalyze a transformation toward data-driven, climate-resilient agriculture that enhances both farm-level sustainability and global food security.

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