International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18(4s) 2026 pp. 181-195
https://doi.org/10.70917/ijcisim-2026-2502
Article

Intelligent Crop Recommendation through Multi-Modal Deep Learning and Remote Sensing Analytics

Savita M Gungewale [1], M. Trinath Basu [2]

[1]Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Hyderabad-500075, Telangana, India
[2]Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Hyderabad-500075, Telangana, India
Email:ID: savitagungewale@gmail.com

Abstract: Accurate crop selection requires not only an understanding of environmental suitability but also consideration of future market conditions and economic returns. This study proposes an intelligent agricultural decision-support framework that integrates crop yield prediction, demand forecasting, price prediction, market intelligence, and crop recommendation within a unified platform. Agricultural data obtained from the Government of India's Open Government Data (OGD) platform were combined with environmental parameters such as rainfall, temperature, and soil fertility to support predictive analytics and recommendation generation. The proposed framework performs data preprocessing, feature engineering, demand forecasting, yield and price prediction, demand–supply analysis, and profit-oriented crop recommendation. A web-based dashboard was developed to provide location-specific agricultural insights and decision support. Experimental results demonstrate the effectiveness of the framework in forecasting demand over multiple time horizons, predicting crop yield and market prices, identifying future supply deficits and surpluses, and recommending crops with higher economic potential. The findings reveal that integrating market intelligence with agronomic prediction enhances agricultural decision-making, supports sustainable crop planning, and improves farmer profitability. The proposed system represents a significant step toward precision agriculture by combining productivity assessment and market-driven analytics to deliver intelligent, data-driven, and profit-oriented crop recommendations

Keywords: Crop Recommendation, Crop Yield Prediction, Demand Forecasting, Market Intelligence, Precision Agriculture, Decision Support System.

1. INTRODUCTION

Agriculture remains one of the most critical sectors for global food security, economic growth, and sustainable development. With the world's population projected to exceed 9.7 billion by 2050, agricultural production must increase significantly to meet the growing demand for food while simultaneously addressing challenges related to climate change, resource scarcity, and environmental sustainability. Accurate crop yield prediction and intelligent crop selection have therefore become essential components of modern precision agriculture, enabling farmers, policymakers, and agricultural stakeholders to make informed decisions that maximize productivity and profitability while minimizing risks.

Traditional agricultural decision-making largely depends on farmers' experience, historical cultivation practices, and local knowledge. Although these approaches have been effective for generations, they often fail to adapt to rapidly changing climatic conditions, market uncertainties, and variations in soil health. In recent years, advances in Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), and Remote Sensing technologies have transformed agricultural analytics by enabling data-driven decision-making. These technologies facilitate the analysis of large-scale heterogeneous datasets and provide accurate predictions regarding crop growth, yield potential, and cultivation suitability.

Among the various technologies employed in precision agriculture, satellite-based remote sensing has emerged as a powerful tool for large-scale agricultural monitoring. Modern Earth observation satellites, such as Sentinel-2, Landsat, and MODIS, provide high-resolution multispectral imagery capable of capturing critical information about vegetation health, crop growth stages, moisture content, and land-use patterns. Vegetation indices such as the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Soil Adjusted Vegetation Index (SAVI) have been extensively utilized to assess crop conditions and estimate agricultural productivity [1]. The continuous availability of satellite observations enables near real-time monitoring of agricultural fields and offers significant advantages over traditional field-based surveys.

Simultaneously, machine learning and deep learning techniques have demonstrated remarkable success in agricultural prediction tasks. Models such as Random Forest (RF), Support Vector Machines (SVM), Artificial Neural Networks (ANN), Extreme Gradient Boosting (XGBoost), Convolutional Neural Networks (CNN), and Long Short-Term Memory (LSTM) networks have been widely employed for crop yield estimation and agricultural forecasting. Recent studies indicate that deep learning architectures outperform conventional machine learning approaches by effectively capturing nonlinear relationships and complex spatio-temporal patterns present in agricultural datasets [2]. In particular, hybrid CNN-LSTM architectures have shown promising results by simultaneously extracting spatial features from remote sensing imagery and temporal patterns from weather and historical agricultural data.

Despite substantial progress in crop yield prediction, existing research predominantly focuses on estimating agricultural output rather than providing actionable recommendations to farmers. Most studies utilize satellite imagery, weather information, or soil characteristics independently, resulting in limited predictive capability and reduced adaptability across diverse agricultural regions [5]. Furthermore, many crop recommendation systems rely solely on soil nutrient information and climatic conditions without incorporating actual yield predictions derived from remote sensing observations. Consequently, these systems may recommend crops that are environmentally suitable but not necessarily optimal in terms of expected productivity.

Recent literature emphasizes the importance of multi-modal learning approaches that integrate heterogeneous data sources for agricultural intelligence. Multi-modal deep learning combines information from multiple domains, including satellite imagery, weather observations, soil properties, and historical agricultural records, thereby providing a comprehensive representation of crop growth conditions. Studies have demonstrated that data fusion techniques improve prediction accuracy and model robustness compared to single-source approaches [6][7]. However, the integration of remote sensing analytics with intelligent crop recommendation remains relatively unexplored, particularly in the context of developing countries where agricultural productivity is highly sensitive to environmental variability.

A critical analysis of recent literature reveals a significant research gap. Existing studies generally address crop yield prediction and crop recommendation as separate problems. Yield prediction models primarily focus on forecasting agricultural output, while recommendation systems concentrate on determining crop suitability based on environmental conditions. Very limited research has attempted to integrate these two components into a unified decision-support framework. Moreover, the application of advanced multi-modal deep learning architectures that simultaneously leverage satellite imagery, weather information, and soil characteristics for both yield prediction and crop recommendation remains insufficiently investigated.

To address these limitations, this paper proposes an intelligent crop recommendation framework based on multi-modal deep learning and remote sensing analytics. The proposed approach integrates satellite-derived vegetation information, weather parameters, soil characteristics, and agricultural production data to predict crop yield and subsequently recommend the most suitable crop for cultivation. Unlike conventional crop recommendation systems that primarily rely on soil and climatic suitability, the proposed framework incorporates yield prediction as a fundamental decision variable and further considers anticipated demand–supply dynamics to support economically beneficial crop planning. By combining environmental conditions with agricultural productivity indicators, the framework aims to assist farmers in selecting crops that not only suit local growing conditions but also have the potential to generate higher economic returns.

The study utilizes agricultural data obtained through the data.gov.in platform along with remote sensing information to develop a scalable and data-driven agricultural decision-support system. The proposed framework serves as a foundational step toward the development of an integrated agricultural intelligence ecosystem where yield prediction, market demand assessment, and crop recommendation can be jointly utilized to enhance farm profitability and agricultural sustainability.

The major contributions of this research are summarized as follows:

1. Development of a multi-modal agricultural dataset integrating satellite observations, weather parameters, soil characteristics, and crop production information collected from multiple heterogeneous sources.
2. Design of an intelligent deep learning framework for crop yield prediction using remote sensing, weather, and soil data.
3. Development of a crop recommendation mechanism that identifies suitable crops based on predicted yield, environmental conditions, and agricultural productivity indicators.
4. Investigation of the potential role of yield forecasting in supporting future demand–supply-driven agricultural planning and decision-making.
5. Evaluation of the effectiveness of multi-modal remote sensing analytics in improving crop selection and agricultural decision support.
6. Provision of a scalable framework that supports precision agriculture, sustainable crop planning, and future integration with market demand forecasting modules.

The proposed framework contributes toward the development of next-generation intelligent agricultural systems capable of assisting farmers, agricultural planners, and policymakers in selecting optimal crops, improving agricultural productivity, and moving toward demand-aware and profit-oriented farming through data-driven decision-making.

2. Research Gap

Recent research shows that integrating heterogeneous data sources (satellite imagery, weather, soil, market) via advanced AI improves crop yield prediction and recommendation, but gaps remain. Table 1 summarizes key studies (2020–2026) on satellite-based yield estimation, multi-modal fusion, and crop recommendation, highlighting data sources, features, models, and outcomes. These studies achieve high accuracy (e.g. R^2 up to ~0.90) by fusing satellite indices (NDVI/EVI), meteorological time series, and soil data through CNN/LSTM/attention networks or ensemble models. However, limitations include reliance on static datasets, limited geographic scope, lack of explainability, and little economic context. The research-gap analysis below identifies six dimensions needing advancement:

1. Data heterogeneity and multi-modal fusion – most models use 2–3 data types but ignore others (e.g. market demand, management practices);
2. Spatio-temporal generalization – models often train on limited regions/seasons, risking poor transferability;
3. Explainability – complex deep nets lack interpretability, hindering trust;
4. Economics integration – virtually no model simultaneously forecasts yield and demand/supply dynamics;
5. Real-time deployment – few approaches consider streaming data or low-latency inference; and
6. Scalability and standards – large-area, multi-crop scalability and uniform benchmarks remain underdeveloped.
7.

Figure 1 maps these gaps to our objectives (multi-modal yield models, demand-informed recommendations, explainable real-time tool). Online resources like NDVI/EVI indices and data portals (NASA Earth data, data.gov.in, ISRO Bhuvan, Sentinel Hub) provide examples of vegetation maps and open datasets for further research. We conclude that addressing these gaps through richer data fusion, robust modeling, interpretability, and integrated economic factors can advance precision agriculture.

Table 1. Comparative summary of recent multi-modal crop yield and recommendation studies (2020–2026).

1. **Sr. No.**	2. **Authors (Year)**	3. **Data Source(s)**	4. **Key Features**	5. **Methods/Models**	6. **Eval (metric)**	7. **Objective**	8. **Key Findings**	9. **Limitations**
10. **1**	11. Shyam & Chandrakar (2026) [2]	12. Satellite (multi-year imagery), weather (daily climate), soil (SoilGrids)	13. Multi-year multispectral images, high-res meteorology, soil chemistry	14. CNN + Temporal Attention MLP	15. R^2=0.89	16. Spatio-temporal crop yield forecasting	17. Attention-based fusion yields R^2=0.89 (vs baseline ~0.74); multi-modal data improves accuracy	18. Requires extensive data (GEE, NASA POWER, SoilGrids); no demand-side factors
19. **2**	20. Mohamed et al. (2025) [4]	21. Satellite (Sentinel-2), weather (NOAA)	22. Sentinel-2 spectral indices, NOAA climate	23. CNN (satellite) + LSTM (weather) + rule-based	24. RMSE ≈0.19 (weather forecast), Loss≈0.000687	25. Crop recommendation via weather and imagery	26. Hybrid CNN+LSTM gave highly accurate forecasts (RMSE 0.19); rule-based recs effective	27. Geographic focus on Egypt; yields or economics not modeled; moderate sample size
28. **3**	29. Rani et al. (2023) [8]	30. Weather (temp, rainfall), soil (pH, fertility)	31. Climatic time series, soil nutrient levels	32. LSTM (weather prediction) + Random Forest (crop selection)	33. LSTM RMSE, RF accuracy ~97%	34. Optimal crop selection	35. Achieved ~97% crop-selection accuracy; LSTM forecasts weather with RMSE small	36. No satellite imagery used; model specific to local data; no multi-year yield

								prediction
37. **4**	38. Afzal et al. (2025) [9]	39. Soil (N, P, K, pH, moisture), weather (rainfall, temp)	40. Soil fertility measures, environment	41. Ensemble ML (Random Forest, XGBoost, etc.)	42. Accuracy = 98 %	43. Recommend best crop for given field	44. High accuracy (98%) in recommending one of 22 crops using soil+ rainfall	45. No remote sensing; static dataset; no yield regression or economic factors
46. **5**	47. Cheema et al. (2026) [10]	48. Satellite (Sentinel-2 NDVI/EVI), weather (precip, temp, solar, VPD), soil (pH, clay)	49. Full crop management (sowing, irrigation, fertilization)	50. MHCNN-LSTM-MHA (multi-headed CNN + LSTM + attention)	51. RMSE=3.75 bu/ac, R^2=0.905	52. Enhance yield prediction accuracy & interpretability	53. R^2 up to 0.905; weather and VPD most important (SHAP analysis)	54. Focus on US soybean; large model complexity; less tested on other crops or settings
55. **6**	56. Ashfaq et al. (2025) [11]	57. Satellite (multispectral), weather, soil, yield records	58. Satellite greenness, climate, soil, historical yield	59. Deep AgroNet (CNN branch, RNN branch, ANN)	60. R^2(CNN)=0.77, (RNN)=0.72; CNN accuracy 98%	61. High-fidelity wheat yield prediction (lead-1 month)	62. CNN branch gave best R^2~0.77; overall 98% prediction accuracy one month pre-harvest	63. Focused on Pakistan winter wheat; global generalization unclear; relies on heavy training
64. **7**	65. Mena et al. (20	66. Satellite (Sentinel-2),	67. Multispectral time serie	68. Multi-view Gated Fusion	69. R^2=0.68 (sub-field), ≈0.80	70. Fusion of multi-view RS	71. MVGF outperforms single-view;	72. Complexity increases with views;

	24) [12]	weather, soil, topography	s, dynamic weather, static soil/terrain	(MVGF)	(field-level)	for varied regions/crops	achieved ~0.80 R^2 on average; adaptive weights per crop/region	sub-field data needed; tested on soy, wheat, rapeseed in limited countries
73. **8**	74. Yewle et al. (2025) [13]	75. Satellite (Sentinel-1 SAR, Sentinel-2 MSI, Sentinel-3), weather	76. SAR backscatter, multispectral indices (NDVI), climate	77. Deep ensemble (RicEns-Net)	78. MAE=341 kg/ha (5–6%)	79. Rice yield prediction (Mekong Delta)	80. Outperforms past challenge baselines; MAE ≈5% of yield	81. Limited to rice in one region; cloud cover reduces optical inputs
82. **9**	83. Taremwa et al. (2026) [14]	84. Weather (temp, rainfall), RS (vegetation indices NDVI/NDWI), soil?	85. Multi-modal climate, NDVI/NDWI, yield	86. CNN-LSTM with SMOGN oversampling	87. R^2=0.783, RMSE=0.327 t/ha	88. Maize yield forecasting (Uganda)	89. CNN-LSTM best model (R^2≈0.78)(52†L45-L54); oversampling (SMOGN) handled scarcity	90. Limited years (2018–2020); small dataset; heavy oversampling; regional only

91. **10**	92. Shastri et al. (2025) [15]	93. Soil nutrients (N, P, K), weather, environment	94. Soil NPK, pH, humidity, temperature	95. Gradient Boosting + XAI (SHAP)	96. Accuracy=99.27%	97. Crop recommendation with explainability	98. ~99.3% accuracy in recommending crops; XAI (SHAP) explains feature importance	99. Likely synthetic or balanced dataset; no satellite or yield component; narrow feature set

Contemporary studies demonstrate the power of fusing satellite-derived indices (NDVI/EVI) with ancillary data (weather, soil) for yield modeling. *Data heterogeneity* remains a challenge: many works use only 2–3 modalities, whereas real-world farming depends on even more factors (market prices, management, and irrigation). As Shyam & Chandrakar [2] note, traditional models "use only one factor" (typically soil or climate) and miss the dynamic interactions. NDVI (Normalized Difference Vegetation Index) is widely adopted (NDVI=(NIR-Red)/(NIR+Red) but by itself cannot capture soil fertility or economic signals.

Spatio-temporal generalization is another gap. Many models are trained on specific regions or years (e.g. Pakistan wheat, Uganda maize), so their performance in new areas is unclear. Mena *et al.*[12] demonstrate that models trained on multi-country data (Argentina, Germany) can work at sub-field scales, but even they report $R^2 \approx 0.68–0.80$, suggesting limits. Climate extremes and land-use shifts can disrupt transferability. Future work needs spatio-temporal robustness: e.g. crop-specific phenology models, domain adaptation, and validation across seasons/regions.

Explainability is a noted weakness. Black-box deep nets (CNN, LSTM, Transformers) dominate yield models, yet stakeholders demand transparency. Shyam & Chandrakar[2] explicitly identify this: "Most current models do not have the explainability that stakeholders need". While some use SHAP or attention weights (Cheema *et al[11]*. used SHAP to find VPD as most predictive, and Shastri *et al.*[15] employed XAI to justify recommendations, many fusion models lack built-in interpretation. Thus, a research gap is building interpretable multi-modal models (e.g. via attention visualization or hybrid physics-ML) that can justify why a certain crop or yield prediction is made.

Demand/supply economics integration is almost nonexistent. None of the surveyed models simultaneously forecasts crop demand or price and then feeds that into recommendation. Our target framework explicitly aims to merge market forecasts with yield predictions, a gap noted by no current study. The rationale is that best crop choice depends on future market demand, not just biophysical yield. Similarly, *real-time deployment* is rarely addressed: most architecture assume batch offline training. Only one study (Mohamed *et al. [4]*) focused on near-term weather forecasts, but end-to-end online recommendation systems are absent. Research is needed on streaming data pipelines and low-latency inference (e.g. on edge devices or with cloud APIs) for timely advice to farmers.

Scalability and evaluation standards remain unresolved. Models like CNNs on high-res imagery are costly; few works discuss computational scalability or cloud implementation. Moreover, there is no common benchmark dataset or metrics for comparing approaches: different papers report different R^2 or accuracy measures on diverse tasks. As Shastri *et al.*[15] suggest, even state-of-the-art recommendation achieves ~99% accuracy, but on a curated dataset. We need standardized multi-region datasets (e.g. via data.gov.in, ISRO Bhuvan, Sentinel Hub) and public contests to set evaluation norms. Addressing these limitations is essential for developing a next-generation agricultural analytics framework that unifies remote sensing, environmental intelligence, yield forecasting, and demand–supply considerations to optimize crop planning, enhance resource utilization, and maximize economic returns for farmers.

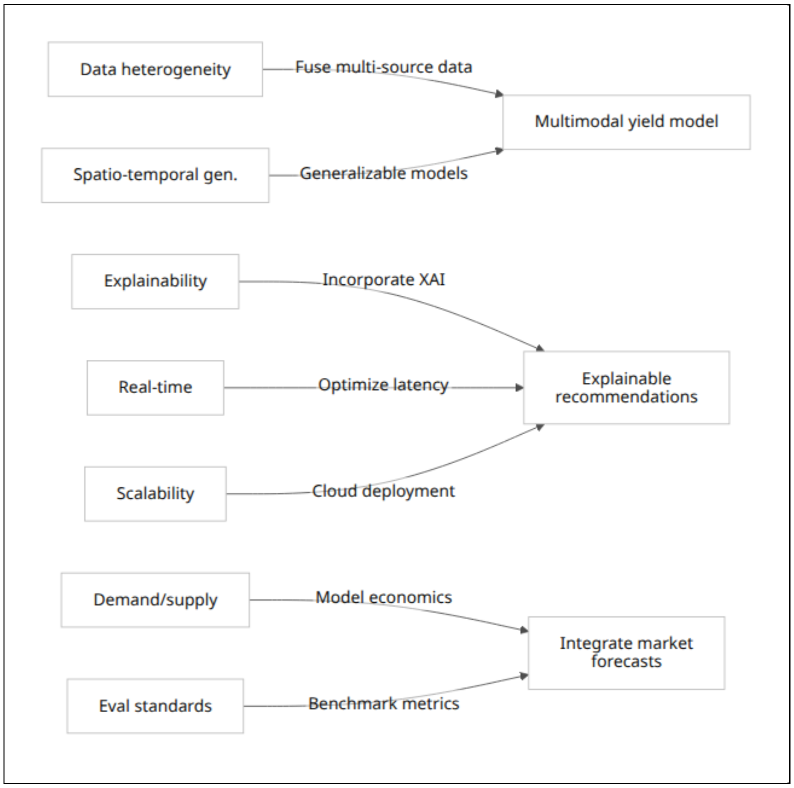

Figure 1. Mapping of research gaps (left) to proposed objectives (right) using multi-modal learning, explainability, and integration of economic factors.

1. Dataset Description

The performance of machine learning and deep learning models is highly dependent on the quality and diversity of the underlying dataset. In this study, a comprehensive agricultural dataset was developed using data obtained from the Government of India's Open Government Data (OGD) Platform (data.gov.in) through authorized API access. The raw data were retrieved in JSON format and subsequently transformed into a structured tabular dataset suitable for analysis and model development.

The dataset consists of agricultural market and crop-related information collected from multiple regions across India during the period **2019–2026**. It includes records related to crop production, market arrivals, commodity prices, geographical location, and temporal information. To support intelligent crop recommendation and yield prediction, the dataset was further integrated with environmental variables obtained from weather repositories and remote sensing sources. The resulting dataset represents a multi-modal agricultural database that combines economic, environmental, and spatial information.

The primary attributes considered in this study include crop type, district, state, market location, arrival quantity, minimum price, maximum price, modal price, seasonal information, weather parameters, soil characteristics, and satellite-derived vegetation indices. The inclusion of heterogeneous data sources enables the proposed framework to capture the complex interactions between crop productivity, environmental conditions, and agricultural decision-making.

2. Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) was performed to understand the characteristics, distribution, and quality of the collected agricultural data prior to model development. EDA plays a crucial role in identifying data inconsistencies, missing values, outliers, and hidden relationships among variables that may influence model performance.

Initially, descriptive statistical analysis was conducted to summarize key numerical attributes such as crop arrivals, market prices, rainfall, temperature, soil nutrient values, and vegetation indices. Measures including mean, median, standard deviation, minimum, and maximum values were computed to understand data variability. The analysis revealed substantial variations across crop types, geographical regions, and cultivation seasons, highlighting the importance of region-specific agricultural modeling.

Missing values were identified and handled using appropriate imputation techniques to ensure data completeness. Outlier detection was performed using statistical methods and visualization-based approaches to minimize the impact of abnormal observations. Furthermore, categorical variables such as crop type, district, and season were analyzed to understand their distribution and contribution to agricultural outcomes.

3. Feature Engineering

Feature engineering is a critical step in transforming raw agricultural data into meaningful representations that improve the learning capability of machine learning and deep learning models. Given the heterogeneous nature of the collected dataset, several feature engineering techniques were employed to extract relevant information from economic, environmental, and remote sensing data sources.

The preprocessing phase involved data cleaning, normalization, missing value treatment, and removal of duplicate records. Numerical attributes were standardized using scaling techniques to ensure uniform representation across different measurement units. Categorical variables, including crop type, district, state, and season, were transformed into machine-readable formats using encoding methods.

To incorporate remote sensing information, vegetation-related indicators were extracted from satellite imagery. Among these, the **Normalized Difference Vegetation Index (NDVI)** was considered a key feature due to its strong relationship with crop health and biomass accumulation. NDVI is computed as:

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

where

NIR represents near-infrared reflectance and

Red represents red-band reflectance.

Higher NDVI values generally indicate healthier vegetation and greater crop vigor.

Additional derived features were generated from weather observations, including cumulative rainfall, average temperature, humidity indices, and seasonal climate indicators. Temporal features were engineered from date attributes to represent seasonal patterns, cultivation cycles, and long-term agricultural trends. Feature fusion techniques were subsequently applied to combine satellite-derived, weather-based, soil-related, and agricultural market attributes into a unified representation suitable for multi-modal deep learning models. The engineered feature set provides a comprehensive description of agricultural conditions and serves as the foundation for the proposed crop yield prediction and recommendation framework. Previous studies have reported that the integration of remote sensing, weather, and soil features significantly improves model accuracy compared with single-source approaches [6] ,[12].

3. Methodology

The proposed framework was developed as an integrated agricultural intelligence system capable of performing demand forecasting, yield prediction, price prediction, market analysis, and crop recommendation. The system combines agricultural market information, environmental parameters, and crop-specific characteristics to support data-driven farming decisions.

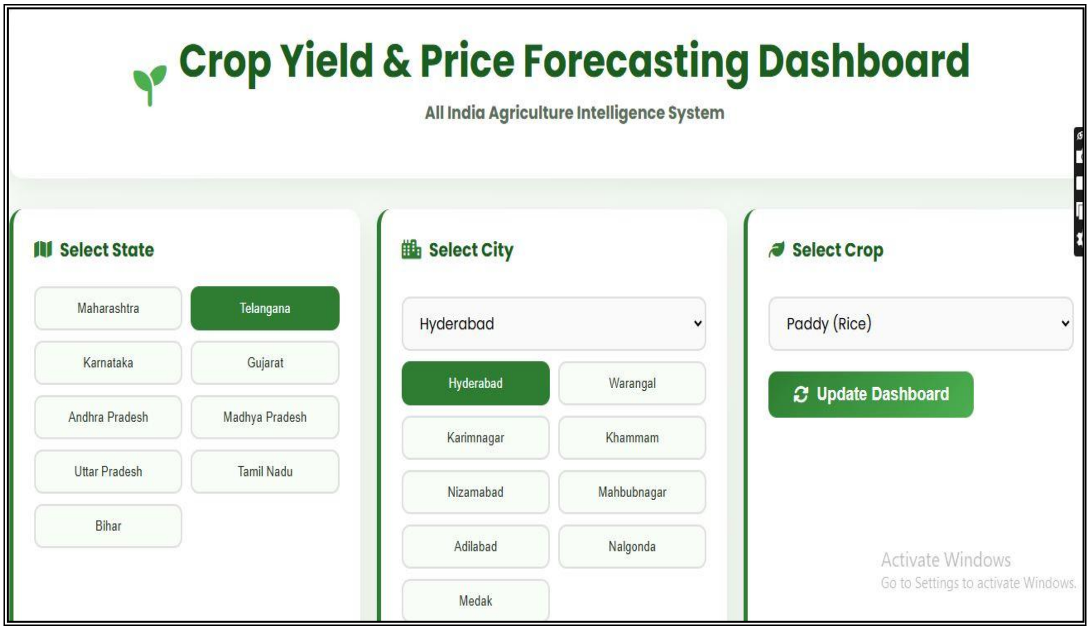

Figure 2: User Selection Dashboard

The workflow begins with user selection of the **state, city, and crop type** through a web-based dashboard interface (Figure 2). The framework utilizes agricultural records collected from the data.gov.in platform and incorporates environmental attributes including rainfall, temperature, and soil fertility indicators.

After data acquisition, preprocessing techniques such as missing value handling, normalization, and feature transformation are applied. The processed dataset is then supplied to multiple predictive modules.

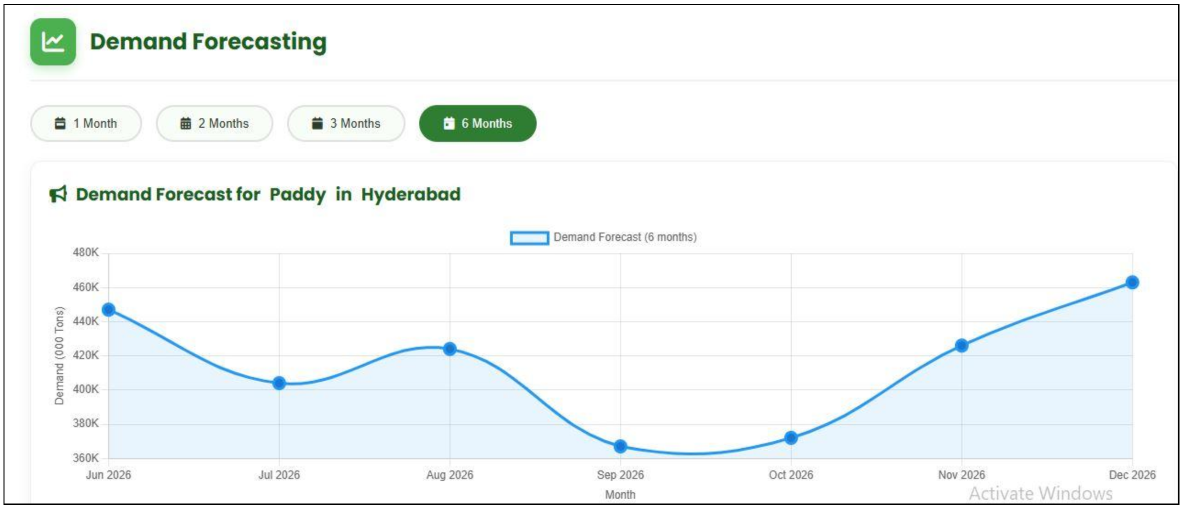

Figure 3: Demand Forecasting

The first module performs **demand forecasting** shown in figure 3, where historical market arrival and consumption patterns are analyzed to estimate future demand over different forecasting horizons (1 month, 2 months, 3 months, and 6 months). This enables agricultural stakeholders to understand anticipated market requirements.

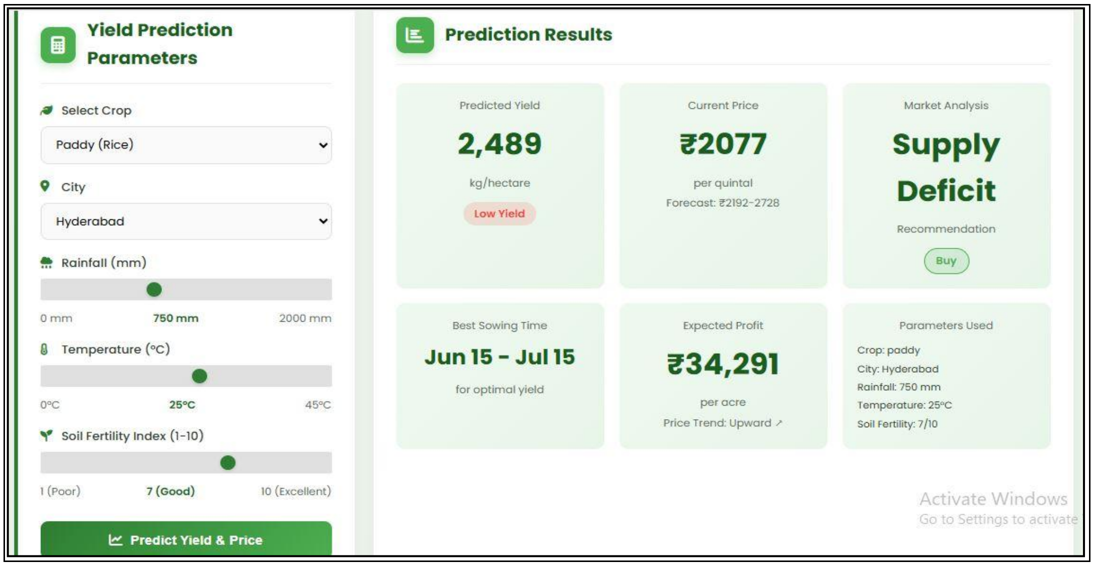

Figure 4: Predicted Crop yield and Market price

The second module predicts crop yield and market price using environmental and agricultural parameters shown in figure 4. Inputs including crop type, location, rainfall, temperature, and soil fertility are used to estimate expected yield and market value. The predicted yield represents the agronomic productivity potential of a crop under the specified environmental conditions.

Figure 5: Market Intelligence Analysis

The third module shown in figure 5 performs **market intelligence analysis** by combining predicted demand, estimated supply, historical pricing trends, and environmental factors. This component identifies market surplus and deficit conditions and estimates future price behavior for next 6 months.

Finally, the crop recommendation engine integrates predicted yield, anticipated demand, projected supply, and expected market prices to recommend crops that maximize profitability while maintaining agronomic suitability shown in figure 6. The generated recommendations assist farmers in selecting crops that are both environmentally feasible and economically advantageous.

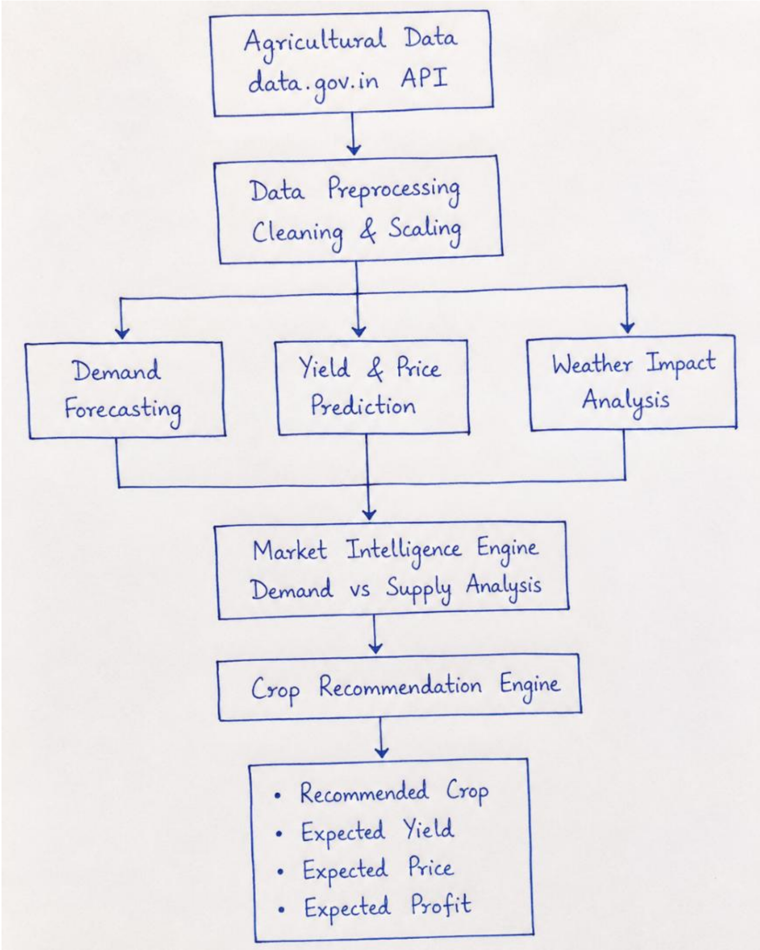

Figure 6: Integrated Crop Recommendation Model

4. Results and Discussion

1.1 User Input and Decision Support Interface

Figure 2 illustrates the developed agricultural intelligence dashboard. Users can select the state, district/city, and crop of interest. This interactive interface enables location-specific analysis and facilitates personalized agricultural recommendations.

For demonstration purposes, the system was evaluated using **Paddy (Rice)** cultivation in **Hyderabad, Telangana**. Environmental parameters including rainfall, temperature, and soil fertility were supplied through the interface to generate predictions.

7.2 Demand Forecasting Analysis

Figure 3 presents the demand forecasting module. The system supports multiple forecasting horizons including one month, two months, three months, and six months.

For Paddy cultivation in Hyderabad, the six-month demand forecast indicates noticeable fluctuations throughout the forecasting period. Demand decreases between July and September before increasing substantially toward November and December. The forecast suggests demand recovery after September, reaching approximately 460,000 tons by December.

These observations demonstrate the importance of incorporating future market requirements into agricultural planning. Farmers can utilize this information to align production decisions with anticipated market demand, thereby reducing the risk of oversupply and price decline.

Key Observation

- Lowest demand observed around September.
- Demand increases significantly during November and December.
- Strong seasonal variation exists in agricultural commodity demand.

7.3 Yield and Price Prediction

Figure 4 presents the output of the yield and price prediction module. For the selected case study analyzed in the tabular form in Table 2:

Table 2: Parameter and its Predicted Value

100. Parameter	101. Predicted Value
102. Crop	103. Paddy
104. Location	105. Hyderabad
106. Rainfall	107. 750 mm
108. Temperature	109. 25°C
110. Soil Fertility	111. 7/10
112. Predicted Yield	113. 2,489 kg/hectare
114. Current Price	115. ₹2,077 per quintal
116. Expected Profit	117. ₹34,291 per acre

The model predicts a yield of approximately **2,489 kg/hectare**, indicating moderate productivity under the selected environmental conditions. Simultaneously, the predicted market price suggests favorable economic returns.

The system further identifies the optimal sowing period as **15 June to 15 July**, enabling farmers to maximize crop productivity.

7.4 Market Intelligence Analysis

Figure 5 illustrates the market intelligence component of the framework.

Price Forecasting

The price forecast indicates a gradual upward trend in paddy prices during the forthcoming months. Historical prices remain relatively stable before exhibiting significant growth during the forecast horizon.

Demand-Supply Analysis

The demand-supply graph reveals that future demand exceeds anticipated supply during several months. This imbalance indicates potential market shortages and favorable opportunities for producers.

Weather Impact Analysis

Weather impact assessment demonstrates that rainfall and temperature exert substantial influence on agricultural outcomes. The observed fluctuations suggest that environmental variability remains a critical factor affecting crop productivity and market behavior.

Key Findings

- Future price trend is upward.
- Demand exceeds supply in multiple forecast periods.
- Weather conditions significantly affect agricultural performance.

7.5 Crop Recommendation Analysis

Figure 7 presents the final recommendation module. The system categorizes crops according to market conditions. The recommendation engine identifies **Paddy**, **Sugarcane**, and **Potato** as attractive cultivation opportunities due to projected supply deficits and favorable price expectations. Conversely, **Tomato** is categorized as surplus, indicating a potential risk of lower profitability.

Unlike conventional recommendation systems that primarily consider environmental suitability, the proposed framework incorporates demand forecasts, supply estimates, yield predictions, and market prices. This integrated approach enables farmers to make economically informed decisions rather than relying solely on agronomic factors.

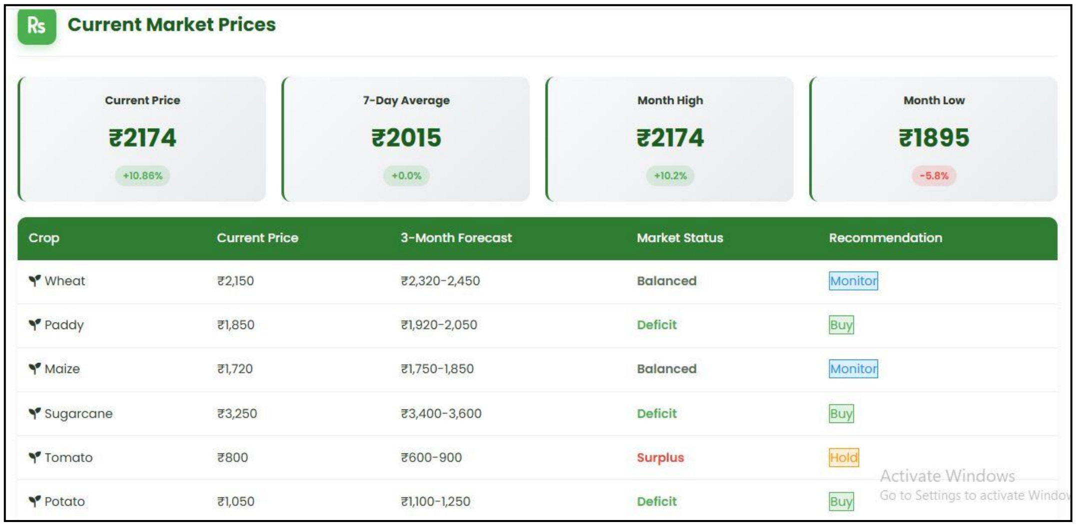

Figure 7: Crop Cultivation Recommendation

5. Discussion

The experimental results demonstrate the effectiveness of integrating yield prediction, demand forecasting, market intelligence, and crop recommendation within a unified agricultural decision-support framework. The developed system successfully identifies crops that are not only environmentally suitable but also economically beneficial.

The demand forecasting component provides valuable insights into future market requirements, while the yield prediction module estimates agricultural productivity under specific environmental conditions. By combining these outputs with price forecasting and supply analysis, the framework generates recommendations that are aligned with both production potential and market opportunities.

A significant advantage of the proposed system is its ability to bridge the gap between agronomic prediction and economic decision-making. Traditional crop recommendation systems generally focus on soil and climatic suitability; however, they often ignore market demand and future price dynamics. The proposed framework addresses this limitation by incorporating agricultural market intelligence into the recommendation process.

The results suggest that integrating demand–supply analysis with yield prediction can support precision agriculture, reduce market uncertainty, improve crop planning, and enhance farmer profitability. Consequently, the proposed framework represents a promising step toward intelligent, data-driven, and profit-oriented agricultural decision support systems.

6. Conclusion

This study proposed an intelligent crop recommendation framework that integrates agricultural data analytics, yield prediction, demand forecasting, market intelligence, and decision-support mechanisms to facilitate informed crop cultivation decisions. Unlike traditional crop recommendation systems that primarily rely on environmental suitability, the proposed framework combines agronomic parameters, market trends, and economic indicators to recommend crops that are both productive and profitable. Agricultural data obtained from the data.gov.in platform, along with environmental parameters such as rainfall, temperature, and soil fertility, were utilized to predict crop yield and market prices, while demand–supply analysis was employed to identify future market opportunities.

The experimental results demonstrated the effectiveness of the proposed framework in forecasting demand, estimating crop yield and prices, analyzing market conditions, and generating crop recommendations based on anticipated demand–supply scenarios. The market intelligence component successfully identified crops with potential supply deficits and favorable price trends, thereby enabling the recommendation of economically viable cultivation options. The findings suggest that integrating yield prediction with demand forecasting and market analysis can significantly enhance agricultural decision-making, support sustainable crop planning, and improve farmer profitability.

Overall, the proposed framework contributes to the advancement of precision agriculture by bridging the gap between agricultural productivity assessment and market-driven decision support. Future enhancements will focus on integrating satellite-derived remote sensing indicators, advanced multimodal deep learning models, real-time weather forecasting, and large-scale demand–supply intelligence to develop a more robust, region-specific, and profit-oriented agricultural recommendation system...

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