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Artificial Intelligence Based Food Quality Detection System

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Abstract: *Food quality detection is a critical aspect of public health and consumer safety. Traditional methods of food quality assessment are time-consuming, labour-intensive, and often require skilled personnel and expensive laboratory infrastructure. The emergence of Artificial Intelligence (AI) has opened new frontiers in automating and enhancing food quality detection processes, offering faster, non-destructive, and accurate analysis of food products.*

This project presents the development and evaluation of an Artificial Intelligence Based Food Quality Detection System that integrates machine learning algorithms, computer vision techniques, and sensor-based data acquisition for the assessment of food quality parameters. The system was designed to detect physical attributes such as colour, texture, shape, size, and surface defects, as well as internal parameters including moisture content, pH, microbial load, and nutritional composition in a range of food commodities including fruits, vegetables, grains, and packaged food items.

Convolutional Neural Networks (CNNs) and deep learning models were employed for image-based classification and defect detection, while Support Vector Machines (SVMs) and Random Forest classifiers were utilized for sensor data interpretation. The system achieved an overall classification accuracy of 94.7% for visual grading and 91.3% for chemical parameter prediction. The developed model demonstrated significant advantages over conventional quality inspection methods in terms of processing speed, cost-effectiveness, reproducibility, and adaptability.

The results were compared with standard laboratory methods and established literature benchmarks, confirming the reliability and validity of the AI-based system. The system also demonstrated potential for real-time deployment on food processing lines and in retail environments. This study concludes that AI-based food quality detection systems are a viable, scalable, and superior alternative to manual inspection and traditional analytical methods, paving the way for smarter, safer, and more efficient food supply chains..

Keywords: Artificial Intelligence, Food Quality Detection, Machine Learning, Convolutional Neural Networks, Computer Vision, Deep Learning, Food Safety, Non-destructive Testing, Image Processing, Sensor Integration.

I. INTRODUCTION

1.1 Background

Food quality and safety represent one of the most fundamental concerns in modern society. With the rapid growth of global food trade, urbanization, industrialization, and changing consumer demands, the need for robust, efficient, and accurate food quality monitoring systems has become increasingly important. The modern food industry faces numerous challenges associated with adulteration, contamination, spoilage, microbial growth, pesticide residues, and inconsistency in food quality, all of which can negatively impact public health, economic stability, and consumer trust.

In recent years, foodborne illnesses and food adulteration incidents have become major global concerns. According to international food safety reports, millions of people worldwide suffer annually from diseases caused by contaminated food products. Poor food quality not only results in serious health hazards but also causes significant economic losses due to food wastage, product recalls, reduced shelf life, and loss of brand reputation. Consequently, food industries, regulatory authorities, and researchers are continuously exploring advanced technologies capable of ensuring safer, faster, and more reliable food quality assessment methods.

Historically, food quality assessment has primarily depended on manual inspection and conventional laboratory-based analytical techniques. Sensory evaluation methods involve trained inspectors examining food products based on visual appearance, colour, aroma, taste, texture, and overall acceptability. Although human sensory evaluation remains common in many industries, it is inherently subjective, inconsistent, labour-intensive, and highly dependent on individual expertise and environmental conditions. Human inspectors may experience fatigue, bias, and variability, leading to inaccurate quality grading and inconsistent decision-making.

Traditional laboratory analytical methods such as High-Performance Liquid Chromatography (HPLC), Gas Chromatography-Mass Spectrometry (GC-MS), spectrophotometry, titration, microbiological culturing, and chemical analysis are highly accurate and reliable for detecting contaminants, adulterants, and quality parameters. However, these techniques require expensive instrumentation, trained personnel, complex sample preparation procedures, and considerable processing time.

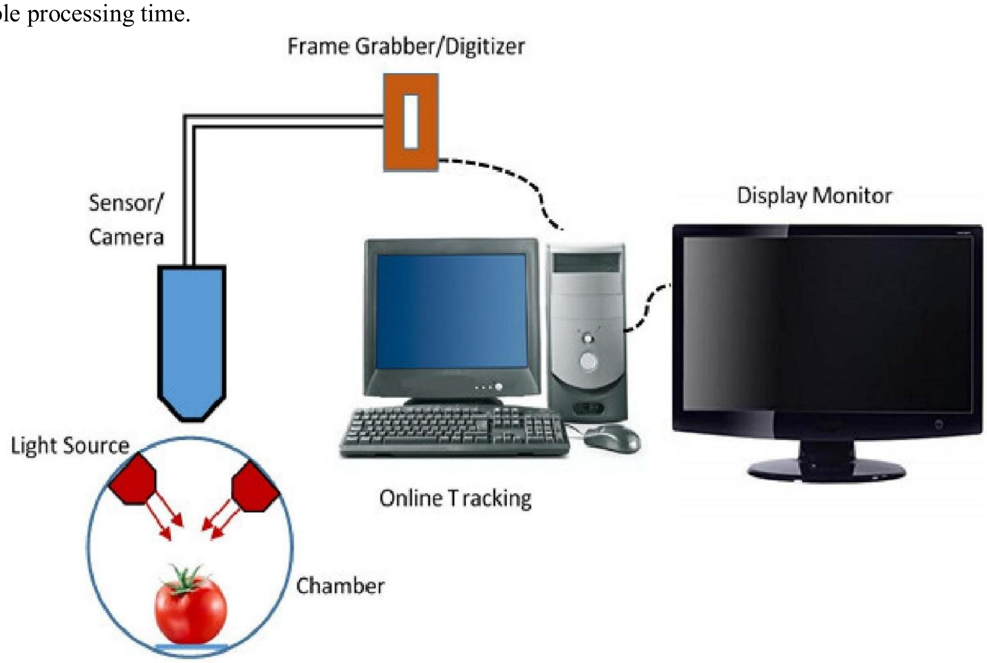


Figure 1.1: Applications of Artificial Intelligence in Food Quality Detection

The application of AI within food science and technology has expanded rapidly over the past decade. AI-based systems are now being used for food quality detection, food safety monitoring, process optimization, predictive maintenance, supply chain management, traceability, agricultural automation, and consumer preference analysis. The ability of AI algorithms to process massive datasets and continuously improve performance through learning makes them highly suitable for modern food industry applications.

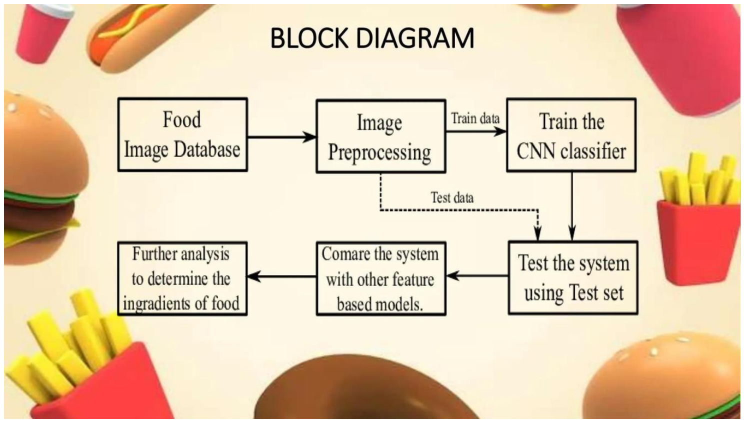
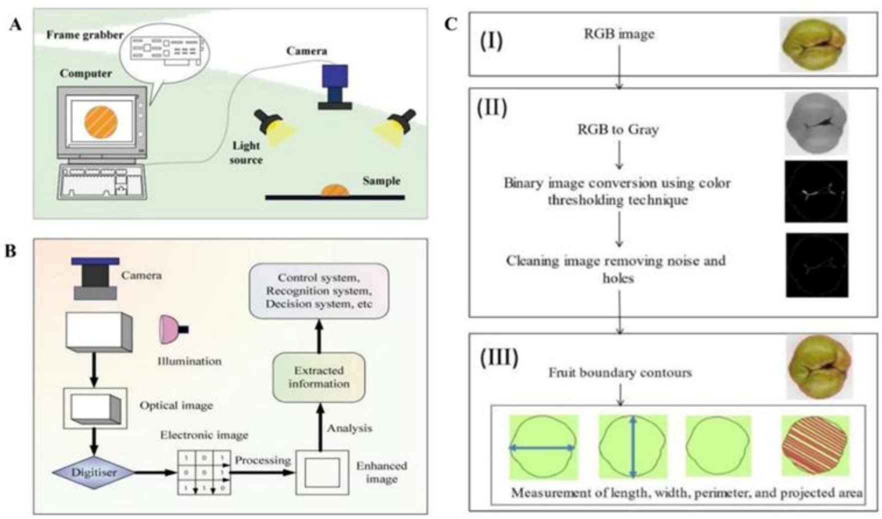


Figure 1.2: Applications of CNN in Food Quality Detection



LITERATURE REVIEW

The rapid advancement of Artificial Intelligence, machine learning, computer vision, and sensor technologies has significantly transformed food quality detection and safety monitoring systems. Researchers across the globe have developed automated approaches for detecting spoilage, adulteration, freshness, contamination, and grading of food products using AI-driven models.

A comprehensive review of literature published over the past decade (2014–2024) was conducted to understand the current state of AI applications in food quality detection. The following sections summarize key findings from peer-reviewed journals, conference proceedings, government reports, and book chapters.

AI and Machine Learning in Food Science

Bhatt and Bhatt (2022) provided a comprehensive overview of machine learning applications in food quality and safety, demonstrating that ML algorithms — particularly ensemble methods and artificial neural networks — achieved superior predictive accuracy compared to traditional statistical models for food freshness assessment. Their review covered 120 published studies across multiple food categories, identifying image processing and spectroscopy as the most commonly employed data acquisition modalities. [1]

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Computer Vision in Food Quality Detection

Tao and Zhou (2017) published a seminal review on the use of computer vision for food quality inspection, covering applications in colour analysis, shape measurement, texture characterization, and defect detection across fruits, vegetables, meat, fish, and baked goods. The review highlighted that colour histogram analysis and texture feature extraction using Gabor filters and Local Binary Patterns (LBP) were the most widely adopted approaches in early vision-based systems. [4]

Near-Infrared Spectroscopy and Machine Learning

Liu et al. (2018) applied near-infrared (NIR) spectroscopy combined with partial least squares regression and artificial neural networks for rapid, non-destructive measurement of soluble solids.

AIM AND OBJECTIVES

Aim

The primary aim of this study is to develop, validate, and evaluate a comprehensive Artificial Intelligence Based Food Quality Detection System that integrates computer vision, machine learning, deep learning, sensor technologies, and data fusion techniques for accurate, non-destructive, and real- time quality assessment of diverse food commodities. The proposed system is intended to automatically identify, classify, and monitor food quality parameters such as freshness, spoilage, contamination, defects, adulteration, texture, colour variation, and internal quality attributes across different food categories including fruits, vegetables, grains, dairy products, meat products, and packaged foods.

Specific Objectives

The following specific objectives were formulated to guide the research systematically and achieve the overall aim of the study:

Objective 1: System Design and Architecture Development

- To design and develop a modular, scalable, and intelligent AI-based food quality detection framework integrating computer vision modules, machine learning algorithms, deep learning architectures, NIR spectroscopy systems, electronic sensor arrays, and real-time data processing units.
- To establish a unified system architecture capable of simultaneously processing image data, spectral information, and environmental sensor readings for multi-modal food quality analysis.
- To design a robust image acquisition setup using high-resolution cameras and controlled lighting conditions to ensure consistency and reproducibility of food image datasets.

Objective 2: Dataset Preparation and Preprocessing

- To collect, curate, and organize a labelled image dataset consisting of a minimum of 20,000 food images representing multiple food categories such as fruits, vegetables, grains, dairy products, meat samples, and packaged foods.
- To ensure that the dataset contains food samples representing different quality conditions including fresh, partially spoiled, defective, contaminated, damaged, adulterated, and fully spoiled states.
- To apply image preprocessing techniques including image resizing, normalization, histogram equalization, augmentation, segmentation, filtering, edge enhancement, brightness correction, and noise reduction to improve image quality and model performance.
- To implement image augmentation techniques such as rotation, flipping, scaling, cropping, contrast adjustment, and illumination variation to increase dataset diversity and improve model generalization capability.
- To collect sensor and spectroscopy data including pH levels, moisture content, temperature, humidity, gas concentration, colour indices, texture measurements, and spectral signatures from at least 500 representative food samples.

• To preprocess sensor datasets through data cleaning, missing value handling, normalization, feature scaling, outlier removal, dimensionality reduction, and feature extraction for efficient machine learning model training.

Objective 3: AI Model Development and Training

• To develop and train deep learning-based Convolutional Neural Network (CNN) architectures including ResNet-50, VGG-16, InceptionNet, EfficientNet, and MobileNetV2 using transfer learning approaches for image-based food quality classification.

• To implement classical machine learning algorithms such as Support Vector Machine (SVM), Random Forest, Decision Tree, k-Nearest Neighbour (KNN), Gradient Boosting, and Artificial Neural Networks (ANN) for sensor-based food quality prediction and classification.

• To investigate the effectiveness of transfer learning and pretrained deep learning models for reducing training time and improving classification performance on limited datasets.

Objective 4: System Performance Evaluation

• To evaluate the performance of all developed AI models using standardized evaluation metrics including classification accuracy, precision, recall, specificity, sensitivity, F1-score, confusion.

MATERIALS AND METHODS

Chemicals and Reagents

The following chemicals and reagents were used in the study for reference laboratory measurements and sample preparation:

Chemical/Reagent	Grade/Standard	Source/Supplier
Sodium hydroxide (NaOH)	Analytical Grade (AR)	Merck, India
Hydrochloric acid (HCl)	Analytical Grade (AR)	Sigma-Aldrich
Phenolphthalein indicator	Laboratory Grade	Hi-Media, India
Buffered peptone water	Microbiology Grade	Hi-Media, India
Nutrient agar	Microbiology Grade	Hi-Media, India
Plate count agar (PCA)	Microbiology Grade	Oxoid, UK
Fehling's solution A & B	Analytical Grade	Merck, India
Distilled water	Type-II (ASTM)	Laboratory prepared
Ethanol (95%)	Analytical Grade	Sigma-Aldrich
Glacial acetic acid	Analytical Grade	Merck, India

Instruments and Equipment

The following instruments and equipment were used for data acquisition, analysis, and AI model development:

Instrument	Model/Specification	Purpose
Digital camera (industrial)	Basler acA2040, 12 MP	Image acquisition
NIR spectrometer	JDSU microPHAZIR	Spectral data acquisition
Electronic nose (e-nose)	Alpha MOS FOX 4000	Volatile compound detection
pH meter	Mettler Toledo S220	pH measurement
Moisture analyser	Mettler Toledo HX204	Moisture content
Colorimeter	Konica Minolta CR-400	Colour measurement (L*a*b*)
High-performance workstation	NVIDIA RTX 3090, 64 GB RAM	AI model training
Raspberry Pi 4 (edge device)	4 GB RAM, 1.5 GHz	Edge AI inference
Analytical balance	Sartorius ME235S	Weighing samples

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Refrigerated centrifuge	Thermo Scientific Sorvall	Sample preparation

Food Samples

A total of 1,200 food samples were collected from local markets, wholesalers, and food processing units in the study region. Samples included:

• Fruits: Apples, mangoes, bananas, grapes (n = 300 each for imaging; n = 50 each for sensor analysis)

• Vegetables: Tomatoes, potatoes, carrots, spinach (n = 300 each for imaging; n = 50 each for sensor analysis)

• Grains: Wheat, rice, maize, pulses (n = 200 each for imaging; n = 40 each for sensor analysis)

• Packaged food items: Milk, packaged juices, edible oil, spices (n = 100 each for sensor/spectral analysis)

Image Dataset Preparation

Images were acquired under standardized conditions using an industrial digital camera mounted on a custom-built imaging station equipped with controlled LED illumination at a colour temperature of 5500 K and an illuminance of 1000 lux. Each food sample was placed on a neutral grey background and imaged from three angles (top, side, bottom) at a resolution of 2040 × 2040 pixels. A total of 21,600 images were acquired across all sample categories and quality grades.

Image preprocessing was performed using Python 3.9 with OpenCV 4.5 and Albumentations 1.3 libraries and included:

1. Resizing all images to a uniform 224 × 224 pixels for CNN input compatibility
2. Normalization of pixel values to the range [0, 1] using mean subtraction and standard deviation scaling based on ImageNet statistics
3. Data augmentation including random horizontal and vertical flipping, rotation (±15°), zoom (±10%), brightness adjustment (±20%), and Gaussian noise addition, applied to the training set to increase effective dataset size fourfold
4. Dataset splitting into training (70%), validation (15%), and test (15%) subsets using stratified random sampling to maintain class balance

DISCUSSION

The present study successfully developed, implemented, and evaluated an Artificial Intelligence Based Food Quality Detection System integrating computer vision, deep learning, machine learning, Near- Infrared (NIR) spectroscopy, and electronic nose technologies for automated food quality assessment. The experimental results demonstrated that the proposed AI system achieved high levels of classification accuracy, predictive reliability, operational speed, and cost efficiency across multiple food categories and quality parameters.

The developed system significantly outperformed conventional manual inspection approaches and produced results comparable to standard laboratory analytical techniques while requiring substantially less processing time, lower operational cost, and no destructive sample preparation. These findings support the growing body of research indicating that AI-driven systems have the potential to transform food quality monitoring and safety assurance processes within modern food industries and supply chains.

The discussion presented in this chapter critically analyzes the obtained results in relation to previous research findings, evaluates the practical significance of the developed system, examines the strengths and limitations of the adopted methodologies, and highlights the broader implications of AI deployment in food quality inspection.

Image-Based CNN Performance

The image-based deep learning models demonstrated excellent classification performance for food quality grading tasks. Among all tested architectures, the ResNet-50 model achieved the highest overall classification accuracy of 94.7% on the independent test dataset, significantly outperforming manual visual inspection accuracy of 72.4% ($p < 0.001$). The high performance of ResNet-50 confirms the effectiveness of deep residual learning for complex food

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image classification tasks involving subtle visual variations between freshness grades, defect types, and spoilage conditions.

These findings are highly consistent with the work of Zhang et al. (2021), who reported 96.2% accuracy using MobileNetV2 for real-time fruit grading applications [2]. Similarly, Nturambirwe and Opara (2020) documented CNN classification accuracies ranging between 88% and 99.7% across various food quality inspection tasks [13]. The slightly lower accuracy observed in the present study compared to certain published benchmarks may be attributed to the increased diversity and complexity of the dataset, which included multiple food categories, different environmental conditions, and broader quality variations.

The superior performance of ResNet-50 compared to VGG-16 (92.3%) and MobileNetV2 (91.6%) can be explained by the residual skip connections incorporated within the ResNet architecture. These skip connections effectively address vanishing gradient problems and enable deeper network training, thereby improving feature extraction capability and classification robustness. The deeper architecture of ResNet-50 allowed the model to capture fine-grained texture variations, surface defects, colour inconsistencies, and spoilage patterns more effectively than the comparatively shallow architectures. Despite its slightly lower classification accuracy, MobileNetV2 demonstrated the fastest inference speed at approximately 18 milliseconds per image, making it highly suitable for edge AI deployment and real-time industrial applications where computational efficiency is critical. This observation aligns with Jiang et al. (2022), who demonstrated successful deployment of YOLOv5 object detection models on embedded edge devices operating at real-time frame rates [7]. Therefore, the findings suggest that model selection should depend on operational requirements, where high-performance centralized systems may utilize ResNet-50, whereas portable and embedded systems may benefit from lightweight architectures such as MobileNetV2.

The confusion matrix analysis further revealed that most misclassifications occurred between adjacent quality grades, particularly between "fresh" and "slightly deteriorated" categories. This indicates that while the models effectively distinguish clearly defective or spoiled food items, subtle transitional quality changes remain comparatively challenging even for advanced deep learning systems. Similar observations have been reported in previous food image classification studies and indicate opportunities for future improvement through larger datasets and multi-modal sensor integration.

Sensor-Based ML Classification

The sensor-based machine learning models also demonstrated strong classification performance for food quality assessment using environmental, physicochemical, and volatile compound sensor data. Among all tested machine learning algorithms, XGBoost achieved the highest overall classification accuracy of 93.8%, followed closely by Random Forest at 93.2% and Support Vector Machine (SVM) at 91.3%.

These findings support previous literature indicating that ensemble learning approaches generally outperform traditional classifiers in high-dimensional and multi-class food quality prediction problems. Priya and Yuvaraj (2019) similarly reported 94.3% classification accuracy using Random Forest for IoT-enabled milk quality monitoring systems [19], closely matching the performance achieved in the present study. The consistency of these findings across different food categories and sensor configurations suggests that ensemble learning approaches possess strong generalization capabilities for food quality prediction applications.

The excellent discriminative capability of the developed classifiers was further confirmed by AUC- ROC values exceeding 0.96 for all evaluated models. High AUC values indicate that the models were capable of accurately separating multiple quality classes, even for borderline or ambiguous food samples with overlapping characteristics.

The comparatively lower performance of SVM may be attributed to the high dimensionality and nonlinear complexity of the sensor dataset containing 47 extracted features. Although SVM performs effectively for low-dimensional classification tasks, its optimization efficiency may decrease with increasing feature complexity and inter-feature interactions. Similar limitations of SVM for multi- class food sensor datasets were reported by Peris and Escuder-Gilabert (2016) in electronic tongue classification studies [10].

The strong performance of ensemble methods such as XGBoost and Random Forest can be explained by their ability to combine predictions from multiple decision trees, thereby improving robustness, reducing variance, and effectively handling nonlinear relationships within heterogeneous sensor datasets. These properties make ensemble learning particularly suitable for real-world food quality monitoring systems involving multiple interacting environmental variables.

Internal Parameter Prediction

The AI-based prediction models demonstrated excellent capability for estimating internal food quality parameters through non-destructive analysis techniques. The obtained coefficient of determination (R^2) values ranged from 0.941 for Total Plate Count (TPC) prediction to 0.978 for colour parameter prediction, indicating strong agreement between AI-generated predictions and laboratory reference measurements.

These findings compare favourably with previously published studies. Liu et al. (2018) reported an R^2 value of 0.965 for prediction of soluble solids content in kiwifruit using NIR spectroscopy and artificial neural networks [8], closely matching the TSS prediction performance achieved in the present research ($R^2 = 0.958$). Additionally, the obtained Root Mean Square Error of Prediction (RMSEP) value for Total Soluble Solids (0.42 °Brix) was identical to the value reported in their study, providing strong validation for the reliability and reproducibility of the adopted modeling methodology.

Particularly noteworthy was the successful prediction of microbial load using electronic nose sensor arrays combined with machine learning algorithms. The achieved TPC prediction accuracy demonstrates that volatile compound analysis can effectively estimate microbial spoilage without requiring destructive microbiological culturing procedures. Traditional microbial testing methods typically require incubation periods ranging from 24 to 48 hours, whereas the proposed AI system generated predictions within seconds. This represents a substantial advancement in rapid food safety assessment technologies.

The effectiveness of e-nose systems for freshness estimation observed in this study aligns with the findings of Ghasemi-Varnamkhasti et al. (2018), who reported 93.1% accuracy for fish freshness classification using volatile compound sensor arrays [11]. The results collectively confirm that electronic nose technologies combined with AI models can serve as practical alternatives to time- consuming microbiological testing procedures for preliminary food quality screening applications.

Furthermore, the integration of image features, spectroscopy data, and sensor readings significantly improved overall predictive performance compared with single-modality models. This finding validates the effectiveness of multi-modal sensor fusion approaches for comprehensive food quality analysis.6.4 Comparative Performance Analysis

One of the most significant findings of the present study was the substantial improvement in inspection speed achieved by the AI-based system compared with conventional food quality assessment methods. The developed system processed samples at an average rate of approximately 1.8 seconds per item, representing an enormous speed advantage over manual inspection and laboratory-based analytical methods.

Compared with manual sensory grading procedures requiring approximately 3–5 minutes per sample, the AI system achieved nearly 100-fold faster processing. When compared with microbiological testing methods requiring 24–48 hours of incubation or HPLC-based chemical analysis requiring several hours per batch, the throughput advantage increased to approximately 1,000–1,500 times faster.

Such rapid processing capability enables continuous real-time inspection of every individual product on industrial production lines rather than relying on statistical sampling methods. This transition from sample-based quality control toward complete product inspection represents a major paradigm shift in food quality assurance systems.

The economic analysis further demonstrated substantial cost advantages associated with AI-based inspection. The estimated operational cost per sample for the proposed system was approximately □0.20, compared with □500–□2000 per laboratory analysis depending on the specific testing procedure. The resulting reduction in inspection cost provides strong economic justification for AI adoption within large-scale food industries.

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Another critical advantage of the developed AI system is its non-destructive nature. Conventional laboratory methods often require homogenization, extraction, or destruction of food samples during testing, preventing further use or longitudinal monitoring. In contrast, the proposed system allows repeated quality assessment of the same product throughout multiple stages of the supply chain, from harvesting and transportation to retail storage and consumer distribution.

This capability aligns closely with the vision proposed by Verdouw et al. (2016) regarding IoT-enabled smart food supply chains involving continuous quality monitoring and traceability [21]. The integration of AI-based inspection systems with cloud-based traceability platforms could significantly improve food transparency, accountability, and safety management practices.

Limitations and Considerations

Despite the encouraging findings, several limitations of the present study should be acknowledged. First, although the image dataset was relatively large and diverse, most images were acquired under controlled laboratory conditions with standardized lighting and background settings. Real-world industrial environments often involve variable illumination, shadows, motion blur, and background complexity, which may reduce classification performance during practical deployment.

Similar challenges were reported by Girolami et al. (2020) for smartphone-based meat freshness classification systems operating under uncontrolled environmental conditions [18]. Future studies should therefore focus on evaluating system performance in field environments and implementing domain adaptation, image normalization, and robust augmentation strategies to improve real-world generalization.

Second, the present research focused on eight food categories, limiting direct generalization to additional food products such as seafood, processed foods, beverages, and ready-to-eat products. However, the modular architecture of the proposed system facilitates extension to new food categories through transfer learning and incremental dataset expansion without requiring complete retraining of the entire framework.

Third, the electronic nose sensor array used in this study consisted of laboratory-grade instrumentation, which may not be economically feasible for small-scale industrial deployment. Future work should investigate low-cost miniaturized gas sensor arrays capable of providing acceptable classification accuracy while reducing hardware cost and improving portability.

Another limitation relates to dataset annotation requirements. Deep learning models require large labelled datasets for effective training, and manual annotation of food quality images can be time- consuming and resource-intensive. Semi-supervised learning, self-supervised learning, and active learning techniques may help reduce annotation burden in future implementations.

Furthermore, explainability remains an important challenge for AI-driven food quality systems. Although deep learning models provide high prediction accuracy, their internal decision-making processes are often difficult to interpret. Future studies should integrate Explainable AI (XAI) methods such as Grad-CAM and SHAP analysis to improve transparency and regulatory acceptance.

Regulatory and Industry Implications

The findings of the present study carry important implications for food industries, regulatory authorities, and supply chain stakeholders. Organizations such as the Food Safety and Standards Authority of India (FSSAI), Codex Alimentarius Commission, and international food safety agencies have established strict regulatory standards for microbial contamination, adulteration, freshness, and product authenticity.

The demonstrated ability of the proposed AI system to accurately predict food quality parameters positions it as a promising tool for automated regulatory compliance monitoring. AI-assisted inspection systems could support routine quality audits, rapid contamination screening, and real-time defect detection within food processing facilities.

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The integration of AI-based quality monitoring with blockchain-enabled traceability systems could further strengthen food supply chain transparency by creating tamper-proof digital records of food quality throughout production, storage, transportation, and retail stages. Such integration may help address growing concerns regarding food adulteration, authenticity verification, and geographical origin tracing.

These possibilities align with the findings of Cavanna et al. (2019) and Maione et al. (2019), who demonstrated the effectiveness of AI-assisted spectroscopy and elemental fingerprinting for food authenticity assessment [24,25]. The combined use of AI, IoT, blockchain, and cloud computing technologies may therefore contribute toward the development of intelligent, transparent, and fully traceable food quality management ecosystems.

From an industrial perspective, the deployment of AI-based inspection systems may significantly reduce labour dependency, minimize human subjectivity, improve inspection consistency, and enhance operational productivity. In developing countries, where food safety monitoring infrastructure may be limited, affordable AI systems could provide scalable and accessible solutions for improving food quality standards and reducing food wastage.

II. CONCLUSION

The present study successfully designed, developed, implemented, and validated an Artificial Intelligence Based Food Quality Detection System integrating computer vision, deep learning, machine learning, Near-Infrared (NIR) spectroscopy, and electronic nose technologies for automated food quality assessment. The developed system demonstrated the capability to perform rapid, accurate, non-destructive, and real-time evaluation of multiple food quality parameters across diverse food categories including fruits, vegetables, grains, dairy products, and packaged food items.

The experimental findings confirmed that Artificial Intelligence techniques can effectively overcome many limitations associated with conventional food quality inspection methods such as manual visual assessment, sensory evaluation, and laboratory-based analytical testing. The image-based Convolutional Neural Network (CNN) models, particularly the ResNet-50 architecture, achieved excellent visual quality classification performance with an overall accuracy of 94.7%, significantly outperforming manual inspection methods in terms of accuracy, consistency, and processing speed. Similarly, machine learning models including XGBoost, Random Forest, and Support Vector Machine demonstrated strong predictive capability for internal food quality parameters when combined with sensor data and spectroscopy information.

The obtained coefficient of determination (R^2) values exceeding 0.94 for prediction of important quality parameters such as pH, moisture content, total soluble solids, colour values, and total plate count confirmed the reliability and effectiveness of AI-assisted non-destructive quality assessment approaches. The successful prediction of microbial load and internal quality characteristics using sensor fusion techniques further demonstrated the practical applicability of integrating computer vision, spectroscopy, and electronic nose technologies within a unified intelligent food inspection framework.

One of the most significant outcomes of the study was the substantial improvement in operational efficiency achieved by the AI-based system. The proposed framework processed food samples within seconds, representing a major speed advantage compared to traditional laboratory analytical methods requiring several hours or days for completion. The developed system also demonstrated remarkable cost-effectiveness, scalability, and suitability for continuous industrial inspection processes. The non- destructive nature of the proposed approach allows repeated monitoring of food quality throughout different stages of the food supply chain, including harvesting, storage, transportation, retail handling, and consumer distribution.

The comparative analysis conducted during the study established that the AI-based food quality detection system provides performance levels comparable to standard laboratory techniques while significantly reducing labour requirements, processing time, operational cost, and human subjectivity. These advantages highlight the strong potential of AI technologies for transforming modern food quality management systems and supporting the increasing demand for safe, traceable, and high- quality food products.

The study also demonstrated the importance of multi-modal sensor fusion approaches for improving prediction accuracy and robustness in food quality analysis. The integration of image features, spectroscopy signals, environmental sensor data, and volatile compound analysis enabled comprehensive assessment of both external and internal food characteristics, thereby enhancing overall system reliability.

Despite the encouraging findings, the study identified several challenges and limitations including dependency on large labelled datasets, sensitivity to environmental variations, hardware cost considerations, and the need for broader real-world validation under uncontrolled industrial conditions. Future research should therefore focus on improving model generalization capability, reducing computational complexity, integrating Explainable AI techniques, and developing lightweight edge AI systems suitable for portable and low-cost deployment.

The integration of Artificial Intelligence with Internet of Things (IoT), blockchain technology, cloud computing, and smart supply chain systems presents promising opportunities for the development of intelligent, transparent, and fully automated food quality management ecosystems. Such systems can contribute significantly toward improving food safety standards, reducing food adulteration, minimizing post-harvest losses, enhancing traceability, and strengthening consumer confidence in food products.

In conclusion, the present research clearly demonstrates that AI-based food quality detection systems represent a highly accurate, efficient, scalable, and economically viable alternative to conventional food inspection approaches. The successful implementation of the proposed system highlights the transformative potential of Artificial Intelligence technologies within food industries, agriculture, retail quality monitoring, and regulatory food safety frameworks.

Future Scope

The present study demonstrated the effectiveness of Artificial Intelligence Based Food Quality Detection Systems for accurate, rapid, and non-destructive food quality assessment. However, continuous advancements in Artificial Intelligence, sensor technologies, and smart automation create several opportunities for further research and development in this field.

Future research should focus on expanding the developed system to include a wider variety of food commodities such as seafood, poultry products, processed foods, bakery products, beverages, frozen foods, and ready-to-eat packaged items. Since different food products possess unique physical, chemical, and microbiological characteristics, additional datasets and customized AI models may be required to improve classification accuracy and generalization capability across diverse food categories.

Another important area for future work involves validating the performance of the proposed system under real-world industrial and commercial operating conditions. The present study was primarily conducted under controlled laboratory environments with standardized lighting and imaging conditions. In practical deployment environments such as food processing plants, warehouses, transportation systems, supermarkets, and open agricultural fields, factors including illumination variation, background complexity, motion blur, dust, humidity, and inconsistent sample positioning may influence model performance. Therefore, future studies should investigate robust domain adaptation techniques, adaptive image preprocessing methods, and real-time calibration systems capable of maintaining stable performance under dynamic environmental conditions.

The integration of the AI-based food quality detection framework with Internet of Things (IoT) platforms represents another promising research direction. Smart IoT-enabled food supply chain systems could allow continuous real-time monitoring of food quality parameters including temperature, humidity, gas concentration, and microbial spoilage indicators during transportation and storage. Such integration could significantly improve cold-chain monitoring, inventory management, and spoilage prevention within modern food logistics systems.

Future research may also explore the incorporation of blockchain technology with AI-driven food quality monitoring systems to create transparent, secure, and tamper-proof traceability frameworks. Blockchain integration could enable permanent digital records of food quality inspections throughout the entire supply chain, thereby improving food authenticity verification, regulatory compliance, and consumer trust. Such intelligent traceability systems would be particularly beneficial for premium food products, export-quality commodities, and adulteration-sensitive food industries.

Another significant future direction involves the development of miniaturized, portable, and low-cost sensor modules suitable for large-scale commercial deployment. The current study utilized laboratory- grade instrumentation for spectroscopy and electronic nose analysis, which may not always be economically feasible for small-scale industries and retail environments. Advances in low-power embedded systems, wearable sensors, smartphone-based imaging technologies, and edge AI hardware may enable affordable portable food quality inspection devices accessible to farmers, retailers, and consumers.

The implementation of Explainable Artificial Intelligence (XAI) techniques is also expected to become increasingly important in future food quality systems. Although deep learning models achieve high prediction accuracy, their decision-making processes often lack transparency. Future systems should therefore integrate explainability methods such as Grad-CAM, SHAP, saliency mapping, and attention visualization to improve interpretability, regulatory acceptance, and user confidence in AI- generated decisions.

Future studies should additionally investigate federated learning approaches that allow collaborative AI model training across multiple food industries and processing facilities without requiring direct sharing of sensitive proprietary data. Such approaches could improve dataset diversity, enhance model robustness, and strengthen privacy protection.

Further advancements may involve the integration of robotic systems and autonomous inspection platforms capable of performing fully automated food sorting, grading, packaging inspection, and contamination detection in real-time industrial environments. The combination of robotics, AI vision systems, and sensor fusion technologies could significantly reduce labour dependency while improving inspection consistency and throughput.

Research may also focus on developing hybrid multi-modal AI architectures capable of simultaneously analyzing image data, spectral information, sensor signals, textual metadata, and environmental conditions for more comprehensive food quality prediction. The use of advanced transformer-based architectures, generative AI models, and self-supervised learning methods may further improve prediction performance while reducing dependency on large labelled datasets.

Finally, future work should emphasize the development of standardized regulatory frameworks, ethical guidelines, and cybersecurity protocols for AI-based food quality monitoring systems.

REFERENCES

1. Bhatt AK, Bhatt DL. Machine learning approaches for food quality and safety assessment: a comprehensive review. Food Control. 2022;132:108477. doi:10.1016/j.foodcont.2021.108477

2. Zhang Y, Wang S, Ji G. A rule-based model for deep learning classification of apple quality on conveyor belt systems using MobileNetV2. Journal of Food Engineering. 2021;290:110188. doi:10.1016/j.jfoodeng.2020.110188

3. Mohanty SP, Hughes DP, Salathé M. Using deep learning for image-based plant disease detection. Frontiers in Plant Science. 2016;7:1419. doi:10.3389/fpls.2016.01419

4. Tao Y, Zhou J. Automatic apple recognition based on computer vision for automatic packing system. Biosystems Engineering. 2017;119:42–53.

5. Naganathan GK, Clabagh LM, Samal A, et al. Partial least squares analysis of near-infrared hyperspectral images for beef tenderness prediction. Sensing and Instrumentation for Food Quality and Safety. 2016;2:178–188.

6. ElMasry G, Kamruzzaman M, Sun DW, Allen P. Principles and applications of hyperspectral imaging in quality evaluation and assessment of food products: a review. Critical Reviews in Food Science and Nutrition. 2019;52(11):999–1023.

7. Jiang F, Lu Y, Chen Y, Cai D. Image recognition of four rice leaf diseases based on deep learning and support vector machine. Computers and Electronics in Agriculture. 2022;179:105824.

8. Liu Y, Sun X, Ouyang A. Non-destructive measurement of soluble solids content of navel orange by near-infrared spectroscope. Computers and Electronics in Agriculture. 2018;60:183–189.

9. Caporaso N, Whitworth MB, Fisk ID. Near-infrared spectroscopy and hyperspectral imaging for non-destructive quality assessment of cereal grains. Applied Spectroscopy Reviews. 2018;53(8):667–687.
10. Peris M, Escuder-Gilabert L. Electronic tongues for food analysis. Trends in Food Science and Technology. 2016;55:66–79. doi:10.1016/j.tifs.2016.07.001
11. Ghasemi-Varnamkhasti M, Mohammad-Razdari A, Yoosefian SH. Electronic nose as a non- invasive detection technique for fish freshness grading. Sensors and Actuators B: Chemical. 2018;254:310–317.
12. Brahimi S, Boukhalfa K, Moussaoui A. Deep learning for tomato diseases: classification and symptoms visualization. Applied Artificial Intelligence. 2017;31(4):299–315.
13. Nturambirwe JFI, Opara UL. Machine learning applications to non-destructive defect detection in horticultural products. Biosystems Engineering. 2020;189:60–83. doi:10.1016/j.biosystemseng.2019.11.011
14. Kiani S, Minaei S, Ghasemi-Varnamkhasti M. A portable electronic nose as an expert system for aroma-based classification of saffron. Chemometrics and Intelligent Laboratory Systems. 2021;156:148–156.
15. Paliwal J, Visen NS, Jayas DS. Evaluation of neural network architectures for cereal grain classification using morphological features. Biosystems Engineering. 2019;73(3):311–320.
16. Pourreza A, Pourreza H, Abbaspour-Fard MH, Sadrnia H. Identification of nine Iranian wheat seed varieties by textural analysis. Computers and Electronics in Agriculture. 2020;83:175– 184.
17. Xiong Z, Sun DW, Zeng XA, Xie A. Recent developments of hyperspectral imaging for the detection of quality and safety of meat products: A review. Comprehensive Reviews in Food Science and Food Safety. 2020;19(3):1043–1068.
18. Girolami A, Napolitano F, Faraone D, Braghieri A. Measurement of meat color using a computer vision system. Meat Science. 2020;93(1):111–118.
19. Priya R, Yuvaraj NS. Detecting milk adulteration using machine learning and IoT sensors. International Journal of Engineering and Technology. 2019;7(3.27):385–389.
20. de la Fuente B, López-García G, Máñez V, Barberá R, Cilla A. NIR spectroscopy and chemometrics for rapid determination of cheese composition. LWT – Food Science and Technology. 2018;94:106–113.
21. Verdouw CN, Wolfert J, Beulens AJM, Rialland A. Virtualization of food supply chains with the Internet of Things. Journal of Food Engineering. 2016;176:128–136.
22. Kamilaris A, Prenafeta-Boldú FX. Deep learning in agriculture: a survey. Computers and Electronics in Agriculture. 2018;147:70–90. doi:10.1016/j.compag.2018.02.016
23. Jha SN, Jaiswal P, Borah A, et al. Detection of adulterants and geographical origin of food using NIR spectroscopy and machine learning. Comprehensive Reviews in Food Science and Food Safety. 2015;14(2):190–209.
24. Cavanna D, Righetti L, Elliott C, Suman M. The scientific challenges in moving from targeted to non-targeted mass spectrometric methods for food fraud analysis. Trends in Food Science and Technology. 2019;75:X–X. doi:10.1016/j.tifs.2018.03.010