International Journal of Computational Research in Science and Technology
E-ISSN: 3108-0871, Volume 2 Issue 5
Sep-Oct- 2026, PP 01-06

Artificial Intelligence In The Food Industry: A Review Of Quality Inspection, Spoilage Prediction, Demand Forecasting And Traceability

Galande Atharva Satish[1]; Prof. N. G. Rokade[2]; Prof. M. C. Kolse[3]; Prof. S. K. Said[4]
Department Of Artificial Intelligence And Data Science Jaihind College Of Engineering Pune, Maharashtra, Indi

Abstract—The food industry must produce safe, fresh and affordable food for a growing population while reducing waste and cost, yet roughly one-third of food produced is lost or wasted. Many operations such as sorting, inspection, storage monitoring and demand planning are still performed manually, which makes them slow, inconsistent and dependent on human experience. This paper reviews how Artificial Intelligence supports food producers, processors, retailers and restaurants. It examines computer vision and convolutional neural networks for quality grading and defect inspection, electronic noses and IoT sensors combined with machine learning for spoilage detection and shelf-life prediction, time-series forecasting for demand planning, and digital traceability, including blockchain pilots, for food safety. Classical neural-network applications in food science and recent deep learning reviews are surveyed. A five-layer AI food management architecture with image capture, sensor monitoring, analytics modules, alerts and a traceability dashboard is proposed, with research gaps, objectives, a comparison of techniques and a discussion of challenges including variable natural products, data scarcity, hygiene constraints and cost for small enterprises. The review concludes that AI can improve consistency, reduce waste and strengthen food safety across the supply chain.

Index Terms—Artificial intelligence, food industry, computer vision, quality inspection, shelf-life prediction, demand forecasting, food waste, traceability

I. Introduction

Food passes through many hands between farm and plate: harvesting, grading, processing, packaging, storage, transport, retail and cooking. At each stage, quality can deteriorate and products can be lost. The FAO estimated that about one-third of food produced for human consumption is lost or wasted globally [1]. In India, gaps in cold chains and manual handling contribute significantly to post-harvest losses.

Many quality and planning decisions still rely on human judgement: a worker sorts fruit by eye, a manager estimates how much to order, and spoilage is noticed only when a product smells bad. Artificial intelligence can make these decisions faster, more consistent and data-driven. Min *et al.* [2] describe “food computing” as the use of computational methods to analyse food data across the supply chain.

This paper reviews AI applications in the food industry and proposes an integrated architecture.

II. Related Work

Brosnan and Sun [3] reviewed computer vision for food quality inspection and showed that image analysis could measure colour, size, shape and surface defects of fruits, vegetables, meat and grains more consistently than human inspectors. Ma *et al.* [4] updated this review, highlighting hyperspectral imaging that reveals internal quality and contamination.

Zhou *et al.* [5] reviewed deep learning in food, including CNN-based recognition, quality grading and adulteration detection, and found that deep models generally outperform hand-crafted features when enough labelled data exist. Kakani *et al.* [6]

International Journal of Computational Research in Science and Technology
E-ISSN: 3108-0871, Volume 2 Issue 5
Sep-Oct- 2026, PP 01-06

reviewed computer vision and AI across the food industry and discussed practical deployment issues such as lighting and hygiene. Kamilaris and Prenafeta-Boldú [7] surveyed deep learning in agriculture, the starting point of the food chain.

For spoilage, Loutfi *et al.* [8] reviewed electronic noses, arrays of gas sensors combined with pattern recognition, for detecting freshness and spoilage of meat, fish and other products. For planning, the Prophet model [9] forecasts demand with trend and seasonal components such as festivals and weekends.

For traceability, Kamath [10] described pilots in which a large retailer used blockchain to trace pork and mangoes, reducing the time to trace a product's origin from days to seconds. Table I summarizes these works.

TABLE I Summary of Literature Survey

Ref.	Method	Key Findings	Limitations
[3]	Computer vision quality inspection	Consistent measurement of external quality	Hand-crafted features
[4]	Advances in food computer vision	Hyperspectral internal quality	Expensive equipment
[5]	Review of deep learning in food	DL outperforms traditional features	Labelled data needed
[6]	Review of CV and AI in food	Deployment considerations	Survey only
[8]	Electronic noses for food	Freshness and spoilage detection	Sensor drift
[11]	ANNs in food science	Modelled complex food relationships	Small datasets
[10]	Blockchain traceability pilots	Seconds-level origin tracing	Industry case study
[2]	Survey of food computing	Unified view of food data analysis	Broad scope

III. Preliminaries

3.1 Application Areas

Fig. 1 summarizes the main application areas: quality inspection, spoilage and shelf-life prediction, demand forecasting, process control and traceability.

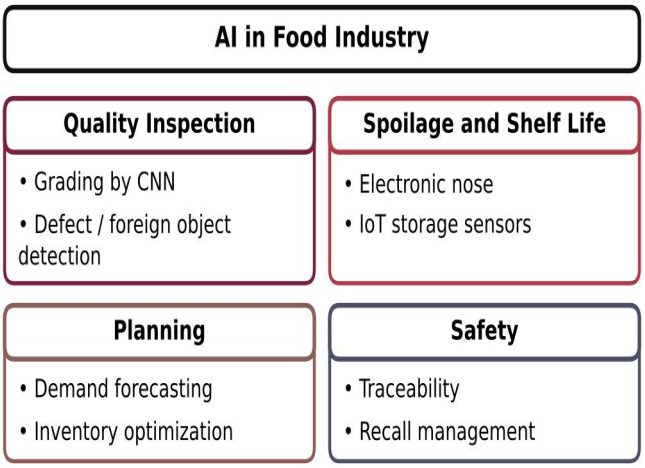


Fig. 1. AI application areas in the food industry.

International Journal of Computational Research in Science and Technology
E-ISSN: 3108-0871, Volume 2 Issue 5
Sep-Oct- 2026, PP 01-06

3.2 Data Sources

Data include RGB and hyperspectral images, readings from temperature, humidity and gas sensors, sales records and supply-chain events. Huang *et al.* [11] showed early on that artificial neural networks can model complex relationships in food science data.

IV. Problem Statement and Objectives

4.1 Identified Research Gaps

- **G1:** Natural variability in food makes models trained on one variety or season less reliable on others.
- **G2:** Labelled datasets for Indian produce and dishes are limited.
- **G3:** Shelf-life models rarely combine sensor data with storage history across the supply chain.
- **G4:** Small and medium enterprises lack affordable, integrated AI solutions.
- **G5:** Few studies measure actual reductions in waste after deploying AI.

4.2 Objectives of the Review

- 1. To review AI techniques for food quality inspection and spoilage detection.
- 2. To examine demand forecasting and traceability applications.
- 3. To propose an integrated five-layer AI food management architecture.
- 4. To compare techniques in accuracy, cost and practicality.
- 5. To identify challenges and future directions.

4.3 Proposed Framework

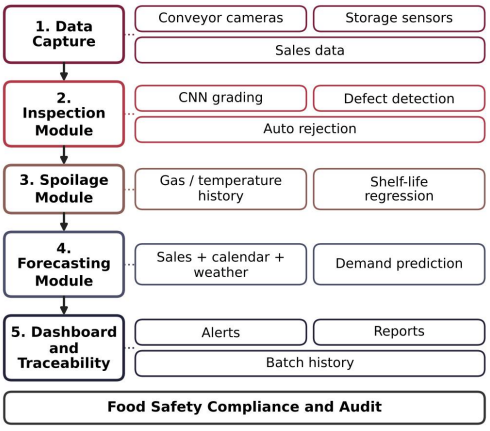


Fig. 2 shows the proposed architecture.

Fig. 2. Proposed five-layer AI food management architecture.

International Journal of Computational Research in Science and Technology
E-ISSN: 3108-0871, Volume 2 Issue 5
Sep-Oct- 2026, PP 01-06

4.4 Data Capture Layer

Cameras on conveyor belts photograph products; IoT sensors in storage rooms and trucks record temperature, humidity and gases such as ammonia or ethylene.

4.5 Inspection Module

A CNN classifies each item into grades and detects defects such as bruises, mould or foreign objects, triggering automatic rejection.

4.6 Spoilage and Shelf-Life Module

Sensor histories feed a regression model that estimates remaining shelf life; an alert is raised when the estimate falls below a threshold.

4.7 Demand Forecasting Module

Sales, calendar and weather data feed a time-series model that predicts demand to guide ordering and production.

4.8 Dashboard and Traceability Layer

Managers view quality statistics, alerts, forecasts and batch histories; each batch's journey is recorded for recalls and audits.

V. Working Methodology

Fig. 3 outlines the workflow. Shelf life is often modelled with first-order kinetics, in which a quality attribute Q decays as

$$Q(t) = Q_0 \cdot e^{(-k\,t)} \quad (1)$$

where the rate k depends on temperature according to the Arrhenius relation $k = A \cdot e^{(-E_a/RT)}$. Machine learning can learn these relationships directly from sensor data when kinetic parameters are unknown. Forecast accuracy is measured by mean absolute percentage error

$$MAPE = (100/n)\,\Sigma\,|y_i - \hat{y}_i| / y_i \quad (2)$$

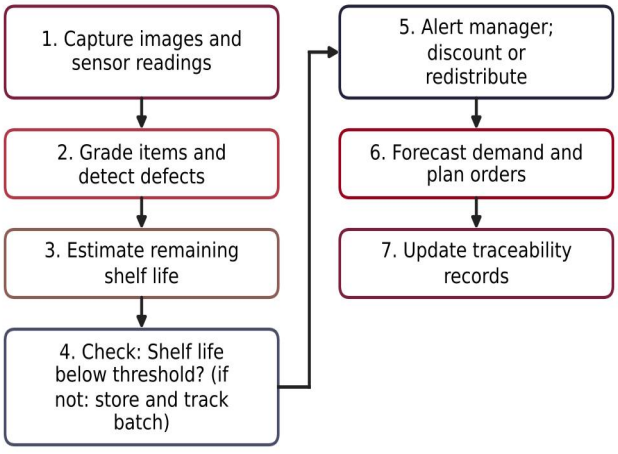


Fig. 3. AI-based food quality and planning workflow.

International Journal of Computational Research in Science and Technology
E-ISSN: 3108-0871, Volume 2 Issue 5
Sep-Oct- 2026, PP 01-06

VI. Discussion

6.1 Comparison of Approaches

Table II compares techniques. CNN vision is accurate for surface quality, hyperspectral imaging reveals internal defects at higher cost, electronic noses detect spoilage gases, and time-series models reduce over-ordering.

TABLE II Comparison of AI Techniques in the Food Industry

Technique	Purpose	Cost	Maturity
CNN vision	Surface quality, defects	Low–Medium	High
Hyperspectral + ML	Internal quality	High	Medium
Electronic nose + ML	Spoilage detection	Medium	Medium
Time-series forecasting	Demand planning	Low	High
Blockchain traceability	Origin tracking	Medium	Emerging

6.2 Open Challenges and Future Work

Table III summarizes challenges. Future directions include low-cost smartphone-based inspection for small vendors, AI-driven dynamic pricing to sell near-expiry food, robotics for hygienic handling and nutrition-aware recommendation for consumers.

Challenge	Mitigation
Natural variability	Diverse training data; periodic retraining
Data scarcity	Transfer learning; data sharing
Hygiene constraints	Non-contact sensing; washable enclosures
Cost for small firms	Smartphone and cloud solutions
Sensor drift	Regular calibration

TABLE III Challenges and Mitigation

VII. Conclusion and Future Work

AI can make the food supply chain more efficient, safer and less wasteful. The reviewed literature shows that computer vision delivers consistent quality inspection, sensor-based models predict spoilage, forecasting reduces over-production, and digital traceability speeds recalls. Integrating these capabilities in an affordable system, adapted to local produce and conditions, can help food businesses deliver fresh and safe food at lower cost.

7.1 Acknowledgment

The authors express their sincere gratitude to the Department of Artificial Intelligence and Data Science, Jaihind College of Engineering, Pune, for providing the facilities, guidance and encouragement needed to carry out this work. The authors also thank the faculty members and colleagues whose valuable suggestions helped improve the quality of this review.

References

1. J. Gustavsson, C. Cederberg, U. Sonesson, R. van Otterdijk, and A. Meybeck, Global Food Losses and Food Waste: Extent, Causes and Prevention. Rome, Italy: FAO, 2011.

2. W. Min, S. Jiang, L. Liu, Y. Rui, and R. Jain, "A survey on food computing," ACM Comput. Surv., vol. 52, no. 5, Art. no. 92, 2019.
3. T. Brosnan and D.-W. Sun, "Improving quality inspection of food products by computer vision—A review," J. Food Eng., vol. 61, no. 1, pp. 3–16, 2004.
4. J. Ma, D.-W. Sun, J.-H. Qu, D. Liu, H. Pu, W.-H. Gao, and X.-A. Zeng, "Applications of computer vision for assessing quality of agri-food products: A review of recent research advances," Crit. Rev. Food Sci. Nutr., vol. 56, no. 1, pp. 113–127, 2016.
5. L. Zhou, C. Zhang, F. Liu, Z. Qiu, and Y. He, "Application of deep learning in food: A review," Compr. Rev. Food Sci. Food Saf., vol. 18, no. 6, pp. 1793–1811, 2019.
6. V. Kakani, V. H. Nguyen, B. P. Kumar, H. Kim, and V. R. Pasupuleti, "A critical review on computer vision and artificial intelligence in food industry," J. Agric. Food Res., vol. 2, Art. no. 100033, 2020.
7. A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," Comput. Electron. Agric., vol. 147, pp. 70–90, 2018.
8. A. Loutfi, S. Coradeschi, G. K. Mani, P. Shankar, and J. B. B. Rayappan, "Electronic noses for food quality: A review," J. Food Eng., vol. 144, pp. 103–111, 2015.
9. S. J. Taylor and B. Letham, "Forecasting at scale," Amer. Statistician, vol. 72, no. 1, pp. 37–45, 2018.
10. R. Kamath, "Food traceability on blockchain: Walmart's pork and mango pilots with IBM," J. Br. Blockchain Assoc., vol. 1, no. 1, 2018.
11. Y. Huang, L. J. Kangas, and B. A. Rasco, "Applications of artificial neural networks (ANNs) in food science," Crit. Rev. Food Sci. Nutr., vol. 47, no. 2, pp. 113–126, 2007.