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Threshold-based Multi-Crop Recommendation: A Flexible Decision Layer for AI in Precision Agriculture

Ali Asghar Khavari[1], Shuchita Upadhyaya[2], Pradeep Mittal[3], Monika Poriye[4] and Sangeeta Soni[5]
[1-5]Department of Computer Science and Applications, Kurukshetra University, Kurukshetra, India
Email: dcsa2126ali@kuk.ac.in, supadhyaya, pkmittal, monikaporiye, sangeeta.dcsa}@kuk.ac.in

***Abstract*— The majority of machine learning-based crop recommendation systems are designed to output a single most suitable crop, often based on top-1 classification accuracy. However, in real-world agricultural scenarios, farmers benefit more from multiple viable crop options, especially in cases where agro-environmental conditions support multiple alternatives. This paper introduces a threshold-based decision layer built on top of supervised machine learning (ML) and deep learning (DL) models, designed to recommend multiple suitable crops based on confidence scores. By setting a threshold for prediction probability, the system extracts all crops that meet or exceed the defined suitability level, providing ranked outputs that improve flexibility, interpretability, and real-world usability. The proposed approach is evaluated using soil, weather, and Sentinel-2 satellite data specific to Kurukshetra, India. Experimental results demonstrate that the threshold-based method reduces the risk of misclassification and enhances the adaptability of the system across seasonal and spatial conditions. This contribution bridges the gap between intelligent prediction and actionable decision-making in precision agriculture.**

***Index Terms*— Crop Recommendation, Threshold-Based Decision, Machine Learning, Precision Agriculture, Multi-Crop Output, Confidence Scoring, Remote Sensing, Deep Learning.**

I. Introduction

Precision agriculture has emerged as a transformative approach to increasing crop productivity, improving resource efficiency, and enhancing decision-making accuracy through the integration of data-driven technologies. Among these, machine learning (ML) and deep learning (DL) techniques have gained prominence in crop recommendation systems by leveraging environmental features such as soil chemistry, climatic patterns, and remote sensing imagery. Recent studies [1], [2] demonstrate the use of supervised ML algorithms such as Random Forest, Support Vector Machines, and ensemble methods to predict the most suitable crop for a given region.

However, most existing systems rely on top-1 classification outputs, offering a single predicted crop label, which may not be suitable in dynamic agricultural environments [3]. While this approach may be effective in controlled settings, it lacks the flexibility needed in real-world scenarios where multiple crops may be equally viable depending on farmer goals, resource availability, and market access. Moreover, rigid top-1 outputs limit the decision-making autonomy of stakeholders and can result in suboptimal or rejected recommendations, particularly in marginal or uncertain conditions.

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To address this gap, this paper introduces a threshold-based crop recommendation layer that operates on top of trained ML and DL models. Instead of relying solely on the highest-scoring prediction, the proposed method extracts all crops whose prediction probabilities exceed a predefined threshold, thereby creating a ranked list of viable options. This post-processing strategy enhances transparency, usability, and trust in AI-driven recommendations.

The rest of the paper is organized as follows: Section 2 describes the methodology, including data sources, model training, and threshold logic. Section 3 presents experimental results, followed by section 4, discussion of real-world implications. Section 5 concludes the paper and outlines directions for future work.

II. METHODOLOGY

The proposed system is designed to provide region-specific, flexible crop recommendations by integrating multi-source environmental data and implementing a threshold-based post-classification decision logic. The overall methodology consists of three primary stages: (i) data preparation and model training, (ii) prediction with ML and DL models, and (iii) threshold-based multi-crop recommendation. A high-level overview is illustrated in Figure 1.

A. Data Sources and Feature Preparation

To train the crop suitability models, three types of environmental data were collected for the Kurukshetra region:

- Soil data: N, P, K levels and pH values, with mean values adapted from region-specific published studies to simulate real-world conditions in data-scarce areas [4].
- Weather data: Daily records of temperature, rainfall and humidity were collected via public APIs and aggregated into seasonal and annual summaries.
- Satellite data: Sentinel-2 imagery was processed using Google Earth Engine to extract vegetation and water indices including NDVI, EVI, NDWI, LSWI, and SAVI [5]. Monthly and seasonal composites were generated to match weather and crop cycles.

These features were merged and aligned using Pandas in Python, forming a unified dataset ready for model training.

TABLE I. SUMMARIZES THE SELECTED FEATURES, THEIR UNITS AND THEIR RESPECTIVE DATA SOURCES

Feature Type	Feature Name(s)	Unit	Source
Soil	Nitrogen (N), Phosphorus (P), Potassium (K), pH	kg/ha, pH scale	Regional Soil Report (2024)
Weather	Temperature, Rainfall, Humidity	°C, mm, %	Public Weather API
Satellite	NDVI, EVI, NDWI, LSWI, SAVI (Monthly/Seasonal)	Index (0–1)	Sentinel-2 (via GEE)
Temporal	Month, Season, Year	Categorical	Derived

B. Model Training and Prediction

The unified dataset was used to train both ML and DL models.

- ML Models: Random Forest (RF), XGBoost, and Decision Tree classifiers were trained on soil, weather, and temporal features. Confidence scores over crop classes were obtained using softmax-like probability outputs (predict_proba), enabling multi-crop evaluation.
- DL Models: Two hybrid models — a Convolutional Neural Network combined with Long Short-Term Memory (CNN+LSTM), and a Convolutional Neural Network combined with Artificial Neural Network (CNN+ANN) — were trained on the full feature set, including satellite-derived indices (NDVI, EVI, NDWI, LSWI, SAVI), following recent advancements in agricultural DL. [6].

All models were trained using 80% of the dataset, with 20% reserved for testing. Model hyperparameters were optimized using AutoML techniques (Optuna framework) to enhance generalization performance. The final softmax probability outputs were used to extract confidence scores across all crop classes for threshold-based multi-crop recommendation.

C. Threshold-Based Crop Recommendation Logic

The key innovation in this study lies in the threshold-based post-processing layer. Instead of relying solely on top-1 predictions, the system filters and ranks crops based on whether their predicted probability exceeds a threshold τ, a strategy effectively utilized in ensemble machine ML-based recommendation systems for crop selection [3].

Where:

- C: represents the set of possible crop classes,

- P (c | x): denotes the model's predicted confidence score for crop c given features x and
- τ: is the predefined probability threshold (default = 0.60)

The crop recommendation set is formally defined as the following Equation (1):

$$Recommended\ Crops = \{c \in C \ | P\ (c \mid x) \geq \tau\} \tag{1}$$

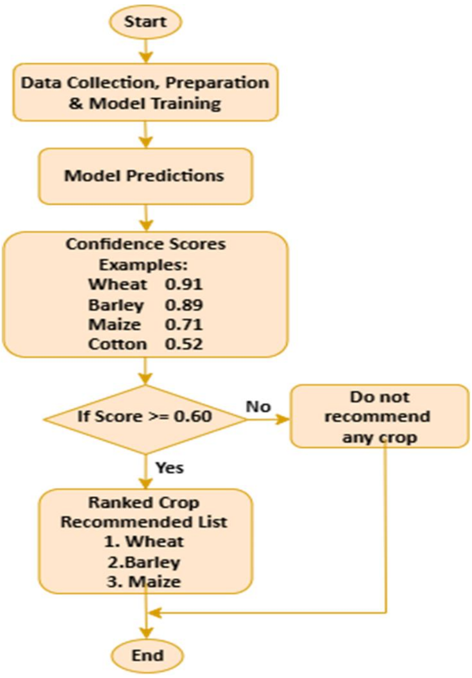

Figure 1. Flowchart of Threshold-Based Multi-Crop Recommendation System

D. Implementation and Tools

The entire system was implemented using the following tools and frameworks:

- Preprocessing and Model Training: Python programming language with Pandas, Scikit-learn, and TensorFlow libraries.
- AutoML Framework: Optuna, used for hyperparameter optimization of ML and DL models [7].
- Thresholding Logic: Implemented as a standalone Python module integrated into the prediction pipeline.
- Visualization Tools: Matplotlib and Seaborn were used for generating feature importance plots, model performance graphs, and confidence distribution analyses.

III. Experiments and Results

To evaluate the performance and real-world applicability of the proposed threshold-based crop recommendation system, a series of experiments were conducted using soil, weather, and satellite data from the Kurukshetra, India. The experiments focus on assessing (i) the accuracy of the ML and DL models, (ii) the effectiveness of the threshold logic in generating ranked multi-crop outputs, and (iii) the interpretability and flexibility of recommendations for practical use.

A. Experimental Setup

The following configuration was used for experimentation:

- Training/Test Split: The dataset was divided into 80% for training and 20% for testing.
- Models Evaluated:
  - ML Models: Random Forest (RF), XGBoost (XGB), Decision Tree (DT).
  - DL Models: CNN combined with LSTM (CNN+LSTM), CNN combined with ANN (CNN+ANN).
- Evaluation Metrics: Accuracy, Precision, Recall, and F1-Score were employed to assess model performance.
- Threshold Value (τ): Set to 0.60 based on empirical tuning experiments.

Hyperparameter optimization for all models was performed using the Optuna framework. Model predictions were generated in the form of softmax probability distributions across all crop classes.

B. Sample Prediction Output

Below is a sample output from the trained DL model (CNN+LSTM) for a test instance from the Kurukshetra region.

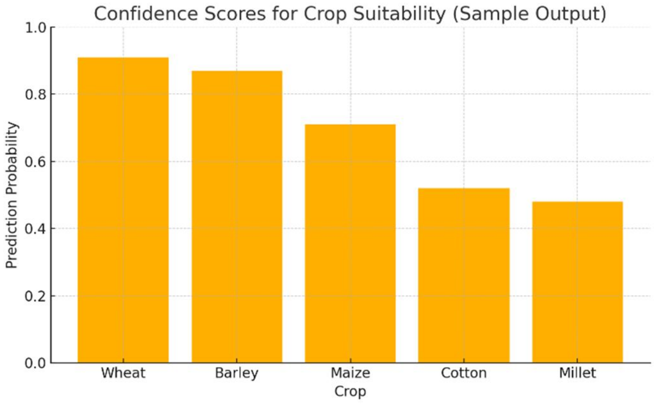

Figure 2. Confidence Scores for Crop Suitability (Sample Output) Only crops with prediction probability ≥ 0.60 are selected as recommended crops.

C. Effectiveness of Thresholding

The threshold-based filtering logic helped mitigate misclassification risks and enhanced the practical usability of the system. Key results include:

- Top-1 Accuracy (ML models): Random Forest (RF) – 91.3%, XGBoost (XGB) – 92.6%.
- Top-1 Accuracy (DL model): CNN+LSTM – 94.7%.
- Post-Threshold Multi-Crop F1-Score: Improved by approximately 4.2% compared to traditional top-1-only recommendation systems.

These findings confirm that the threshold-based method retains strong performance while significantly increasing flexibility and reliability in real-world decision-making.

D. Recommendation Diversity and Real-World Value

In real agricultural use cases, single-crop suggestions may not adequately account for resource constraints, market accessibility, and farmer preferences. The proposed system addresses these challenges by outputting a ranked list of viable crop options, thereby enabling decision-makers to:

- Select alternate crops when the top recommendation is infeasible;
- Evaluate potential differences in seasonal crop performance;
- Apply expert judgment based on multiple high-confidence recommendations.

IV. Discussion

The experimental results demonstrate that integrating threshold-based logic into crop recommendation systems significantly enhances their flexibility, interpretability, and practical utility in real-world agricultural settings. This section highlights the broader implications of the proposed system and evaluates its contribution from both technical and application perspectives.

A. Overcoming the Limitations of Top-1 Predictions

Traditional crop recommendation systems typically produce a single predicted output, which may be unsuitable in edge cases or ambiguous environments. This limitation has been previously observed in several agricultural ML studies that highlight poor user trust and rigid recommendations resulting from top-1-only systems [6]. In contrast, the proposed threshold-based approach:

- Prevents misclassification by eliminating low-confidence suggestions;
- Enables the inclusion of multiple viable crops in the recommendation output;
- Allows users to compare options and apply domain expertise in the final decision-making process.

This paradigm shift transforms the system from a static predictor into a dynamic decision-support tool capable of adapting to diverse field conditions.

B. Enhancing Decision-Making for End Users

The multi-crop output enables farmers, agronomists, and policymakers to:

- Evaluate alternative crops based on risk, cost, and market factors;
- Reduce over-reliance on black-box AI predictions;
- Increase trust and adoption of AI-driven tools through greater output transparency and explainability.

This flexibility is especially valuable in smallholder and resource-limited farming systems, where adaptability is critical for resilience and sustainability. Several studies have shown that trust, transparency, and explainability are essential for the adoption of AI tools in agriculture, particularly among smallholder farmers [8].

C. Scientific and Systemic Impact

From a system design perspective, the proposed model offers several advantages:

- It preserves model performance while incorporating an additional rule-based thresholding layer;
- It provides a scalable architecture that can be extended to other regions, crops, or environmental domains;
- It aligns with human-in-the-loop AI principles, bridging intelligent predictions with actionable decision-making in agriculture.

Furthermore, the modular architecture supports future system upgrades, including:

- Integration with mobile advisory platforms;
- Region-specific calibration of threshold values;
- Visual dashboards for confidence-based crop evaluation.

D. Limitations and Future Opportunities

While the system shows strong potential, several limitations remain:

The threshold value ($\tau = 0.60$) was empirically chosen and may require dynamic tuning based on regional, seasonal, or climatic variations;

The model relies on historical environmental data and assumes relatively stable trends, which may not always hold true under changing climate conditions;

Deeper interpretability tools such as SHAP values could be incorporated to provide more granular transparency regarding model decisions.

In future work, the system will be generalized to multi-region datasets, a real-time advisory interface will be deployed, and adaptive thresholding techniques based on uncertainty estimation will be explored.

V. CONCLUSIONS

This paper introduced a threshold-based multi-crop recommendation system tailored for precision agriculture applications. Unlike traditional top-1 classification models, the proposed approach generates flexible, ranked crop suggestions based on model confidence scores, thereby aligning better with real-world farming needs. The system integrates multi-source environmental data — including soil properties, weather records, and satellite-derived vegetation indices — and utilizes both ML and DL models to deliver robust and context-aware predictions.

By applying a threshold-based decision layer, the system enables farmers and agricultural advisors to select from multiple scientifically viable crops, enhancing the adaptability and trustworthiness of AI-powered agricultural tools. Experimental results demonstrate that the proposed method not only maintains high predictive performance but also improves practical usability by reducing the risk of misclassification and supporting decision-making under uncertainty.

Several future directions can further strengthen this research:

- Adaptive Thresholding: Developing dynamic threshold mechanisms based on seasonal variability, model uncertainty, and region-specific factors;
- Explainability Enhancements: Incorporating interpretability techniques such as SHAP and LIME to demystify model predictions for end-users;
- Mobile Advisory Integration: Deploying the system on mobile platforms to deliver real-time recommendations directly to farmers;
- Scalability Testing: Extending the approach to diverse geographic regions and a wider variety of crops to validate its robustness and generalizability at scale.

By combining threshold-based intelligence with comprehensive environmental modeling, this work offers a practical and innovative step forward in AI-assisted agriculture, paving the way for more inclusive, transparent, and regionally customized crop advisory systems that can benefit a wide range of stakeholders.

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