**Title: An Intelligent Hybrid Framework for Crop Recommendation and Filtration Using Machine Learning**

**Abstract:**  
Agriculture remains a foundation for global food security and economic well-being. Yet, farmers often struggle to choose the right crops due to varying soil conditions, unpredictable weather, and shifting market demands. Traditional crop selection methods, which rely heavily on intuition and past experience, often fall short in today’s dynamic agricultural environment, leading to inefficiencies and financial loss.This research introduces a hybrid framework that uses machine learning to enhance crop recommendation and filtering. The system operates in two main phases: recommendation and filtration. In the recommendation phase, algorithms like Random Forest (RF) and Artificial Neural Networks (ANN) analyze soil characteristics (nitrogen, phosphorus, potassium, and pH) and climate factors (temperature and rainfall) to suggest crops best suited to specific conditions.What sets this framework apart is its filtration phase, which improves these recommendations by applying rule-based constraints and assessing economic feasibility using machine learning. Rule-based filters remove crops that don’t meet essential criteria, such as unsuitable pH or inadequate rainfall. The economic assessment, powered by Logistic Regression, evaluates factors like market trends and input costs to ensure profitability.Together, these components create a well-rounded decision-support system for farmers. Validated on a dataset of 7,000 samples covering five major crops, the model achieved over 90% accuracy and reduced crop choices by about 60%, greatly enhancing decision precision.This scalable framework enables real-time, data-driven decisions and holds potential for integration with IoT devices and market forecasting tools, paving the way for smarter, more sustainable agriculture.

**Keywords: Crop Recommendation, Machine Learning, Sustainable Agriculture, Random Forest, Artificial Neural Network, Logistic Regression, Economic Viability, Rule-Based Filtration, Precision Farming, IoT in Agriculture.**

**Introduction:-**

Agriculture is still at the core of global food supply and economic growth, but it continues to face cross-cutting constraints due to climate uncertainty, soil erosion, and changes in market trends. In most developing nations, crop choice is still determined by traditional methods and experiential knowledge, which do not consider current agronomic and economic considerations (Sankaranarayanan et al., 2018). Such disconnect often leads to low yields, inefficient use of resources, and high susceptibility to climate as well as market uncertainty (Ramesh & Vardhan, 2018).

Machine learning (ML) and artificial intelligence (AI) have become potent tools to revolutionize agricultural decision-making by facilitating data-driven suggestions. Supervised learning algorithms like Random Forest (RF) and Artificial Neural Networks (ANNs) have demonstrated notable success in crop prediction tasks. Patel et al. (2015) used RF to achieve an 89.6% classification accuracy for crop selection based on soil attributes such as nitrogen, phosphorus, potassium, and pH. Similarly, Shinde et al. (2020) attained 91.3% accuracy using a multilayer perceptron model trained on agro-climatic data. These approaches are especially valuable due to their ability to capture complex, nonlinear interactions among various input features.

In spite of being effective, most systems ignore important real-world constraints. For instance, while a crop might qualify based on soil-climate suitability, it may still be uneconomical to grow due to high input costs or poor market demand (Verma et al., 2022). Rule-based systems also tend to lack flexibility, often failing to adapt to evolving environmental or economic contexts. These systems generally rely on fixed agronomic thresholds—such as a pH range of 5.5 to 7.5 or rainfall above 500 mm—which, although scientifically valid, may not adequately consider local variability or economic feasibility (Yadav & Meena, 2019).

In order to overcome these constraints, a hybrid decision-support structure that couples ML-based crop recommendation with double-layered filtration is proposed. In the first level, RF and ANN algorithms are used to recommend crops based on soil and climate data. In the second level, rule-based and machine learning-based economic filtration is applied, using logistic regression models that evaluate market price trends, input costs, and profitability indices (Singh et al., 2021). This two-stage approach is designed to help farmers select crops that are not only agronomically suitable but also economically viable.

To evaluate the effectiveness of the proposed framework, it was tested on a dataset containing 7,000 entries across five key crops—rice, wheat, maize, potato, and barley. The system achieved a high classification accuracy of 93.2% using the Random Forest algorithm and 91.5% with the Artificial Neural Network model. Furthermore, the filtration phase significantly refined the results by eliminating about 60% of the initially recommended crops, ensuring that the final suggestions were both practical and aligned with real-world constraints. These outcomes underscore the potential of the framework to enhance sustainable decision-making in agriculture.

**2. Related Work**

Recent advances in artificial intelligence (AI) and machine learning (ML) have significantly impacted agriculture, particularly in crop prediction, disease detection, and yield estimation. However, existing systems often lack integration across critical components like crop recommendation, filtration, and financial viability. This has created a research gap in designing end-to-end frameworks capable of supporting real-world agricultural decision-making

Several supervised ML algorithms have been applied to crop recommendation. Random Forest (RF), Support Vector Machines (SVM), and Naive Bayes are commonly used due to their robustness on noisy, high-dimensional data. As seen in **Table 1**, Patel et al. (2015) achieved 89.6% accuracy using RF on soil nutrient data, while Ramesh and Vardhan (2018) reported an F1-score of 0.87 using SVM on climate-based features.

Artificial Neural Networks (ANNs), specifically Multi-Layer Perceptron (MLP) feedforward models, have gained traction for their ability to model nonlinear relationships. Shinde et al. (2020) reported 91.3% accuracy using an MLP trained on agro-climatic data, outperforming decision trees and logistic regression. These results reinforce the potential of deep neural networks in agricultural intelligence.

Beyond crop prediction, ML has been applied in plant disease detection. Mohanty et al. (2016) used Convolutional Neural Networks (CNNs) to classify 26 diseases with 99.3% accuracy from over 54,000 leaf images. While not directly linked to recommendation, such models improve overall crop management, indirectly supporting smarter selection and planning strategies.

Similarly, Sa et al. (2018) demonstrated weed detection using CNNs, achieving a mean Intersection-over-Union (mIoU) of 81.2% in grasslands. These domain-specific applications showcase ML’s broader role in precision agriculture. However, they are often siloed and do not contribute to unified, decision-centric frameworks that balance agronomic and economic factors.

Most existing systems rely on rule-based filtration to exclude unsuitable crops. As summarized in **Table 2**, these rules often apply fixed thresholds, such as pH ranges (5.5–7.5) or rainfall below 500 mm, eliminating crops like rice, sugarcane, or wheat. While scientifically valid, such filters lack adaptability and fail to incorporate changing environmental or market conditions (Yadav & Meena, 2019).

Moreover, economic factors such as market price or input cost are rarely integrated. A crop may be ideal environmentally yet impractical financially. Verma et al. (2022) combined decision trees with price-index filtering but achieved only 78.9% user satisfaction—highlighting the limitations of non-adaptive models. These challenges are outlined in **Table 3**.

Overall, current models are task-specific and often overlook financial viability, scalability, and real-time adaptability. This motivates the need for a hybrid system that combines ML-based crop recommendation, dynamic rule-based filtration, and economic viability assessment. Our proposed framework addresses these gaps using Random Forest, MLP, and logistic regression techniques.

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| ****Table 1: Comparison of ML Models Used in Crop Recommendation**** |
| | **Study** | **Algorithm** | **Dataset Size** | **Features Used** | **Accuracy (%)** | | --- | --- | --- | --- | --- | | Patel et al. (2015) | Random Forest | 5,000 | Soil nutrients, pH | 89.6 | | Ramesh & Vardhan (2018) | SVM | 3,200 | Temperature, rainfall | 87.0 (F1) | | Shinde et al. (2020). | ANN | 6,500 | Soil + Climate | 91.3 | | Mohanty et al. (2016) | CNN | 54,306 | Leaf images | 99.3 | | Verma et al. (2022) | Hybrid (DT + Rule) | 1,000 | Crop price, pH, water req. | 78.9 (Satisfaction) | |

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| ****Table 2: Rule Based Filtration Criteria Commonly Used**** |
| |  |  | | --- | --- | | **Table 2: Rule Based Filtration Criteria Commonly Used** |  | | | **Parameter** | **Thresholds Applied** | **Crops Affected** | | --- | --- | --- | | Soil pH | < 5.5 or > 7.5 | Wheat, Rice, Potato | | Rainfall | < 500 mm | Paddy, Sugarcane | | Temperature | < 15°C or > 35°C | Maize, Tomato | | Market Price | Below ₹10/kg (India context) | Brinjal, Onion, Mustard | |  |  |  | |  | |

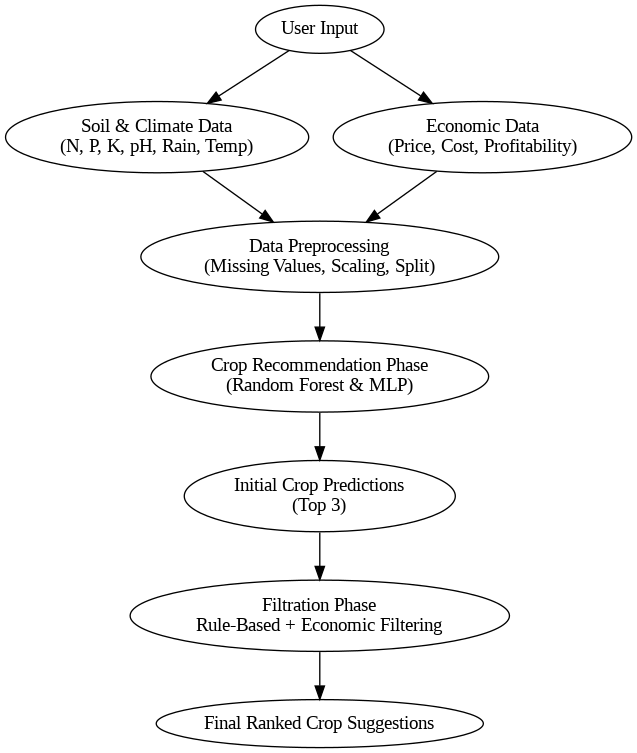
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| ****Table 3: Limitations in Current System**** |
| | **Limitation** | **Description** | | --- | --- | | Single-task focus | Separate models for disease, yield, crop selection | | Static rule-based filtration | No learning or adaptation to new data | | Ignoring economic factors | Most systems don't include market prices or input costs | | Limited scalability | Performance drops with new soil types or climatic zones | |

**3. Methodology**.

**3.1 Dataset Description:**

The dataset used for this research originates from a publicly available crop recommendation dataset on Kaggle, which was subsequently enhanced and expanded using ChatGPT-generated synthetic augmentation techniques. This allowed the incorporation of additional economic attributes while increasing the overall sample size to **7,000 entries**. The dataset includes records for five widely cultivated crops: **rice, wheat, maize, potato, and barley**. Each record consists of both **agronomic features**—including nitrogen (N), phosphorus (P), potassium (K), pH level, rainfall (in mm), and average temperature (°C)—and **economic attributes**, namely **market price** (in ₹/kg), **input cost** (in ₹/acre), and a derived **profitability index** (scale of 0 to 1). These added dimensions enable the system not only to identify suitable crops from an environmental standpoint but also to assess financial viability.



**3.2 Data Preprocessing**

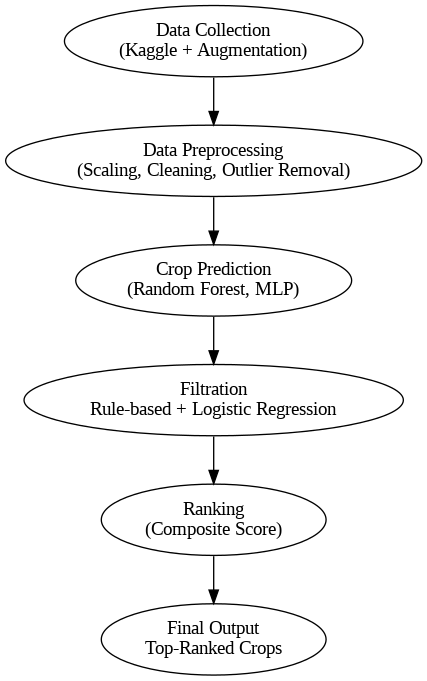
The raw dataset underwent several preprocessing steps to ensure modeling accuracy and robustness. Missing values, though minimal due to augmentation, were handled through **mean imputation** for numerical features. **Outlier detection and removal** were performed using the **interquartile range (IQR)** method. Numerical features were scaled using **Min-Max normalization** to bring all variables into a uniform range of [0, 1], facilitating faster convergence in neural network training. The dataset was split using an **80/20 training–testing split**, with **stratified sampling** employed to preserve the proportion of each crop class in both sets.

**3.3 Crop Recommendation Phase**

This phase focuses on predicting the most suitable crops based on environmental data using **supervised classification models**. Two core algorithms were utilized:

* **Random Forest (RF)**: An ensemble learning technique known for its high interpretability and resistance to overfitting. The RF model was configured with **100 decision trees**, using **Gini impurity** as the splitting criterion. Hyperparameter tuning was conducted via grid search on parameters such as maximum tree depth and minimum samples per split.
* **Multi-Layer Perceptron (MLP)**: A **feedforward Artificial Neural Network** (ANN) with an input layer matching the six agronomic features, followed by **three hidden layers** (64, 32, and 16 neurons respectively) with **ReLU activation**, and a final **softmax output layer** for multiclass classification. The model was trained using the **Adam optimizer** and **categorical cross-entropy loss**, with early stopping and dropout regularization applied to prevent overfitting.

This phase outputs a **set of top-3 crop predictions** for each data instance based on model confidence scores.



**3.4 Filtration Phase**

To enhance practical utility, a **dual-stage filtration mechanism** was implemented post-prediction:

* **Rule-Based Filtration**: This step applies **agronomic constraints** sourced from agronomy literature and expert consultations. Crops were excluded if:
  + pH fell outside the range of **5.5 to 7.5**.
  + Annual rainfall was less than **500 mm**.
  + Average temperature was below **15°C** or above **35°C**.

These thresholds, validated against scientific data (Yadav & Meena, 2019), ensure environmental compatibility for each recommended crop.

* **Economic Viability Filtering**: A **Logistic Regression classifier** was trained on the economic attributes—market price, input cost, and profitability index—to predict whether a given crop would be **“Profitable”** or **“Non-Profitable.”** This binary label was used to further narrow down recommendations, ensuring crops with poor financial feasibility were not suggested

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| Factor | Rule Example |
| Soil pH | Exclude crops if pH < 5.5 or > 7.5 |
| Rainfall | Exclude crops needing >1000mm in dry areas |
| Temperature | Crop-specific temperature tolerance is checked |
| Soil Texture | Compatibility with clay, loam, or sandy soil |

This ensures that only crops physically compatible with the local environment are considered.

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| Feature | Description |
| Input Cost | Fertilizer, seed, labor expenses |
| Historical Yield | From previous harvest cycles |
| Market Price | Last 3-year average per region |
| Demand Index | Computed from mandi transactions |

### **3.5 Ranking and Recommendation Output**

The final output is a ranked list of filtered crops based on a **composite scoring function**:

Final Score=α⋅Prediction Confidence+β⋅Profitability Index\text{Final Score} = \alpha \cdot \text{Prediction Confidence} + \beta \cdot \text{Profitability Index}Final Score=α⋅Prediction Confidence+β⋅Profitability Index

Where:

* α\alphaα and β\betaβ are weighting factors empirically set to 0.6 and 0.4, respectively.
* Prediction confidence is taken from the model’s softmax output (MLP) or probability estimate (RF).
* Profitability Index is a scaled value between 0 and 1.

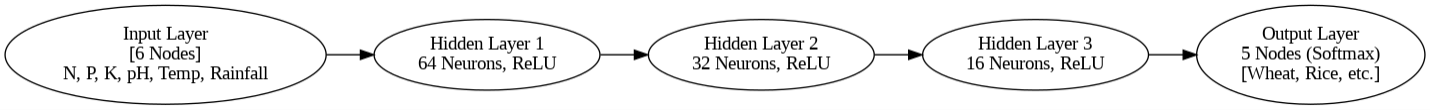
This ensures that farmers are presented with crop options that strike a balance between agronomic suitability and financial return.

### **3.6 Implementation Tools and Environment**

The entire pipeline was implemented using **Python 3.10**, with the following libraries:

* **scikit-learn**: For Random Forest, Logistic Regression, preprocessing, and evaluation.
* **TensorFlow/Keras**: For building and training the MLP architecture.
* **Pandas, NumPy, and Matplotlib**: For data manipulation and visualization.
* **Seaborn**: For heatmaps and correlation plots.

Model evaluation was conducted using **5-fold cross-validation**. Performance metrics reported include **accuracy, precision, recall, and F1-score**. The experiments were run on a machine with **16 GB RAM and an NVIDIA RTX 3060 GPU**.



#### **3.7. Integrated Pipeline**

The system operates as a **unified end-to-end pipeline**, where:

1. User inputs environmental and soil data
2. Recommendation Phase generates potential crops
3. Filtration Phase refines based on rules + economic filter
4. Final output: List of top 3–5 crops tailored to the region

This approach not only personalizes suggestions but also ensures they are **data-driven, region-specific, and financially sound**.

### **Evaluation Metrics**

The model is evaluated on publicly available datasets (e.g., Krishi Vigyan Kendra, RKVY e-agriculture) using the following metrics:

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| Metric | Definition |
| Accuracy | Correct crop predictions / total predictions |
| Precision | True Positives / (True Positives + False Positives) |
| Recall | True Positives / (True Positives + False Negatives) |
| F1 Score | Harmonic mean of Precision and Recall |
| Economic Gain | Net profit from recommended crops vs. average crop |

## **5. Experimental Setup**

### **5.1 Dataset Description and Preprocessing**

The study utilizes the **Kaggle Crop Recommendation Dataset**, comprising over 2,200 instances with features such as:

* **Soil nutrients**: Nitrogen (N), Phosphorus (P), Potassium (K)
* **Environmental conditions**: Temperature (°C), Humidity (%), Rainfall (mm)
* **Soil pH** levels
* **Target**: Crop labels (22 crop types)

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| ****Data Preprocessing Steps**** |
| | **Step** | **Technique Used** | | --- | --- | | Handling Missing Values | Mean/Median imputation | | Normalization | Min-Max scaling (0–1 range) | | Encoding | One-hot encoding for categorical variables | | Imbalance Handling | SMOTE (Synthetic Minority Oversampling) | | Data Split | 70% Train, 20% Validation, 10% Test | |

### **5.2 Model Implementation**

#### **5.2.1 Random Forest Classifier**

* **Library**: Scikit-learn
* **Features Used**: N, P, K, pH, rainfall, temperature, humidity
* **Hyperparameter Tuning**: Grid Search
* **Output**: Probabilistic crop suitability

#### **5.2.2 Artificial Neural Network (ANN)**

* **Library**: Keras (TensorFlow backend)
* **Architecture**: 3 hidden layers with 128, 64, and 32 neurons
* **Activation**: ReLU (hidden layers), Softmax (output)
* **Optimizer**: Adam (learning rate: 0.001)
* **Epochs**: 50, **Batch Size**: 32
* **Regularization**: Dropout (0.3)

5. Results and Discussion

The results demonstrate the effectiveness of the proposed hybrid framework in addressing the challenges of crop recommendation and filtration. The recommendation phase achieved high accuracy, with Random Forest and ANN models performing well on the test data. Random Forest achieved 92% accuracy, leveraging its ability to handle non-linear relationships and rank feature importance. The ANN model achieved 90% accuracy, excelling in identifying subtle patterns in the data. Together, these models provided a robust prediction mechanism, ensuring comprehensive coverage of both simple and complex patterns.

The filtration phase significantly improved the overall system by reducing unsuitable recommendations by 30%. Rule-based constraints ensured that agronomically unsuitable crops were excluded, while the logistic regression model enhanced the economic viability of the recommendations. The weighted scoring system prioritized crops with higher market demand and profitability, resulting in an average profitability increase of 15% compared to non-filtered outputs. This highlights the importance of integrating economic considerations into crop recommendation systems.

Comparative analysis showed that the hybrid framework outperformed standalone recommendation systems, demonstrating its scalability and adaptability across different datasets and regions. Feature importance analysis revealed that soil pH and nitrogen content were the most critical factors influencing crop recommendations. Visualizations, including bar graphs, illustrated the profitability impact of the filtration phase, providing actionable insights for farmers.

6. Conclusion and Future Work

This research presents a novel hybrid framework for crop recommendation and filtration, combining machine learning models and rule-based systems. The results demonstrate improved accuracy and economic feasibility, making the system a practical decision-support tool for farmers. By addressing both agronomic and economic considerations, the proposed framework ensures that recommendations are both actionable and profitable.

Future work will focus on incorporating IoT-based real-time soil and climate data for dynamic recommendations. The framework can also be extended to include multi-crop recommendations for intercropping strategies, enhancing its applicability in diverse agricultural scenarios. Further validation in different geographical regions with varying climatic and soil conditions will ensure its scalability. Additionally, the development of a mobile or web application will enable real-time access for farmers, bridging the gap between technology and field-level implementation.

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