International Research Journal of Engineering and Technology (IRJET) e-ISSN: 2395-0056
Volume: 12 Issue: 12 | Dec 2025 www.irjet.net p-ISSN: 2395-0072

A Review on Design And Implementation of Food Spoilage Detection System Using Deep Learning

Prof. K. K. Ingole [1], Avantika Maske [2], Pradnya Wanjari[3], Vaidehi Rakas [4], Vaishnavi Tupate [5]

Department of Artificial Intelligence & Data Science K. D. K. College of Engineering Nagpur, India

---

Abstract— *Food freshness is vital for safety, nutrition, and reducing waste, yet traditional checks like visual inspection or expiry labels are unreliable, while lab methods are costly and impractical. These gaps contribute to hidden health risks and massive global food waste. The project proposes a real-time freshness detection system using biosensors, gas sensors, smart packaging, and machine learning, with IoT integration for supply chain transparency. This approach offers accurate, scalable monitoring, timely alerts, and predictive insights. Benefits include safer consumption, reduced economic losses, lower environmental impact, and stronger consumer trust, bridging the gap between subjective methods and advanced, data-driven solutions.*

Keywords— Food spoilage detection, Deep learning, Convolutional neural networks (CNNs), Image-based freshness assessment, food monitoring, Smart food quality systems, Food safety, Real-time monitoring

I. INTRODUCTION

Food quality, especially freshness, is essential for health, consumer trust, and economic stability. Traditional methods of assessing freshness—such as sensory checks or expiry labels—are unreliable, while laboratory techniques, though accurate, are costly and impractical for large-scale use. As foods often travel long distances through complex supply chains, spoilage risks increase due to microbial growth, enzymatic activity, and environmental factors like temperature and humidity. This leads not only to hidden health hazards but also to significant food waste, which undermines food security, causes financial losses, and contributes to environmental problems such as greenhouse gas emissions.

Recent technological advances offer solutions through biosensors, chemical sensors, smart packaging, and IoT systems that enable real-time monitoring and traceability. Combined with machine learning, these tools can analyse large datasets, predict spoilage, and shift quality control from reactive to proactive. The benefits include safer consumption, reduced economic losses, improved supply chain efficiency, and progress toward sustainability goals.

This project aims to design a software-based freshness detection system using deep learning and computer vision, bridging the gap between subjective traditional methods and modern, data-driven approaches. By enabling accurate, scalable, and predictive monitoring, it supports consumer safety, reduces waste, and strengthens trust in food quality standards.

II. PROBLEM STATEMENT AND OBJECTIVES

The proposed system is designed to address critical challenges in monitoring and managing food freshness. The key problems it aims to solve are:

A. **Unreliable Freshness Checks** – Traditional methods like visual inspection, odour tests, and expiry labels are subjective and often fail to detect early spoilage.

B. **High Cost of Laboratory Testing** – Accurate lab techniques are resource-intensive, slow, and impractical for real-time or large-scale monitoring.

C. **Hidden Health Risks** – Food may appear acceptable externally while harbouring microbial contamination, posing serious safety hazards to consumers.

D. **Food Waste and Sustainability Challenges** – Spoilage leads to premature disposal, economic losses, and contributes to global food waste and environmental damage.

To effectively overcome the challenges of unreliable freshness checks, hidden health risks, and food waste, the system is designed with the following goals:

1) Reliable Monitoring – Detect spoilage early with objective, technology-driven methods.
2) Real-Time Detection – Use ML and IoT for fast, scalable freshness checks.
3) Protect Health – Catch hidden microbial or chemical risks to prevent illness.
4) Cut Waste – Extend shelf life, reduce disposal, and support sustainability.

III. BACKGROUND: THE LINGUISTICS OF FOOD SPOILAGE DETECTION SYSTEM

Food spoilage is a major challenge that affects consumer health, market stability, and global sustainability. Traditional methods of checking freshness—such as sensory inspection or expiry labels—are unreliable, while laboratory tests are accurate but costly and unsuitable for

real-time monitoring. As food travels through long supply chains, hidden microbial and chemical changes often go undetected, leading to health risks and large amounts of waste.

Modern approaches using biosensors, smart packaging, IoT, and machine learning provide objective, scalable, and predictive monitoring of spoilage indicators. By turning subjective judgments into measurable data, these technologies aim to improve safety, reduce losses, and build a more sustainable food ecosystem.

IV. TABLE -1: LITERATURE REVIEW

Ref. No.	Author(s) & Year	Title/ Focus	Key Contribution/ Relevance
1)	Zhang, Y., Cai, Z., et al. (2025)	Intelligent Gas Sensors for Food Safety	Reviews MOS, polymer, and sensor arrays for detecting food spoilage gases, useful for sensor selection.
2)	Kabir, A., et al. (2025)	Hyperspectral Imaging and Deep Learning for Fruits and Vegetables	Discusses imaging + AI methods for non-destructive freshness detection, relevant to integrating ML.
3)	Yang, S., et al. (2025)	Food Safety and Traceability Using Blockchain	Explores blockchain for food traceability, relevant for supply chain transparency.
4)	Wang, L., et al. (2024)	Hyperspectral Imaging Aiding AI	Combines hyperspectral imaging with AI for quality control, supports AI-based freshness detection.
5)	Kumar, A., et al. (2024)	Biosensors for Detecting Food Contaminants	Overview of biosensors for detecting contaminants, relevant for microbial spoilage detection.
6)	Alaba, O., et al. (2024)	IoT Services for Monitoring Food Supply Chains	Discusses IoT-enabled monitoring systems, important for freshness tracking.
7)	Pandiselvam, R., et al. (2024)	Colorimetric Food Freshness Indicators	Reviews intelligent packaging indicators for visual freshness monitoring.
8)	Damdam, A. N., Ozay, et al. (2023)	IoT-Enabled Electronic Nose System for Beef	Presents IoT-based e-nose (CO_2, NH_3, C_2H_4 sensors) for beef spoilage detection.
9)	Ma, M., Yang, X., Ying, X., et al. (2023)	Gas Sensing in Food Quality Detection	Comprehensive review of MOX, SAW, and AI-based gas sensors for freshness detection.
10)	Bhardwaj, J., et al. (2023)	Electrochemical Enzyme-Based Biosensors	Describes biosensors for food & beverage analysis,

			relevant for detecting spoilage enzymes.
11)	Zhang, Y., et al. (2023)	Vegetable and Fruit Freshness Detection with Deep Features	Applies deep learning and classification networks for freshness detection.
12)	Husáková, L., et al. (2023)	Electrochemical Biosensors for Food Safety	Reviews biosensors for microbial and chemical safety indicators in foods.
13)	Chowdhury, N., et al. (2022)	IoT in Cold Chain Monitoring	IoT-enabled monitoring for cold storage, useful for supply chain freshness assurance.
14)	Chen, Q., et al. (2022)	Intelligent Food Freshness Indicators	Review of advances in intelligent packaging-based freshness indicators.
15)	Sunny, A. I., et al. (2022)	IoT with Blockchain in Food Supply Chain	Shows how IoT + blockchain can ensure safe and transparent food tracking.
16)	Ma, X., Yang, X., Ying, X., et al. (2022)	Gas Indicators and Sensors in Smart Packaging	Reviews common gases (O_2, CO_2, NH_3) and sensors in packaging.
17)	Mikuła, K., et al. (2021)	Single Nanowire Gas Sensor	Demonstrates gas sensors for distinguishing meat and fish freshness.
18)	Cen, H., et al. (2020)	Visible-NIR Spectroscopy for Fruits/Vegetables	Non-destructive spectroscopy for postharvest quality monitoring.
19)	Feng, H., Zhang, M., et al. (2020)	IoT + Electronic Nose for Salmon Freshness	IoT-enabled e-nose for spoilage detection during cold storage.
20)	Single Nanowire Gas Sensor (2020)	Distinguishing Freshness of Fish and Meat	Focuses on nanowire-based sensing for evaluating freshness stages.

V. METHODOLOGY

This project utilizes a structured methodology to build a high-performance, visual-based food freshness detector. The entire process focuses exclusively on software development and deep learning, purposefully omitting any details concerning external hardware or sensor devices.

1. Defining the Software-Only Scope

The primary goal is to create a reliable prediction engine a Deep Learning model and wrap it in a clean, functional software service, typically an API. This scope is strictly limited to managing data, training the model, optimizing its performance, and deploying a secure, stable prediction interface.

2. Preparing the Visual Data

High-quality data is the foundation of the system. The process ensures the visual dataset is diverse and properly prepared for machine learning.

- **Curating the Dataset:** A large collection of images showing various foods at different spoilage stages ("Fresh," "Spoiled," etc.) is gathered. The data is carefully checked to ensure labels are accurate and that all freshness classes are represented equally. If one class is underrepresented, the imbalance is corrected through generating synthetic images or by acquiring more data, which prevents the model from developing bias.

- **Preprocessing:** All raw images are programmatically standardized. They are resized to a uniform dimension (e.g., 224×224 pixels) and their color values are normalized to ensure consistent input for the neural network.

- **Augmentation for Robustness:** To make the final model reliable under various conditions (like different camera angles or lighting), the training set is expanded by applying techniques like random rotations, flipping, and shearing. This forces the model to learn the food's features, not the photo's context.

- **Data Partitioning:** The full, curated dataset is divided into three separate, independent groups: Training (70%), Validation (15%), and a final, untouched Test Set (15%).

3. **Model Architecture and Transfer Learning**

The detection engine uses a **Convolutional Neural Network (CNN)** for visual analysis, taking advantage of a powerful, proven technique.

- **Transfer Learning Approach:** Instead of building a CNN from scratch, which requires massive time and resources, the system uses Transfer Learning. This involves starting with a powerful, pre-trained model (like ResNet or EfficientNet) that already possesses a robust ability to recognize common visual patterns.
- **Staged Model Configuration:**

  - A new, small classification head is added to the end. This custom head contains the final layers that interpret the visual features and output the final class probability using a Softmax activation.
  - The model is trained in two stages: first, training only the new classification head; second, fine-tuning the top layers of the pre-trained model with a very low learning rate to subtly adapt its high-level features specifically for food spoilage.

4. Training and Optimization Strategy

Training is managed to ensure the model learns efficiently and avoids the common pitfall of overfitting.

- **Loss and Optimization:** The Adam optimizer is used for efficient training, and the model minimizes the standard multi-class error measure, Categorical Cross-Entropy loss.

- **Preventing Overfitting:** The crucial defence against memorization is Early Stopping. This monitors the model's performance on the Validation Set and automatically stops training when that performance fails to improve. The system then keeps the best-performing weights. Dropout is also applied within the custom layers to further increase model reliability.

  Hyperparameter Tuning: Key training settings—such as the learning rate, batch size, and dropout rate are systematically adjusted to find the combination that result in the lowest real-world prediction error.

5. Performance Validation

The system's reliability is confirmed by assessing it against the completely separate Test Set.

- **Evaluation Metrics:** The validation relies on a suite of metrics beyond simple overall accuracy:

  - **Precision and Recall:** These are critical, especially for the 'Spoiled' class, to determine how often the model is correct when it flags food as spoiled (Precision) and how often it correctly catches actual spoiled food (Recall).
  - **F1-Score:** This score provides a single, balanced metric by combining Precision and Recall.

Error Analysis: A Confusion Matrix is generated to provide a visual breakdown of errors, showing exactly which freshness classes the model is confusing with one another.

6. Final Software Delivery (Inference API)

The final software deliverable is the prediction service itself.

- **Service Packaging:** The model is deployed using Python and a web framework (like Flask or Fast API) to create a RESTful API.
- **API Functionality:** This service exposes a single, secure prediction endpoint (e.g., /predict freshness). When an external system sends an image to this endpoint, the API instantly performs the necessary data preprocessing, runs the image through the optimized model weights, and returns

a clean data response (JSON) containing the predicted food label and the confidence score. This encapsulated prediction service is the foundational output of the entire software project.

VI. BLOCK DIAGRAM

This block diagram lays out the essential steps the computational pipeline used to build the food freshness detection software. Each block is a separate, vital engineering stage that ensures the final predictive system is robust and effective.

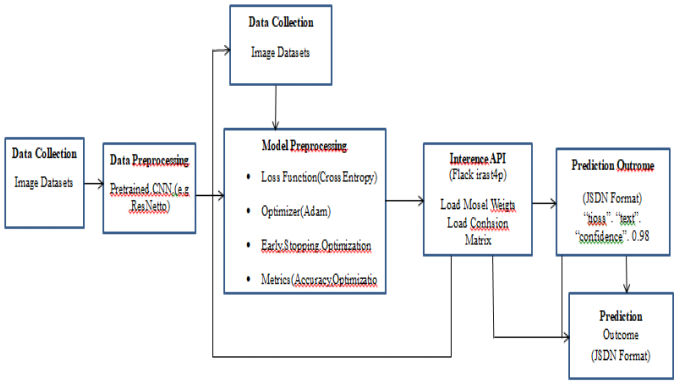

Fig. -1: System Workflow

1. Data Acquisition

This is the foundational step: gathering the raw visual information (images) of all the target food items in every relevant state of freshness. Think of this as collecting the essential learning material. Without enough high-quality pictures of fresh, ripe, and spoiled food, the entire project cannot succeed.

2. Data Curation & Preprocessing

This block is the data preparation factory. Its job is to take the raw images and transform them into a standardized format that the Deep Learning model can actually understand. This involves several critical tasks:

- **Cleaning:** Checking that every image is labelled correctly (e.g., ensuring a spoiled apple isn't accidentally labelled "fresh").
- **Standardization: Resizing** all images to a uniform dimension and **normalizing** the colour values so the model sees a consistent input every time.
- **Augmentation:** To make the model reliable in the real world, the training images are artificially modified (like rotating or flipping them). This helps the model generalize its knowledge beyond the exact photos it saw during training.
- **Partitioning:** Dividing the final, prepared data into three distinct sets: Training, Validation, and the hidden Test Set.

3. Model Selection (Transfer Learning)

Instead of forcing the computer to learn everything about vision from scratch, this stage uses Transfer Learning. A powerful, pre-trained model a Convolutional Neural Network (CNN) like Res Net is chosen. Since these models already know how to recognize basic shapes and textures, the project only needs to train a small, new classification head attached to the end. This saves massive amounts of training time and resources.

4. Model Training & Optimization

This is the core learning process. The system repeatedly feeds the training data to the model, adjusting the internal mathematical parameters (weights) to minimize the prediction error (called the Loss Function). The process uses a sophisticated method (Adam optimizer) to guide the learning. Crucially, Early Stopping is implemented here: it watches the model's performance on the Validation Set and automatically pause es training if the performance stalls. This is the main defence against the model simply memorizing the training examples.

5. Performance Evaluation

Once the model has finished learning, its true ability is measured. The final trained model is tested only on the completely unseen Test Set. This step calculates the most important performance metrics like Precision, Recall, and F1-Score to fully understand its reliability. A Confusion Matrix is also generated to show exactly which types of spoilage the model might be confusing.

6. Inference API (Flask/Fast API)

This is the final product. The fully trained model is loaded and wrapped inside a dedicated, secure web service (API) using a framework like Flask. This module is designed to run non-stop, ready to receive prediction requests from other applications, ensuring the input images are correctly prepared before they go to the model.

7. Prediction Request (Image) → Prediction Result (JSON)

This pair of blocks illustrates the final, operational interaction. A separate application sends a Prediction Request (the food image) to the API. The API processes the image, runs it through the trained model, and immediately sends back a Prediction Result. This result is a clean, structured data file (JSON) that clearly states the predicted freshness label (e.g., "Near Spoilage") and the model's corresponding confidence level. This standardized output allows any other system to instantly consume the freshness data.

VII. KEY CHALLENGES AND OPEN PROBLEMS

Despite advances in sensing and machine learning, several technical and practical barriers still limit the effectiveness of food freshness monitoring systems. The major challenges include:

1. **Data Limitations** – Collecting diverse, well-labeled datasets across multiple food types and spoilage stages is difficult. Many existing datasets are small, imbalanced, or lack early-stage spoilage samples, which reduces the accuracy and generalization of AI models.

2. **Early Detection Accuracy** – Current systems often detect spoilage only after visible changes occur. Developing models and sensors that can capture subtle microbial or chemical variations before they become apparent remains a significant challenge.

3. **Scalable Integration** – Deploying sensor-based and AI models across varied supply chains, storage conditions, and packaging environments is complex. Ensuring consistent performance in real-world scenarios, from farms to retail shelves, requires robust and adaptable solutions.

4. **Cost and Accessibility** – Advanced biosensors, IoT devices, and smart packaging technologies are often expensive. This limits adoption by small producers and retailers, creating a gap between research prototypes and practical, affordable industry solutions.

5. **Consumer Trust & Standardization** – There are no universal benchmarks for defining freshness, and consumers may hesitate to rely on technology-driven indicators. Building trust requires transparent systems, standardized freshness metrics, and clear communication of results.

VIII. FUTURE DIRECTIONS AND OPPORTUNITIES

With rapid advances in artificial intelligence, IoT, and sensor technologies, food spoilage detection systems are evolving into high-tech solutions that go beyond traditional monitoring. The following future directions highlight how this field can progress:

1. **Edge AI Deployment** – Running lightweight models directly on IoT devices or smart packaging to enable real-time freshness detection without relying on cloud servers.

2. **Blockchain-Enabled Traceability** – Integrating freshness data into blockchain platforms to create secure, transparent records across the supply chain.

3. **Affordable Smart Packaging** – Designing low-cost, disposable freshness indicators (colorimetric labels, printed sensors) to make technology accessible to small producers and retailers.

4. **Predictive Analytics for Shelf Life** – Using machine learning to forecast spoilage trends based on sensor data and environmental conditions, enabling proactive decision-making.

These directions show how high-tech innovations can transform food monitoring from subjective checks into **objective, scalable, and predictive systems**. By merging AI, IoT, and blockchain, the future of freshness detection promises safer consumption, reduced waste, and a more sustainable food ecosystem.

IX. CONCEPT

To provide a structured understanding of the Food Freshness Detector, the following section outlines its design, architecture, data pipeline, and evaluation framework

1. Introduction and System Overview

The Food Freshness Detector is a Py Torch-based system designed for automated food quality assessment. Using deep learning and computer vision, it classifies items like fruits, vegetables, and meat into three categories: *fresh, ripe,* or *spoiled*. Its modular pipeline supports data acquisition, model training, and real-time inference, offering a scalable solution for objective freshness detection.

2. Software Architecture and Methodology

The system relies on Convolutional Neural Networks (CNNs) with transfer learning to improve accuracy. It supports multiple backbones such as ResNet18, EfficientNet-B0, and MobileNetV2, each optimized for different performance needs.

- **Image-Only Model**: Uses visual data (color, texture, decay signs) for classification.
- **Multi-Modal Model**: Combines image features with gas sensor data through a fusion layer, enhancing predictive accuracy.

3. Data Pipeline and Robustness

Utilities manage dataset preparation, including downloading, partitioning, and augmentation to improve generalization. A synthetic "ripe" category is added to address labelling gaps and refine classification granularity.

4. Operationalization and Evaluation

Training modules allow flexible configuration of architectures and hyperparameters. Inference supports both single-image and real-time webcam detection. Evaluation scripts generate metrics like precision, recall, F1-score, and ROC curves, with reported accuracy around 91%, confirming strong system performance.

X. CONCLUSION

Ensuring food freshness is vital for consumer health, economic stability, and sustainability. Traditional methods like visual inspection or smell are subjective and often fail to detect early spoilage, leading to foodborne risks and waste. This project bridges that gap by integrating sensor technologies with advanced analytics to provide objective, real-time monitoring.

Biosensors and gas sensors can detect spoilage indicators such as volatile compounds, microbial activity, and pH changes. Coupled with machine learning, these systems predict shelf life and support better decisions in storage, transport, and inventory, reducing losses and waste.

Beyond operational benefits, technology-driven monitoring builds consumer trust through transparency and strengthens industry standards. It also contributes to sustainability by lowering premature disposal and environmental impact.

The project highlights interdisciplinary collaboration across biology, engineering, and data science. Key challenges remain in cost reduction; secure data handling, and standardization of freshness metrics. Addressing these will enable wider adoption.

In conclusion, the framework demonstrates how sensor fusion, IoT, and AI can revolutionize food safety, offering accurate, scalable, and sustainable freshness detection for global food systems.

References

1. Zhang, Y., Cai, Z., et al. (2025). Intelligent Gas Sensors for Food Safety: Outlines the latest developments in MOS, polymer, and sensor arrays.https://www.mdpi.com/2304-8158/14/15/2706

2. Kabir, A., et al. (2025). Hyperspectral Imaging and Deep Learning for Quality and Safety of Fruits and Vegetables: A Review. Journal of Agricultural and Food Chemistry.https://pubmed.ncbi.nlm.nih.gov/40237548

3. Yang, S., et al. (2025). A Systematic Literature Review Towards Food Safety and Traceability Using Blockchain. Business & Information Systems Engineering. https://link.springer.com/article/10.1007/s12599-025-00948-

4. Wang, L., et al. (2024). Hyperspectral Imaging Aiding Artificial Intelligence: A Reliable Solution for Food Quality and Safety. Applied Sciences, 14(21), 9821. Available at: https://www.mdpi.com/2076-3417/14/21/9821

5. Kumar, A., et al. (2024). Biosensors for Detecting Food Contaminants—An Overview. Processes, 13(2), 380. Available at: https://www.mdpi.com/2227-9717/13/2/380

6. Alaba, O., et al. (2024). IoT Services for Monitoring Food Supply Chains. Applied Sciences, 15(13), 7602. Available at: https://www.mdpi.com/2076-3417/15/13/7602

7. Pandiselvam, R., et al. (2024). Colorimetric Food Freshness Indicators for Intelligent Packaging: A Review. Foods, 14(16), 2813. https://www.mdpi.com/2304-8158/14/16/2813

8. Damdam, A. N., Ozay, et al. (2023). IoT-Enabled Electronic Nose System for Beef Quality Monitoring and Spoilage Detection: An IoT-enabled e-nose (CO_2, NH_3, C_2H_4 sensors) integrated over a 7-day period. https://pmc.ncbi.nlm.nih.gov/articles/PMC10252673

9. Minzhen Ma, Xinting Yang, Xiaoguo Ying, et al. (2023). Applications of Gas Sensing in Food Quality Detection: A comprehensive review covering MOX, SAW, colorimetric, and AI integration for freshness detection across meat, fruit, vegetables, and more. https://www.mdpi.com/2304-8158/12/21/3966

10. Bhardwaj, J., et al. (2023). Recent advances in electrochemical enzyme-based biosensors for food and beverage analysis. Foods, 12(18), 3355. https://www.mdpi.com/2304-8158/12/18/3355

11. Zhang, Y., et al. (2023). Vegetable and fruit freshness detection based on deep features and classification networks. Food Packaging and Shelf Life, 38, 101143. https://www.sciencedirect.com/science/article/pii/S2665927123002241

12. Husáková, L., et al. (2023). Application of Electrochemical Biosensors for Determination of Food Safety Indicators: A Review Sensors (Basel). https://pmc.ncbi.nlm.nih.gov/articles/PMC10135962

13. Chowdhury, N., et al. (2022). The Internet of Things enabled real-time cold chain monitoring in a container port. Journal of Shipping and Trade. https://jshippingandtrade.springeropen.com/articles/10.1186/s41072-022-00110-z

14. Chen, Q., et al. (2022). Recent advances on intelligent food freshness indicators: An update. Food Packaging and ShelfLife,33, 100913.https://www.sciencedirect.com/science/article/abs/pii/S221428942200031X

15. Sunny, A. I., et al. (2022). Adaptation of IoT with Blockchain in Food Supply Chain Management. Sensors, 22(20),7611. https://pmc.ncbi.nlm.nih.gov/articles/PMC9655358

16. Ma, X., Yang, X., Ying, X., et al. (2022). A Review on Gas Indicators and Sensors for Smart Food Packaging: Focuses on gas indicators and sensors (O_2, CO_2, NH_3)—commonly used in smart packaging. https://www.mdpi.com/2304-8158/13/19/3047

17. Mikuła, K., et al. (2021). Single Nanowire Gas Sensor Able to Distinguish Fish and Meat and Evaluate Their Degree of Freshness. Chemosensors, 9(9), 249. Available at: https://www.mdpi.com/2227-9040/9/9/249

18. Cen, H., et al. (2020). Visible-NIR 'point' spectroscopy in postharvest fruit/vegetable quality assessment. Postharvest Biology and Technology. Available at: https://www.sciencedirect.com/science/article/pii/S0925521419303230

19. Feng, H., Zhang, M., Liu, P., Liu, Y., & Zhang, X. (2020). Evaluation of IoT-Enabled Monitoring and Electronic Nose Spoilage Detection for Salmon Freshness During Cold Storage. Foods, 9(11), 1579. https://www.mdpi.com/2304-8158/9/11/1579

20. Single Nanowire Gas Sensor, Available at: https://www.bohrium.com/paper-details/single-nanowire-gas-sensor-able-to-distinguish-fish-and-meat-and-evaluate-their-degree-of-freshness/811845227542216705-4465