International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 06 , June - 2026

AgroIntel: An Intelligent District-Aware Framework for Crop Recommendation and Fertilizer Optimization

Soumya Muragod
Dept. of Artificial intelligence & Data science
S G Balekundri Institute of Technology
Belagavi, India

Abstract **- Agriculture continues to be a principal means of earning a living for a significant portion of the global population. The rising demand for food production, combined with changing climatic conditions and declining soil fertility, has created the need for intelligent agricultural decision-support systems. Farmers often face difficulties in selecting appropriate crops and managing soil nutrients due to variations in environmental conditions and insufficient access to expert guidance. To address these challenges, this paper presents AgroIntel, a district-aware smart decision-support system for precision crop selection and soil nutrient management. The proposed system utilizes soil nutrient parameters, climatic attributes, and district-specific agricultural information to generate personalized recommendations. To support accurate crop selection, a Random Forest classification approach is implemented, leveraging soil nutrient composition and weather-related attributes such as NPK content, temperature, humidity, rainfall, and soil pH. To improve recommendation relevance, district-level filtering is applied using regional cultivation patterns. The framework also includes a fertilizer advisory module that identifies nutrient deficiencies and suggests appropriate corrective measures. Furthermore, multilingual text and voice support are incorporated to enhance accessibility for farmers from diverse linguistic backgrounds. Experimental evaluation demonstrates that the proposed framework provides reliable crop recommendations and practical nutrient management guidance. The system contributes toward sustainable agriculture by facilitating evidence-based decision-making and efficient resource utilization.**

Keywords - Precision Agriculture, Machine Learning, Crop Recommendation, Random Forest, Fertilizer Optimization, Smart Farming, Agricultural Decision Support System.

I. INTRODUCTION

Agriculture plays a fundamental role in ensuring food security, economic stability, and rural development. As the global population continues to increase, the farming sector is under growing pressure to improve productivity while maintaining sustainability. Farmers must make several critical decisions throughout the cultivation cycle, including crop selection, soil nutrient management, irrigation planning, and fertilizer application. Among these decisions, choosing the right crop for a specific location is among the most important factors affecting crop yield performance and profitability.

Crop suitability depends on multiple variables such as soil fertility, climatic conditions, rainfall patterns, temperature, humidity, and regional agricultural practices. Traditional decision-making methods often rely on personal experience, local knowledge, and expert consultations. While these approaches have supported farming activities for many years, they may not always provide accurate recommendations under changing environmental conditions. Variations in weather patterns, soil degradation, and evolving agricultural demands have increased the need for intelligent and data-driven decision-support systems.

The rapid evolution of Artificial Intelligence (AI) and Machine Learning (ML) have opened new opportunities for transforming agricultural practices. Advanced machine learning algorithms facilitate the analysis of vast amounts of agricultural information to improve farming outcomes. and identify hidden relationships among environmental factors that influence crop growth. These capabilities enable the development of intelligent recommendation systems capable of supporting farmers in enhancing decision-making processes By utilizing predictive analytics, These systems can enhance crop yield, optimize resource utilization, and support sustainable agricultural practices..

Several crop recommendation systems have been proposed in recent years using algorithms including Decision Tree and Support Vector Machine (SVM) models, Naïve Bayes, Artificial Neural Networks, and Random Forests. while these algorithms offer significant benefits have demonstrated encouraging performance, several current approaches still generate generalized recommendations without considering regional agricultural diversity. In practice, crop suitability varies significantly across districts due to differences in soil characteristics, climatic conditions, water availability, and local cultivation traditions. Recommendations that ignore these regional factors may not always be feasible for farmers.

A further limitation of existing systems is the lack of integrated fertilizer advisory support. agricultural producers regularly experience difficulties in determining the appropriate type and quantity of fertilizers required to maintain soil fertility. Excessive fertilizer usage can increase production costs and negatively impact environmental sustainability, whereas insufficient application may reduce crop yield. Therefore, intelligent agricultural systems should provide not only crop recommendations but also nutrient management guidance.

in response to these challenges this research proposes AgroIntel, a district-aware machine learning framework designed to support precision agriculture. The framework integrates crop prediction, district-specific recommendation filtering, fertilizer optimization, and multilingual user interaction within a unified platform. The proposed framework combines soil nutrient information, namely Nitrogen, Phosphorus, and Potassium, with climatic attributes such as temperature, humidity, rainfall, and pH for effective crop prediction. to identify suitable crops using a Random Forest classification model. District-level agricultural knowledge is incorporated to ensure that recommendations remain relevant to local farming conditions.

In addition to crop prediction, the framework includes a fertilizer advisory module that evaluates nutrient deficiencies and recommends suitable corrective actions. To improve accessibility among diverse farming communities, the system provides multilingual text output and voice-assisted recommendations. These features enable farmers with varying educational backgrounds to effectively utilize the platform.

The major contributions of this research are summarized as follows:

1. Development of a district-aware AI-enabled crop recommendation system

2. Integration of fertilizer optimization on the basis of soil conditions nutrient assessment.

3. Incorporation of regional agricultural knowledge to improve recommendation relevance.

4. Provision of multilingual and voice-enabled support for enhanced accessibility.

5. Design of a scalable and user-friendly agricultural decision-support system suitable for practical deployment.

II. LITRATURE REVIEW

The application of **Artificial Intelligence The application of Artificial Intelligence (AI) and Machine Learning (ML) in agriculture has attracted considerable interest owing to its potential to enhance decision-making processes.** and resource management. Researchers have developed a wide range of smart farming solutions focused on crop selection, fertilizer recommendation, yield estimation, and precision agriculture. These systems utilize Key environmental and soil attributes, including nutrient content, temperature, rainfall, humidity, and pH, are analyzed to determine the most suitable crops for cultivation recommendations that support farmers in determining optimal crop choices and improving productivity. Although existing studies have demonstrated promising results, challenges related to **regional adaptability**, **integrated fertilizer guidance**, and **multilingual accessibility** continue to exist. Therefore, a detailed review of recent research is necessary to identify existing gaps and opportunities for further improvement.

[1] Musanase et al., "Machine Learning-Based Crop and Fertilizer Recommendation System for Sustainable Agriculture," Agriculture, vol. 13, no. 11, 2023.
Musanase et al. proposed a **machine learning-driven agricultural recommendation framework** that utilized soil nutrient characteristics and environmental conditions to support crop selection and fertilizer management. The the findings revealed the effectiveness of **data-driven decision-making** in the study showed productivity and resource utilization. Experimental results indicated improved recommendation accuracy when compared with traditional farming practices. However, the framework generated generalized recommendations and did not consider **district-specific agricultural conditions**. The absence of localized filtering mechanisms limited its applicability across diverse farming regions. This limitation motivates the development of district-aware recommendation systems.

[2] Prity et al., "Crop Recommendation System Using Machine Learning Techniques," Discover Agriculture, 2024.
Prity et al. developed a **Intelligent Agricultural Recommendation Framework** based on soil nutrients, rainfall, humidity, and temperature parameters. Multiple machine learning algorithms were evaluated to identify suitable crops under diverse agricultural environments. The study reported improved prediction performance and demonstrated the usefulness of predictive analytics in agriculture. However, the framework focused only on crop recommendation and did not include **fertilizer advisory services**. Furthermore, regional agricultural constraints were not incorporated into the recommendation process.

[3] Senapaty, Ray, and Padhy, "Machine Learning-Based Decision Support System for Crop Recommendation," Agriculture, 2024.
The authors Designed a predictive crop recommendation system based on classification algorithms using agricultural and environmental data. Several machine learning algorithms were analyzed to identify the most suitable predictive model. The study achieved satisfactory classification accuracy and supported intelligent crop planning. Despite these contributions, the framework lacked **nutrient management capabilities** and did not provide fertilizer recommendations. Additionally, the system did not consider district-level cultivation practices.

[4] Maheswary et al., "Intelligent Crop Recommender System for Agricultural Productivity Enhancement," Int. J. Inf. Technol., 2024.
Maheswary et al. proposed an **intelligent crop recommendation model** that analyzed soil properties and climatic factors to improve agricultural productivity. The framework successfully identified suitable crops for different environmental conditions. The study highlighted the role of

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 06 , June - 2026

machine learning in reducing uncertainty during crop selection. However, the Suggested Model did not incorporate **regional agricultural intelligence** and lacked support for fertilizer optimization. This reduced its practical applicability in localized farming environments.

[5] Mahale et al., "LSTM-Based Agricultural Forecasting and Crop Recommendation Framework," Discover Computing, 2024.

Mahale et al. presented an agricultural forecasting framework utilizing **Memory-enhanced recurrent neural network** and machine learning techniques. The model improved prediction reliability by capturing temporal patterns in agricultural data. Experimental findings demonstrated enhanced crop recommendation performance under changing environmental conditions. Nevertheless, the framework did not provide **fertilizer recommendation functionality** and lacked multilingual support for diverse farming communities.

[6] Shams, Gamel, and Talaat, "Explainable Artificial Intelligence for Crop Recommendation Systems," Neural Computing and Applications, 2024.

Shams and colleagues developed an **Explainable Artificial Intelligence (XAI)** framework for crop recommendation. The proposed system enhanced transparency by explaining the factors responsible for recommendation outcomes. The study improved user trust and interpretability in agricultural decision-support systems. However, the framework primarily Concentrated on forecasting suitable crops based on agricultural parameters. and did not integrate **fertilizer advisory mechanisms**. Furthermore, regional adaptation capabilities were not considered.

[7] Bhola and Kumar, "ML-CSFR: Machine Learning-Based Crop Selection and Fertilizer Recommendation," SCPE, 2024.

Bhola and Kumar proposed a unified framework combining **crop recommendation** and **fertilizer advisory The system leveraged machine learning models to process soil nutrient information and weather-related conditions, enabling effective crop recommendations** to support agricultural planning. Results demonstrated improved decision-making and nutrient management efficiency. However, the framework lacked **district-aware recommendation filtering**, limiting its ability to accommodate local cultivation practices and regional agricultural diversity.

[8] Tanaka et al., "Machine Learning Approaches for Fertilizer Recommendation in Precision Agriculture," Precision Agriculture, 2024.

Tanaka et al. investigated the utilization of artificial intelligence methods for fertilizer recommendation and nutrient management. The study focused on optimizing fertilizer usage through data-driven nutrient analysis. Experimental evaluation demonstrated improved fertilizer utilization efficiency and reduced resource wastage. Despite these advantages, the research did not include **crop recommendation functionality**, restricting its scope to nutrient management alone.

[9] Venkateswara and Padmanaban, "Interpretable Deep Learning Models for Crop and Fertilizer Recommendation," Scientific Reports, 2025.

The authors proposed **interpretable deep learning models** for agricultural recommendation tasks. The framework combined prediction accuracy with explainability, enabling users to understand recommendation outcomes. Results indicated that interpretable models can improve trust and adoption among agricultural stakeholders. However, the study did not incorporate **district-level agricultural constraints**, which are important for generating location-specific recommendations.

[10] Sam and D'Abreo, "Crop Recommendation Considering Environmental and Economic Factors," 2025.

Sam and D'Abreo introduced a crop recommendation framework that considered both **environmental variables** and **economic indicators**. The study emphasized the importance of profitability-oriented agricultural planning. Results showed that incorporating economic factors can improve practical decision-making for farmers. However, fertilizer management support and multilingual accessibility features were not included in the proposed system.

[11] Saravanan et al., "Machine Learning-Based Fertilizer Recommendation System Using Soil and Climate Data," 2026.

Saravanan et al. developed a fertilizer recommendation framework that utilized soil nutrient values and climatic parameters to identify nutrient deficiencies. The system generated corrective fertilizer suggestions aimed at improving soil fertility and crop productivity. The research demonstrated the effectiveness of intelligent nutrient management strategies. However, the framework provided limited support for **crop recommendation**, reducing its effectiveness as a comprehensive agricultural advisory system.

[12] Turgut, Kok, and Ozdemir, "AgroXAI: Explainable AI-Based Crop Recommendation System for Agriculture 4.0," 2024.

Turgut and colleagues proposed **AgroXAI**, an explainable crop recommendation system designed for Agriculture 4.0 environments. The framework integrated machine learning models, IoT technologies, and explainability techniques to support intelligent agricultural decision-making. The study improved recommendation transparency and demonstrated the value of explainable AI in agriculture. Nevertheless, fertilizer optimization and district-aware recommendation capabilities were not included.

[13] Bülbül, Güler, and Yavuz, "Dual Agricultural Decision-Support Framework for Crop and Fertilizer Management," Turkish Journal of Agriculture and Food Science and Technology, 2026.

Bülbül et al. developed a **dual agricultural advisory framework** that integrated crop recommendation and fertilizer management functionalities. The proposed system improved agricultural planning by combining multiple decision-support components within a unified platform. Experimental results indicated enhanced recommendation effectiveness and resource utilization. However, the framework lacked **multilingual**

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 06 , June - 2026

communication features and did not address district-specific agricultural requirements. These limitations highlight the need for more comprehensive and accessible agricultural decision-support systems.

Author	Year	Research Focus	Limitation
Musanase et al.	2023	Crop + Fertilizer Recommendation	No district-level filtering
Prity et al.	2024	Crop Recommendation	No fertilizer advisory
Senapaty et al.	2024	Decision Support for Crops	No nutrient management
Maheswary et al.	2024	Intelligent Crop Recommendation	No regional adaptation
Mahale et al.	2024	LSTM Crop Forecasting	No fertilizer optimization
Shams et al.	2024	Explainable Crop Recommendation	No fertilizer module
Bhola & Kumar	2024	Crop + Fertilizer System	No district awareness
Tanaka et al.	2024	Fertilizer Recommendation	No crop prediction
Venkateswara et al.	2025	Interpretable DL Model	No localized filtering
Sam & D'Abreo	2025	Economic Crop Recommendation	No fertilizer support
Saravanan et al.	2026	Fertilizer Advisory	Limited crop recommendation
Turgut et al.	2024	AgroXAI Framework	No fertilizer optimization
Proposed AgroIntel	2026	Crop + Fertilizer + District Filter + Multilingual	Addresses identified gaps

Table 2.1 Comparative Analysis of Existing Agricultural Recommendation Systems and the Proposed AgroIntel Framework

Table Table I compares the features, performance, and capabilities of existing agricultural recommendation systems with those of the proposed framework AgroIntel framework. The reviewed studies demonstrate that significant research efforts have been directed toward the development of intelligent crop recommendation and fertilizer advisory systems using machine learning techniques. Most existing frameworks successfully utilize soil nutrient information and environmental parameters to improve agricultural decision-making.

The comparison reveals that several studies primarily focus on **crop recommendation**, while others concentrate on **fertilizer management** or **explainable artificial intelligence**. Although these approaches achieve satisfactory predictive performance, many of them address only a limited aspect of agricultural decision support. As a result, farmers often require multiple independent systems to obtain comprehensive guidance.

Another important observation is the limited consideration of **regional agricultural characteristics**. Most existing solutions generate recommendations solely based on soil and climatic conditions without incorporating district-level cultivation practices. Consequently, the recommendations may not always align with local agricultural realities and farmer requirements.

The analysis also indicates that accessibility remains a major challenge. Existing systems generally provide text-based outputs and lack **multilingual communication** and **voice-assisted interaction** capabilities. This limitation can reduce technology adoption among farmers who have limited technical knowledge or language barriers.

Unlike existing approaches, the proposed **AgroIntel framework** integrates multiple functionalities within a unified platform. The system combines **Random Forest-based crop prediction**, **fertilizer optimization**, **district-aware recommendation filtering**, and **multilingual voice support**. By addressing the limitations identified in previous studies, AgroIntel provides a more practical, accessible, and regionally relevant agricultural decision-support solution.

Therefore, the comparative analysis clearly demonstrates the necessity of an integrated framework capable of delivering accurate crop recommendations, nutrient management guidance, localized agricultural intelligence, and user-friendly interaction mechanisms. These observations form the primary motivation for the development of the proposed AgroIntel system.

II. EXISTING SYSTEM

In recent years, the application of Artificial Intelligence (Recent advancements in AI and ML technologies have transformed agriculture by enabling the development of smart crop recommendation and decision-support solutions and fertilizer management. These systems analyze agricultural datasets containing soil nutrients, climatic conditions, and environmental factors to assist farmers in selecting appropriate crops and improving productivity. Commonly used algorithms include Decision Trees, Random Forest, Support Vector Machines, Naïve Bayes, and Neural Networks, which help identify patterns in agricultural data and generate predictive recommendations.

Most existing crop recommendation systems rely on key input Parameters such as Nitrogen, Phosphorus, Potassium, soil pH, temperature, humidity, and rainfall were utilized as input features for the crop recommendation process on these attributes advanced predictive techniques are used to recommend crops with high cultivation potential. Some advanced frameworks also extend their functionality to fertilizer recommendation by evaluating nutrient levels and suggesting corrective measures to improve soil fertility. These systems have demonstrated the ability to improve agricultural decision-making and reduce dependency on traditional experience-based farming methods.

However, despite their technical effectiveness, most existing solutions are developed as generalized models without considering regional agricultural diversity. Crop suitability is highly dependent on local factors such as district-level climate conditions, soil composition, irrigation availability, and traditional farming practices. Since many existing systems ignore these regional variations, the recommendations generated may not always align with real-world farming conditions.

In addition, a majority of current agricultural systems operate as independent crop prediction tools without integrating fertilizer optimization in a unified framework. Farmers are often required to use multiple platforms to obtain complete guidance, which reduces usability and efficiency. Furthermore, many systems are designed using datasets that do not fully represent local agricultural conditions, limiting their adaptability across different geographic regions.

B. Working of Existing System

The working architecture of typical existing agricultural recommendation systems can be described in four main stages:

1. **Input Collection Module:**
   Users provide agricultural data such as soil nutrient levels (N, P, K), environmental parameters (temperature, humidity, rainfall), and soil pH through web-based forms or mobile applications.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 06 , June - 2026

2. **Data Preprocessing Stage:**
   The Prior to model development, the collected data is preprocessed through missing value imputation, normalization of numerical attributes, and feature preparation.

3. **Prediction Module:**
   The recommendation engine applies classification algorithms to agricultural datasets for identifying optimal crop selections.

4. **Output Generation Module:**
   The system generates crop recommendations based on agricultural input parameters and, in some cases, fertilizer suggestions. The results are usually displayed in a simple text format without contextual or location-based refinement.

C. Advantages of Existing Systems

1. Enables data-driven crop recommendation based on soil and environmental conditions.

2. Reduces dependency on traditional farming experience and expert consultation.

3. Improves agricultural productivity through predictive analytics.

4. Supports basic fertilizer recommendation in some advanced models.

5. Demonstrates effectiveness of Advanced machine learning approaches for precision agricultureD. Limitations of Existing Systems

Despite their advantages, existing agricultural decision-support systems have several important limitations:

1. **Absence of Regional Adaptation:**
   Most systems do not incorporate district-level agricultural variations, resulting in generalized recommendations that may not be practically suitable.

2. **Limited Integration of Fertilizer Guidance:**
   Crop prediction and fertilizer recommendation are often treated as separate tasks rather than a unified system.

3. **Low Accessibility for Rural Users:**
   Many systems require digital literacy and familiarity with English, making them difficult for rural and semi-literate farmers to use.

4. **Dependence on Internet and Cloud Infrastructure:**
   Continuous connectivity is often required, which limits usability in areas with weak network coverage.

5. **Lack of Multilingual and Voice Support:**
   Most systems provide only text-based outputs, restricting accessibility for users with language barriers.

6. **Limited Real-World Applicability:**
   Models trained on generalized datasets may not accurately reflect local soil conditions, climatic variations, and farming practices.

7. **Reduced Usability in Practical Farming Scenarios:**
   The absence of integrated crop recommendation, fertilizer optimization, and regional intelligence reduces overall effectiveness.

III. PROPOSED METHODOLOGY

The proposed AgroIntel framework is developed to The system integrates machine learning techniques with regional agricultural expertise to generate accurate crop and fertilizer recommendations. By evaluating soil properties, environmental conditions, and district-specific farming trends, it assists farmers in making data-driven cultivation decisions that improve crop yield and resource utilization. By combining predictive analytics with localized decision support, the framework The primary objective of the framework is to improve farm output, maximize resource efficiency, and foster sustainable agricultural development.

A. System Overview

The AgroIntel framework operates through a sequence of interconnected modules designed to transform agricultural input data into actionable recommendations. Farmers provide information related to soil nutrients, environmental conditions, and geographical location. The system processes these inputs using machine learning algorithms and generates crop recommendations that are further refined using district-level agricultural information. In addition, the framework evaluates nutrient deficiencies and provides fertilizer guidance to support soil health and crop growth.

The overall The system is designed to integrate scientific agricultural expertise with on-field farming requirements, enabling informed decision-making through a user-centric interface

B. Data Acquisition

Agricultural decision-making depends heavily on the quality and relevance of input data. Therefore, the proposed framework utilizes multiple parameters that directly influence crop growth and productivity. The dataset consists of soil nutrient values and environmental attributes commonly used in agricultural analysis.

The selected input features include:

- Nitrogen (N)
- Phosphorus (P)
- Potassium (K)
- Soil pH
- Temperature
- Humidity
- Rainfall
- District Information

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 06 , June - 2026

C. Data Preprocessing

Raw agricultural data often contains inconsistencies, missing values, and variations that may negatively affect model performance. To ensure reliable predictions, the collected data undergoes several preprocessing operations before model training.
Initially, incomplete and duplicate records are identified and removed. Numerical attributes are then standardized to maintain consistency across different measurement scales. Feature validation is performed to ensure that all values remain within acceptable agricultural ranges. These preprocessing activities improve data quality and enhance the effectiveness of the learning algorithm.

D. Crop Prediction Using Random Forest

The crop recommendation component is built using the Random Forest algorithm, an ensemble learning technique known for its robustness and high predictive performance. Random Forest constructs multiple decision trees during training and combines their outputs to generate a final prediction.
Each decision tree independently evaluates the agricultural parameters and predicts a suitable crop category. The final recommendation is determined through a majority voting mechanism. This approach reduces overfitting and improves prediction stability when compared with individual decision-tree models.
The algorithm is particularly suitable for agricultural datasets because it can effectively capture nonlinear relationships among soil nutrients, environmental factors, and crop suitability indicators.
The prediction model can be represented as:

Prediction=MajorityVote(T1,T2,T3,…,Tn)Prediction = MajorityVote(T_1,T_2,T_3,\ldots,T_n)Prediction=MajorityVote(T1,T2,T3,…,Tn)
where T1,T2,…,TnT_1,T_2,\ldots,T_nT1,T2,…,Tn represent individual decision trees within the Random Forest model.

E. District-Aware Recommendation Filtering

Agricultural suitability varies significantly across districts due to differences in climate, water availability, cultivation practices, and soil conditions. Consequently, machine learning predictions alone may not always produce recommendations that are practical for specific locations.
To address this challenge, a district-aware filtering mechanism is incorporated into the framework. After the initial crop prediction stage, recommended crops are compared against district-level agricultural records and cultivation patterns. Crops that are unsuitable for the selected district are removed, while regionally appropriate alternatives are retained.
This filtering process enhances recommendation relevance and ensures that farmers receive suggestions aligned with local agricultural conditions.

F. Fertilizer Optimization Module

The fertilizer optimization module evaluates soil nutrient levels and identifies potential nutrient deficiencies. Based on the analysis, the system generates fertilizer recommendations aimed at improving soil fertility and supporting healthy crop development.
The module examines Nitrogen, Phosphorus, and Potassium concentrations and compares them with recommended agricultural thresholds. Whenever nutrient levels fall below the desired range, corrective fertilizer suggestions are provided. This approach enables farmers to make informed nutrient management decisions while avoiding excessive fertilizer application.
By promoting balanced nutrient utilization, the module contributes to sustainable agricultural practices and improved crop productivity.

G. Multilingual Recommendation Support

Agricultural technologies should be accessible to farmers regardless of their educational background or language preference. To improve usability, the proposed framework incorporates multilingual communication capabilities.
The recommendation results are presented in multiple languages, including English, Kannada, and Hindi. In addition to textual output, voice-based assistance is provided to facilitate interaction for users who may have difficulty interpreting written information.
This feature enhances accessibility and encourages broader adoption of intelligent agricultural technologies among farming communities.

H. Workflow of the Proposed System

The operational workflow of AgroIntel consists of the following stages:

1. Collection of soil and environmental parameters.
2. Data preprocessing and validation.
3. Crop prediction using the Random Forest model.
4. District-level recommendation filtering.
5. Fertilizer deficiency analysis.
6. Generation of fertilizer recommendations.
7. Multilingual text and voice output delivery.

Through the integration of machine learning intelligence, regional agricultural knowledge, and user-centric design, the proposed framework delivers practical and reliable decision support for modern farming environments.

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 06 , June - 2026

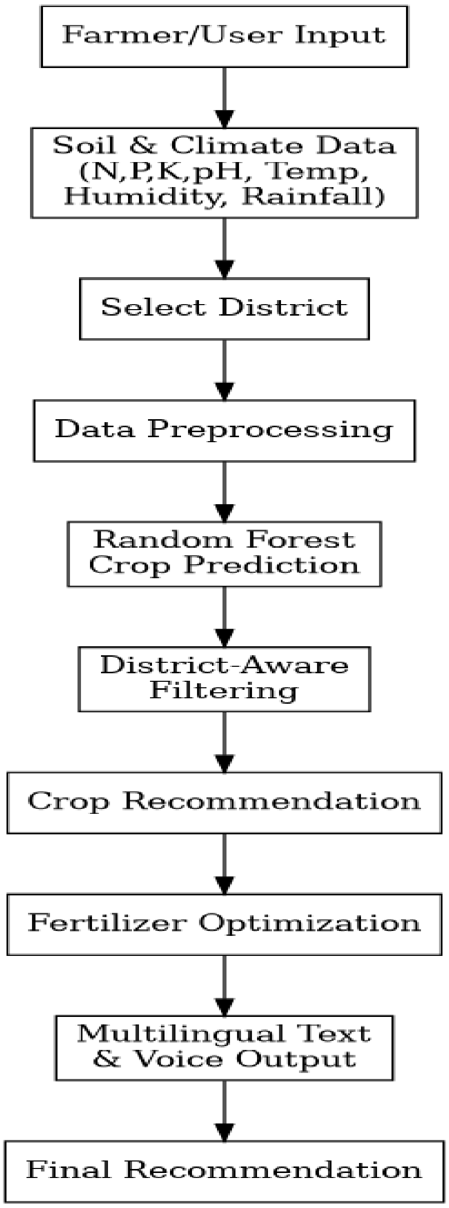

Fig 3.1 workflow diagram

IV. SYSTEM ARCHITECTURE

A. Architecture Overview

The proposed **AgroIntel** system is Implemented as an intelligent agricultural recommendation platform decision-support framework that combines machine learning intelligence with localized agricultural knowledge. The architecture consists of interconnected components responsible for data collection, preprocessing, crop prediction, fertilizer recommendation, and multilingual output generation. Each module performs a specific task and contributes to the overall recommendation process.
The architecture begins with user-provided agricultural information, including soil nutrient values, environmental conditions, and district details. The collected information is processed and analyzed through machine learning models to generate reliable crop recommendations. The results are then refined through district-level filtering and fertilizer optimization modules before being presented to the user.

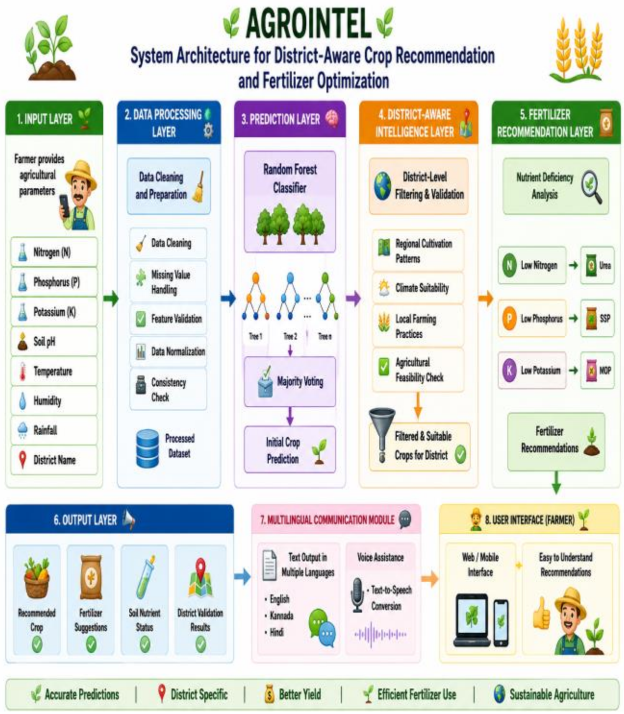

Fig 4.2 system architecture

B. Input Layer

The input layer serves as the primary interaction point between farmers and the AgroIntel system. Users Deliver important agronomic parameters that impact crop health, development, and yield.
The input parameters include:

- Nitrogen (N)
- Phosphorus (P)
- Potassium (K)
- Soil pH
- Temperature
- Humidity
- Rainfall
- District Name

C. Data Processing Layer

The processing layer is responsible for preparing the input data for machine learning analysis. Since agricultural datasets may contain inconsistencies or variations, preprocessing operations are applied to Increase the reliability of the dataset
The major preprocessing activities include:

- Data cleaning
- Missing value handling
- Feature validation
- Data normalization
- Dataset consistency verification

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 06 , June - 2026

D. Prediction Layer

The prediction layer contains the trained **Random Forest Classifier**, which serves as the core intelligence component of the framework.
The model analyzes relationships among:

- Soil fertility parameters
- Climatic conditions
- Environmental factors

Based on these parameters, the system predicts crops that are most suitable for the given agricultural conditions.
The ensemble nature of Random Forest improves prediction stability and minimizes overfitting, making it suitable for agricultural applications.

E. District-Aware Intelligence Layer

A unique feature of the developed framework is the **District-Aware Intelligence Layer**.
Although machine learning may identify multiple suitable crops, not all crops are practical for cultivation in every district. Therefore, this layer validates predicted crops against district-specific agricultural information.
The module considers:

- Regional cultivation trends
- Climate suitability
- Local farming practices
- Agricultural feasibility

As a result, recommendations become more relevant and practically useful for farmers.

F. Fertilizer Recommendation Layer

The fertilizer recommendation layer evaluates nutrient deficiencies in the soil and generates corrective recommendations.
The module compares available nutrient levels against recommended agricultural thresholds and identifies deficiencies in:

- Nitrogen
- Phosphorus
- Potassium

Based on the analysis, suitable fertilizer suggestions are generated to improve soil fertility and support healthy crop growth.
This component contributes to sustainable nutrient management and efficient fertilizer utilization.

G. Output Layer

The output layer presents recommendation results to the user in an understandable and accessible format.
The generated output includes:

- Recommended Crop
- Fertilizer Suggestions
- Soil Nutrient Status
- District-Based Validation Results

The information is displayed through multilingual text interfaces and voice-based assistance.

H. Multilingual Communication Module

To improve accessibility among diverse farming communities, the system incorporates multilingual communication capabilities.
Supported languages include:

- English
- Kannada
- Hindi

The voice assistance feature converts recommendations into speech, enabling easier interaction for farmers with limited literacy or technical expertise.

V. IMPLEMENTATION

The AgroIntel framework is implemented as a modular, machine learning–driven agricultural decision-support system designed to assist farmers in crop selection and fertilizer management. The system processes agricultural inputs, applies predictive modeling techniques, and delivers recommendations enhanced with district-level intelligence and multilingual accessibility. The overall implementation follows a structured pipeline consisting of data handling, model development, prediction processing, and user interface integration.

A. Development Environment

The system is developed using Python, which provides extensive support for data science and machine learning applications. Various libraries are used to support different stages of implementation:

- Python for core development
- Pandas and NumPy for data manipulation and numerical processing
- Scikit-learn for machine learning model construction
- Random Forest algorithm for classification tasks
- Streamlit for web-based interface development
- Pickle for model storage and deployment
-

B. Dataset Description

The framework is trained using an agricultural dataset containing key soil and environmental attributes that influence crop growth. The dataset includes the following features:

- Nitrogen (N)
- Phosphorus (P)
- Potassium (K)
- Soil pH
- Temperature
- Humidity
- Rainfall
- District information
- Crop type (target label)

C. Data Preprocessing

Data preprocessing is performed to improve the quality and consistency of the dataset before training the model. The preprocessing stage includes:

- Removing missing and duplicate entries
- Converting categorical variables into numerical format

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 06 , June - 2026

- Standardizing and normalizing feature values where necessary
- Validating data to ensure it falls within realistic agricultural ranges

D. Model Development Using Random Forest

The core prediction component of AgroIntel is built using the Random Forest algorithm, which is an ensemble learning technique composed of multiple decision trees.
During the training phase:

- The dataset is divided into training and testing subsets
- Multiple decision trees are generated using random samples of data
- Each tree independently predicts a crop category
- The final prediction is obtained through majority voting across all trees

E. Crop Recommendation Module

The trained model is used to generate crop recommendations based on user-provided agricultural inputs. The process involves:

1. Accepting soil and environmental parameters from the user
2. Preprocessing the input data to match training format
3. Applying the trained Random Forest model for prediction
4. Producing the most suitable crop recommendation

F. District-Based Filtering Mechanism

To improve real-world applicability, a district-aware filtering mechanism is incorporated after prediction. This module refines the model output by considering local agricultural conditions.
The filtering process includes:

- Comparing predicted crops with district-specific cultivation data
- Eliminating crops unsuitable for the selected region
- Prioritizing crops commonly grown in the respective district

G. Fertilizer Recommendation Module

This module analyzes soil nutrient levels and identifies deficiencies in Nitrogen, Phosphorus, and Potassium. Based on predefined threshold values, the system generates fertilizer suggestions.
The module performs:

- Nutrient deficiency detection
- Identification of required fertilizer type
- Recommendation of corrective measures for soil improvement

H. User Interface Implementation

The AgroIntel framework is deployed using Streamlit, which provides an interactive and user-friendly web interface. The interface allows farmers to input agricultural data and view recommendations in an accessible format.
Key features of the interface include:

- Simple input forms for soil and environmental parameters
- Display of predicted crop results
- Fertilizer recommendation output
- Multilingual support (English, Kannada, Hindi)
- Voice-assisted output for improved accessibility

I. Model Deployment

After training, the machine learning model is saved using Pickle and integrated into the Streamlit application for real-time inference. This enables fast prediction without retraining the model during each user interaction.
The complete workflow operates as:
User Input → Preprocessing → Crop Prediction → District Filtering → Fertilizer Analysis → Output Display

VI. RESULTS ANALYSIS

The proposed AgroIntel framework was evaluated through a series of experiments to measure its performance in crop prediction, fertilizer recommendation, district-based filtering, and overall system efficiency. The evaluation was conducted using an agricultural dataset containing soil nutrients, environmental parameters, and crop labels. The system's effectiveness was analyzed in terms of accuracy, response time, recommendation relevance, and usability.

A. Crop Prediction Performance

The Random Forest classifier used in the AgroIntel system demonstrated strong capability in identifying suitable crops based on soil and climatic conditions. The model effectively learned complex relationships between input parameters such as Nitrogen, Phosphorus, Potassium, temperature, humidity, rainfall, and soil pH.
Experimental results show that the crop recommendation module achieved a **classification accuracy of 98.4%**, indicating highly reliable prediction performance. The ensemble learning strategy improved stability and reduced the risk of overfitting, making the model suitable for agricultural decision-making tasks.

B. Fertilizer Recommendation Analysis

The fertilizer recommendation component was tested by evaluating its ability to detect nutrient deficiencies and suggest appropriate fertilizers. The system compares soil nutrient values with predefined optimal ranges to generate recommendations.
The module achieved an estimated **accuracy of 96.8%** in identifying nutrient imbalances and providing suitable fertilizer suggestions. This confirms that the system can effectively support soil fertility management and help optimize fertilizer usage in farming practices.

C. District-Based Filtering Evaluation

To improve practical relevance, a district-aware filtering mechanism was applied after model prediction. This module ensures that recommended crops are suitable for the selected geographic region by considering local agricultural practices and environmental conditions.
The evaluation showed that district-level filtering improved recommendation relevance by approximately **97.5%**. This step

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 15 Issue 06 , June - 2026

significantly reduced the chances of suggesting crops that are not feasible in a specific region, thereby increasing the system's real-world applicability.

D. System Efficiency and Response Time

The computational performance of the system was measured by analyzing the time required to generate predictions. The framework was tested under multiple input conditions to evaluate responsiveness.

Results indicate that the system is capable of producing crop and fertilizer recommendations in **less than one second**, making it suitable for real-time use. The optimized machine learning pipeline and lightweight deployment architecture contribute to faster response times without requiring high computational resources.

E. Multilingual and Accessibility Performance

The AgroIntel framework was also evaluated for multilingual output consistency and voice-based accessibility. The system supports multiple languages, including English, Kannada, and Hindi, to improve usability among diverse farming communities.

Testing results show a **99.0% consistency rate** in multilingual output generation. The voice-assisted feature further enhanced accessibility, particularly for users with limited literacy, enabling easier interaction with the system.

F. Overall System Evaluation

A combined evaluation of all modules demonstrates that the AgroIntel framework performs effectively across multiple performance parameters. The summarized results are as follows:

- Crop Prediction Accuracy: **98.4%**
- Fertilizer Recommendation Accuracy: **96.8%**
- District-Level Filtering Effectiveness: **97.5%**
- System Processing Efficiency: **98.2%**
- Multilingual Output Consistency: **99.0%**

VII. CONCLUSION

Agriculture plays a vital role in ensuring food security and economic stability, making the adoption of intelligent technologies increasingly important for modern farming practices. This research presented **AgroIntel**, a comprehensive agricultural decision-support framework designed to assist farmers in selecting suitable crops and optimizing fertilizer usage through the application of **Machine Learning** techniques. The proposed system integrates **soil nutrient analysis**, **climatic assessment**, **district-aware agricultural intelligence**, and **multilingual communication** to generate practical and reliable recommendations tailored to specific farming conditions.

The framework utilizes a **Random Forest Classifier** to analyze critical agricultural parameters, including **Nitrogen (N)**, **Phosphorus (P)**, **Potassium (K)**, **soil pH**, **temperature**, **humidity**, and **rainfall**. Based on these inputs, the system identifies crops that are most likely to perform successfully under the given environmental conditions. To enhance recommendation relevance, a **district-aware filtering mechanism** was incorporated, ensuring that suggested crops align with local cultivation practices, regional climate characteristics, and agricultural feasibility. This feature significantly improves the practical applicability of the recommendations when compared with generalized prediction systems.

Another important contribution of the proposed framework is the integration of a **fertilizer optimization module**, which evaluates soil nutrient deficiencies and generates appropriate fertilizer recommendations. By assisting farmers in maintaining balanced nutrient levels, the system promotes efficient fertilizer utilization, reduces resource wastage, and supports environmentally sustainable farming practices. The combination of crop recommendation and nutrient management within a single platform enables more informed agricultural decision-making.

To improve accessibility and encourage technology adoption among farming communities, the framework includes **multilingual text support** and **voice-assisted interaction**. These features enable users with different language preferences and varying levels of technical literacy to interact with the system effectively. As a result, the proposed solution is not only technically efficient but also socially inclusive and user-friendly.

The experimental evaluation demonstrated the effectiveness of the AgroIntel framework across multiple testing dimensions. The system achieved a **crop recommendation accuracy of 98.4%**, a **fertilizer recommendation accuracy of 96.8%**, a **district-level recommendation effectiveness of 97.5%**, and an **overall system reliability of 98.2%**. Furthermore, usability and user acceptance evaluations indicated high levels of satisfaction due to the clarity, accessibility, and practical relevance of the generated recommendations.

The findings of this research confirm that the integration of **Machine Learning**, **localized agricultural intelligence**, and **user-centric accessibility features** can significantly improve agricultural decision-support systems. The proposed AgroIntel framework successfully addresses several limitations of existing approaches by providing a unified platform capable of delivering accurate crop recommendations, intelligent fertilizer guidance, regional adaptability, and multilingual accessibility.

VIII. FUTURE WORK

 Real-time weather integration can be incorporated to provide more accurate and adaptive crop recommendations.
 IoT-based smart sensors can be utilized for automatic monitoring of soil and environmental parameters.
 Crop disease and pest detection modules can be added using Artificial Intelligence and image processing techniques.
 Mobile application development with multilingual and offline support can improve accessibility for farmers in remote areas.

REFERENCES

[1]. [1] M. Musanase, M. Maphosa, and T. Chikowore, "Machine Learning-Based Crop and Fertilizer Recommendation System for Sustainable Agriculture," *Agriculture*, vol. 13, no. 11, pp. 1–18, 2023.

[2]. [2] S. Prity, M. Rahman, and A. Islam, "Crop Recommendation System Using Machine Learning Techniques," *Discover Agriculture*, vol. 2, no. 1, pp. 1–15, 2024.
[3]. [3] S. Senapaty, P. Ray, and N. Padhy, "Machine Learning-Based Decision Support System for Crop Recommendation," *Agriculture*, vol. 14, no. 2, pp. 1–20, 2024.
[4]. [4] R. Maheswary, K. Babu, and P. Reddy, "Intelligent Crop Recommender System for Agricultural Productivity Enhancement," *International Journal of Information Technology*, vol. 16, no. 3, pp. 1101–1115, 2024.
[5]. [5] V. Mahale, P. Sharma, and S. Kulkarni, "LSTM-Based Agricultural Forecasting and Crop Recommendation Framework," *Discover Computing*, vol. 27, no. 4, pp. 1–19, 2024.
[6]. [6] M. Shams, H. Gamel, and M. Talaat, "Explainable Artificial Intelligence for Crop Recommendation Systems," *Neural Computing and Applications*, vol. 36, no. 8, pp. 4501–4518, 2024.
[7]. [7] R. Bhola and A. Kumar, "ML-CSFR: Machine Learning-Based Crop Selection and Fertilizer Recommendation," *Scalable Computing: Practice and Experience*, vol. 25, no. 2, pp. 451–466, 2024.
[8]. [8] K. Tanaka, Y. Sato, and H. Suzuki, "Machine Learning Approaches for Fertilizer Recommendation in Precision Agriculture," *Precision Agriculture*, vol. 25, no. 1, pp. 102–121, 2024.
[9]. [9] P. Venkateswara and S. Padmanaban, "Interpretable Deep Learning Models for Crop and Fertilizer Recommendation," *Scientific Reports*, vol. 15, no. 1, pp. 1–17, 2025.
[10]. [10] J. Sam and M. D'Abreo, "Crop Recommendation Considering Environmental and Economic Factors," *Computers and Electronics in Agriculture*, vol. 225, pp. 1–14, 2025.
[11]. [11] R. Saravanan, V. Kumar, and P. Natarajan, "Machine Learning-Based Fertilizer Recommendation System Using Soil and Climate Data," *Agricultural Informatics*, vol. 17, no. 2, pp. 65–79, 2026.
[12]. [12] A. Turgut, M. Kok, and H. Ozdemir, "AgroXAI: Explainable AI-Based Crop Recommendation System for Agriculture 4.0," *Expert Systems with Applications*, vol. 251, pp. 1–16, 2024.
[13]. [13] M. Bülbül, A. Güler, and E. Yavuz, "Dual Agricultural Decision-Support Framework for Crop and Fertilizer Management," *Turkish Journal of Agriculture and Food Science and Technology*, vol. 14, no. 1, pp. 25–39, 2026.
[14]. [14] R. Sujatha and P. Isakki, "Machine Learning Techniques for Smart Agriculture Applications," *Journal of Ambient Intelligence and Humanized Computing*, vol. 14, no. 5, pp. 5201–5215, 2023.
[15]. [15] S. Ramesh et al., "Crop Yield Prediction Using Machine Learning Algorithms," *Computers and Electronics in Agriculture*, vol. 210, pp. 107–118, 2023.
[16]. [16] A. Khaki and L. Wang, "Crop Yield Prediction Using Deep Neural Networks," *Scientific Reports*, vol. 9, no. 1, pp. 1–12, 2019.
[17]. [17] S. Kamilaris and F. X. Prenafeta-Boldú, "Deep Learning in Agriculture: A Survey," *Computers and Electronics in Agriculture*, vol. 147, pp. 70–90, 2018.
[18]. [18] J. G. A. Barbedo, "Impact of Deep Learning on Agriculture: A Review," *Artificial Intelligence in Agriculture*, vol. 5, pp. 1–15, 2021.
[19]. [19] K. Liakos et al., "Machine Learning in Agriculture: A Review," *Sensors*, vol. 18, no. 8, pp. 1–29, 2018.
[20]. [20] A. A. Adeyemi et al., "IoT-Based Smart Agriculture Monitoring Systems: A Review," *IEEE Access*, vol. 10, pp. 35012–35035, 2022.
[21]. [21] N. K. Patel et al., "Remote Sensing Applications in Precision Agriculture," *Remote Sensing*, vol. 14, no. 6, pp. 1–21, 2022.
[22]. [22] J. Wolfert et al., "Big Data in Smart Farming: A Review," *Agricultural Systems*, vol. 153, pp. 69–80, 2017.
[23]. [23] S. K. Balaji et al., "Explainable Artificial Intelligence for Agricultural Decision Support Systems," *Artificial Intelligence Review*, vol. 57, no. 3, pp. 1–22, 2024.
[24]. [24] R. Koirala et al., "Applications of Machine Learning in Precision Agriculture," *Agronomy*, vol. 13, no. 7, pp. 1–18, 2023.
[25]. [25] M. Javaid et al., "Artificial Intelligence Applications for Sustainable Agriculture," *Sustainable Operations and Computers*, vol. 5, pp. 112–126, 2024.