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Climate-Aware Crop Prediction System Using Multi-Parameter Machine Learning Models

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Abstract –
Climate change significantly influences agricultural productivity, and this is evident in regions such as Karnataka, where shifts in temperature, humidity, and rainfall patterns directly affect crop yields. This paper proposes a climate responsive crop recommendation system that predicts the most suitable crops for a given climatic condition with just three key environmental variables: temperature, humidity, and rainfall. A machine learning model, XGBoost, is used to classify and rank the best crops suitable for current and future climate conditions using a Kaggle-prepared crop recommendation dataset. The proposed method offers prioritized recommendations for various crops suitable for the Karnataka region to farmers and other stakeholders, while also illustrating each crop's development stages from sowing through to full maturity. Experimental results show the efficiency of an XGBoost model in capturing climate-to crop relationships even when restricted to a small set of climatic features to provide reliable recommendations. The proposed approach is an extension to climate-resilient agriculture, where informed decisions about crop planning can be made in response to climatic variability.
Index Terms: *Crop Recommendation, Climate Change, XG Boost, Agriculture, Karnataka, Temperature, Humidity, Rainfall.*

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I. Introduction

A. Background and Problem Motivation - This review provides valuable insights into the increasing impact of climate variability, erratic rainfall, and temperature rise on agricultural productivity. Conventional approaches to crop selection are done intuitively by farmers and are becom ing insufficient to cope with rapid climatic changes. Several machine learning-based crop recommendation systems have appeared, but most provide only static or short-term forecasts and do not consider the performance of crops during the complete growth cycle. Such shortcomings impede farmers from being able to predict periods of stress, plan appropriate interventions, or estimate yield reliability. The current study introduces a Lifecycle Impact Assessment and Lifecycle Recommendation System that seamlessly integrates real-time weather forecasting with machine learning. Using a 14-day weather forecast in combination with an XGBoost-based model, the system recommends the most suitable crop for any specified location. It also projects climatic conditions across the entire growing season for each crop type and evaluates, on a day-by-day basis, how suitable these conditions are with respect to optimal temperature, humidity, and rainfall ranges. The proposed framework enables stage specific impact assessment, stress detection, and prediction of harvesting conditions, thereby supporting improved decision making and strengthening climate resilience in agriculture.

B. Problem Statement - The project aims to devise a data-driven system that can predict crop yield under a changing climate by applying statistical analyses and machine learning models. By analysing the key climatic variables of temperature, precipitation, and humidity in concert with historical crop-yield records, the system seeks to identify influential factors and produce accurate yield estimates. Moreover, it calculates the growth-stage progression from sowing to harvest, gives an impact analysis score and a stress score toward assessing the impact of climate on crop development, and returns the most suitable crops for a given region according to prevailing climatic conditions.

C. Proposed Solution - To address these limitations, this paper proposes a smart crop recommendation and lifecycle impact assessment system. The system combines a pre-trained XGBoost model with fourteen-day real-time weather forecasts from the Visual Crossing API. The proposed system predicts the most highly recommended crops for a given location and extends the forecast across the full crop duration using stage-wise growth profiles. A daily impact score (0–100) is calculated based on the deviations from ideal climatic ranges for a particular crop.

D. Objectives - The primary objectives of the study are as follows: To predict the crop yield using statistical analysis along with machine learning models based on climatic variable features like temperature, rainfall, and humidity. • To determine the major climatic factors prevailing in the area and that considerably affect crop production. • Estimate stages of growth of crops from sowing up to harvest, considering model-driven analytics. • Develop climate impact and stress scores to assess the impact of environmental conditions on crop development. • To recommend the best crop for a given region using prevailing climatic conditions and historical data patterns. • Visualization of climate trends, yield variability, and model output to improve understanding and decision making.

E. Scope - The scope of this project is defined as follows: • The system focuses on climate-based crop yield predic tion using historical climate and crop yield datasets. • The analysis includes key environmental parameters such as temperature, rainfall, and humidity. • The project includes the visualization of climate–yield relationships, factor importance, and trend analysis. • The system provides model-generated outputs such as crop growth stage estimation, climate impact scores, and stress scores. • The project recommends top suitable crops for specific regions based on climatic conditions and model insights. • The scope is limited to climate-based prediction and does not include soil, fertilizer, pest, or irrigation-related factors. • The implementation includes machine learning models, evaluation metrics, and a user interface for displaying predictions and insights.

F. Overview of Methods - This project applies a data-driven approach, using an XG Boost machine learning model to predict yield forecasts and analyse climatic impacts. Gathered climate variables include temperature, precipitation, and relative humidity, all cleaned and pre-processed to match existing yield historical records. Exploratory data analysis is performed on climate trends, their intercorrelations, and their consequences on crop productivity. This pre-processed dataset trains the XGBoost model, which generates highly accurate yield predictions and determines the climatic factor influences that drive yield variation. Model derived insights estimate the stages of crop growth from sowing to harvest, calculating impact analyses and stress scores showing how environmental fluctuations affect the development of crops. It measures regional climate conditions and suggests the best crops for a given area based on historical climate-crop performance patterns. Data visualizations are created that outline the trends, factor importance, and model output for better interpretation, enhancing decision-making for agricultural planning.

G. Paper Organization - The rest of the manuscript is structured as follows. Section II covers the related literature with respect to climate-driven crop prediction and machine learning applications in agriculture. Section III delineates the methodology, which includes data processing, exploratory analysis, the XGBoost model, growth stage estimation, and scoring mechanisms. Section IV de scribes the system architecture along with the implementation details. Section V presents the results, supporting visualizations, and discussion. Section VI concludes the manuscript by summarizing the key findings and discussing future research directions.

II. Related Work

A. Literature Survey - With the increased attention given to maintaining good health, people are more sensitive to the influence of advertisements. The current state of research on climate change and agriculture focuses on the increasing reliance on satellite observations, climate indices, and machine learning methodologies to explain environmental trends and their implications on crop productivity. Various variables, including rising temperatures and rainfall variability, vegetation health, soil moisture, and the concentration of greenhouse gases, emerge as major de terminates of agricultural performance in comparative studies across Africa, Eurasia, and Central Asia. Modelling approaches based on CNN, LSTM, Random Forest, XGBoost, and remote sensing indicators, such as EVI, VHI, SPI, among others, have been widely used to model climate patterns, detect drought, assess suitability of land for crops, and forecast vegetation stress. Predictions from these investigations have shown strong predictability, but equally common challenges are noisy satellite data, models suitable for particular regions, limited spatial resolution, and restricted generalization for a wide variety of agricultural settings. Contemporary work, beyond crop yield prediction, emphasizes decision-support systems, Internet of Things-based monitoring, and integrated climate-agriculture platforms to support farmers in adapting to climate variability. Studies that integrate real-field data, simulation models, and multi-source climate datasets present model improvements; large-scale analyses uncover global CO2 trends and long-term risks to cereal production. Although significant progress has been made, the literature shows a lack of unified systems addressing yield prediction, climate impact assessment, crop growth monitoring, and regional crop recommendation simultaneously. These gaps ensure that comprehensive, data-driven frameworks-such as the proposed system-are developed to provide consensus through multiple climate indicators for more accurate and actionable agriculture decision-making.

B. Identified Research Gap - Despite the large volume of research on climate variability, crop prediction, and environmental change, there is a deep chasm between research prototypes and field-level applicability of a single, interpretable, multi-factor climate-impact prediction system that works for a variety of crops. The existing literature is typically limited to small datasets, focuses on a single crop or region, or relies on deep learning models that are complex, not interpretable, and not useful in practice. Furthermore, very few studies incorporate stage-specific crop conditions, such as seedling versus harvest phases, which are critical to understand differential climate impacts across growth stages. Finally, most state-of-the-art frameworks do not provide a lightweight and scalable solution for real-time agricultural decision support. High-accuracy and interpretable models remain clearly absent in rural or resource-constrained settings. This situation creates an imperative need for our system, using XGBoost for reliable and stage-aware predictions and bridging the gap between a research prototype and field level applicability.

III. Methodology And Proposed System

A. Description of Data Input and Preprocessing - The dataset used for this study is the Crop Recommendation Dataset, sourced from Kaggle. Even though the original corpus contains many agronomic parameters, this research focuses only on three climate-dependent features that significantly influence the growth of crops: temperature (°C), humidity (%), and rainfall (mm). It was imported using the pandas library and was first subjected to an exploratory assessment in terms of its dimensions, number of crop categories present, and if there were any missing values in it. No null entries were found, which meant no extra cleaning or imputation would be required on this dataset. The target variable related to crop type is categorically distributed. In order to prepare the target variable to be used by machine learning algorithms, the labels of crops were converted into numeric values by using Label Encoding. Following feature extraction, the data was split into training and test sets with an 80:20 ratio, respectively, using stratified sampling to maintain a consistent distribution of classes across splits. Thus, its preprocessing pipeline involved three major steps: i) the use of temperature, humidity, and rainfall as input features; ii) encoding of categorical labels of crops to numeric format; and iii) splitting the dataset as stratified train–test subsets. This limited preprocessing assured a quality and model-ready input to the XGBoost classifier that will be used at later stages.

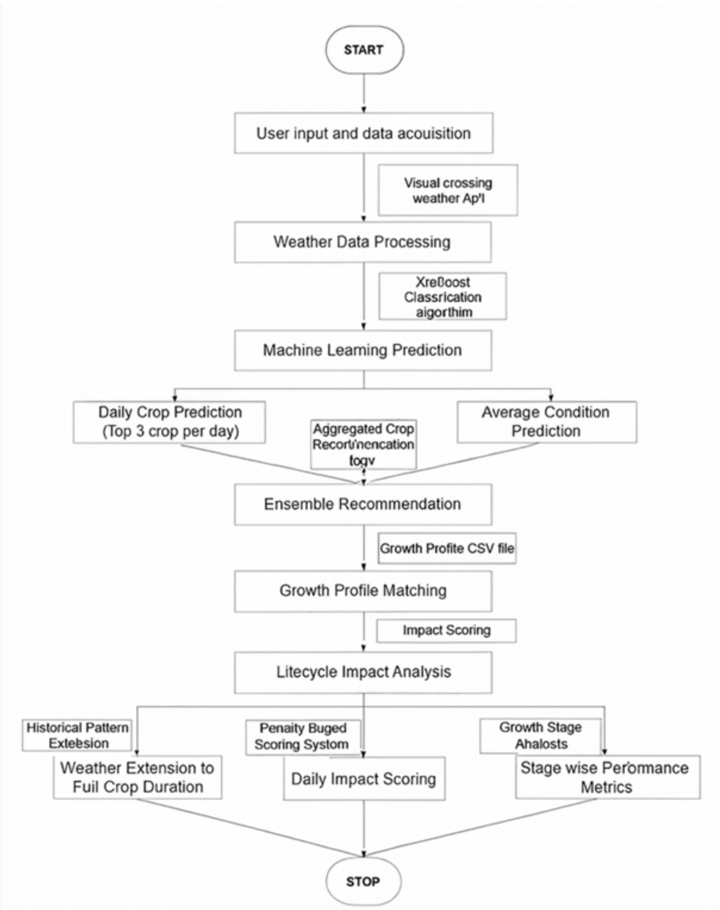

Fig. 1. Multi-Stage Processing Pipeline for Weather-Informed Crop Recommendation

B. System Architecture and Digital Workflow – System Workflow: The proposed crop recommendation system employs a modular, data-driven architecture that integrates real-time weather analytics with machine learning-based prediction. This design enhances adaptability, accuracy, and maintainability throughout the crop evaluation pipeline. The workflow is illustrated in Fig. 1 and proceeds as follows: 1) Data Acquisition and Weather Processing: User provided location details trigger automated retrieval of climatic parameters through the Visual Crossing Weather API. The acquired data is preprocessed through normalization, feature extraction, and temporal alignment prior to model inference. 2) ML-Based Crop Prediction: An XGBoost classification model generates two parallel outputs: • daily crop suitability scores (top three crops per day), and • aggregated suitability based on long-term climatic trends. These outputs support subsequent ensemble-level decision-making. 3) Ensemble Recommendation: Daily and aggregated pre dictions are combined to generate a refined shortlist of suitable crops. This ensures that both short-term climatic variations and broader weather trends are incorporated into the recommendation. 4) Growth Profile Matching: Each shortlisted crop is mapped to its growth requirements using a structured Growth Profile CSV file. Alignment between crop growth stages and predicted weather conditions is evaluated to remove incompatible options. 5) Lifecycle Impact Analysis: Stage-wise performance metrics, weather deviation penalties, and extended climatic patterns derived from historical records are used to compute daily impact scores, determining the overall feasibility of each crop.

C. Algorithms, Models, and Techniques Used - The proposed system incorporates various machine learning techniques and methods of optimization to develop an accurate and Explainable Crop Recommendation Model. Major Com ponents are summarized below: • XGBoost Classifier: Used as the main model for multi class crop prediction. XGBoost creates boosted Decision trees to learn complex and nonlinear relation The rela tionship between temperature, humidity, and rainfall. • Hyperparameter Tuning- GridSearchCV: A systematic search over parameters such as learning rate, maximum depth, number of estimators, subsample ratio and column sampling rate to identify the optimal configuretion is necessary to attain better accuracy and generalization. • Label Encoding: Turns categorical names of crops into numerical labels appropriate for supervised classification. Train-Test Split with Stratification: The original dataset is are split into training and testing subsets, respectively, while maintaining the proportion of every category of crop for balanced test • Model Evaluation Techniques: The system employs ac curacy score, classification report (precision, recall, F1 score), and confusion matrix visualizations to assess Predictive performance. • Feature Importance Analysis: The inbuilt feature of XG Boost, Ture importance metrics can be used to quantify the contribution of each climate parameter to the model's decisions. • SHAP: SHapley Additive exPlanations SHAP provide global and local model interpretability. Summary plots, bar charts, and beeswarm plots highlight temperature, humidity and rainfall, which are agents in determining crop forecasting. • Model Exporting (Joblib): The final, trained XGBoost model and label encoder are saved to deploy seamlessly investment in the crop recommendation system.

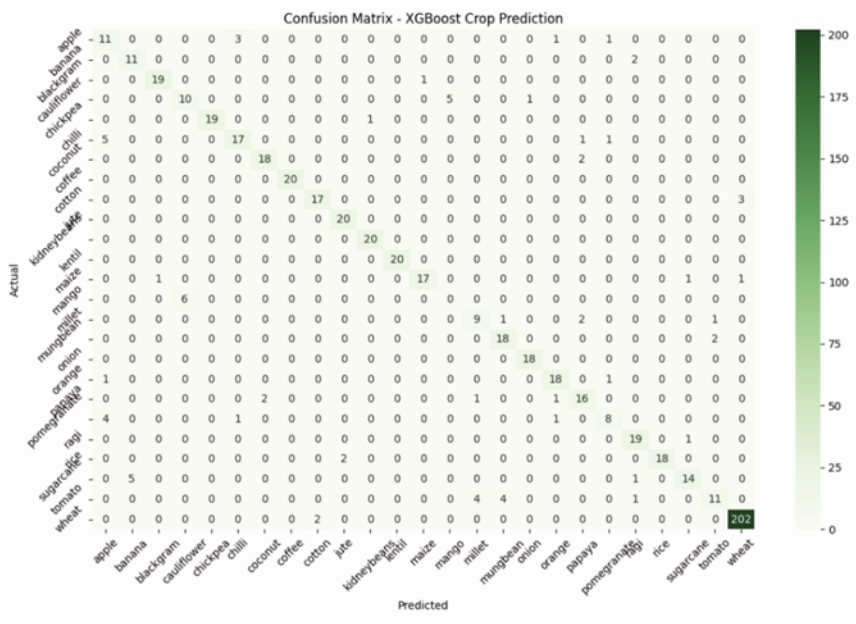

Fig. 2. Confusion Matrix of XGBoost Crop Prediction Model.

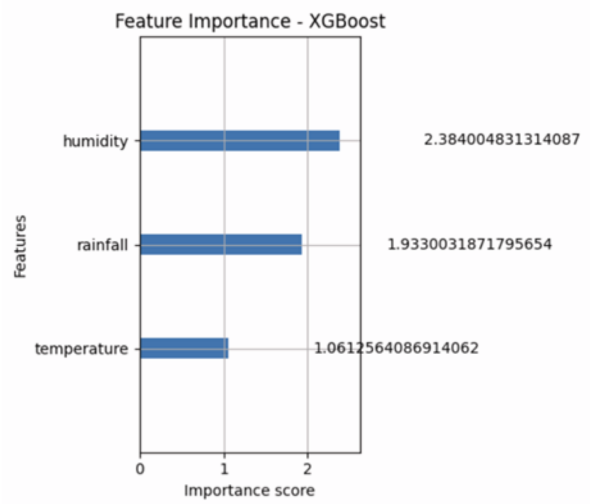

Fig. 3. Feature Importance Plot Showing Contribution of Temperature, Humidity, and Rainfall in the XGBoost Model

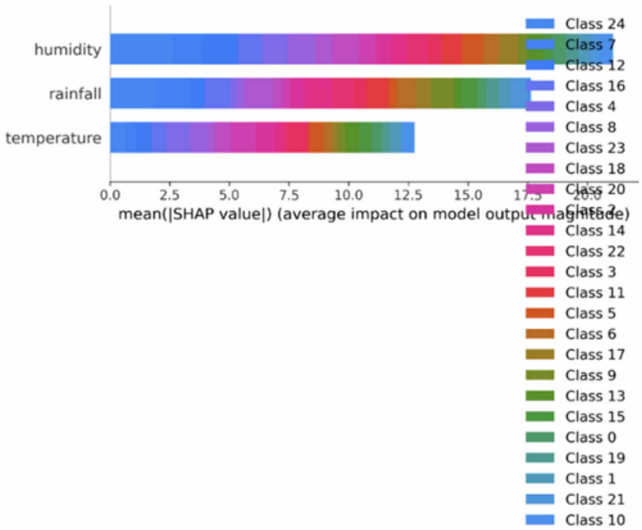

Fig. 4. SHAP Summary Plot Showing Feature Contributions to XGBoost Crop Recommendation Model

D. Mathematical Models and Methodology - This subsection presents the mathematical foundations of the proposed Smart Crop Recommender and Lifecycle Impact Prediction System. The methodology integrates weather smoothing, machine learning-based crop prediction, lifecycle weather extension, stress scoring, and growth stage modelling.

1) Crop Suitability Prediction using XGBoost : Each day's weather is represented as a feature vector:
$X = [T, H, R]$
where
T = Temperature,
H = Humidity,
R = Rainfall.
The XGBoost model prediction is given by:
$\hat{y}(X) = \sum$ (from m = 1 to M) $f(X)$, $f \in F = \{ f(x) = wq(x) \}$
The probability of choosing crop *c* is computed using the softmax function:
$P(c \mid X) = \exp(\hat{y}c) / \sum$ (from j = 1 to K) $\exp(\hat{y}j)$

2) Aggregated Crop Recommendation Logic: Daily top predicted crops are selected as:
$C_a = \{ c \quad d1 \quad , c \quad d2 \quad , c \quad d3 \quad \}$
Daily voting count for each crop:
$V(c) = \sum$ (from d = 1 to 14) $(c \in C_a)$

Overall top crop from voting:
TopOverall = arg max V(c)
Average climatic conditions over 14 days:
$\bar{T} = (1 / 14) \sum$ (from d = 1 to 14) T_d
$\bar{H} = (1 / 14) \sum$ (from d = 1 to 14) H_d
$\bar{R} = (1 / 14) \sum$ (from d = 1 to 14) R_d
Final recommended set:
C_final = unique(TopOverall $\cup$ C_a)

3) Lifecycle Weather Extension Model: To maintain column width, the piecewise definitions are presented compactly.
Temperature:
T_d = {
T_obs^d, d ≤ 14
$\bar{T}$, d > 14
}
Humidity:
H_d = {
H_obs^d, d ≤ 14
$\bar{H}$, d > 14
}
Rainfall:
R_d = {
R_obs^d, d ≤ 14
$\bar{R}$, d > 14
}

4) Climate Stress Impact Score Model: Ideal climatic ranges:
[T_min, T_max], [H_min, H_max], [R_min, R_max]
Base score:
S = 100
a) Temperature penalty:
P_T = {
2(T_min − T), T < T_min
2(T − T_max), T > T_max
0, otherwise
}
b) Humidity penalty:
P_H = {
1.5(H_min − H), H < H_min
1.5(H − H_max), H > H_max
0, otherwise
}
c) Rainfall penalty:
P_R = {
0.05(R_min − R), R < R_min
0.05(R − R_max), R > R_max
, otherwise
}
d) Final daily impact score:
S = max(0, min(100, S − (P_T + P_H + P_R)))

5) Growth Stage Modelling: Crop growth intervals:
S_k = [a_k, b_k], k = 1, … , N
Daily stage assignment:
Stage(d) = {
s_k, a_k ≤ d ≤ b_k
Unknown, otherwise
}

6) Overall Lifecycle Productivity Outlook
Average lifecycle score:
$S\_overall = (1 / D) \sum (\text{from } d = 1 \text{ to } D)\ S\_d$
Stage-wise score:
$S(s\_k) = (1 / (b\_k - a\_k + 1)) \sum (\text{from } d = a\_k \text{ to } b\_k)\ S\_d$
Final classification:
Status(S) = {
Excellent, $S \geq 80$
Moderate, $50 \leq S < 80$
Risky, $30 \leq S < 50$
Poor, $S < 30$
}

E. Implementation Details and Modular Design

The system follows a modular software architecture to ensure scalability and efficient processing. The primary components are described below: • Backend Processing: Implemented in Python using Flask for data preprocessing and XGBoost for multi-class classification. The inference module is optimized for lightweight and fast execution. • Weather Pipeline: Real-time weather data is retrieved through REST calls to the Visual Crossing API, cleaned, normalized, and structured before being passed to the prediction model. • Model Integration: Each day, the XGBoost model outputs aggregated suitability scores, which are then combined using ensemble logic for greater stability in prediction. • Growth Profiles: Crop-specific biological requirements are stored in CSV-based schemas. A growth-profile matching module aligns stage-wise ideal conditions with predicted environmental parameters. • Scoring Engine: A penalty-based deviation mechanism evaluates how far predicted conditions diverge from optimal crop requirements. Historical climatic patterns are incorporated to improve estimates when forecast data is incomplete. • System Coordination: Modules exchange data in standardized JSON and CSV formats, ensuring maintainability, modularity, and clear separation of responsibilities across system components.

IV. Results And Discussion

A. Experimental Setup and Metrics: The intelligence layer of the system was trained using the XGBoost model, with only three climatic variables: temperature, humidity, and rainfall. The dataset contains 644 instances for 24 crop classes. A standard 80–20 train-test split was used in this work. Model performance evaluation was done by using multi-class evaluation metrics such as Accuracy, Precision, Recall, and F1 Score to objectively evaluate the climate-crop suitability prediction.

B. Analysis of Prediction Metrics: The model achieved an overall accuracy of 88.50%, demonstrating climate-based classification capability. A macro F1-Score of 0.81 and a weighted F1-Score of 0.88 indicate balanced and reliable performance across all crop classes. Fig. 5 illustrates the comparison of Accuracy, Recall, F1-Score, and Precision.

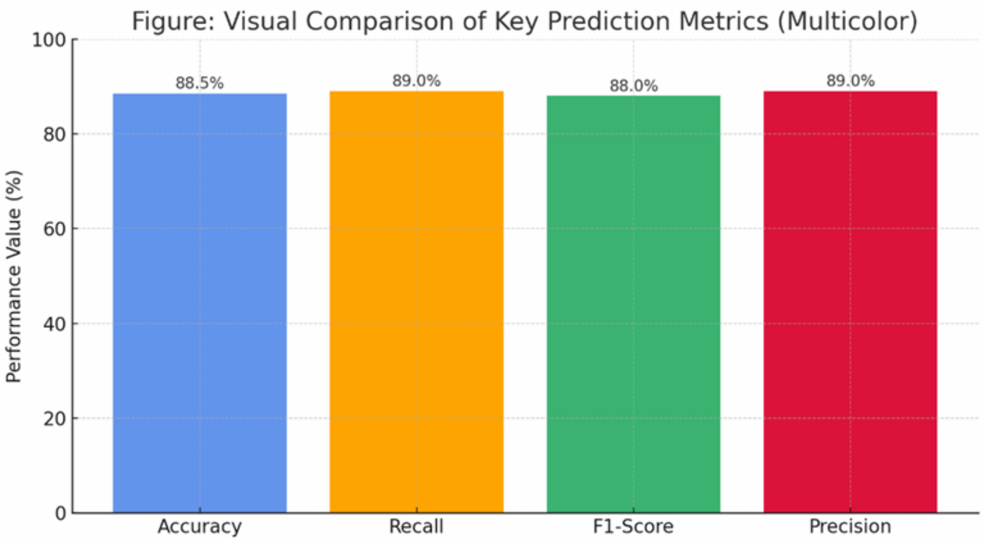

Fig. 5. Comparative Analysis

Given the climate-driven structure of the system, high Recall (macro-0.81) is critical to avoid missing suitable crops. High-performing crop classes-including blackgram, chickpea, coconut, coffee, kidney beans, lentil, onion, orange, rice, and wheat-achieved Recall and Precision values between 0.90–1.00, indicating clear climatic distinguishability. Moderate performance in apple, cauliflower, chilli, millet, papaya, pomegranate, and tomato reflects overlapping climatic requirements.

These results demonstrate that the model reliably identifies suitable crops even when trained on minimal climatic feature sets.

C. Discussion on Allocation and Efficiency

The strong accuracy achieved using only three features highlights the significance of basic climate parameters in determining crop suitability. The XGBoost model provided: • Fast inference, suitable for real-time agricultural applications. • High accuracy (88.50%) with minimal input variables. • Stable class-wise performance for crops with distinct climate profiles. • Low computational overhead compared to deep learning-based models.

These results confirm the model's suitability for operational agricultural platforms requiring rapid, climate-driven decision making.

V. Evaluation And Analysis

A. Operational Significance of Predictive Metrics: A high recall of about 90% ensures the system will identify most viable crops, hence minimizing the likelihood of having viable options overlooked by farmers. The marginally lower precision, at around 88–89%, is acceptable in this context, given that false positives are less harmful than false negatives in crop-planning scenarios. These relatively balanced F1-score, around 89–90%, further justifies the overall strong reliability of the model and underscores practical and data-driven agricultural decision-making.

B. Robustness and Error Analysis: The system's performance is influenced by its dependency on external weather APIs, where forecast inaccuracies particularly in rainfall and humidity may affect the stability of crop recommendation. Furthermore, generalization across bioclimatic zones may suffer due to regional variations in cultivars, soil water-level differences, leading to reduced precision in real-world deployments. The absence of ground-truth yield validation also limits the ability to assess long-term predictive accuracy. These constraints emphasize the need for localized calibration and the integration of richer agronomic inputs in future system enhancements.

C. Addressing Limitations and External Constraints: The system is constrained by its reliance on external weather APIs, where inaccuracies particularly in rainfall and humidity forecasts can impact prediction stability. Additionally, the use of generalized crop thresholds does not consider local soil conditions or cultivation variations, thereby reducing real-world prediction accuracy. The absence of ground-truth yield data for validation further limits the assessment of long-term predictive accuracy. These factors highlight the need for localized calibration and the incorporation of richer agronomic inputs in future system iterations.

VI. Conclusion And Future Work

A. Conclusion: The study presented here deals with a climate-driven crop recommendation system using an XGBoost model trained on temperature, humidity, and rainfall. After training, the model achieved an accuracy of 88.50%, with a macro F1-score of 0.81 and a weighted F1-score of 0.88, demonstrating that even limited climatic features can reliably classify suitable crops. The system also establishes a scalable foundation for integrating advanced modules such as climate-stress assessment and health-monitoring features to support more adaptive agricultural planning.

B. Future Work: Future enhancements will focus on strengthening the system through the following advancements: 1) Enhanced Environmental Inputs: Incorporating soil nutrient profiles, pH levels, and remote-sensing indices such as NDVI and LST to refine crop differentiation and reduce prediction ambiguity. 2) Image-Based Health and Stress Detection: Integrating a vision module capable of detecting early disease symptoms, moisture stress, and leaf-level anomalies to provide real-time crop health scoring. 3) Geospatial and Climate-Risk Modeling: Utilizing satellite imagery and spatial weather patterns to generate region-specific climate-vulnerability maps and deliver more location-aware recommendations. 4) Adaptive Learning from Field Feedback: Enabling the model to retrain periodically using farmer feedback, seasonal outcomes, and evolving climatic variations to ensure improved long-term accuracy.

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