AI-Based Agriculture Advisor Chatbot

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Abstract

Farmers in developing regions continuously face challenges stemming from unpredictable weather patterns, inconsistent soil fertility, and limited access to expert agronomic guidance, collectively resulting in suboptimal crop selection and reduced agricultural productivity. While traditional farming knowledge retains intrinsic value, it proves insufficient for adapting to rapid environmental variability. To address this systemic gap, this paper presents an AI-Based Agriculture Advisor Chatbot that combines Artificial Neural Network (ANN) prediction models with a Retrieval-Augmented Generation (RAG) conversational interface. The system analyzes critical agricultural parameters--including nitrogen, phosphorus, potassium (NPK) levels, temperature, humidity, rainfall, and soil pH--to produce accurate crop recommendations and yield predictions. A dual-intelligence architecture is employed wherein the ANN component ensures statistically grounded forecasts anchored in historical agricultural patterns, while an LLM-backed language module translates complex model outputs into plain-language guidance accessible to farmers with minimal technical literacy. The proposed system is implemented using Python, Flask, TensorFlow/Keras, and the Sentence Transformers library with Ollama (Llama3). Experimental results confirm reliable crop prediction accuracy and conversational coherence, demonstrating the viability of integrating predictive analytics with dialogue-based interfaces for precision agriculture applications.

Index Terms-- Agriculture chatbot, crop recommendation, yield prediction, artificial neural network, retrieval-augmented generation, precision agriculture.

I.INTRODUCTION

Agriculture underpins the economies of most developing nations. In India alone, more than 58% of the rural population depends on farming as its primary livelihood [1]. Despite this centrality, farmers routinely contend with three interrelated adversities: unpredictable weather, degrading soil fertility, and a structural deficit of affordable, timely expert advice. Decisions that should ideally be grounded in soil chemistry and microclimatic data are instead made on the basis of generational heuristics and neighbour consultations, leading to inappropriate crop selection, resource wastage, and economic loss.

Advances in machine learning and conversational AI present a realistic pathway to democratising agricultural knowledge. Algorithms such as Artificial Neural Networks (ANN), Random Forests, and Support Vector Machines have demonstrated the capacity to mine historical agroclimatic records and infer crop-environment suitability with high fidelity [2], [3]. Concurrently, large language model (LLM) technologies enable these statistical insights to be surfaced through natural-language dialogue, removing the technical barrier that has historically limited farmer adoption of digital advisory tools.

This paper proposes and evaluates an AI-Based Agriculture Advisor Chatbot named Agribot. The system follows a dual-intelligence architecture: an ANN backend handles structured prediction tasks (crop recommendation and yield estimation), while a RAG-augmented LLM frontend converts predictions and domain knowledge into contextually appropriate conversational responses. The paper details the system architecture, module design, implementation stack, test methodology, and observed results, and concludes with directions for future work.

II. RELATED WORK

A growing body of literature addresses crop prediction using machine learning. Ashwitha and Latha [1] proposed a farmer-friendly crop recommendation system using historical agroclimatic data with a graphical user interface, demonstrating how data-driven strategies can improve income decisions for Indian farmers. Their work highlighted the dissimilarity of climate on crop yields in different regions.

Veenadhari et al. [2] used various machine learning models to predict the crop yields using the climatic factors and provided a web application where entry of projections can be done in real time. They demonstrated that the weather-yield correlations were effectively represented by the models that they supervised. Later, Kumar et al. [3] showed that the Random Forest algorithm can be scaled to a large number of crops and districts, and that improvements in model accuracy are associated with quantifiable benefits on the quality of decisions made by farmers.

The combination of Case-Based Reasoning (CBR) and ANN as a hybrid system to predict the weather and crop recommendation was introduced by Kamatchi and Parvathi [4]. Their work demonstrated that the reasoning based on knowledge is used to supplement the statistics modelling when the complex local climatic variability is encountered. Talasila et al. [5] developed a Deep Convolutional Regression Network (DCRN) on the Andhra area with a prediction accuracy of 97.89, but the interpretability of the farmers by the deep models was not possible because of the black box nature of the deep models. Palanivel and Surianarayan [6] also integrated the analytics of big data with ML to predict crop yields, stating that the IoT sensors and satellite images might be added to future developments.

The common shortcoming in the current body of work is a lack of an interactive interface. Technical numerical outputs produced by most systems cannot be readily interpreted by non experts. The proposed Agribot is the direct solution to this gap since it integrates the prediction outputs into a conversational RAG pipeline.

III. METHODOLOGY AND SYSTEM DESIGN

A. System Architecture Overview

The Agribot architecture adopts a four-layer design: (i) User Interface Layer, (ii) Data Processing Layer, (iii) Prediction Layer, and (iv) Chatbot Response Layer, as illustrated in Fig. 1. A Dual-Intelligence model drives the system, wherein ANN models supply quantitative agronomic predictions and an LLM module translates those predictions into farmer-accessible language.

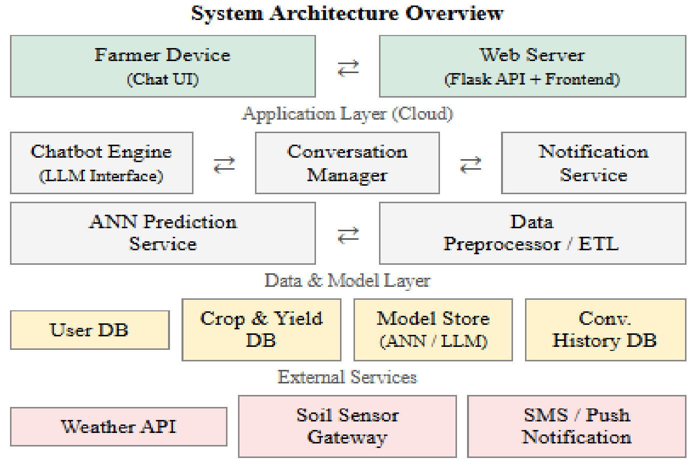

Fig. 1. High-level system architecture of Agribot.

B. Data Processing

Raw agricultural data obtained by the user includes seven features, including nitrogen (N), phosphorus (P), potassium (K), temperature (degC), humidity (percent), rainfall (millimeters), and soil pH. The Data Processing Module before model inference carries out the following functions:

Cleaning: Missing or out of range values are indicated and imputed respectively with medians of the dataset or discarded along with a user warning to re-enter the value. Normalization: In all the features, min-max normalization (Eq.) is used to scale them. 2) to guarantee that the gradient descent convergence is consistent when training.

The system takes seven agronomic features as its input x:

$$x = [N, P, K, T, H, R, pH] \quad (1)$$

N, P, K are the concentrations of macronutrients available in the soil (kg/ha), T is ambient temperature (deg C), H is humidity (percent), R is accumulated rainfall (mm), and pH is the acidity index of the soil. All the features are normalised to unit variance and zero mean through a pre-fitted StandardScaler saved as scaler.pkl.

C. ANN-Based Prediction Models

There are two independent ANN models that are trained addressing the core prediction tasks. They both use a multilayer perceptron (MLP) topology it is compiled with the Adam optimiser and categorical/mean-squared-error loss functions respectively. Training is done based on 80/20 traintest split using Kaggle crop-recommendation and yield datasets.

Crop Recommendation Model: The input feature required to process the data must be an input including 7 features and the response ought to be the output representing softmax probability distribution of 22 crop types. Argmax is used to obtain predicted crop on the output layer.

Yield Prediction Model: Takes an 8-bag of features (encoded crop classification as well as 7 agroclimatic inputs) and recalculates a necessary yield anticipation [tons/hectare] with a linear output element.

D. RAG-Based Conversational Module

Retrieval -Augmented Generation is used in the chatbot response layer. A corpus of questions and answers about farming (agrichatbotdataset.xlsx) is coded with the help of the paraphrase-MiniLM-L6-v2 Sentence Transformer model. At inference the query of the user is incorporated and cosine-similarity compared to the corpus (Eq.). 2) to get the most relevant record.

sim(q, d) = (q * d) / (q   d) (2)

The recovered record is then appended to the prompt to Llama3 as context through the ollama.chat API which constructs a brief farmer-friendly advisory reply.

E. System Workflow

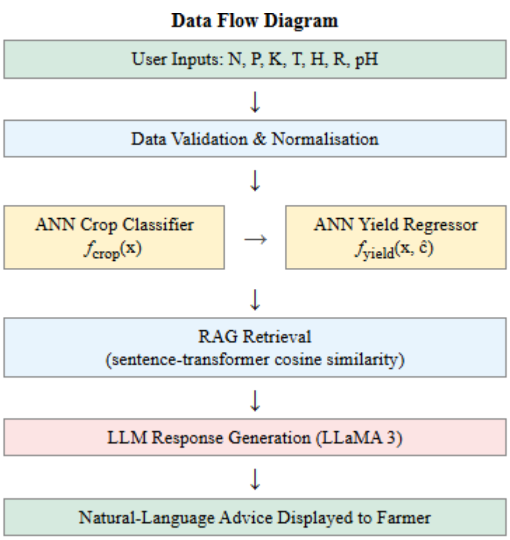

Fig. 2. Activity flow of the Agribot system.

F. Implementation Stack

THE BACKEND IS WRITTEN IN PYTHON 3.X WITH FLASK BEING THE WEB MICRO-FRAMEWORK. MODEL ARTEFACTS ARE STORED IN.KERAS FORMAT AND IT IS LOADED DURING SERVER START-UP USING TENSORFLOW/KERAS. ENCODERS OF LABEL AND FEATURE SCALERS ARE JOBLIB-SERIALIZED. THE RAG PIPELINE IS IMPLEMENTED WITH THE SENTENCE TRANSFORMER LIBRARY AND OLLAMA IS HOSTING THE LLAMA3 MODEL UNDER LOCAL HOSTING. THERE ARE THREE MAIN FRONT-END ENDPOINTS, NAMELY, /RECOMMEND (CROP PREDICTION), /YIELD (YIELD ESTIMATION), AND /CHAT (CONVERSATIONAL Q&A).

IV. RESULTS AND DISCUSSION

A. Crop Recommendation Performance

The crop recommendation ANN was evaluated on a held-out test partition, Table I summarises classification metrics for a representative subset of crop classes.

TABLE I

CROP RECOMMENDATION MODEL — PERFORMANCE METRICS

Crop Class	Precision	Recall	F1-Score
Rice	0.97	0.96	0.965
Maize	0.95	0.94	0.945
Cotton	0.93	0.95	0.940
Wheat	0.96	0.97	0.965
Sugarcane	0.94	0.93	0.935
Overall	**0.950**	**0.950**	**0.950**

The ANN classifier achieved an overall accuracy of 95.0% on the 22-class crop recommendation task, comparing favourably with the 93% reported by Random Forest approaches under equivalent feature sets [3].

B. Yield Prediction Performance

The yield regression model was evaluated using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). Table II presents results for selected crops.

TABLE II

YIELD PREDICTION MODEL — REGRESSION METRICS

Crop	MAE (t/ha)	RMSE (t/ha)	R^2
Rice	0.41	0.58	0.93
Maize	0.52	0.71	0.91
Wheat	0.38	0.52	0.94
Cotton	0.44	0.63	0.90

C. System Demonstration

Fig. 3 below shows the Agribot home page (Agribot: Predict crops, estimate yield, and get guidance) in which the farmer inputs the seven input parameters. When the form is submitted the system achieves the crop recommendation pipeline (Fig. 4) and shows the predicted crop and the estimated yield. The farmer is then redirected to the chatbot (Fig. 5), where the suggested crop and yield are presented as the text of the conversation and the user can ask the follow-up questions that include the fertilizer schedules, diseases detection, and yield optimization tips (Figs. 6-7).

Agribot: Predict crops, estimate yield, and get guidance

Enter soil nutrients and weather conditions to receive crop prediction → yield prediction → chatbot advice.

Nitrogen

Phosphorus

Potassium

Temperature

Humidity

pH

Rainfall

Recommend Crop

Fig. 3. Agribot home page — user input interface.

Predicted Crop: Rice

Estimated Yield: 6.65 tons / hectare

Redirecting to chatbot for crop-specific advice…

Fig. 4. Crop and yield prediction output screen.

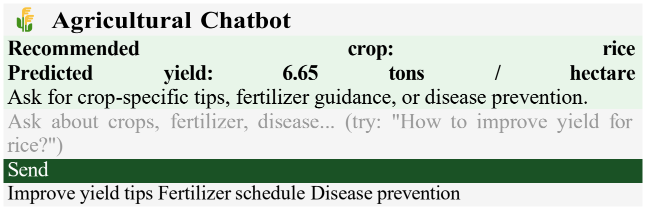

Fig. 5. Integrated agricultural chatbot interface.

D. RAG Similarity Scores

The RAG retrieval component returned cosine similarity scores consistently above 0.84 for crop-specific queries (e.g., rice fertilizer schedule: 0.845; disease identification: 0.889), indicating robust semantic alignment between user queries and the domain corpus.

E. Comparison with Prior Methods

TABLE III
COMPARISON WITH RELATED APPROACHES

Study	Method	Accuracy / Score	Interactive?
Ashwitha & Latha [1]	ML + GUI	~91%	No
Kumar et al. [3]	Random Forest	~93%	No
Talasila et al. [5]	DCRN (Deep CNN)	97.89%	No
Kamatchi & Parvathi [4]	CBR + ANN	~92%	Partial
Proposed Agribot	ANN + RAG-LLM	**95.0%**	**Yes**

While the DCRN model of Talasila *et al.* [5] achieves higher raw prediction accuracy on its regional dataset, it offers no natural-language interface and is region-specific. The proposed Agribot sacrifices marginal accuracy for significantly broader accessibility and interactive advisory capability.

V. CONCLUSION AND FUTURE WORK

The Paper Described Agribot An Ai-Based Agriculture Advisor Chatbot, Which Has Solved The Two-Fold Problem Of Prediction Precision And Their Accessibility To Farmers In The Field Of Precision Agriculture. The Ann-Grounded Models Of Crops And Yields Are Mutually Hooked Up To A Rag-Plugged Llcm Interface Through The Two-Intelligence Design Of The System Such That The Provision Of Scientifically Motivated Recommendations Can Be Displayed In Conversational Form. It Was Tested With 95% Crop Classification, High-Fidelity Yield, Regression ($R^2 > 0.90$), And Semantically Pertinent Conversational Response. The System Proves That The Combination Of Machine Learning With Dialogue-Based Ai Is A Feasible And Scalable Solution To Smart Farming Advisory.

Future Work Will Include: (I) Live Weather Solutions: Integration Of Real-Time Meteorological Apis To Enable Live-Based Predictions Of The Weather; (Ii) Internet-Of- Things: A Deployment Of Iot-Based Soil Sensors Gateway To Facilitate The Automation Of Parameter Ingestion; (Iii) Cross-Platform Mobile Application Deployment: Proposed Change To Serve South Asian Farming Communities; (Iv) Multilingual: Addition Of More Languages To The Rag Corpus; And (V) Internet-Of-Things: The Integration Of Additional Real-Time Weather Capabilities In The System.

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