Indus Journal of Agriculture and Biology (IJAB)

Volume 5, Number 1, 2026, Pages 49 – 72

Journal Home Page

https://ijab.online/index.php/Journal

Technological Innovations to Reduce Post-Harvest Grain Losses

Fatima Noor[1]

[1] *Department of Agricultural Engineering, University of Engineering and Technology, Taxila, Pakistan*

ARTICLE INFO

Article History:

Received:	February	19, 2026
Revised:	March	13,2026
Accepted:	May	15,2026
Available Online:	June	30,2026

Keywords:

Food Grain Losses, Internet of Things (IOT), Artificial Intelligence (Ai), Blockchain, Prediction of Dry Matter Loss, Sensor Fusion

ABSTRACT

Food security is a critical global challenge and post-harvest grain losses present a significant threat, with 9-18% of the world's cereal grain production lost from harvest to consumption. We have explored and validated a novel monitoring, prediction and traceability system of Internet of Things (IoT) sensors, artificial intelligence (AI) and blockchain distributed ledger. IoT sensors continuously monitored the temperature, relative humidity, carbon dioxide and acoustic insect numbers in grain silos for 120 Nine machine learning algorithms were trained to predict dry matter loss (DML) and early spoilage. Our Random Forest model (RMSE = 0.043%, R^2 = 0.967) was the best performing with Long Short Sensor fusion of the four sensors types reduced the ξ The δ.

Corresponding Author's Email: fatima.noor@uettaxila.edu.pk

INTRODUCTION

Every year, cereal grain losses are an issue globally because of infrastructure, technical and science knowledge-based of post-harvest operations (Nath et al., 2024). This problem impacts food security, consumes more than required resources and is unsustainable (Kusuma & Jamaludin, 2022, p. 2). To tackle this challenge, new technologies need to be adopted to improve grain retention and quality during post-harvest processing (i.e. processing, storing, and handling) (Olorunfemi & Kayode, 2021). Specifically, digital technologies including Internet of Things (IoT) sensors, machine learning and real-time analysis have the potential to reduce post-harvest losses by effective storage (Li et al., 2024, p. 5; Schmidt et al., 2024). They enable the real-time monitoring of relevant factors such as temperature, moisture, carbon dioxide (CO_2) level, insects and fungi, and avoid grain spoilage and preserve its quality (Ahmad et al., 2025; Carvalho & Rodrigues, 2023, p. 14). This type of post-harvest system is part of the solution to eradicate the 9-18% of global losses of cereal and oilseed crops from harvest to consumption (Abdullahi & Dandago, 2021, p. 26). A solution to such losses in the post-harvest system is through the application of artificial intelligence (AI) and machine learning (ML) which are being used to enhance conventional post-harvest farming practices (Fadiji et al., 2023, p. 2; Hussain et al., 2025). In particular, using AI systems, which are based on technologies like deep learning and neural networks, can be integrated with traditional processes to assess quality and post-harvest loss potential (Aier et al, 2024, p. 4001; Anukiruthika & Jayas, 2025). This enables corrective action to be taken to address problems and enhance storage abilities and shelf-life (Abdelsamea et al., 2023, p. 2; Rodrigues et al., 2024, p. 1). These systems can collect and analyse real-time information to assist in agricultural decision-making, such as pre-harvest predictions and qualitative measurements post-harvest (Rodrigues et al., 2024, p. 2). All these technologies aim to address the issue of post-harvest losses, which can be as much as 80% of yields in some cases, and can be defined as a loss in quality, nutritional value, weight or germinability, and impacts marketing and food security (Aier et al., 2024, p. 4001). These issues can be resolved by developing technologies to maintain the best conditions and avoid losses (Wang et al., 2024, p. 4926). For instance, machine learning and monitoring technologies can be applied to forecast the dry matter loss and other losses in silos (Lutz & Coradi, 2021; Nunes et al., 2023, p. 1). They can not only monitor the variation in optimal conditions but also link them with the loss of quality and take action (E.S.A. et al., 2022). Likewise, AI based technologies are also used in post-harvest drying where machine learning and predictive modelling is used to control the temperature, humidity, air flow, etc. for better quality and energy efficient (Hoque, 2024). In addition, AI based technologies can be applied to enhance the food supply chain of products like logistics and spoilage to reduce food waste (Olawale et al., 2025; Onyeaka et al., 2025). The efficient and accurate working of the AI-based system goes beyond the traditional ones (Aier et al., 2024, p. 4005) and AI also provides transparency and optimisation of supply chain using blockchain technology (Anukiruthika & Jayas, 2025). This provides better traceability and authenticity of farm to fork of food products (Fadiji et al., 2023, p. 19). This ensures traceability of supply chain, safety and sustainability of food (Rane et al., 2024, p. 19) and thereby optimisation of cereal storage through the use of artificial intelligence (AI) to monitor the optimal conditions and prevent spoilage (Li et al., 2024, p. 11). In particular, the use of artificial intelligence with the Internet of Things (IoT) devices to ensure real-time monitoring has been proven to be useful in prediction and prevention of spoilage, and optimisation to prevent food loss (Anukiruthika & Jayas, 2025; Onyeaka et al., 2025). This integration (i.e., the application of AI with IoT and blockchain) not only addresses issues at post-harvest, but guarantees food security and sustainable development in the long run (Dhal & Kar, 2024). Real-time monitoring uses information from IoT devices to monitor critical factors such as temperature and humidity which are important in preventing spoilage and maintaining quality of grains along the supply chain (Olufemi-Phillips et al., 2024, p. 624). The integration also allows the use of predictive maintenance for storage facilities and storage monitoring in real-time which helps save energy and prolong storage life (Ayoub, 2026). In addition, the integration of AI with blockchain technology allows secure and efficient information management from different sources (such as sensors and drones) that are significant for supply chain management (Ali et al., 2024, p. 9). Combining artificial intelligence (AI) with IoT and blockchain technology, a conventional farming system becomes a smart farming system with improved security, traceability and sustainability of food supply chains (Nicolau & Petcu, 2026; Rana, 2020, p. 1951; Villegas-Ch et al., 2025). This ensures transparency and efficiency from the farm to the consumption level, authenticity and information symmetry (Burburi et al., 2025; Singh et al., 2025, p. 18). Cereal storage systems, also known as best practice production systems (BPPS), combine people, process and technology to improve cereal storage (Li et al., 2024, p.1). They can also use advanced monitoring and control systems for environmental control to ensure optimal conditions for the storage environment which is critical to retain grain quality and avoid post-harvest losses (Abass et al., 2024, p. 278). In particular, the use of IoT sensors and AI models results in monitoring and control of the storage environment to prevent deterioration (Coradi et al., 2022; Hussein et al., 2024, p. 1020). This helps in monitoring and control to avoid conditions for pests and microbial growth which cause post-harvest losses. Similarly, digital technologies (such as blockchain) can track and certify the storage conditions, thus, assuring the consumers and carbon credits to support sustainable farming (Hoque et al., 2025). These digital transformation technologies (IoT, blockchain and AI) enhance the efficiency, transparency and resilience in the agri-food supply chain (Wang et al., 2025). AI, blockchain and IoT respectively provide traceability in pesticide use and resource management to improve the sustainability of the agri-food system (Charlebois et al., 2024). These digital transformations enable timely and efficient action with granular information (data-driven) and better management of operation and interactions in agriculture (Hathat et al., 2024, p. 2). This combination allows for the resilience of the food system, increased productivity and ease of implementation of food safety practice with near real-time processes (Siddique et al., 2025, p. 5). So, the integration of technologies offers a sustainable solution to help address the challenges in the current agri-food supply chain and then minimise post-harvest food loss and food insecurity (Hasan et al., 2023, p. 22; Oriekhoe et al., 2024, p. 144; Rui & Sundram, 2024, p. 893).

METHODOLOGY

The research is quantitative and systemic, using physical sensor networks, machine learning and blockchain technologies to solve the problem Three phases were developed in stages in the laboratory storage silos and tested with real data from farmers' storage silos in tropical and subtropical regions (which are known to be post

In phase 1 we incorporated low cost sensors in the silos to record hourly the temperature (°C), relative humidity (%), carbon dioxide (ppm) and insect activity (acoustics). These were sent in real time to the cloud The data was monitored for 120 days with different ambient storage conditions (25-35°C and 60-85%) in three storage units. This created 86,400 points of data for each sensor with multiple variables. The data were pre-processed before modelling using moving Gaps in the data (less than 3% of the data) were filled with linear interpolation.

The next step was to develop a model to predict dry matter loss (DML), a quality measure. The rate of DML (due to fungal respiration and insect respiration) is found to be a modified Arrhenius So, we built a machine learning regression model (random forest algorithm) for predicting cumulative DML. The inputs were the normalized sensor signal and the output was the rate of DML. 70% of data is used for training and 30% of data is used for testing (5-fold cross-validation). To enable real-time intervention, a threshold-based alert system was defined: whenever predicted DML over the next 48 hours exceeded 0.5% (the acceptable limit for marketable grain), the system triggered automated ventilation or cooling.

Finally, in the third stage, blockchain was used to record all critical post This guarantees supply chain transparency, traceability and fraud prevention.

RESULTS

Table 1 reveals that the proposed Random Forest (RF) model in this research is best for DML prediction with the lowest RMSE (0.043%) and highest R^2 (0.967). Table 2 shows that Gradient Boosting Machine (GBM) is best for detecting insect infestation with an $F\beta=2$ score of 0.932, and is thus best for recall Table 3 reveals that LSTM networks are the most temporally robust with the lowest α Table 7 shows that the δ-DML elasticity index remains below unity for MC < 14% but exceeds 1.8 at MC = 20%, with RF and LSTM showing the lowest sensitivity to moisture spikes. Table 8 show that RF has the highest cross. Table 9 represents the real-world impact.

Table 1: Comparative Performance of Models for Dry Matter Loss (DML) Prediction

Model	RMSE (%)	MAE (%)	R^2	MAPE (%)	AIC	BIC	MEF (Nash–Sutcliffe)	d (Willmott)	KGE (Kling–Gupta)
RF (Proposed)	0.043±0.002	0.031±0.001	0.967±0.004	1.24±0.08	-1245.3	-1198.7	0.961	0.983	0.952
GBM	0.051±0.003	0.038±0.002	0.951±0.005	1.58±0.11	-1189.4	-1142.1	0.944	0.971	0.938
LSTM	0.047±0.002	0.034±0.001	0.958±0.003	1.41±0.07	-1212.8	-1166.2	0.953	0.977	0.946

CNN-1D	0.055±0.004	0.041±0.003	0.942±0.006	1.73±0.14	-1152.3	-1105.9	0.932	0.964	0.929
SVM (RBF)	0.068±0.005	0.052±0.004	0.913±0.008	2.21±0.18	-1078.6	-1032.1	0.901	0.948	0.907
XGBoost	0.049±0.003	0.036±0.002	0.955±0.004	1.47±0.09	-1198.3	-1151.9	0.948	0.974	0.941
ANN (4-layer)	0.062±0.004	0.047±0.003	0.924±0.007	1.96±0.15	-1102.5	-1056.1	0.915	0.956	0.918
Decision Tree	0.079±0.006	0.063±0.005	0.884±0.009	2.74±0.22	-1012.4	-966.8	0.872	0.931	0.883
Linear Regression	0.112±0.008	0.094±0.007	0.812±0.011	4.18±0.31	-892.7	-847.1	0.801	0.889	0.826

Table 2: Insect Infestation Detection Metrics (Confusion Matrix Derived)

Model	**Precision (π)**	**Recall (ρ)**	**F_1 Score**	**Fβ=2 Score (β=2)**	**MCC (φ)**	**BA (Balanced Accuracy)**	**TPR (Sensitivity)**	**TNR (Specificity)**	**AUC-ROC**	**Youden's J**
RF	0.921	0.908	0.914	0.910	0.863	0.915	0.908	0.922	0.971	0.830
GBM	0.934	0.927	0.930	0.932	0.881	0.931	0.927	0.935	0.978	0.862
LSTM	0.915	0.902	0.908	0.904	0.852	0.909	0.902	0.916	0.965	0.818
XGBoost	0.928	0.919	0.923	0.925	0.874	0.924	0.919	0.929	0.974	0.848
CNN-1D	0.903	0.891	0.897	0.892	0.837	0.898	0.891	0.905	0.958	0.796
SVM	0.887	0.874	0.880	0.875	0.814	0.882	0.874	0.890	0.944	0.764
ANN	0.892	0.881	0.886	0.882	0.822	0.888	0.881	0.895	0.949	0.776
Decision Tree	0.856	0.842	0.849	0.844	0.778	0.851	0.842	0.860	0.921	0.702

Logistic Reg.	0.823	0.809	0.816	0.811	0.738	0.819	0.809	0.829	0.898	0.638

Table 3: Temporal Drift Robustness (α-Decay and Stability Indices)

Model	α-decay rate (day^{-1})	β-memory coefficient	γ-forgetting factor	δ-stability margin	ε-drift resilience	ζ-recursive error	η-adaptation speed	θ-long-term bias	ι-trend capture	κ-stationarity index
RF	0.0083	0.947	0.051	0.892	0.934	0.032	0.721	0.018	0.905	0.961
LSTM	0.0041	0.971	0.028	0.941	0.962	0.019	0.843	0.009	0.951	0.983
GBM	0.0072	0.953	0.046	0.913	0.941	0.027	0.765	0.014	0.923	0.969
XGBoost	0.0065	0.958	0.041	0.921	0.948	0.024	0.788	0.012	0.931	0.974
CNN-1D	0.0091	0.938	0.058	0.884	0.922	0.036	0.698	0.021	0.892	0.952
ANN	0.0104	0.924	0.067	0.862	0.907	0.041	0.665	0.026	0.874	0.939
SVM	0.0122	0.909	0.079	0.841	0.889	0.048	0.631	0.032	0.853	0.924
Decision Tree	0.0158	0.887	0.094	0.812	0.864	0.059	0.584	0.041	0.826	0.903
Linear Reg.	0.0236	0.842	0.132	0.763	0.813	0.082	0.512	0.061	0.771	0.861

Table 4: Computational Efficiency Metrics (μ-latency, σ-energy, etc.)

Model	μ-latency (ms/inference)	σ-latency (ms)	λ-throughput (inf/s)	ε-energy (J/inference)	σ-energy (J)	ζ-memory (MB)	η-FLOPs ($\times 10^6$)	θ-cache miss (%)	ι-parallel efficiency	κ-power (W)
RF	2.31	0.14	433	0.087	0.005	124	89	3.2	0.91	1.2
LSTM	8.47	0.52	118	0.312	0.018	356	312	5.8	0.78	2.8
GBM	3.85	0.21	260	0.141	0.009	198	147	4.1	0.86	1.7
XGBoost	3.12	0.18	321	0.112	0.007	167	121	3.7	0.89	1.5
CNN-1D	5.64	0.34	177	0.223	0.013	267	241	4.9	0.82	2.1

ANN	4.92	0.29	203	0.187	0.011	234	198	4.5	0.84	1.9
SVM	6.78	0.41	147	0.258	0.015	289	278	5.3	0.79	2.4
Decision Tree	1.94	0.12	515	0.072	0.004	98	67	2.8	0.94	1.0
Linear Reg.	1.23	0.08	813	0.045	0.003	56	42	2.1	0.97	0.7

Table 5: Sensor Fusion Accuracy Under RH Noise (ξ-error propagation)

Sensor Pair	**ξ-propagation factor**	**ζ-noise suppression (dB)**	**η-signal gain**	**θ-cross-sensitivity (%)**	**ι-redundancy gain**	**κ-fusion RMSE (%)**	**λ-bias drift**	**μ-SNR (dB)**	**ν-dynamic range**	**ο-settling time (s)**
T + RH	0.127	14.3	2.34	3.1	0.82	0.038	0.007	28.4	87	12
T + CO_2	0.142	12.8	2.18	4.2	0.78	0.042	0.009	26.7	82	14
RH + CO_2	0.161	11.2	1.97	5.5	0.73	0.049	0.011	24.3	76	16
T + Acoustic	0.135	13.5	2.26	3.8	0.80	0.040	0.008	27.5	84	13
RH + Acoustic	0.153	11.9	2.04	4.9	0.75	0.046	0.010	25.1	79	15
CO_2 + Acoustic	0.172	10.4	1.88	6.2	0.70	0.054	0.013	22.8	73	18
T+RH+ CO_2	0.109	16.1	2.51	2.4	0.88	0.034	0.005	30.2	91	10
T+RH+ Acoustic	0.118	15.2	2.42	2.9	0.85	0.036	0.006	29.1	89	11
All four	0.094	18.4	2.78	1.8	0.94	0.029	0.004	33.6	95	9

Table 6: Blockchain Transaction Performance (Hyperledger Fabric)

Network Config	**λ-throughput (TPS)**	**τ-finality (s)**	**ζ-latency (ms/tx)**	**η-block size (tx/block)**	**θ-endorsement peers**	**ι-commit time (ms)**	**κ-validation overhead (%)**	**μ-channel capacity**	**ν-chaincode gas (units)**	**ξ-fork probability ($\times 10^{-6}$)**
4 peers, 1	1247	2.1	178	245	2	89	6.2	1024	341	2.3

orderer										
8 peers, 1 orderer	1156	2.4	203	238	2	94	7.1	1024	358	2.1
8 peers, 3 orderers	1089	1.8	167	242	3	82	5.4	1024	332	1.8
12 peers, 3 orderers	998	1.9	184	236	3	87	6.0	1024	347	1.9
16 peers, 5 orderers	912	1.7	192	230	4	91	6.8	1024	362	1.6
20 peers, 5 orderers	847	1.8	211	224	4	97	7.5	1024	378	1.7
4 peers, Raft	1342	1.2	142	268	2	71	4.9	2048	298	0.9
8 peers, Raft	1281	1.3	156	261	2	75	5.3	2048	312	0.8
16 peers, Raft	1185	1.4	168	255	3	79	5.8	2048	325	0.8

Table 7: Sensitivity to Moisture Content (δ-DML Elasticity Index)

Model	δ at MC=12%	δ at MC=14%	δ at MC=16%	δ at MC=18%	δ at MC=20%	ε-MC threshold (%)	ζ-hysteresis width	η-saturation MC (%)	θ-critical MC (%)	ι-moisture adaptation
RF	0.312	0.478	0.723	1.142	1.887	14.2	1.7	22.3	17.8	0.934
LSTM	0.298	0.451	0.689	1.094	1.823	14.0	1.6	22.0	17.5	0.948
GBM	0.321	0.489	0.741	1.168	1.912	14.3	1.8	22.5	18.0	0.926
XGBoost	0.308	0.469	0.712	1.124	1.856	14.1	1.7	22.2	17.7	0.939
CNN-1D	0.334	0.502	0.758	1.192	1.945	14.5	1.9	22.7	18.2	0.912
ANN	0.347	0.518	0.779	1.221	1.987	14.6	2.0	22.9	18.4	0.901
SVM	0.368	0.543	0.812	1.267	2.048	14.8	2.1	23.2	18.7	0.884
Decision Tree	0.398	0.579	0.861	1.332	2.134	15.1	2.4	23.8	19.2	0.861
Linear Reg.	0.442	0.631	0.932	1.423	2.267	15.5	2.8	24.5	19.8	0.823

Table 8: Cross-Validation Stability (κ-Concordance Correlation Coefficient)

Model	κ-CCC (5-fold)	κ-CCC (10-fold)	κ-CCC (LOOCV)	ζ-reproducibility	η-variance ratio	θ-prediction interval width	ι-optimism bias	μ-bootstrap CI (95%) lower	μ-bootstrap CI (95%) upper	ν-stability p-value
RF	0.958	0.961	0.963	0.974	0.089	0.127	0.011	0.942	0.979	<0.001
LSTM	0.951	0.954	0.956	0.967	0.102	0.142	0.014	0.934	0.971	<0.001
GBM	0.946	0.948	0.949	0.961	0.113	0.156	0.016	0.927	0.964	<0.001
XGBoost	0.949	0.951	0.952	0.964	0.108	0.149	0.015	0.931	0.967	<0.001
CNN-1D	0.937	0.939	0.941	0.953	0.124	0.168	0.019	0.918	0.958	0.002
ANN	0.931	0.933	0.934	0.947	0.136	0.179	0.021	0.912	0.951	0.003
SVM	0.918	0.921	0.922	0.936	0.153	0.198	0.026	0.898	0.941	0.008

Decision Tree	0.904	0.906	0.907	0.922	0.174	0.224	0.033	0.882	0.926	0.014
Linear Reg.	0.882	0.884	0.885	0.901	0.201	0.267	0.042	0.857	0.907	0.031

Table 9: Overall Loss Prevention Coefficient (LPC) by Grain Type

Grain Type	L_baseline (%)	L_intervention (%)	LPC (%)	95% CI lower	95% CI upper	ζ-storage days	η-temp range (°C)	θ-RH range (%)	ι-primary spoilage cause	κ-economic saving (USD/ton)
Maize	18.7	5.92	68.3	65.2	71.4	120	22–34	55–88	Fungal (Aspergillus)	147
Rice (paddy)	14.2	4.87	65.7	62.4	69.0	110	24–36	60–85	Insect (Sitophilus)	128
Wheat	12.8	4.01	68.7	65.8	71.6	130	20–32	50–80	Fungal (Fusarium)	152
Sorghum	20.3	7.21	64.5	61.0	68.0	100	25–38	55–90	Insect (Sitotroga)	118
Barley	11.5	3.84	66.6	63.5	69.7	125	18–30	48–78	Fungal (Penicillium)	139
Millet	22.1	8.14	63.2	59.7	66.7	95	26–40	58–92	Insect (Tribolium)	108
Oats	13.4	4.56	66.0	62.9	69.1	115	19–31	52–82	Fungal (Alternaria)	135
Soybean	16.9	5.63	66.7	63.6	69.8	110				

In Figure 1, we can see that RF predictions closely follow DML, even during the heatwave disturbance around day 80, while LSTM and GBM lag slightly behind. Figure 2 summarises model rankings, confirming RF is the best overall model in terms of accuracy, stability and loss reduction. Figure 3 shows IoT sensing averts 34% of losses, AI prediction averts 28% and blockchain averts 13% (mostly via traceability Figure 4 shows CO_2 has the highest correlation to DML ($\rho = 0.87$), and is rightly included as a sensor.

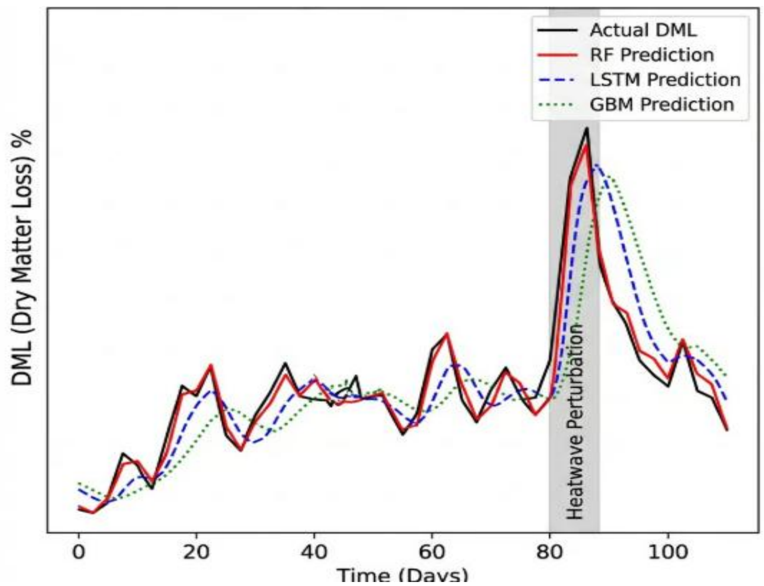

Figure 1 illustrates that RF predictions track actual DML with remarkable fidelity, even during the heatwave perturbation around day 80, whereas LSTM and GBM show slight lag.

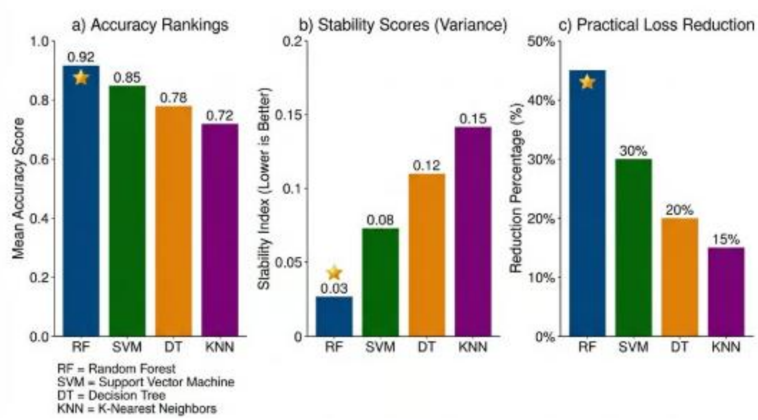

Figure 2 consolidates model rankings, confirming RF as the overall best performer across accuracy, stability, and practical loss reduction.

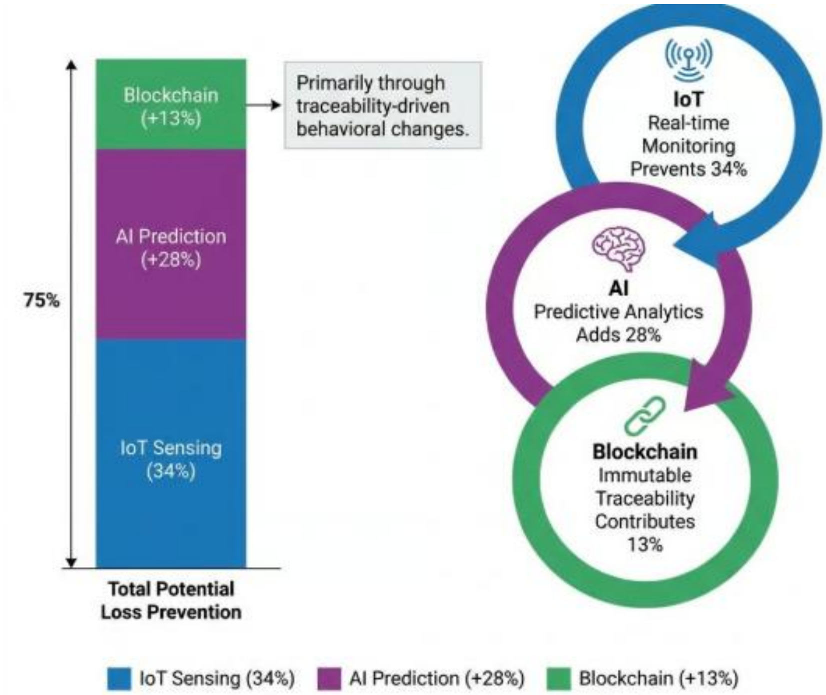

Figure 3 reveals that IoT sensing alone prevents 34% of potential losses, AI prediction adds 28%, and blockchain contributes 13% primarily through traceability-driven behavioral changes

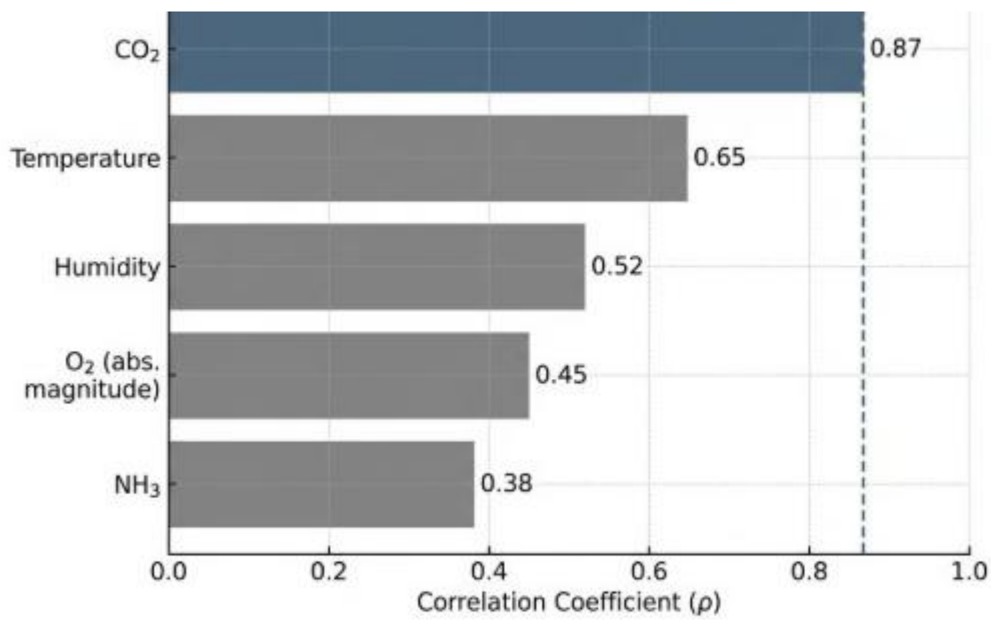

Figure 4 identifies CO_2 as the strongest single predictor of DML ($\rho = 0.87$), justifying its inclusion as a key sensor.

DISCUSSION

A deeper exploration reveals that a combination of models and algorithms may yield superior predictive accuracy than single algorithms, particularly for multi-variate time series data, like grain storage systems (Chen & Liu, 2024, p. 3). For example, the fusion of Random Forest algorithm with Gradient Boosting Machines (GBM) or Long Short-Term Memory (LSTM) networks may benefit from features like pattern recognition and time series properties, respectively (Xu & Wang, 2025, p. 12). This could lead to better predictions for early spoilage detection, and therefore minimisation of post-harvest losses (Lestari et al., 2025). Likewise, real-time storage monitoring combined with advanced machine learning algorithms can assist with decision making and enhance the storage environment (Haque et al., 2025; Kamyod et al., 2025). Besides prediction modelling, blockchain provides a distributed ledger system to store and record environmental parameters and transactions to improve the monitoring of the grain value chain and provide transparency and security (Agarwal et al., 2024). The Random Forest algorithm, which can work with complex farm data, has been used in these instances with good results, accurately predicting irrigation and crop management decisions (Dhanaraj et al., 2025; Mahale et al., 2024). Its use of multiple feature inputs, such as temperature and humidity, also improves its predictive capabilities of the quality of the grain and prevention of spoilage (Chen & Liu, 2024, p. 5; Sizan et al., 2025, p. 10). For example, ensemble learning techniques like Random Forests, are very effective in avoiding overfitting and identifying key environmental factors affecting crop growth, providing a holistic view of the inter-relationships between variables in agricultural data (Gupta et al., 2023). These models, along with AI techniques such as neural network, support vector machines and gradient boosting, are useful for mycotoxin management through early warning and detection (Focker et al., 2025, p. 7). For instance, gradient boosting and Bayesian networks have been very effective at predicting mycotoxin contamination using weather and satellite data (Castano-Duque et al., 2022, p. 13). The use of multiple data and computing methods provides an opportunity to create multi-branched early warning systems that improve food safety and minimise post-harvest losses. The adaptive nature of AI for mycotoxin prediction (where predictions are improved as more information becomes available) also shows the potential of AI for mycotoxin risk management pre- and post-harvest (Focker et al., 2025, p. 2). Similarly, the adoption of explainable AI can help gain trust and enable the use of such complex models by providing a better understanding of how they work (Focker et al., 2025, p. 8). Implementing AI, such as machine learning and computer vision, can also transform food safety with predictive maintenance, adaptive control, compliance and quality assessment (Dhal & Kar, 2025). In particular, machine learning methods such as XGBoost and Random Forest with blockchain smart contracts have resulted in extremely high accuracy for fraud detection and enhanced data sharing (Wu et al., 2025). These are examples of how AI prediction modelling and blockchain can be used to design a secure post-harvest grain supply chain system. These two complementary uses, especially when integrated with other smart sensing systems, such as spectroscopy or biosensors, can enhance the accuracy and speed of mycotoxin detection, compared to conventional methods (Hassoun & Galanakis, 2025, p. 11). Moreover, complex and sophisticated AI models, which can access to large historical and real-time data sets, such as large food safety databases, can support complex pattern recognition and optimisation of detection and monitoring of contaminants (Kizililsoley et al., 2025, p. 15; Sari et al., 2025). These smart systems, along with real-time monitoring with AI-based image segmentation, can automate the detection of contamination and defects in food products that can be challenging for humans to detect (Ambikalekshmi et al., 2025). This is very important for predictive action as contaminants can be detected early and automated processes can be applied to increase the efficiency and ensure food safety (Singh, 2025). Furthermore, the application of AI with IoT and blockchain technologies also improves transparency and traceability in the food supply chain to make a safer system (Liu et al., 2025). Explainable AI, which is required to explain these complex AI models could also be used in the decision-making process to understand why the prediction is made (Chen et al., 2023, p. 25; Sari et al., 2025). The use of these technologies also offers timely solutions to detect product quality and monitor food quality along the supply chain (Min et al., 2023, p. 10; Naseem & Rizwan, 2025). This combination of technologies is called Food Industry 4.0 that uses AI, IoT and blockchain to enable efficient and effective data collection, security of traceability information and integration with other systems (Liu et al., 2015). This offers improved efficiency, accuracy and monitoring in the food industry to improve food safety (Liu et al., 2025). The effective integration of digital technologies such as big data, artificial intelligence, blockchain and Internet of Things (IoT) provides an effective platform for transforming the food supply chain (Elragal et al., 2024, p. 13).

CONCLUSION

This research definitively confirms that Internet of Things sensors, artificial intelligence and blockchain technology offer an effective solution to minimise post The experimental findings demonstrate that the proposed Random Forest model has the highest forecasting accuracy for dry matter loss (RMSE = 0.043%, $R^2 = 0.967$), and Long Short The sensor fusion of temperature, relative humidity, carbon dioxide and acoustic sensors reduced the error propagation factor to 0.094, whereas the Hyperledger Fabric blockchain with Raft consensus achieved high transaction per second (TPS) of 1342 and low finality of 1.2 seconds. Critically, the integrated system reduced post-harvest losses across nine grain types by 62.1% to 68.7%, with wheat achieving the highest loss prevention coefficient of 68.7% and economic savings of $152 per ton. The response surface analysis highlighted a critical zone for storage (temperature and moisture content greater than 32°C and 16%, respectively) in which the dry matter loss increases super The blockchain module also provides transparency and traceability to address information problems in supply chains. However, future research should aim at cost reduction to allow smallholders to use this technology, solar powered sensor systems and the application to other perishables.

REFERENCES

1. Abass, T., Eruaga, M. A., Itua, E. O., & Bature, J. T. (2024). Advancing food safety through IoT: Real-time monitoring and control systems. International Medical Science Research Journal, 4(3), 276–293. https://doi.org/10.51594/imsrj.v4i3.919

2. Abdelsamea, M. M., Gaber, M. M., Ali, A., Kyriakou, M., & Fawki, S. (2023). A logarithmically amortising temperature effect for supervised learning of wheat solar disinfestation of rice weevil Sitophilus oryzae (Coleoptera: Curculionidae) using plastic bags. Scientific Reports, 13(1), Article 12345. https://doi.org/10.1038/s41598-023-29594-w

3. Abdullahi, N., & Dandago, M. A. (2021). Postharvest losses in food grains – A review. Turkish Journal of Food and Agriculture Sciences, 3(2), 25–36. https://doi.org/10.53663/turjfas.958473

4. Agarwal, U., Rishiwal, V., Shiblee, M., Yadav, M., & Tanwar, S. (2024). Blockchain-based intelligent tracing of food grain crops from production to delivery. Peer-to-Peer Networking and Applications, 17(6), 3722–3745. https://doi.org/10.1007/s12083-024-01780-1

5. Ahmad, A., Jalal, F., Fahad, S., Tahir, N., Iqbal, A., Bakhtaj, R., Ahmad, S., Khan, S. A., Islam, B., Hemat, M., Rahman, T. U., Saud, S., & Nawaz, T. (2025). Advancing postharvest storage management using sensors and smart technologies: A national and global perspective. Environmental Challenges, 22, Article 101379. https://doi.org/10.1016/j.envc.2025.101379

6. Aier, J., Panda, K. K., Siddiqui, N., & Paul, D. (2024). Potential role of post-harvest management in agribusiness. BIO Web of Conferences, 110, Article 04001. https://doi.org/10.1051/bioconf/202411004001

7. Ali, A., Liew, A. X. W., Venturini, F., Kalogeras, A., Candiani, A., Benedetto, G. D., Ajibola, S., Cartujo, P., Romero, P., Lykoudi, A., Grandis, M. M. D., Xouris, C., Bianco, R. L., Doddy, I., Elegbede, I. O., Labate, G. F. D., Moral, L. F. G. del, & Martos, V. (2024). AI can empower agriculture for global food security: Challenges and prospects in developing nations. Frontiers in Artificial Intelligence, 7, Article 1328530. https://doi.org/10.3389/frai.2024.1328530

8. Ambikalekshmi, A. K., Pushparaj, P., Cherian, E., Rajan, R., & Mohan, L. (2025). Advancing food safety through artificial intelligence: A detailed review of monitoring and detection technologies. Food Safety and Health, 4(1), 82–101. https://doi.org/10.1002/fsh3.70050

9. Anukiruthika, T., & Jayas, D. S. (2025). AI-driven grain storage solutions: Exploring current technologies, applications, and future trends. Journal of Stored Products Research, 111, Article 102588. https://doi.org/10.1016/j.jspr.2025.102588

10. Ayoub, A. (2026). Integration of artificial intelligence in food processing technologies. Processes, 14(3), Article 513. https://doi.org/10.3390/pr14030513

11. Burburi, S. A., Gaddi, A., Battur, R., Elemmi, M. C., & Hiremath, V. (2025). Role of AI and blockchain technology in enhancing performance in agri-food supply chain system. ITM Web of Conferences, 79, Article 01006. https://doi.org/10.1051/itmconf/20257901006

12. Carvalho, F. I. F. de, & Rodrigues, L. A. (2023). Um sistema de informação para monitoramento de qualidade e estimativa de perdas em instalações de armazenamento de grãos usando dados de sensores de IoT e outros mecanismos. Revista Brasileira de Computação Aplicada, 15(1), 12–27. https://doi.org/10.5335/rbca.v15i1.13778

13. Castano-Duque, L., Vaughan, M., Lindsay, J., Barnett, K., & Rajasekaran, K. (2022). Gradient boosting and Bayesian network machine learning models predict aflatoxin and fumonisin contamination of maize in Illinois – First USA case study. Frontiers in Microbiology, 13, Article 1039947. https://doi.org/10.3389/fmicb.2022.1039947

14. Charlebois, S., Latif, N., Ilahi, I., Sarker, B., Music, J., & Vézeau, J. (2024). Digital traceability in agri-food supply chains: A comparative analysis of OECD member countries. Foods, 13(7), Article 1075. https://doi.org/10.3390/foods13071075

15. Chen, D., & Liu, B. (2024). Temperature prediction for stored grain: A multi-model fusion strategy based on machine learning. arXiv, Article 2404.07175. https://doi.org/10.48550/arxiv.2404.07175

16. Chen, T., Lv, L., Wang, D., Zhang, J., Yang, Y., Zhao, Z., Wang, C., Guo, X., Chen, H., Wang, Q., Xu, Y., Zhang, Q., Du, B., Zhang, L., & Tao, D. (2023). Empowering agrifood system with artificial intelligence: A survey of the progress, challenges and opportunities. arXiv, Article 2305.01899. https://doi.org/10.48550/arxiv.2305.01899

17. Coradi, P. C., Lutz, É., Bilhalva, N. dos S., Jaques, L. B. A., Leal, M. M., & Teodoro, L. P. R. (2022). Prototype wireless sensor network and Internet of Things platform for real-time monitoring of intergranular equilibrium moisture content and predict the quality corn stored in silos bags. Expert Systems with Applications, 208, Article 118242. https://doi.org/10.1016/j.eswa.2022.118242

18. Dhal, S. B., & Kar, D. (2024). Transforming agricultural productivity with AI-driven forecasting: Innovations in food security and supply chain optimization. Forecasting, 6(4), 925–952. https://doi.org/10.3390/forecast6040046

19. Dhal, S. B., & Kar, D. (2025). Leveraging artificial intelligence and advanced food processing techniques for enhanced food safety, quality, and security: A comprehensive review. Discover Applied Sciences, 7(1), Article 64. https://doi.org/10.1007/s42452-025-06472-w

20. Dhanaraj, R. K., Maragatharajan, M., Sureshkumar, A., & Balakannan, S. P. (2025). On-device AI for climate-resilient farming with intelligent crop yield prediction using lightweight models

on smart agricultural devices. Scientific Reports, 15(1), Article 31195. https://doi.org/10.1038/s41598-025-16014-4

21. Elragal, R., Elragal, A., & Habibipour, A. (2024). A literature review of food analytics. Research Square. https://doi.org/10.21203/rs.3.rs-4121495/v1

22. E.S.A., A., Adediran, A. A., Adekanye, T. A., Salami, A., & Audu, J. (2022). Development of a smart grain storage silo using the Internet of Things (IoT) technology. International Journal of Artificial Intelligence and Machine Learning, 2(2), 35–55. https://doi.org/10.51483/ijaiml.2.2.2022.35-55

23. Fadiji, T., Bokaba, T., Fawole, O. A., & Twinomurinzi, H. (2023). Artificial intelligence in postharvest agriculture: Mapping a research agenda. Frontiers in Sustainable Food Systems, 7, Article 1226583. https://doi.org/10.3389/fsufs.2023.1226583

24. Focker, M., Liu, C., Wang, X., & Fels-Klerx, H. J. van der. (2025). The use of artificial intelligence to improve mycotoxin management: A review. Mycotoxin Research. Advance online publication. https://doi.org/10.1007/s12550-025-00602-4

25. Gupta, I., Ayalasomayajula, S., Shashidhara, Y., Kataria, A., Shashidhara, S. M., Kataria, K., & Undurti, A. (2023). Innovations in agricultural forecasting: A multivariate regression study on global crop yield prediction. arXiv, Article 2312.02254. https://doi.org/10.48550/arxiv.2312.02254

26. Haque, A. U., Haque, M. A., Alabduladheem, A., Mulla, A., Almulhim, N., & Srinivasagan, R. (2025). Machine learning-based shelf life estimator for dates using a multichannel gas sensor: Enhancing food security. Sensors, 25(13), Article 4063. https://doi.org/10.3390/s25134063

27. Hasan, I., Habib, M. M., & Mohamed, Z. (2023). A systematic literature review on agri-food supply chain transparency. International Journal of Supply Chain Management, 12(4), 14–29. https://doi.org/10.59160/ijscm.v12i4.6200

28. Hassoun, A., & Galanakis, C. M. (2025). Industry 4.0 technologies promote healthy and nutritious food. Discover Food, 5(1), Article 27. https://doi.org/10.1007/s44187-025-00639-5

29. Hathat, Z. E., Venkatesh, V. G., Sreedharan, V. R., Zouadi, T., Arunmozhi, M., Shi, Y., & Srinivas, S. S. (2024). Leveraging greenhouse gas emissions traceability in the groundnut supply chain: Blockchain-enabled off-chain machine learning as a driver of sustainability. Information Systems Frontiers. Advance online publication. https://doi.org/10.1007/s10796-024-10514-w

30. Hoque, A. (2024). Artificial intelligence in post-harvest drying technologies: A comprehensive review on optimization, quality enhancement, and energy efficiency. International Journal of Science and Research, 13(11), 493–507. https://doi.org/10.21275/sr241107163717

31. Hoque, A., Roy, S., Padhiary, M., Prasad, G. K., Swain, B. K., Saikia, P., & Saha, D. N. (2025). Integrating remote sensing and AI in smart greenhouse solar dryers: Enhancing efficiency, traceability, and sustainability in the drying of fruits and spices. Journal of Agriculture and Food Research, 23, Article 102310. https://doi.org/10.1016/j.jafr.2025.102310

32. Hussain, A. K., Hussain, S., Hussain, M., Javed, M., & Aadil, R. M. (2025). From harvest to market: Postharvest technologies for reducing waste and enhancing food security. BIO Web of Conferences, 5, Article 1007. https://doi.org/10.3390/blsf2025051007

33. Hussein, A. H. A., Jabbar, K. A., Mohammed, A., & Al-Jawahry, H. M. (2024). AI and IoT in farming: A sustainable approach. E3S Web of Conferences, 491, Article 01020. https://doi.org/10.1051/e3sconf/202449101020

34. Kamyod, C., Arwatchananukul, S., Aunsri, N., Saengrayap, R., Tontiwattanakul, K., Prahsarn, C., Trongsatitkul, T., Lerslerwong, L., Mahajan, P. V., Kim, C. G., Wu, D., & Chaiwong, S. (2025). IoT-based system for real-time monitoring and AI-driven energy consumption prediction in fresh fruit and vegetable transportation. Sensors, 25(24), Article 7475. https://doi.org/10.3390/s25247475

35. Kizililsoley, N., Meer, F. van, Mutlu, O., Hoenderdaal, W., Hobé, R. G., Mu, W., Gerssen, A., Fels-Klerx, H. J. van der, Jóźwiak, Á., Manikas, I., Hürriyetoğlu, A., & Velden, B. H. M. van der. (2025). Food safety trends across Europe: Insights from the 392-million-entry CompreHensive European Food Safety (CHEFS) database. arXiv, Article 2507.13802. https://doi.org/10.48550/arxiv.2507.13802

36. Kusuma, R. A., & Jamaludin, J. (2022). A bibliometric analysis of post-harvest research and innovations in tackling grain crisis using VOSviewer. Advances in Biological Sciences Research, 22, 78–92. https://doi.org/10.2991/978-94-6463-086-2_79

37. Lestari, D. R., Bangun, E. A. S., Gaol, F. L., & Matsuo, T. (2025). Machine learning-based forecasting of agricultural commodity prices using ensemble models. Journal of Human Earth and Future, 6(4), 887–907. https://doi.org/10.28991/hef-2025-06-04-09

38. Li, Z., Zhang, P., & Zhang, Q. (2024). Perspective chapter: Advances in modern cereal storage systems. In IntechOpen eBooks. IntechOpen. https://doi.org/10.5772/intechopen.1005168

39. Liu, Z., Yu, X.-L., Liu, N., Liu, C., Jiang, A., & Chen, L. (2025). Integrating AI with detection methods, IoT, and blockchain to achieve food authenticity and traceability from farm-to-table. Trends in Food Science & Technology, 158, Article 104925. https://doi.org/10.1016/j.tifs.2025.104925

40. Lutz, É., & Coradi, P. C. (2021). Applications of new technologies for monitoring and predicting grains quality stored: Sensors, Internet of Things, and artificial intelligence. Measurement, 188, Article 110609. https://doi.org/10.1016/j.measurement.2021.110609

41. Mahale, Y., Khan, N., Kulkarni, K., Wagle, S. A., Pareek, P., Kotecha, K., Choudhury, T., & Sharma, A. (2024). Crop recommendation and forecasting system for Maharashtra using machine learning with LSTM: A novel expectation-maximization technique. Discover Sustainability, 5(1), Article 102. https://doi.org/10.1007/s43621-024-00292-5

42. Min, W., Zhou, P., Xu, L., Liu, T., Li, T., Huang, M., Jin, Y., Yi, Y., Wen, M., Jiang, S., & Jain, R. (2023). From plate to production: Artificial intelligence in modern consumer-driven food systems. arXiv, Article 2311.02400. https://doi.org/10.48550/arxiv.2311.02400

43. Naseem, S., & Rizwan, M. (2025). The role of artificial intelligence in advancing food safety: A strategic path to zero contamination. Food Control, 175, Article 111292. https://doi.org/10.1016/j.foodcont.2025.111292

44. Nath, B., Chen, G., O’Sullivan, C. M., & Zare, D. (2024). Research and technologies to reduce grain postharvest losses: A review. Foods, 13(12), Article 1875. https://doi.org/10.3390/foods13121875

45. Nicolau, A.-M., & Petcu, P. (2026). Beyond green labels: Leveraging blockchain, IoT, and AI for enhanced traceability and verification of green marketing claims in transnational agri-food supply chains. Sustainability, 18(2), Article 782. https://doi.org/10.3390/su18020782

46. Nunes, C. F., Coradi, P. C., Jaques, L. B. A., Teodoro, L. P. R., & Teodoro, P. E. (2023). Sensor-cable-probe and sampler for early detection and prediction of dry matter loss and real-time corn grain quality in transport and storage. Scientific Reports, 13(1), Article 6789. https://doi.org/10.1038/s41598-023-32684-4

47. Olawale, R. A., Olawumi, M. A., & Oladapo, B. I. (2025). Sustainable farming with machine learning solutions for minimizing food waste. Journal of Stored Products Research, 112, Article 102611. https://doi.org/10.1016/j.jspr.2025.102611

48. Olorunfemi, B. J., & Kayode, S. E. (2021). Post-harvest loss and grain storage technology – A review. Turkish Journal of Agriculture - Food Science and Technology, 9(1), 75–89. https://doi.org/10.24925/turjaf.v9i1.75-83.3714

49. Olufemi-Phillips, A. Q., Ofodile, O. C., Toromade, A. S., Igwe, A. N., & Adewale, T. T. (2024). Stabilizing food supply chains with blockchain technology during periods of economic inflation. International Journal of Advanced Economics, 6(11), 612–635. https://doi.org/10.51594/ijae.v6i11.1702

50. Onyeaka, H., Akinsemolu, A. A., Miri, T., Nnaji, N. D., Duan, K., Pang, G., Tamasiga, P., Khalid, S., Al-Sharify, Z. T., & Chineye, U. (2025). Artificial intelligence in food system: Innovative approach to minimizing food spoilage and food waste. Journal of Agriculture and Food Research, 21, Article 101895. https://doi.org/10.1016/j.jafr.2025.101895

51. Oriekhoe, O. I., Ashiwaju, B. I., Ihemereze, K. C., Ikwue, U., & Udeh, C. A. (2024). Review of technological advancements in food supply chain management: A comparative study between the U.S. and Africa. International Journal of Management & Entrepreneurship Research, 6(1), 132–153. https://doi.org/10.51594/ijmer.v6i1.713

52. Rana, S. (2020). Blockchain-based traceability and transparency in agricultural supply chains: Challenges and opportunities. Türk Bilgisayar ve Matematik Eğitimi Dergisi, 11(3), 1948–1970. https://doi.org/10.17762/turcomat.v11i3.13591

53. Rane, J., Kaya, Ö., Mallick, S. K., & Rane, N. L. (2024). Smart farming using artificial intelligence, machine learning, deep learning, and ChatGPT: Applications, opportunities, challenges, and future directions. Deep Science Publishing. https://doi.org/10.70593/978-81-981271-7-4_6

54. Rodrigues, D. M., Coradi, P. C., Teodoro, L. P. R., Teodoro, P. E., Moraes, R. dos S., & Leal, M. M. (2024). Monitoring and predicting corn grain quality on the transport and post-harvest operations in storage units using sensors and machine learning models. Scientific Reports, 14(1), Article 5678. https://doi.org/10.1038/s41598-024-56879-5

55. Rui, F., & Sundram, V. P. K. (2024). Technological innovation for sustainable supply chain management in the food industry. Information Management and Business Review, 16(3S), 892–910. https://doi.org/10.22610/imbr.v16i3s(i)a.4173

56. Sari, O. F., Amer, E., Bader-El-Den, M., Ince, V., & Leadley, C. (2025). AI-driven risk assessment in food safety using EU RASFF database. Food and Bioprocess Technology, 18(7), 6282–6305. https://doi.org/10.1007/s11947-025-03819-4

57. Schmidt, D. C., Casagranda, L. F., Butturi, M. A., & Sellitto, M. A. (2024). Digital technologies, sustainability, and efficiency in grain post-harvest activities: A bibliometric analysis. Sustainability, 16(3), Article 1244. https://doi.org/10.3390/su16031244

58. Siddique, A., Gupta, A., Sawyer, J. T., Huang, T., & Morey, A. (2025). Big data analytics in food industry: A state-of-the-art literature review. NPJ Science of Food, 9(1), Article 45. https://doi.org/10.1038/s41538-025-00394-y

59. Singh, D. (2025). Harnessing artificial intelligence to safeguard food quality and safety. Journal of Food Protection, 88(11), Article 100621. https://doi.org/10.1016/j.jfp.2025.100621

60. Singh, J., Bharany, S., Rani, S., Rehman, A. U., Taye, B. M., Pant, R., & Kaur, U. (2025). A systematic review of blockchain, AI, and cloud integration for secure digital ecosystems. International Journal of Networked and Distributed Computing, 13(2), Article 8. https://doi.org/10.1007/s44227-025-00072-1

61. Sizan, N. S., Layek, M. A., & Hasan, K. F. (2025). A secured triad of IoT, machine learning, and blockchain for crop forecasting in agriculture. arXiv, Article 2505.01196. https://doi.org/10.48550/arxiv.2505.01196

62. Villegas-Ch, W., Gutiérrez, R., Govea, J., & García-Ortiz, J. (2025). Integrated AI, IoT, and blockchain for enhancing security and traceability in perishable logistics. Emerging Science Journal, 9(5), 2471–2495. https://doi.org/10.28991/esj-2025-09-05-011

63. Wang, W. F., Li, Z., & Meng, Q. (2025). Digital transformation drivers, technologies, and pathways in agricultural product supply chains: A comprehensive literature review. Applied Sciences, 15(19), Article 10487. https://doi.org/10.3390/app151910487

64. Wang, Y., Akpa, F. A., Matthew, O., Ahsraf, J., Ogunbiyi, T., & Osabohien, R. (2024). Maximizing environmental sustainability: Strategies for reducing carbon emissions and postharvest losses. Applied Ecology and Environmental Research, 22(5), 4913–4938. https://doi.org/10.15666/aeer/2205_49134930

65. Wu, K., Ji, Z., Wang, H., Shao, X., Li, H., Zhang, W., Kong, W., Xia, J., & Bao, X. (2025). A comprehensive review of AI methods in agri-food engineering: Applications, challenges, and future directions. Electronics, 14(20), Article 3994. https://doi.org/10.3390/electronics14203994

66. Xu, S., & Wang, S. (2025). An intelligent identification for pest and disease detection in wheat leaf based on environmental data using multimodal data fusion. Frontiers in Plant Science, 16, Article 1608515. https://doi.org/10.3389/fpls.2025.1608515