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BLOCKCHAIN-ENABLED PREDICTIVE AGRICULTURE: ENSURING TRANSPARENCY AND ACCURACY IN AI-BASED CROP YIELD FORECASTING

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Abstract
Ensuring transparency and accuracy in crop yield forecasting has become a fundamental requirement for agriculture in the era of climate instability, data fragmentation, and rising global food insecurity. Traditional forecasting frameworks often rely on siloed datasets and centralized data handling, leading to concerns regarding data manipulation, poor traceability, and limited trust among stakeholders. This study proposes an integrated predictive agriculture framework that combines blockchain-based data provenance with advanced artificial intelligence techniques for crop yield prediction. Multisource datasets including agronomic inputs, IoT farm sensors, satellite-derived vegetation indices, meteorological variables, and soil profiles are immutably stored and verified using blockchain smart contracts. AI models utilize these tamper-proof datasets to generate reliable, high-resolution yield predictions. By integrating distributed ledger transparency, machine learning interpretability, and multispectral–climatic data fusion, the framework addresses critical challenges in agricultural monitoring such as data integrity, model accountability, and multi-actor trust. The results highlight that blockchain-enabled AI forecasting significantly improves prediction accuracy, mitigates data manipulation risks, enhances end-to-end traceability, and strengthens farmer and institutional confidence in decision-making. This architecture offers a scalable foundation for agricultural ministries, cooperatives, and global food security agencies to implement transparent, data-driven, and climate-resilient forecasting systems.
Keywords: blockchain agriculture, predictive forecasting, AI yield prediction, smart contracts, NDVI, data provenance, distributed ledger, agricultural transparency.

I. INTRODUCTION

The accelerating complexity of global agriculture has amplified the demand for transparent, accurate, and interoperable crop yield forecasting systems. As climatic volatility increases and extreme weather occurrences disrupt cropping cycles, the traditional forecasting pipelines dependent on manual reporting, historical datasets, or centralized government repositories have proven insufficient for modern food-security challenges. These models struggle to incorporate real-time multisource data, maintain traceability, and ensure data quality across complex supply chains and agronomic networks. Centralized data management introduces vulnerabilities resulting from delayed updates, inconsistent reporting, and susceptibility to tampering. At the same time, the rise of AI-driven forecasting has heightened the need for verified datasets, since predictive accuracy depends heavily on the integrity of input variables such as vegetation indices, soil-based parameters, climatic fluctuations, and farm-level management data. Blockchain technology, with its decentralized and immutable architecture, presents a promising solution to these challenges by providing transparent data provenance and verifiable, tamper-proof information pipelines. When fused with AI-based predictive modeling, blockchain transforms agricultural analytics into a trustworthy, end-to-end forecasting ecosystem capable of supporting national policy planning, farm-level decision-making, and global food security initiatives.

Recent advancements in distributed ledger systems have enabled multi-stakeholder collaboration where farmers, agronomists, research institutions, and governmental agencies contribute data into a shared, cryptographically secured environment. Satellite imagery, IoT sensors, meteorological data streams, soil characteristics, farm-management information, and transaction-based agricultural records can be recorded on the ledger to prevent data manipulation and ensure transparency. AI models trained on these authenticated datasets can interpret complex spatial-temporal relationships governing crop growth, detect anomalies in real time, and generate high-fidelity yield predictions. Integrating blockchain and AI not only enhances analytical precision but also ensures that all stakeholders trust the predictions due to immutable data lineage and automated validation via smart contracts. This synergy strengthens agricultural supply chains by reducing informational asymmetry, improving early-warning systems for crop failures, and enabling proactive resource allocation. By establishing a decentralized data infrastructure and leveraging AI-driven modeling, this study builds a robust predictive agriculture framework that ensures transparency, accountability, and scientific reliability in crop yield forecasting.

II. RELATED WORKS

The emergence of blockchain in agriculture has generated significant scholarly interest, particularly in enhancing supply-chain transparency, securing sensitive agronomic datasets, and improving trust across multi-actor networks. Foundational studies highlight blockchain's capability to provide decentralized storage, cryptographic hashing, and immutable data histories that prevent manipulation of agricultural records, ranging from seed provenance to farm-level environmental metrics [1]. Researchers demonstrated that blockchain-supported data collection mitigates inconsistencies caused by manual reporting or fragmented digital systems [2]. Other contributions emphasize the value of smart contracts for automated verification of data inputs, resource allocation, and quality assessment throughout agricultural cycles [3]. In parallel, extensive work in remote sensing has shown that vegetation indices such as NDVI and EVI are critical for monitoring biomass accumulation, chlorophyll concentration, and phenological progression across crop types [4]. Satellite-based monitoring has proven invaluable for detecting early stress signals, determining yield potential, and evaluating post-harvest performance across heterogeneous regions [5].

The integration of artificial intelligence into agricultural prediction has expanded analytical capabilities significantly. Machine learning and deep learning models, including Random Forests, Support Vector Machines, Gradient Boosting, and LSTM networks, have been widely used for modeling nonlinear interactions between climate variables, soil attributes, vegetation indices, and crop performance [6]. Studies demonstrated that ML-driven forecasting surpasses traditional regression-based models due to its ability to capture multi-dimensional data patterns, seasonal fluctuations, and region-specific growth trajectories [7]. Deep learning architectures, particularly sequential models, have shown strong performance in long-term forecasting where weather–yield dependencies evolve dynamically [8]. Research integrating soil moisture, evapotranspiration, hydrological indices, and microclimatic fluctuations further confirmed that multi-domain datasets can significantly enhance forecasting accuracy [9]. The literature consistently highlights the need for high-quality, multi-temporal datasets to ensure robustness in prediction models [10].

More recent research has begun merging blockchain with AI-based yield forecasting to address the challenges of data integrity, provenance, and reproducibility. Several interdisciplinary studies propose blockchain as a foundational infrastructure that ensures transparent and authenticated datasets for ML training [11]. Smart contracts have been used to automate real-time data collection from IoT sensors and enforce data-validation rules before the information becomes part of the predictive pipeline [12]. Other works emphasize combining blockchain-backed satellite observations with climatic time series to enhance cross-platform compatibility and create audit-ready forecasting frameworks [13]. Integrative studies further show that blockchain–AI systems improve accountability, facilitate multi-party trust, and reduce informational asymmetry across agricultural networks [14]. These hybrid systems outperform traditional forecasting setups by preventing data tampering, reducing dependency on centralized authorities, and improving traceability and interpretability of model outputs [15]. Collectively, existing literature affirms the potential of blockchain-enabled AI architectures to deliver transparent, accurate, and future-ready crop yield forecasting systems.

III. METHODOLOGY

3.1 Data Acquisition and Preprocessing

Multisource agricultural datasets were integrated into the blockchain-enabled forecasting framework. Satellite-derived inputs including NDVI, EVI, SAVI, NDWI, land surface temperature, and vegetation reflectance curves were extracted from Sentinel-2 and MODIS archives. IoT sensor data from soil moisture probes, pH monitors, nutrient sensors, and microclimatic devices were streamed into the system and cryptographically hashed for immutable storage. Meteorological datasets rainfall patterns, humidity levels, solar radiation, wind velocity, and evapotranspiration were obtained from national climatic repositories. Each dataset underwent blockchain-based timestamping, ensuring traceability and tamper-proof provenance. Standard preprocessing included radiometric correction, cloud masking, temporal interpolation, and normalization to unify spatial and temporal scales [16].

3.2 Blockchain Layer Integration

A permissioned blockchain architecture was deployed to maintain verifiable data logs. Smart contracts validated incoming sensor data, enforced format standards, and authenticated satellite-derived inputs through automated checks. Data were stored using an off-chain/on-chain hybrid approach: raw files remained in distributed storage while cryptographic hashes were stored on-chain. This ensured scalability while preserving immutability. Ledger-based provenance mapping enabled transparent data lineage tracking across the entire modeling pipeline [17].

Table 1. Key Variables Stored and Validated Through Blockchain

Data Source	Variables	Purpose
IoT Sensors	Soil moisture, pH, EC, temperature	Real-time ground conditions
Satellite Data	NDVI, EVI, LST, NDWI	Crop health and phenology
Meteorological Data	Rainfall, radiation, humidity	Climate-driven growth patterns
Soil Datasets	Organic carbon, texture	Static suitability factors
Farm Records	Crop type, inputs, practices	Management-level metadata

3.3 AI-Based Predictive Modeling

Machine learning models were developed using the blockchain-authenticated datasets. Random Forests, Gradient Boosting, SVR, and LSTM architectures were trained using 70:30 splits and five-fold cross-validation. Feature engineering emphasized vegetation dynamics, soil–water interaction, rainfall anomalies, temperature variability, and blockchain-validated metadata. Hyperparameter optimization used grid search to maximize predictive stability [18].

3.4 Data Synchronization and Feature Fusion

Temporal alignment of satellite, IoT, and climatic datasets was achieved through smart-contract-governed synchronization rules. Spatial aggregation was performed through geospatial tiling. A fused data cube architecture was constructed, combining vegetation indices, climatic sequences, soil features, and ledger-based metadata for each spatial grid cell [19].

Table 2. Model Training Configurations

Model	Key Parameters	Optimization
Random Forest	600 trees, max depth 12	Grid Search
Gradient Boosting	LR=0.04, 350 estimators	Cross-Validation
SVR	RBF kernel, C=12	Grid Search
LSTM	2 layers, 128 units	Adam Optimizer

3.5 Validation and Accuracy Assessment

Performance metrics included R^2, RMSE, MAE, and MAPE. Blockchain audit logs verified dataset integrity during validation, ensuring that only authenticated and untampered inputs were used. Ensemble weighting was applied to consolidate outputs from top-performing models [20].

IV. RESULTS AND ANALYSIS

4.1 Vegetation Dynamics and Blockchain-Provenance Insights

NDVI and EVI sequences revealed consistent phenological transitions and strong correlations with yield outcomes. Blockchain provenance logs confirmed full data traceability, eliminating uncertainty regarding input authenticity.

4.2 Climatic and Soil Interactions

Rainfall anomalies and LST variability produced significant impacts on predicted yield values. Soil moisture signals aligned with water-stress patterns and validated blockchain-stamped IoT readings.

Table 3. Correlation Patterns Across Blockchain-Verified Features

Variable	Region A	Region B	Region C	Region D
NDVI–Yield	0.81	0.85	0.79	0.82
EVI–Yield	0.77	0.82	0.73	0.78
Rainfall–Yield	0.64	0.69	0.58	0.66
LST–Yield	-0.55	-0.59	-0.52	-0.56

4.3 Model Accuracy Comparison

Gradient Boosting achieved highest accuracy, with Random Forests closely behind. Blockchain-based validation ensured consistent performance across regions.

Table 4. Model Performance Metrics

Model	R^2	RMSE	MAE	MAPE
Gradient Boosting	0.91	0.69	0.48	6.1%
Random Forest	0.89	0.76	0.54	7.0%
LSTM	0.86	0.88	0.60	8.0%
SVR	0.81	1.05	0.72	9.8%

V. CONCLUSION

This study introduces a blockchain-enabled predictive agriculture framework that integrates satellite imagery, IoT sensor feeds, meteorological datasets, soil attributes, and AI-based modeling to deliver transparent and highly accurate crop yield forecasting. The immutability and provenance guarantees offered by blockchain address long-standing challenges related to data manipulation, inconsistent reporting, and the fragmented nature of agricultural information systems. Smart contracts automate data validation, ensuring that all inputs feeding the prediction pipeline remain trustworthy, traceable, and verifiable. When combined with advanced machine learning models such as Gradient Boosting, Random Forests, and LSTMs, these authenticated datasets produce significantly improved yield predictions across diverse agro-climatic regions. The analysis highlights the strong predictive power of vegetation indices such as NDVI and EVI, alongside rainfall anomalies and thermal variations, which together form the backbone of modern predictive agriculture. Blockchain's ability to secure and document data lineage enhances trust in the forecasting results, enabling policymakers, cooperatives, and farmers to rely confidently on AI-generated insights for planning, resource optimization, and climate-resilience strategies. Overall, the integration of blockchain and AI establishes a scalable, decentralized, and scientifically robust paradigm for next-generation agricultural forecasting, offering a transformative pathway toward transparent and sustainable food-system management.

VI. FUTURE WORK

Future research may integrate multi-chain interoperability to allow agricultural ministries, meteorological agencies, and global food-security networks to exchange authenticated datasets seamlessly. Advanced AI architectures such as transformers and graph neural networks can further enhance spatial-temporal learning capabilities. Hybrid models combining process-based crop simulators with blockchain-secured machine learning pipelines may improve long-term climate adaptation forecasting. Expansion of sensor networks and on-chain geospatial registries will enable finer resolution analysis, while integration of market datasets, fertilizer logs, and irrigation-flow data can create holistic blockchain-enabled agricultural digital twins. Additionally, user-friendly mobile interfaces should be developed to provide farmers and policymakers with real-time, verifiable predictions derived directly from the decentralized forecasting engine.

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