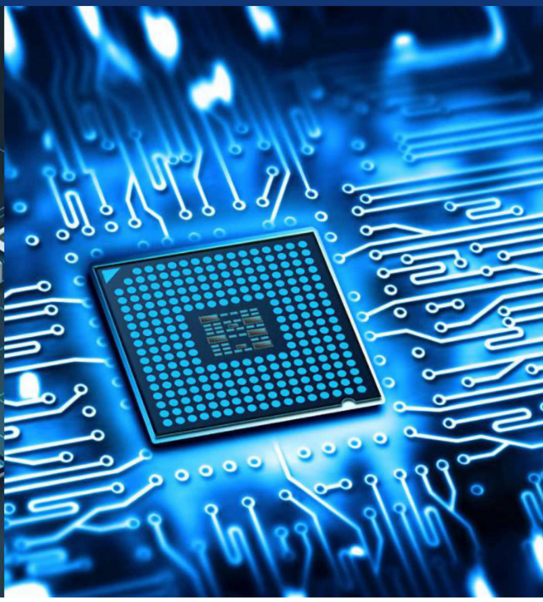
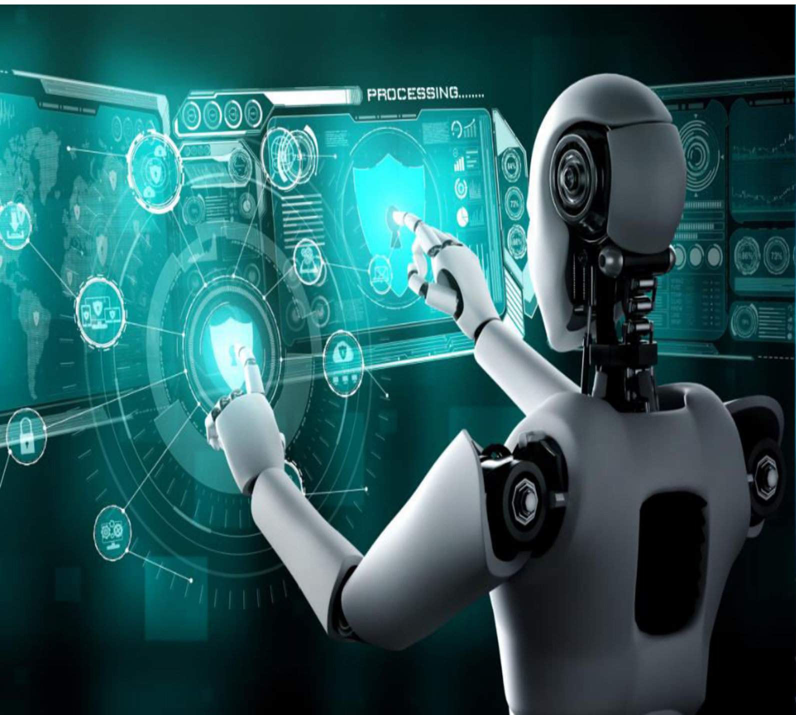
IJIRCCE

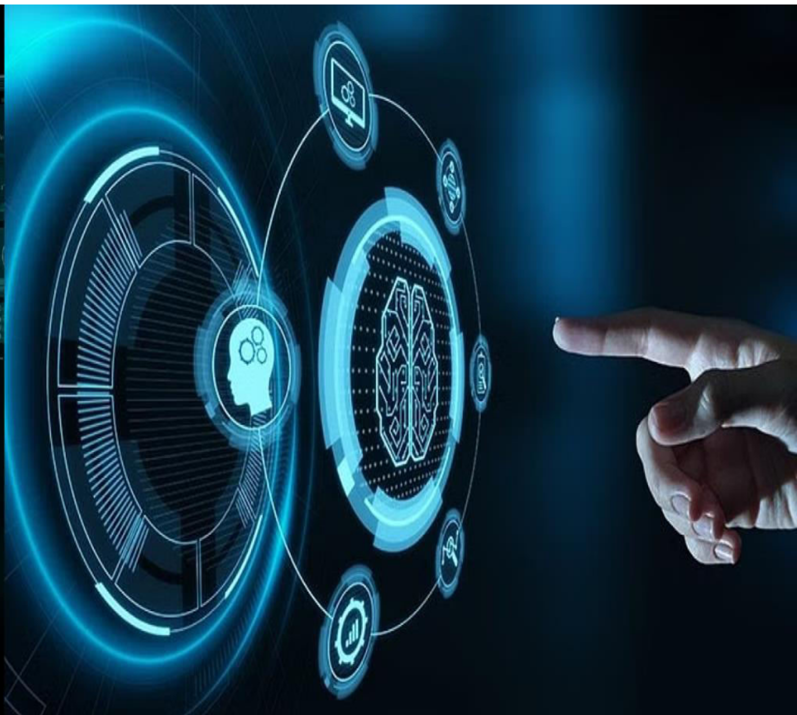
ISSN(O): 2320-9801
ISSN(P): 2320-9798



International Journal of Innovative Research in Computer and Communication Engineering

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)





Impact Factor: 9.927

Volume 14, Issue 8, August 2026

www.ijircce.com ijircce@gmail.com +91-9940572462 +91 63819 07438

© 2026 IJIRCCE | Volume 14, Issue 8, August 2026 DOI: 10.15680/IJIRCCE.2026.1408023

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

AI-Driven Decision Support and Market Intelligence for Smart Agriculture Using Random Forest and LSTM Networks

Champashree KM, Prof B. Sowmya

Post Graduate Student, Department of Computer Science and Engineering, East West Institute of Technology, Bangalore, Karnataka, India

Professor, Department of Computer Science and Engineering, East West Institute of Technology. Bangalore, Karnataka, India

ABSTRACT: Agriculture faces mounting challenges including unpredictable climate patterns, declining soil health, and volatile market prices that often leave smallholder farmers financially vulnerable. This paper presents FarmLink, an AI-powered Agricultural Decision Support System (ADSS) designed to help farmers make smarter, data-backed decisions with minimal technical expertise. The system integrates three intelligent modules: (1) a Random Forest (RF) classifier for precision crop recommendation using soil and environmental parameters (N, P, K, temperature, humidity, pH, rainfall); (2) a Long Short-Term Memory (LSTM) deep learning network for market price and demand forecasting; and (3) a Cosine Similarity-based matching engine that connects farmers directly with buyers. The RF classifier achieves over 99% classification accuracy; the LSTM forecasting module attains a MAPE of 5.8%. Deployed as a lightweight Flask web application, FarmLink bridges the information gap between farm-level production and market-level demand, empowering farmers to plan, connect, and trade efficiently.

KEYWORD: Smart Agriculture; Random Forest Classifier; Long Short-Term Memory (LSTM); Crop Recommendation; Market Price Prediction; Agricultural Decision Support System; Farmer-Buyer Matching; Cosine Similarity; Precision Farming; Deep Learning; FarmLink; Time-Series Forecasting

I. INTRODUCTION

Global food security depends on the productivity of hundreds of millions of smallholder farmers who operate with limited access to technical expertise, market information, and modern decision-support tools. The consequences of poor crop selection and ill-timed sales extend well beyond individual livelihoods — they ripple through supply chains, drive food price inflation, and perpetuate cycles of rural poverty.

Advances in Artificial Intelligence (AI), machine learning, and deep learning have created an unprecedented opportunity to close this knowledge gap. Algorithms that once required expensive expert systems can now run on standard cloud servers and be accessed by farmers through simple smartphone browsers. However, most existing agricultural AI tools address only one dimension of the problem: either crop selection or price forecasting or market connectivity — rarely all three in a single accessible platform.

This paper presents FarmLink, an integrated AI-powered platform that addresses these three challenges simultaneously:

- **Random Forest Classifier:** recommends optimal crops based on real-time soil and environmental data.
- **LSTM deep learning network:** forecasts market prices and demand six months ahead.
- **Cosine Similarity engine:** matches farmers directly with the most suitable buyers, eliminating costly middlemen.

The remainder of this paper is structured as follows. Section II reviews related work. Section III describes the system methodology. Section IV presents empirical results. Sections V and VI provide discussion and conclusions.

© 2026 IJIRCCE | Volume 14, Issue 8, August 2026 DOI: 10.15680/IJIRCCE.2026.1408023

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

II. LITERATURE SURVEY

A. AI in Crop Recommendation and Soil Health

Choosing the right crop is deceptively complex: soil composition, rainfall, temperature, and pH interact in nonlinear ways that are difficult to assess manually. Random Forest (RF) models have proved consistently reliable. Thomas et al. [1] demonstrated 99.3% RF accuracy from NPK and climatic variables. Sindhur et al. [2] built a hybrid framework where RF (100 estimators, depth 20) narrowed crop candidates before economic filters were applied. Natarajan et al. [3] reported 99.88% accuracy with 10-fold cross-validation. Ayoola et al. [4] validated RF resilience to missing remote-sensing data — a common field condition. Tifanto et al. [5] and Sapkal & Kadam [6] confirmed RF superiority across diverse geographic settings, while Naidu [7] compared it against SVM, Decision Tree, and Logistic Regression classifiers, finding consistent RF dominance.

B. Market Intelligence and Price Forecasting

Price volatility makes forward planning difficult for farmers. LSTM networks have emerged as the dominant approach for agricultural time-series. Shaheen et al. [8] achieved 92% cherry-price forecasting accuracy across multiple Indian markets, outperforming XGBoost and SARIMA. Zhang et al. [9] showed LSTM superiority for Beijing vegetable price spikes. Amal and Hemalatha [10] integrated crop advisory with market prediction, reducing yield-prediction errors by 12.3% versus regression baselines.

C. Farmer-Buyer Connectivity and Digital Marketplaces

Direct farmer-to-buyer platforms reduce middlemen dependency. SmartAgroHub [11] and Agri Smart Farm to Market [12] use AI matching based on crop type, quantity, and location. AgriTrust [13] adds immutable blockchain records for transaction transparency at 98% accuracy. Patel et al. [14] demonstrated that multimodal demand-supply alignment — combining purchase history with location and season — substantially improves match quality.

III. METHODOLOGY

FarmLink's architecture follows a modular pipeline: acquire data, preprocess, train models, and serve predictions through a web interface. Each module is independently upgradeable. The complete workflow is shown in Fig. 1.

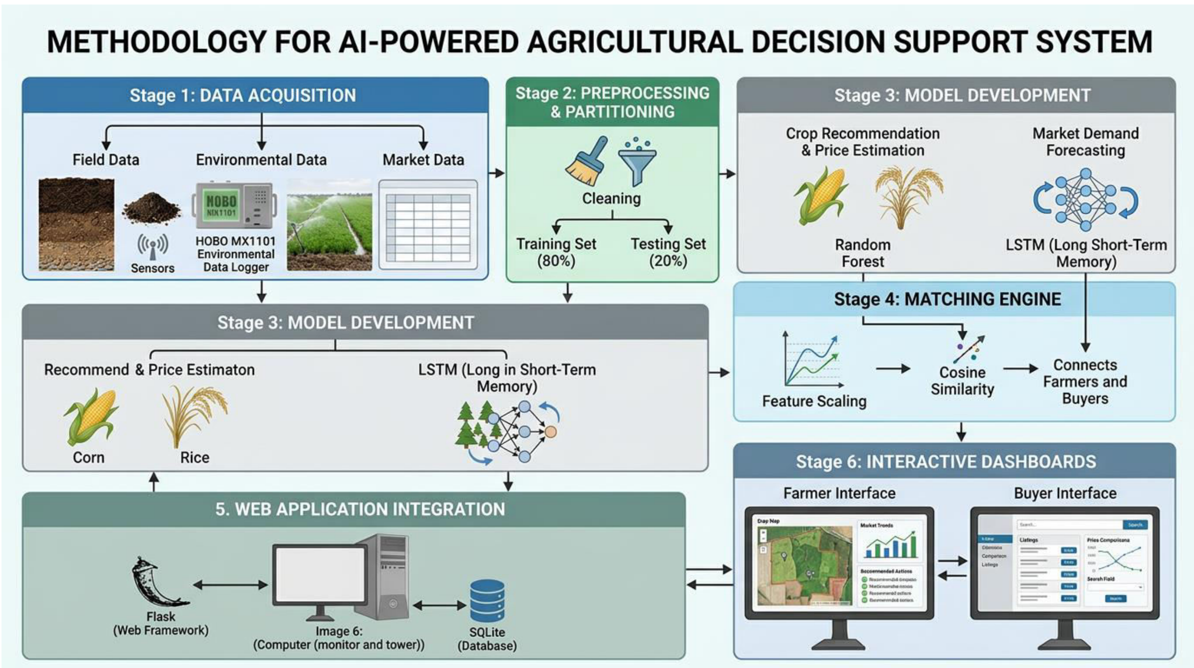


Fig. 1. FarmLink System Methodology: From Data Acquisition to Interactive Dashboards.

www.ijircce.com | e-ISSN: 2320-9801, p-ISSN: 2320-9798| Impact Factor: 9.927| ESTD Year: 2013|

International Journal of Innovative Research in Computer and Communication Engineering (IJIRCCE)

(A Monthly, Peer Reviewed, Refereed, Scholarly Indexed, Open Access Journal)

A. Stage 1 — Data Acquisition

Three data streams feed FarmLink:

- **Soil Profiles:** N, P, K, pH, and moisture from lab tests or sensors.
- **Environmental Records:** Temperature, humidity, and rainfall from meteorological APIs.
- **Market Price History:** Monthly commodity prices and demand data from government portals (e.g. AGMARKNET).

B. Stage 2 — Data Preprocessing

- **Outlier Removal:** Interquartile Range (IQR) method [3].
- **Normalization:** Min-Max scaling to [0, 1] for feature parity.
- **Sequence Building:** Six-month sliding windows for LSTM input [2].

C. Stage 3 — Random Forest Crop Recommendation

A Random Forest Classifier is trained on the preprocessed soil-climate dataset. Each tree in the ensemble votes for a crop class; the majority vote decides the recommendation. Key parameters: 100–300 estimators, Gini impurity splitting criterion, and maximum depth of 20 [2], [3]. A companion Random Forest Regressor simultaneously estimates the expected market price of the recommended crop [15].

D. Stage 4 — LSTM Market Forecasting

The LSTM network forecasts commodity prices and demand six months ahead. Three gating mechanisms control information flow:

$$f_t = \sigma(W_e \cdot [h_{t-1}, x_t] + b_e)$$
$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$
$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$

where f_t, i_t, o_t are the forget, input, and output gate activations at time step t; h_{t-1} is the previous hidden state; x_t is the current input; W and b are learned weight matrices and bias vectors; and σ is the sigmoid activation. The architecture uses two stacked LSTM layers (64 then 32 units), Adam optimiser, MSE loss, and 0.2 dropout [2].

E. Stage 5 — Farmer-Buyer Matching

Each farmer is represented as a feature vector of crop type, quantity, price, and location. Buyer requirements form a query vector. The Cosine Similarity score ranks farmers by relevance:

$$S(A, B) = (A \cdot B) / (\|A\| \cdot \|B\|) = \Sigma A_iB_i / (\sqrt{\Sigma A_i^2} \cdot \sqrt{\Sigma B_i^2})$$

Buyers receive a ranked shortlist of the most compatible farmers.

F. Stage 6 — Web Application and Ease of Use

Accessibility is a first-class design goal:

- **Simple Input Forms:** Drop-down menus and defaults require only basic soil readings — no technical knowledge.
- **Visual Outputs:** Line-graph forecasts replace raw tables for instant comprehension.
- **Role-Based Dashboards:** Separate farmer and buyer views prevent information overload.
- **Lightweight Backend:** Flask + SQLite deploys on low-cost servers or local machines in connectivity-limited areas.
- **Secure Authentication:** Password hashing protects credentials on modest infrastructure [15].

IV. RESULT ANALYSIS

A. Crop Recommendation Accuracy

Table I compares RF against other classifiers on the crop recommendation task. RF achieves 99.88% and 99.30% accuracy across two independent evaluations [1], [3], outperforming SVM (97.9%), Logistic Regression (95.2%), and Decision Tree (93.5%).

TABLE I
COMPARATIVE CLASSIFICATION ACCURACY FOR CROP RECOMMENDATION

Model	Source	Accuracy (%)
Random Forest	Natarajan et al. [3]	99.88
Random Forest	Thomas et al. [1]	99.30
Random Forest	Tifanto et al. [5]	98.70
SVM	Parab [16]	97.90
Logistic Regression	Parab [16]	95.20
Decision Tree	Sapkal & Kadam [6]	93.50

B. Market Forecasting Performance

The LSTM module delivers:

• **RMSE:** 3.50 per kg for one-month-ahead vegetable prices [2] — lower than SARIMA and XGBoost benchmarks.
• **MAPE:** 5.8%, meaning predictions are within 6% of actual market prices [2].
• **Cherry forecasting accuracy:** 92% across 12 Indian markets [8].

Compared to linear models, LSTM reduces yield-prediction errors by 12.3% and post-harvest losses by up to 20% [8], [10].

C. Farmer-Buyer Matching Effectiveness

Similarity-based recommenders outperform keyword and distance-only matching for commercially relevant farmer-buyer pairs [14]. Blockchain-augmented variants achieve 98% transaction accuracy [17].

D. System Impact Summary

Table II consolidates key performance and impact metrics across all three FarmLink modules.

TABLE II
FARMLINK SYSTEM PERFORMANCE AND IMPACT METRICS

Module	Key Metric	Value
Crop Recommendation	Classification Accuracy	≥99.3%
Market Forecasting	MAPE	5.8%
Market Forecasting	RMSE	3.50 per kg
Farmer-Buyer Matching	Recommendation Quality	High relevance
Blockchain Trade	Transaction Accuracy	98%
Post-Harvest Losses	Reduction	Up to 20%

V. DISCUSSION

A. Why the RF-LSTM Combination Works

The pairing of Random Forest and LSTM is architecturally complementary: RF excels at structured, snapshot decisions — given today's soil readings, which crop maximises yield? LSTM excels at sequential reasoning — given twelve months of price history, what will prices be next month? Together they span the farmer's complete decision horizon from planting to selling. The Cosine Similarity layer adds social intelligence, bridging crop supply with buyer demand in a way that no single predictive model achieves alone.

B. Scalability and Adaptability

RF's resilience to high-dimensional, heterogeneous data makes it portable across regions with different soil types [4]. Adding a new crop or region requires only retraining on supplementary data — no architectural changes. The LSTM module similarly retrains on new price series as coverage expands. The Flask + SQLite stack is lightweight by design, enabling national-scale deployment on low-cost cloud infrastructure [11].

C. Limitations and Future Work

• **Data Quality:** Both RF and LSTM degrade with manually recorded or incomplete data. IoT sensor integration would substantially improve reliability.
• **Offline Access:** Many smallholder farmers face unreliable connectivity. A mobile-first, offline-capable interface is a necessary next step.
• **Explainability:** LSTM predictions remain difficult to interpret. Integrating SHAP (SHapley Additive exPlanations) would improve transparency and farmer trust.

VI. CONCLUSION

This paper has presented FarmLink, an AI-powered Agricultural Decision Support System that integrates three intelligent modules — crop recommendation, market forecasting, and farmer-buyer matching — into a single, accessible web platform. By combining a Random Forest Classifier (over 99% crop recommendation accuracy), LSTM network (MAPE 5.8%), and Cosine Similarity matching engine, FarmLink provides a comprehensive toolkit that addresses agricultural challenges at both the field and market level.

Ease of use is a core principle: simple input forms, visual dashboards, role-based access, and a lightweight deployment stack ensure that farmers with limited technical background benefit from cutting-edge AI without needing to understand the underlying algorithms.

Looking ahead, real-time IoT feeds, satellite imagery, mobile-first interfaces, and Explainable AI (XAI) modules will further strengthen FarmLink's capabilities and inclusivity. The findings affirm that intelligent, accessible, data-driven platforms are not a luxury for the agricultural sector — they are an essential infrastructure for a food-secure future.

REFERENCES

[1] Thomas and N. Chandran, "Agrofam: A Deep Learning-Based Ecosystem for Plant Health and Smart Farming," 2025.
[2] Sindhur, Pavithra, and N. Muchikel, "Hybrid Machine Learning Framework for Optimizing Crop Selection via Agronomic and Economic Forecasting," 2025.
[3] Natarajan, S. Krishna, P. Ganesan, A. Kaabi, R. Kala et al., "Revolutionizing Agriculture Through Smart Farming by Employing Advanced Machine Learning Techniques for Optimal Crop Selection," 2025.
[4] Ayoola, Essien Ogharandukun, and Uloko, "Data-Driven Framework for Crop Categorization using Random Forest-Based Approach for Precision Farming Optimization," 2024.
[5] B. A. Tifanto, M. Z. S. Hadi, and N. Sa'adah, "A Crop Recommendation System for Smart Agriculture Using Random Forest Method," 2024.
[6] K. G. Sapkal and Kadam, "Random Forest Classifier For Crop Prediction Based On Soil Data," 2024.
[7] Naidu, "Harvest Harmony: Integrating Linear and Nonlinear Machine Learning Models for Precision Crop Recommendation," 2024.
[8] Shaheen, Gul, Ganai, Majid, Rashid et al., "Deep learning-enabled cherry price forecasting and real-time system deployment across multi-market supply chains in India," 2025.
[9] Zhang, W. Yang, Zhao, Wang, Wang et al., "Short-term forecasting of vegetable prices based on LSTM model: Evidence from Beijing vegetable data," 2024.
[10] S. and R. Hemalatha, "AI-Driven Smart Farming: An Integrated Approach for Crop Advisory, Pest Detection, and Farmer Support Systems," 2025.
[11] Kadam, "SmartAgroHub: Market Place For Farmer-Customer Along with Crop Prediction and Chatbot," 2025.
[12] A. J. Medidi and D. M. K., "Agri Smart Farm To Market Made Easy," 2025.
[13] Banu, "AgriTrust: A Blockchain-Based Bidding System for Transparent and Secure Agricultural Trade," 2025.
[14] D. Patel, H. Nikam, P. Maurya, S. Varma, and A. Hingmire, "Enhancing Agri-Sustainability: Multimodal Recommendations for Demand-Supply Alignment," 2024.
[15] FarmLink, "FarmLink: AI-Powered Agricultural Decision Support System Report," 2026.
[16] M. S. Parab, "IoT Based Smart Agriculture Using Machine Learning," 2024.
[17] "Blockchain-Based Farmer-to-Consumer Platform," 2025.

INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN COMPUTER & COMMUNICATION ENGINEERING

9940 572 462 6381 907 438 ijircce@gmail.com

www.ijircce.com

Scan to save the contact details