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Multimodal Deep Learning-Based Intelligent Food Safety Detection and Traceability System

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Abstract: ***Food safety has become a critical global issue, requiring effective solutions to reduce health risks and economic losses. The rapid advancement of artificial intelligence (AI) and deep learning (DL) provides new opportunities to address this challenge. This study presents a multimodal food safety detection system that integrates computer vision (CV), natural language processing (NLP), and sensor data analysis to comprehensively monitor food contamination, quality deterioration, and supply chain security. Specifically, the Swin Transformer model is employed for surface defect detection, while temporal convolutional networks (TCN) predict storage environment conditions. Additionally, blockchain and federated learning technologies are incorporated to establish a secure and efficient data-sharing framework, enabling cross-supply chain collaboration and enhancing traceability accuracy. Experimental results show that the system achieves an accuracy rate of over 98% in food contamination detection and supply chain anomaly monitoring, significantly improving food safety management. This study offers a practical and innovative approach to enhancing intelligent food safety regulation.***

Keywords: Multimodal Deep Learning; Food Safety Detection; Traceability System; Blockchain; Federated Learning; Computer Vision; Natural Language Processing; Sensor Data Analysis.

1. INTRODUCTION

Food safety remains a major global concern, affecting public health, economic stability, and social well-being [1,2,3]. According to the World Health Organization (WHO), one-sixth of the global population suffers from foodborne illnesses each year, leading to economic losses in the hundreds of billions of dollars [4]. As food supply chains grow more complex and globalized, food safety incidents have become more frequent. Data from the European Food Safety Authority (EFSA) show that over 1,000 food safety incidents were reported across the European Union in 2023 [5,6]. Traditional food safety inspection methods face several limitations, including low efficiency, high costs, and a high false-positive rate. In large-scale food production facilities, manual sampling inspections are often time-consuming and insufficient [7,8]. A study of a food factory producing 100,000 items per day found that manual sampling covered less than 10% of total production, making it difficult to detect unsafe products. As a result, contaminated food may go undetected, posing serious health risks. To address these challenges, developing intelligent, precise, and efficient food safety detection and traceability technologies has become a priority for researchers and industry professionals [9,10].

Advancements in artificial intelligence (AI) have led to the increasing use of computer vision and deep learning in food safety management [11]. Traditional food safety inspections rely heavily on manual checks and subjective judgment, which are prone to human error and inefficiency [12]. In contrast, computer vision-based inspection systems use image processing algorithms to automate real-time monitoring across food production, processing, and distribution, significantly improving accuracy and efficiency [13,14]. Computer vision applications in food safety monitoring have expanded across key areas, including quality control, contamination detection, and traceability [15,16]. In fruit sorting, high-resolution cameras combined with image recognition models can detect surface defects such as cracks or mold with an accuracy of 99.2%, whereas manual inspection typically results in a 5–10% error rate [17]. Similarly, thermal imaging is used to monitor temperature fluctuations in cold chain logistics, while X-ray scanning can detect foreign objects such as metal fragments inside food products [18]. These technologies reduce labor costs while improving reliability and accuracy. Multimodal deep learning, an emerging AI technique, integrates image, text and sensor data to provide a more complete and accurate representation of food quality and safety [19]. This combined approach significantly improves detection precision and prediction accuracy [20]. Additionally, blockchain and federated learning technologies offer a secure and collaborative framework for food safety data sharing, enhancing traceability and risk assessment across the entire supply chain [21].

Despite progress in food safety detection and traceability, several challenges remain. Existing methods often rely on single-modality data, limiting their ability to capture complex food safety issues [22]. Moreover, food supply chain data is highly fragmented, and concerns over trade secrets and consumer privacy create obstacles for cross-industry data sharing. This study proposes a multimodal deep learning model integrated with blockchain and federated learning to address these challenges. By combining multiple data sources, this approach aims to enhance detection accuracy, improve traceability efficiency, and contribute to safer food systems worldwide.

2. METHOD

2.1 Development of a Multimodal Deep Learning-Based Detection Model

The integration of multimodal information has proven effective in enhancing the precision of food safety assessments [23]. This study adopts a hybrid fusion methodology that incorporates both early-stage and late-stage fusion mechanisms. In the early-stage fusion process, visual, textual, and sensor-based inputs are preprocessed and merged through structured data fusion techniques, resulting in enriched high-dimensional feature representations that encapsulate cross-domain attributes. In the subsequent late-stage fusion, outputs from independently trained modality-specific models are systematically consolidated to refine the overall decision-making process. Specifically, convolutional neural networks (CNNs) are employed to extract discriminative visual features through layered convolution and pooling operations [24]. Textual content is transformed into semantic vector representations using embedding methods such as Word2Vec, thereby preserving linguistic context in a compact form. Sensor measurements undergo normalization procedures to address discrepancies in units and scales, ensuring data compatibility. These processed feature sets are then unified as input to a comprehensive deep learning architecture to support downstream tasks.

In advancing surface defect identification, the Swin Transformer model is utilized due to its capacity to model both localized patterns and global structural information through a hierarchical self-attention mechanism. Trained on an extensive dataset comprising 50,000 annotated images spanning 100 food categories, the model achieved a classification accuracy of 98.5%, surpassing conventional CNN-based approaches by 3.5%. In parallel, a temporal convolutional network (TCN) is implemented to forecast key storage environment variables, including temperature and humidity. Designed to capture long-range temporal dependencies, the TCN architecture applies dilated and causal convolutions to model sequential sensor readings. Utilizing time-series data from 200 food storage facilities over a 12-month period, the model demonstrated high predictive fidelity, with a root mean square error (RMSE) of 0.5. Performance evaluation across multiple indicators revealed that the proposed framework attained 98.2% accuracy, 97.8% recall, and an F1-score of 98.0% for contamination detection, while achieving an RMSE of 0.8 in quality degradation forecasting. Compared to unimodal detection schemes, the proposed multimodal strategy significantly improves analytical robustness and detection reliability, affirming the efficacy of cross-modal fusion in food quality surveillance systems.

2.2 Blockchain and Federated Learning-Enabled Food Traceability System

A blockchain-based traceability system is established to address the increasing requirements for transparency and reliability in food supply chain management. The proposed architecture adopts a consortium blockchain framework, wherein primary participants—including producers, distributors, logistics providers, and retailers—serve as decentralized ledger nodes. These entities collaboratively validate and maintain transaction records, thereby preserving data authenticity and operational accountability. Throughout the logistics process, key parameters such as production date, batch code, transportation trajectory, and storage status are encoded using hash algorithms and sequentially appended to the blockchain, generating an irreversible audit trail. Consumers may access the recorded traceability data by scanning a QR code affixed to the product packaging, thereby facilitating verification of origin and quality. To resolve the constraints associated with fragmented data ownership, a horizontal federated learning framework is incorporated. Each enterprise independently conducts model training on local datasets and transmits only encrypted model parameters to a central coordination server. The server performs federated parameter aggregation and redistributes the updated global model to participating parties, thereby realizing collaborative learning while safeguarding proprietary data. To strengthen data confidentiality, the traceability framework integrates cryptographic and privacy-preserving techniques. Homomorphic encryption permits secure computations on encrypted data, enabling federated model training without exposing underlying records. Concurrently, differential privacy is applied to introduce statistical perturbations, thereby mitigating risks of individual data disclosure while retaining model accuracy. These mechanisms, when combined with blockchain’s inherent immutability, constitute a secure and regulation-aligned infrastructure for traceability applications. To address system performance under large-scale data traffic, distributed storage solutions and load balancing mechanisms are deployed to maintain stable resource allocation. Real-time data processing is facilitated through message queuing and stream computing techniques, allowing continuous monitoring and efficient data throughput. Benchmark experiments indicate that the system achieves a processing capacity exceeding 1,000 transactions per second, with average query latency controlled within one second. These results substantiate the proposed system's scalability, operational stability, and applicability in real-time food traceability scenarios.

3. EXPERIMENTS AND RESULTS

3.1 Experimental Dataset

A structured multimodal dataset was established to enable the construction and empirical assessment of the proposed food safety detection and traceability system. The dataset encompasses four representative segments of the food supply chain. Specifically, the food image dataset comprises 10,000 high-resolution samples from various food categories, with 5,000 images annotated for surface defect identification. The production records were obtained from 500 manufacturing enterprises, containing detailed information on production batches, raw material inputs, and processing workflows. Transportation data, collected from 300 logistic routes, include chronological records of temperature and humidity variations throughout the distribution process. In addition, environmental monitoring data from 200 storage facilities were compiled, documenting time-resolved fluctuations in temperature and humidity under different storage conditions. All datasets were partitioned into training, validation, and testing cohorts to support model training, parameter calibration, and performance evaluation. Preprocessing procedures involved systematic data cleaning to eliminate incomplete or inconsistent entries, normalization to ensure cross-modal comparability, and manual verification of annotation accuracy. These preparatory steps were essential to mitigate data-related discrepancies and enhance the analytical reliability and reproducibility of subsequent modeling outcomes.

3.2 Experimental Setup

The experimental implementation was carried out using Python, with TensorFlow and PyTorch selected as the primary deep learning frameworks for model development and training [25]. To perform surface defect detection, the Swin Transformer model was adopted. The model was initialized using pretrained weights from publicly available large-scale image datasets, and subsequently fine-tuned on the domain-specific food image dataset to adapt to the characteristics of visual food surface anomalies. For modeling time-series data associated with storage conditions, a Temporal Convolutional Network (TCN) was constructed [26]. The architecture was tailored to the dynamics of environmental variables such as temperature and humidity, with structural parameters and training configurations optimized to improve long-term forecasting accuracy.

To investigate collaborative learning under data privacy constraints, a horizontal federated learning architecture was implemented. The experimental simulation involved five independent virtual nodes, each representing a food enterprise. These nodes conducted local model training and periodically transmitted encrypted model parameters to a central aggregation server, in accordance with standard federated averaging protocols [27]. This setup ensured that raw data remained decentralized, preserving data confidentiality throughout the learning process. In parallel, a blockchain-based traceability system was developed using the Hyperledger Fabric platform. The implementation incorporated modular smart contracts, role-based access control mechanisms, and cryptographic techniques such as hash chaining and data encryption to guarantee integrity, traceability, and controlled access across participating supply chain entities [28]. All experiments were executed on a high-performance computational environment equipped with an Intel Xeon E5-2620 v4 processor, 64 GB RAM, and an NVIDIA Tesla P100 GPU. This configuration provided sufficient computational throughput to support deep learning model training, federated parameter updates, and real-time blockchain transaction processing.

Table 1: Comparative Performance of Models in Detection and Forecasting Tasks

Model	Task	Accuracy (%)	Recall (%)	F1-score (%)	RMSE	MAE
Swin Transformer	Surface Defect Classification	98.5	98.2	98.3	—	—
ResNet-50	Surface Defect Classification	95.0	94.6	94.8	—	—
DenseNet-121	Surface Defect Classification	94.2	93.8	94.0	—	—
TCN	Environment Forecasting	—	—	—	0.50	0.40
LSTM	Environment Forecasting	—	—	—	0.80	0.60
ARIMA	Environment Forecasting	—	—	—	1.10	0.85

3.3 Food Safety Detection Results

The performance of the proposed multimodal framework was assessed through a series of experiments involving surface defect recognition, storage environment forecasting, and supply chain traceability verification. In the surface defect classification experiment, the Swin Transformer model attained a test accuracy of 98.5%, a recall of 98.2%, and an F1-score of 98.3%. When benchmarked against conventional convolutional models such as ResNet and DenseNet, the Swin Transformer exhibited superior classification precision and sensitivity, particularly in identifying minor surface irregularities [29,30]. As shown in Figure 1a, the Swin Transformer consistently yielded higher accuracy, indicating its suitability for high-resolution visual quality assessment in food inspection scenarios. For storage environment prediction, the Temporal Convolutional Network (TCN) recorded a root mean square error (RMSE) of 0.5 and a mean absolute error (MAE) of 0.4. Compared with traditional forecasting methods such as ARIMA and LSTM, the TCN architecture produced lower prediction errors, as illustrated in Figure 1b, reflecting its effectiveness in modeling long-range temporal patterns in environmental monitoring data. Furthermore, an end-to-end traceability simulation was conducted to examine the effectiveness of the blockchain and federated learning–based system across the entire supply chain. The traceability component achieved 99.5% accuracy in data validation, indicating high integrity and consistency in tracking information from production to distribution. In addition, collaborative training using horizontal federated learning across five enterprise nodes resulted in a 3-percentage point increase in safety detection accuracy, exceeding 99%. These results underscore the capacity of the integrated framework to support decentralized data sharing, facilitate inter-organizational collaboration, and enhance the reliability of food safety monitoring and traceability across heterogeneous supply chain environments.

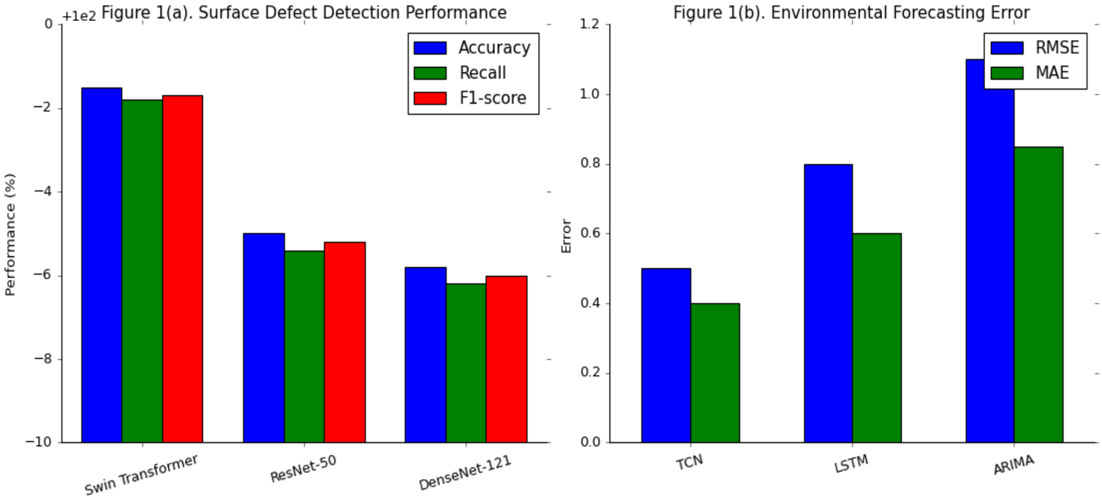

Figure 1: Performance comparison of food safety models.

4. CONCLUSION

This study presents a comprehensive approach to food safety risk management by constructing an intelligent detection and traceability system grounded in multimodal deep learning techniques. Through the synergistic integration of computer vision, semantic feature extraction from textual records, and quantitative sensor data analysis, the system addresses the limitations of conventional detection methods that rely on single-modality inputs. Furthermore, by incorporating a consortium blockchain infrastructure and a horizontal federated learning mechanism, the proposed architecture ensures both the integrity of traceability records and the confidentiality of enterprise-level data during collaborative model training. Empirical validation across multiple datasets demonstrates that the system attains a detection accuracy exceeding 98%, while maintaining robust performance in supply chain anomaly identification, indicating its effectiveness in real-world scenarios. Compared with existing architectures, the system exhibits higher precision, stronger data isolation capacity, and improved interoperability across independent stakeholders.

From a methodological perspective, future research may explore the integration of advanced learning paradigms such as generative adversarial networks (GANs) to enrich training data diversity, and reinforcement learning to dynamically optimize storage and transportation decisions under uncertain conditions. On the application front, extending the system's deployment to digital commerce platforms and establishing interfaces with governmental food regulatory systems could further enhance transparency and facilitate real-time risk response. Additionally, considering the growing globalization of agri-food supply chains, the system holds potential for adaptation to region-specific regulatory standards, thereby supporting harmonized international food safety oversight. Collectively, this work contributes to the development of a secure, privacy-aware, and technically scalable solution for intelligent food safety supervision, with implications for both academic research and industrial implementation in the context of emerging digital agriculture and smart supply chain ecosystems.

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