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FOOD SAFETY AND FRESHNESS THROUGH THE EYES OF ARTIFICIAL INTELLIGENCE: SURVEY, TRENDS, AND CHALLENGES

Niven Ahmad Alibraheem[1], Dr. Mohamad Shady Alrahhal[2]
[1]*Faculty of Technical Engineering, Department of Food Engineering Technologies, Aleppo University, Syrian Arab Republic*
[2]*AIMD Lab, College of Computing, Department of Computer Science, Fahad Bin Sultan University, Saudi Arabia*

***Corresponding Author:** Niven Ahmad Alebrahim*

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ABSTRACT

***Importance of AI and DL**: The integration of Artificial Intelligence (AI) and Deep Learning (DL) into food safety and freshness monitoring is revolutionizing the food industry by enabling real-time, data-driven quality control. This paper explores key AI applications – including electronic nose systems for meat freshness evaluation, computer vision for defect detection, intelligent packaging with smart sensors, and blockchain, enabled traceability, that enhance food safety while reducing waste.*

***AI-based Solutions and Challenges:** AI-driven solutions such as predictive analytics for dynamic shelf-life estimation, hyperspectral imaging for contamination detection, and automated sorting systems demonstrate superior accuracy over traditional methods. However, challenges like sensor reliability, data variability, high implementation costs, and regulatory compliance remain barriers to widespread adoption.*

***Future Trends in Terms of Sustainability:** Emerging trends highlight the potential of edge AI, federated learning, and explainable AI (XAI) to improve scalability and consumer trust. The future of food safety lies in smart, interconnected systems that ensure transparency, efficiency, and sustainability across the supply chain. By addressing current limitations, AI and DL can transform food quality management, delivering safer, fresher, and more sustainable food products to global markets.*

KEYWORDS: *Food Safety and Freshness, Artificial Intelligence, Deep Learning, Electronic Nose, Smart Packaging, Predictive Analytics, Intelligent Traceability, Real-Time Monitoring.*

1. INTRODUCTION

Food is a necessary demand for life of humans. In this context, food safety and freshness are considered major indicators that contribute to make people healthy. On opposite side, providing food with poor quality attributes leads to illness or even to death especially when it comes to talking about food of children or food provided to sick people [1]. For this reason, monitoring quality of food in terms of safety and freshness is critical issue for food-based companies.

1.1. Terms and Definitions

Food Safety: The scientific discipline focused on handling, preparing, and storing food in ways that prevent foodborne illnesses. It involves controlling hazards such as microbial contamination, chemical residues, and physical hazards.

Food Freshness: The quality of food in terms of appearance, texture, flavor, and nutritional value, indicating its suitability for consumption. Freshness is closely linked to shelf life and degradation processes like microbial growth, oxidation, and enzymatic activity.

Food Packaging: The system that protects food from chemical, biological, and physical deterioration, ensuring its safety, freshness, and desirable sensory attributes (flavor, texture, appearance) throughout its expiration life.

Food Quality Indicator: an observable parameter, such as microbial levels, chemical compounds, or physical characteristics, that reflects the safety, freshness, or overall quality of a food product or its production process. These indicators, which can be organisms, metabolic byproducts, or chemical substances, are measured to monitor and assess food quality and shelf life, predict spoilage, and ensure compliance with safety and quality standards.

1.2. Traditional Food Safety and Freshness Systems

There are many traditional systems that are widely used by companies to evaluate food safety and freshness, as described below.

1) **Visual Inspection:** A manual assessment of food quality based on observable characteristics such as color, texture, odor, and visible mold or spoilage [2].

   Problems
   - Highly subjective and dependent on human judgment.
   - Cannot detect microbial contamination, toxins, or chemical hazards that are invisible to the naked eye.
   - Inconsistent across different inspectors, leading to potential safety risks.
2) **Expiration Date Labeling (Use-By/Sell-By Dates):** A printed date indicating the estimated period during

which food is expected to remain safe and retain quality under proper storage conditions [3].

Problem

- Static dates do not account for variations in storage conditions (e.g., temperature abuse, humidity).
- Leads to unnecessary food waste if products are discarded prematurely.
- Does not guarantee safety if food is mishandled before the expiration date

3) **Manual Temperature Checks (Using Thermometers & Logbooks):** Periodic measurement and recording of storage temperatures (e.g., in refrigerators, freezers, or transport vehicles) to ensure food remains within safe limits [4].

Problem

- Time-consuming and prone to human error (e.g., missed readings, incorrect logging).
- Lacks real-time monitoring, increasing the risk of unnoticed temperature fluctuations.
- Inefficient for large-scale operations where continuous monitoring is needed.

4) **Chemical Preservatives (Traditional Additives for Shelf-Life Extension):** The use of synthetic or natural chemical compounds (e.g., sodium benzoate, sulfites, nitrites) to inhibit microbial growth and delay spoilage [5].

Problem

- Some preservatives may pose health risks (e.g., allergies, carcinogenic concerns).
- Consumer demand for "clean-label" products is reducing acceptance of synthetic additives.
- Overuse can lead to resistant microbial strains, reducing effectiveness.

As observed above, these traditional methods, while widely used, have significant limitations that modern technologies aim to address for improved food safety and freshness. This means that there is a pressing need to move towards sophisticated systems that employ advanced technologies, such as Internet of Things (IoT), Artificial Intelligence (AI), and Deep Learning (DL).

2. EMPLOYING ARTIFICIAL INTELLIGENCE FOR FOOD SAFETY AND FRESHNESS

This section provides a taxonomy of artificial intelligence systems that are developed to monitor quality of food in terms of safety and freshness. It is organized so that an overview of artificial intelligent techniques is provided firstly. Then, an indicator-based taxonomy (Gases-Based, Images-Based, Color-Based, and Packaging-Based) is presented. Finally, a comparison between traditional and advanced monitoring systems is discussed.

2.1. Overview of Artificial Intelligence Systems

Artificial Intelligence (AI) Systems: AI systems are computer-based technologies designed to simulate human intelligence by performing tasks such as reasoning, learning, decision-making, and problem-solving. These systems use algorithms and data to recognize patterns, make predictions, and automate complex processes without explicit human programming for every scenario.

Deep Learning (DL) Systems: Deep learning is a specialized branch of machine learning that uses artificial neural networks (ANNs) with multiple layers (hence "deep") to model complex patterns in large datasets. These systems automatically extract hierarchical features from raw data, making them highly effective for tasks like image recognition, speech processing, and predictive analytics [6, 7, 8].

In the context of employing both AI and DL for food safety and freshness

To enhance food safety and freshness using Artificial Intelligence (AI) and Deep Learning (DL), organizations must integrate AI-driven solutions into key stages of the food supply chain from production to consumption [9]. Below is a structured approach to aligning food safety objectives with AI technologies:

1) AI for Real-Time Food Quality Monitoring [10]

Goals

- Detect spoilage, contamination, and freshness degradation in real time.
- Reduce reliance on manual inspections and static expiration dates.

AI Solutions

- **Computer Vision & Hyperspectral Imaging**:
  - ✓ AI-powered cameras and sensors analyze color, texture, and chemical changes (e.g., detecting mold, bacterial growth).
  - ✓ Example: Smart packaging with freshness indicators scanned by AI.
- **Electronic Noses (E-Noses) & Gas Sensors**
  - ✓ AI models detect volatile organic compounds (VOCs) emitted by spoiled food (e.g., ammonia in fish, ethylene in fruits).
- **IoT + AI for Temperature & Humidity Tracking**
  - ✓ AI predicts shelf-life adjustments based on real-time storage conditions.

2) DL for Predictive Analytics & Shelf-Life Optimization [11]

Goals

- Predict spoilage risks before they occur.
- Optimize "use-by" dates dynamically based on storage conditions.

DL Solutions

- **Deep Learning (DL) Models**
  - ✓ Train models on historical spoilage data (temperature, humidity, microbial growth) to forecast shelf life.
  - ✓ Example: DL adjusts expiration dates for dairy products based on real-time cold chain data.

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- **DL for Traceability**
  - ✓ DL analyzes supply chain data to identify contamination sources faster (e.g., pinpointing a Salmonella outbreak).
- **DL for Foreign Object Detection**
  - ✓ Neural networks detect metal, plastic, or glass in food processing lines.

Table 1 summarizes the general stages of developing a monitoring system using AI and DL, where an implementation roadmap consist of four steps\stages. The provided roadmap is considered a common one to develop intelligent monitoring systems.

Table 1: A Roadmap for Implementation of AI Monitoring Systems for Food Safety and Freshness.

Step	Action	AI Technology
1. Data Collection	Gather historical spoilage, sensor, and supply chain data.	IoT
2. Model Training	Train AI on freshness indicators (images, gas emissions, temperature logs).	ML, Deep Learning
3. Deployment	Integrate AI into food processing lines, smart packaging, and cold storage.	Edge AI, Cloud AI
4. Continuous Learning	Use feedback loops to improve AI accuracy over time.	Reinforcement Learning

2.2. Taxonomy of Intelligent Monitoring Systems

In the context of food freshness and safety, this work provides an indicator based classification of monitoring of food quality when using artificial intelligence technology. Figure 1 illustrates the provided taxonomy.

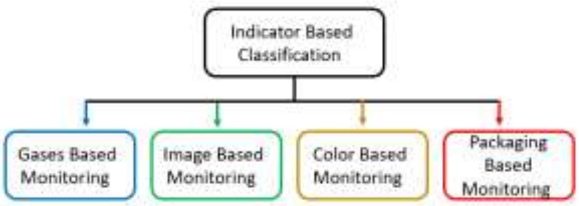

Figure 1: Classification of Intelligent Food Safety and Freshness Systems.

Before providing explanation of each group, it is worth mentioning that all AI based system follow the same common strategy in building such systems, as shown in Figure 2.

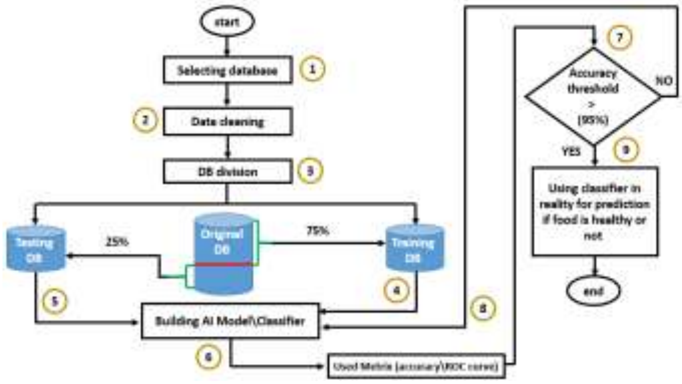

Figure 2: Common Strategy of Building AI Based Systems.

As shown in Figure 2, there are nine steps involved in the strategy. The most important step is selecting the data set used to train the intelligent model. In this context, there are many repositories available online for usage by researchers, such as UCI, which is a deep learning repository with a large collection of datasets in various disciplines. However, there is a golden chance to create a novel dataset related to food safety and freshness by collecting training data from sensors lined to the material\food under monitoring. The output of the system is the accuracy of prediction. Here, we can talk about binary classification (i.e., healthy food or not) or about multi-classification (i.e., the degree to which the food under monitoring is healthy based on a given threshold).

The strategy mentioned above is incorporated within a comprehensive system overview that starts from production of food, passing transportation, and reaching to retail stage. Figure 3 illustrates the comprehensive view of monitoring systems integrated with advanced technologies.

Figure 3: Comprehensive View of Monitoring Systems Integrated with Advanced Technologies [12]

The most important layer included in Figure 3 is food safety detection, where the systems differ in the way used to monitoring food quality based on the groups described below.

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First Group: Gases Based Monitoring

It is also called Electronic Nose (E-Nose) is an AI-powered sensor system that mimics the human olfactory system to detect and analyze volatile organic compounds (VOCs) emitted by food [13]. For chicken meat quality evaluation, it identifies spoilage markers such as:

- Ammonia (NH_3) – Produced by bacterial decomposition.
- Hydrogen Sulfide (H_2S) – Indicates microbial spoilage.
- Trimethylamine (TMA) – A fishy odor linked to bacterial growth.
- Ethanol & Acetic Acid – Byproducts of microbial metabolism.

Figure 4 below illustrates the general architecture of such systems.

How It Works

- **Sample Exposure**: Fresh or spoiled chicken is placed in a controlled chamber.
- **Gas Sensing**: An array of chemical sensors (e.g., metal oxide, electrochemical, or polymer-based) reacts to VOCs.
- **Data Processing**: AI (machine learning/deep learning) analyzes sensor responses to classify freshness levels.
- **Output**: Real-time freshness score (e.g., "Fresh," "Spoiled," or "Marginally Acceptable").

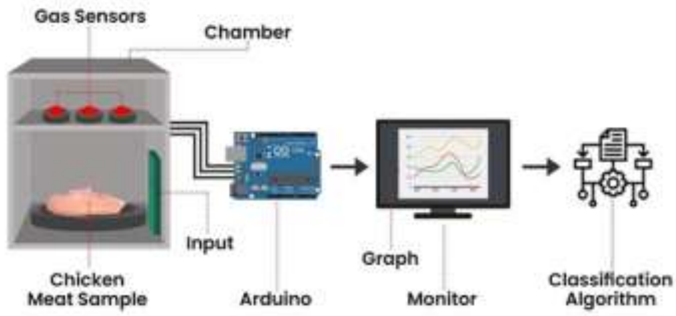

Figure 4: General Architecture of Intelligent Gases Based Monitoring Systems [14].

AI & Machine Learning Integration

- Supervised Learning: Trains models on labeled datasets (fresh vs. spoiled chicken).
- Pattern Recognition: Algorithms like PCA (Principal Component Analysis) and SVM (Support Vector Machines) distinguish spoilage stages.
- Deep Learning: CNNs or RNNs improve accuracy by learning complex VOC patterns.

Advantages Over Traditional Methods

There are several advantages of such systems when compared to traditional ones, as summarized in Table 2.

Table 2: Advantages of Intelligent Gases Based Monitoring Systems.

Method	Traditional (Lab Tests/Sensory Panels)	E-Nose + AI
Speed	Hours to days (microbial culturing)	Minutes (real-time detection)
Accuracy	Subjective (human error in sensory tests)	Objective (AI-driven classification)
Cost	Expensive (lab equipment, reagents)	Lower operational cost (portable devices)
Automation	Manual sampling required	Fully automated (IoT integration possible)

Second Group: Image Based Monitoring

Deep Learning (DL)-based intelligent food quality evaluation leverages artificial neural networks (ANNs) to automatically assess food safety, freshness, and authenticity by analyzing multi-modal data (images, spectral signals, chemical sensors, etc.) [15]. Unlike traditional methods, DL models extract high-level features without manual intervention, enabling real-time, non-destructive, and highly accurate food inspection.

Figure 5 below illustrates the general architecture of such systems.

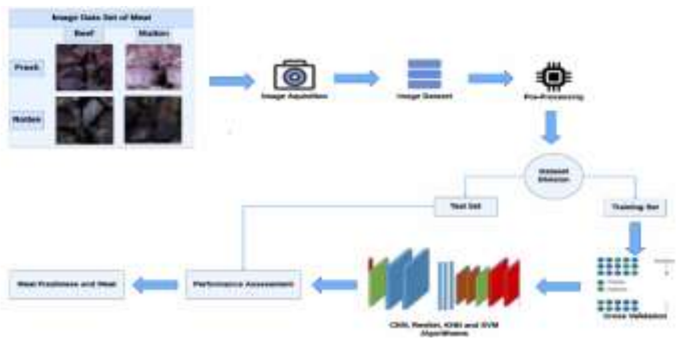

Figure 5: General Architecture of Intelligent Image Based Monitoring Systems [16].

How It Works:

- CNNs analyze pixel-level patterns (texture, shape).
- Trained on labeled datasets (e.g., fresh vs. rotten fruits, mold detection in grains).

AI & Machine Learning Integration:

- Convolutional Neural Networks (CNNs) for Visual Inspection.
- Recurrent Neural Networks (RNNs) & LSTMs for Time-Series Data, where it processes sequential data (temperature logs, gas sensor readings), and then predicts shelf life by learning degradation patterns.
- Deep Spectral Analysis (Hyperspectral & NIR Imaging). DL models (e.g., autoencoders) analyze spectral signatures (400–2500 nm), where it identifies adulteration (e.g., melamine in milk, fake honey).

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Advantages Over Traditional Methods

There are several advantages of such systems when compared to traditional ones, as summarized in Table 3.

Table 3: Advantages of Intelligent Image Based Monitoring Systems.

Feature	Traditional Methods	DL-Based Evaluation
Accuracy	Moderate (human error)	High (AI-driven)
Speed	Slow (lab tests)	Real-time processing
Automation	Manual intervention needed	Fully automated
Scalability	Limited to small batches	Handles large-scale data
Cost Efficiency	High (reagents, labor)	Lower long-term costs

Third Group: Color Based Monitoring

Color-based Deep Learning (DL) for food quality evaluation uses artificial neural networks to analyze color changes in food products, which are strong indicators of freshness, ripeness, spoilage, and contamination [17]. Unlike traditional calorimetry (e.g., spectrophotometers), DL models automatically extract complex color patterns from images, enabling real-time, non-destructive, and high-precision food inspection.

Figure 6 below illustrates the general architecture of such systems.

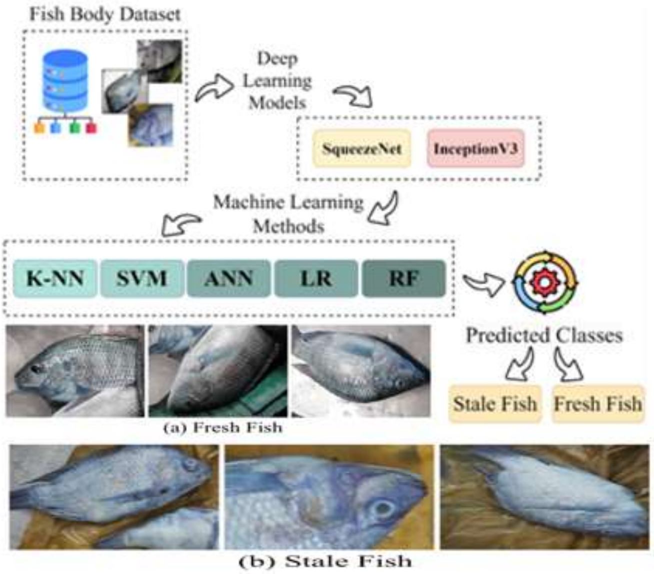

Figure 6: General Architecture of Intelligent Color Based Monitoring Systems [18].

How It Works

- Meat (e.g., chicken turns gray when spoiled).
- Fruits (e.g., banana peel darkens with ripening).
- Tomatoes (green → red).
- Avocados (darkening of skin).
- Mold (blue/green spots on bread).
- Discoloration due to oxidation (browning of apples).

AI & Machine Learning Integration

- **Convolutional Neural Networks (CNNs)**: Classifies food quality based on RGB/HSV color spaces.
- **Vision Transformers (ViTs):** Processes high-resolution food images for fine-grained color analysis.
- **U-Net (Semantic Segmentation):** Identifies localized discoloration (e.g., bruises on apples).

Advantages Over Traditional Methods

There are several advantages of such systems when compared to traditional ones, as summarized in Table 4.

Table 4: Advantages of Intelligent Color Based Monitoring Systems.

Feature	Traditional Calorimetry	DL-Based Color Analysis
Accuracy	Limited to pre-defined thresholds.	Learns complex color patterns.
Speed	Slow (lab-based instruments).	Real-time (embedded in cameras).
Automation	Manual calibration needed.	Fully automated.
Adaptability	Fixed color ranges.	Adjusts to new food types via retraining.

Fourth Group: Packaging Based Monitoring

Intelligent food packaging integrates advanced sensors, indicators, and AI-driven systems to monitor food quality in real time [19]. Unlike traditional packaging, which only provides passive protection, smart packaging actively tracks freshness, detects spoilage, and communicates food safety information to consumers and suppliers.

Figure 7 below illustrates the general architecture of such systems.

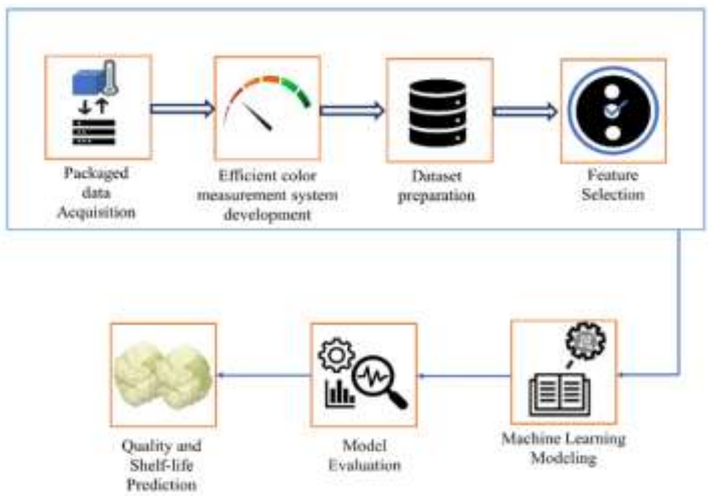

Figure 7: General Architecture of Packaging Based Monitoring Systems [19].

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How It Works: Actually, it combines methodologies of previous systems groups as follows:

- **Gas Sensors (Electronic Noses):** Detect spoilage markers (ammonia, CO_2, ethanol).
- **pH & Temperature Sensors:** Monitor microbial growth and storage conditions.
- **Colorimetric Indicators:** Change color based on food degradation (e.g., freshness labels for meat).

AI, IoT & Machine Learning Integration

- **Predictive Analytics:** AI models forecast shelf life based on sensor data.
- **Computer Vision and IoT:** Scans QR codes of IoT sensors or visual indicators to assess food quality.
- **Blockchain Traceability:** Ensures transparency in supply chain monitoring.

Applications on Food Safety and Freshness

There are several application of such systems when using advanced technologies, as summarized in Table 5.

Table 5: Applications of Smart Packaging with Advanced Technologies.

Application	Technology Used	Example
Real-Time Freshness Monitoring	Gas sensors + AI	Detects spoiled meat in vacuum-sealed packs.
Dynamic Expiration Dates	IoT temperature logs + ML	Adjusts "best before" dates based on storage conditions.
Tamper & Leak Detection	RFID/NFC tags	Alerts if packaging is compromised.
Consumer Interaction	QR codes + smartphone AI	Scans packaging for freshness status.

3. FUTHURE TRENDS AND CHALLENGES

Using advanced technologies to enhance the monitoring process that detects quality of food in terms of safety and freshness reveals many challenges. This section summarizes the future trends and challenges.

1) ***Real-Time Quality Monitoring with Smart Sensors & AI***
   - **Trend**: AI-powered electronic noses, hyperspectral imaging, and IoT sensors detect spoilage markers (e.g., gases, color changes) in real time [20].
   - **Challenge**: **Sensor accuracy** can be affected by environmental factors (humidity, temperature). **High costs** for deploying IoT infrastructure in supply chains.
2) ***Dynamic Expiration Dates Using Predictive AI***
   - **Trend**: ML models adjust "best before" dates based on real-time storage conditions (temperature, humidity) [21].
   - **Challenge**: **Data variability** (different food types, storage conditions) requires extensive training datasets. **Consumer trust** in AI-generated dates over traditional labels.
3) ***AI-Powered Contamination & Fraud Detection***
   - **Trend**: DL models analyze spectral, image, and genomic data to detect pathogens, adulterants, and counterfeit food [22].
   - **Challenge**: **Limited labeled datasets** for rare contaminants (e.g., new food fraud techniques). **Regulatory hurdles** for AI-based detection replacing lab tests.
4) ***Autonomous Food Sorting & Grading with Computer Vision***
   - **Trend**: CNN-based systems classify food quality (e.g., ripeness, defects) in processing plants [23].
   - **Challenge**: **Lighting & occlusion issues** in industrial environments. **Model bias** if trained on limited food varieties.
5) ***Blockchain + AI for Supply Chain Transparency***
   - **Trend**: AI analyzes blockchain-tracked data to trace contamination sources and optimize freshness [24].
   - **Challenge**: **Integration complexity** across fragmented supply chains. **Data privacy concerns** in shared blockchain networks.

To provide a comprehensive picture related to the future trends and corresponding challenges, that helps researchers to define some topics of researches, the following table summarizes them. It is worth mentioning that working on such challenges and employing such advanced technology contributes effectively to enhance sustainability of developing countries, such as my home country (Syria).

Table 6: Trend, AI\DL Role, and Major Challenges.

Trend	AI/DL Role	Major Challenge
Real-Time Monitoring	Gas/color analysis	Sensor reliability & cost
Dynamic Expiry Dates	Predictive ML	Data variability & trust
Contamination Detection	Spectral/image DL	Scarce labeled data
Autonomous Sorting	Computer Vision	Lighting/occlusion errors
Blockchain + AI	Data analytics	Supply chain fragmentation

Possible Solutions

In responding to the challenges listed above, the following possible solutions can be used:

- Federated learning to improve AI models without centralized data.
- Edge AI for low-cost, real-time processing in food facilities.
- Explainable AI (XAI) to build regulatory and consumer trust.

4. CONCLUSION

When it comes to talking about the future of AI & Deep Learning in food safety and freshness, the integration of Artificial Intelligence (AI) and Deep Learning (DL) into food safety and freshness monitoring represents a transformational shift from traditional, manual methods to smart, data-driven systems. Across the various applications discussed, from electronic noses for meat quality evaluation to AI-powered intelligent packaging, these technologies offer real-time, accurate, and automated solutions that enhance food safety, reduce waste, and improve supply chain transparency. The conclusion of this work can be listed in the following points:

- **AI & DL Enable Real-Time Monitoring**
  - ✓ Technologies like electronic noses, hyperspectral imaging, and IoT sensors detect spoilage and contamination faster than lab-based methods.
- **Dynamic Freshness & Shelf-Life Prediction**
  - ✓ Machine Learning models adjust expiration dates based on storage conditions, reducing food waste.
- **Automated Quality Control & Fraud Detection**
  - ✓ Computer Vision and DL classify food defects, ripeness, and adulteration with high precision.
- **Smart Packaging & Consumer Interaction**
  - ✓ AI-driven indicators and QR codes provide real-time freshness updates to consumers.
- **Blockchain and AI for Traceability**
  - ✓ Ensures end-to-end transparency in food supply chains, helping track contamination sources.

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