Hyperspectral Imaging Combined with Deep Learning for Food Composition Analysis: Enhancing Intelligent Engineering Systems through Cyber-Physical Integration

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ABSTRACT

Combining hyperspectral imaging (HSI) with deep learning (DL), we can quickly measure the levels of sugar, protein, fat and counterfeit products without destroying food. This paper reviews what happened in system engineering, network physical system (CPS) and opinions based on information theory from 2019 to 2023. We regard HSI-DL as an important module to observe and make decisions in the intelligent food system. According to this theory, spectral data is like an information source with a large number of dimensions, while DL encoder needs a lot of information, which is helpful for closed-loop control in CPS architecture. We studied the methods of extracting spectral and spatial features, reducing the size and inferring nearby equipment, and the integration of online detection and reinforcement learning of computer vision, and planned in an adaptive way. The application of strawberry maturity assessment, apple internal quality grading, grain protein prediction and meat adult detection shows great improvement in accuracy and throughput, but there are also limitations in domain generalization, model interpretability and real-time calculation constraints. The original idea provides an information-optimized perceptual layer in digital dual-enabled CPS, which maximizes mutual benefit between spectral signatures and variable composition of information, while respecting delay and energy limitations. In conclusion, interdisciplinary verification is needed to make flexible and sustainable food engineering systems using AI.

Keywords: Hyperspectral Imaging; Deep Learning; Food Composition Analysis; Cyber-Physical Systems; Intelligent Engineering Systems; Non-Destructive Evaluation; Spectral-Spatial Feature Extraction; Quality Control Automation.

1. INTRODUCTION

Food supply chains around the world need to know the contents of food accurately and in real time to ensure safety, put information on labels correctly, prevent fraud and improve their work. Traditional methods, such as wet chemistry and chromatography, are accurate, but they destroy food, require a lot of work, and cannot be used with fast and continuous production lines. Hyperspectral imaging solves these problems by taking images of shapes and hundreds of spectral bands at the same time, thus generating a three-dimensional data cube, which contains a lot of information about molecules such as sugar, protein, fat and foreign bodies. Deep learning architecture, especially convolution 3D models and transforming them, is very good at learning representations from these big data, which is better than traditional chemometrics methods in complex and different foods.

From the perspective of systems engineering, food production is a large system made by human beings. The network physical system theory provides us with a formal structure: HSI sensors and actuators are connected to the computer model through bidirectional information flow. Information theory helps us to understand the main problem: we need to maximize the information between the observed spectrum and hidden variables, while reducing unnecessary changes caused by light, direction, plant types and environmental noise. In this framework, HSI-DL works as an intelligent codec pair. It converts the original spectrum and spatial data into the estimated value of real-time decision.

Recent research shows that things are developing rapidly. Important work on strawberry maturity shows that HSI-DL can be used to predict soluble solids [1]. Other studies that collect information about machine learning and hyperspectral imaging in the food chain show that these technologies can really change things when they are put into the network physical architecture [2]. However, when we want to use them in a real industrial CPS system, we will see robustness, response time and explanation problems, which is good enough for the rules. Therefore, this review looks at all this in an organized way of thinking: Section 2 discusses the theoretical basis; Section 3 shows the technical path and AI technology used; Section 4 focuses on use examples; Section 5 discusses the problem and what can be done next. And section 6 provide ideas for working better in intelligent engineering.

2. THEORETICAL FOUNDATIONS OF HYPERSPECTRAL IMAGING AND DEEP LEARNING INTEGRATION IN CYBER-PHYSICAL FOOD SYSTEMS

HSI data can be expressed as a tensor \ (\ mathbf {x} \ in \ mathbb {r} {h \ timesw \ timesb} \), where B is the number of frequency bands. Each spatial pixel contains a high-dimensional reflection or absorption spectrum, and its information is explained by Bell-Lambert absorption law and diffusion phenomenon. Information theory analysis uses mutual information to measure the value I of these data (\ mathbf {x}; \mathbf{C}) \, where $\mathbf{C}$ represents the synthesis parameters of the target. Using DL to select the best tape and feature extraction aims to maintain the maximum mutual useful information while deleting unnecessary sizes. In this way, we can effectively compress the feedback channel of CPS.

DL model is a general approximator of functions. They can learn how to find the reverse path between spectrum and composition. Three-dimensional convolutional networks capture local links between spectrum and space. Pay attention to strengthening the long-term dependence between analog frequency band and position of converter. When they are put into the CPS architecture, these models close the perception-action loop: the estimated combined state issues commands (process set-points) to the actuators. Their effects can be seen in subsequent cycles, which allows adaptive control. The principle of system engineering, especially V- model verification and validation, requires us to show that this model is not only suitable for the laboratory samples being shelved, but also suitable for the operating range of the whole production system, including the extreme cases of culture variation and sensor drift.

A concrete example is strawberry packaging facilities using CPS. HSI linear scanning camera takes a complete image at transmission speed; Small 3D-CNN placed on the edge of the network can calculate the sugar level and ripening stage in less than 80 milliseconds. These estimates help to determine the delivery location of strawberries in real time, and update the digital twins to simulate how strawberries ripen later and how long they can stay on the shelf.

The second example is a grain receiving station. Protein prediction model with hyperspectral provides information for reinforcement learning scheduler, which decides where and when to check batches according to the uncertainty of each batch. More inspections are carried out for batches with great changes, which helps to strike a proper balance between the analysis cost and the risk of poor quality, so as to minimize the expected total loss. This approach goes further than the classical information theory, and regards inspection as an active detection strategy, rather than a fixed program that does not return.

These integrations show a new theoretical idea: HSI-DL pipeline can be used as an information bottle to keep the important information of the task, while limiting the time and energy provided by CPS edge nodes. This method combines spectral physics, statistical learning and control theory into a food system engineering framework.

3. KEY TECHNOLOGIES AND METHODOLOGICAL FRAMEWORKS FOR REAL-TIME SPECTRAL-SPATIAL ANALYSIS

First of all, we accurately calibrate the sensor, correct the dark current, and standardize the radiation measurement so that the color is good even when the light changes. Then, Savitzky-Golay smoothing and multiplier diffusion correction are usually used, and the size is reduced by principal component analysis or paying attention to the selection of guiding bands. These steps shift the amount of data from hundreds of megabytes per minute to smaller data streams, but retain important information.

The deep learning pipeline mainly uses a spectral-spatial hybrid architecture. The first layer carries out 3D convolution to find information about space and color; After that, we add squeeze and excitation or conversion blocks to highlight important zones and areas. Model compression techniques-quantization, preprocessing and knowledge evaporation-can perform calculations on small machines such as NVIDIA Jetson or FPGA accelerator in less than 50 milliseconds, which is fast enough for sorting chain. Computer vision module, usually YOLO detector, first finds every food on the treadmill, and then carries out HSI only in these places, which further reduces the workload.

Edge computing is an important bridge between perception and action in CPS. By reasoning locally, the system avoids the waiting time to enter the cloud server, and can continue to run even if the network is cut off, thus making the system more powerful. Reinforcement learning agents working at the supervisory level can also improve capture parameters, such as exposure time or tape selection, by looking at batch statistics, and they have achieved a good balance between obtaining information and using energy and time.

Using hyperspectral imaging technology and machine learning algorithm to check the quality of internal apples shows that the results of these tasks are very good [3]. Other deep learning methods to find spots on strawberries after harvest have been tested, using different lights, which helps to prepare [4]. Convolutional neural network model performs well in the classification of hyperspectral images in food factories [5]. By mixing convolutional neural network, graphic convolutional network and support vector machine, we improve the accuracy of hyperspectral image classification [6].

An industrial example is the high-speed apple sorting line. The computer vision stage with multiple cameras separates and tracks each fruit; The recorded HSI subcubes are processed by 3D-CNN quantified on edge hardware to predict the solidity and internal distribution of sugar. Pneumatic actuators react in a fruit interval, which matches the reference value of destructive refractive index by more than 98%, while maintaining the flow of more than 8 objects per second. The same architecture has been verified as a carbopol card that rejects fruit infection, showing dual capabilities of composition and defect detection.

Additional examples of meat processing combine HSI with enhanced attention network for fat content regression and adult classification (for example, pork in beef chop steak). The model deployed on the edge is connected with the reinforcement learning planning program, which adjusts the inspection frequency according to the risk status of upstream suppliers, so as to concentrate the analysis work on the places with the highest possibility of composition variability or fraud.

Together, these pipelines show how DL, computer vision, edge computing and reinforcement learning can be combined into a coherent method stack, and the original spectral data can be converted into reliable and low-delay control signals of intelligent engineering systems.

4. APPLICATIONS IN FOOD COMPOSITION ANALYSIS AND QUALITY ASSURANCE

Applications cover a wide range of product categories, and each category has different spectral characteristics and technical limitations. In fruit system, HSI-DL can well predict the soluble solid content and firmness. The important work on strawberry shows that the convolution mixing model can tell the ripening stage and sugar level, and the error is less than 0.8 Brix for several varieties and harvest seasons. Parallel research on apples extends this method to map internal bites and analyze nutrients.

The recent fusion defect detection method for strawberry also shows how the image and depth architecture work together [7]. The research of sensor data fusion combining acoustic and hyperspectral features with machine learning is helpful to classify apples infected by coding madness [8]. The application of cereals involves the detection of protein, moisture and mycotoxins. Hyperspectral estimation of protein in cereals and corn kernels is helpful to classify them for high-quality markets and provide accurate feed for animals. When they are combined with digital twin simulation for grinding, the real-time data of the composition allows the grinding and grinding parameters to be changed, thereby improving the yield and uniformity of flour while using less energy.

The meat and seafood industries use HSI-DL to measure the fat/starch ratio, determine whether the food is fresh by observing the oxidation state of myoglobin, and detect fraud. The minced meat production line with HSI push rod and lightweight transformer has been proved to be able to detect fraud at industrial speed with a success rate of over 95%. This directly helps to abide by the rules and protect trademarks. When combined with the CPS traceability platform, the composition information is put into the digital passport of the product, which makes the supply chain clearer from beginning to end.

When you look closely, you always see the bright side: we need fewer laboratories, we discard fewer products, and we release products faster. But we also see that when things change on the court, things are not so good. When there are differences in seasons, places or varieties, the accuracy may drop by 5 to 15 percentage points. Therefore, we must constantly learn or adjust methods. Failure to detect the risk of dangerous fraud is still a big problem, which shows that we need to be cautious when making decisions and someone needs to monitor it in a sound quality system.

An important idea about the system comes from these deployments: HSI-DL, as a distributed and high-bandwidth sensor structure, fills the semantic knowledge graph with combined attributes. This allows causal reasoning in the whole production system-for example, linking upstream agronomic practices with downstream processing output-thus improving quality control: you can actively optimize based on the model, rather than just reacting to problems.

5. CHALLENGES, LIMITATIONS, AND FUTURE DIRECTIONS IN DEPLOYING AI-ENABLED HYPERSPECTRAL SYSTEMS

Despite the prospect, several problems hinder its wide application in industry. The amount of data is still very large; Full-resolution cube brings huge storage and transmission problems to CPS network. Although reducing the size and using edge reasoning can help shorten the time, too strong compression may lose subtle signals, thus making a difficult choice between speed and quality. The lack of labeled data makes learning more difficult. It is expensive to obtain a large number of real component values, and it will lead to the decline of sample quality, which will lead to the model learning too much from laboratory data. It may be helpful to create synthetic data by using domain adaptation and generating confrontation network, but there are still differences, which make the model less reliable in real life.

Another important problem is that we don't know much about how the model is decided. Deep networks have produced good results, but we don't know how they are done, which brings problems to food safety rules that need clear evidence. Methods such as Grad-CAM and SHAP can show which spectrum is important, but they only tell what is relevant, not the factors that lead to the results, which is not enough for strict audit. We must also consider the energy used: it takes a lot of energy to train a large-scale conversion model on hyperspectral data, and people may wonder whether a high-quality system using AI is really beneficial to the environment.

Integration problems will occur when the HSI-DL module is put into the old machine. Due to humidity, dust and temperature, the calibration of the sensor will change, so it is often necessary to recalibrate and use known unsafe methods.

If the model is attacked, it may make mistakes in composition, which may lead to public health problems and money losses.

The standardized strategy of improving hyperspectral classification has been proved to be helpful to better evaluate the quality of honey [9]. The future development will be more related to digital twins and reinforcement learning. High-precision digital twins from the whole production line can simulate what happens when the composition changes, and can test the order before actual use. Reinforcement learning agents can learn the policy of performing multiple tasks at the same time: improving quality, production and energy, and choosing the best spectrum part or inspection location at the same time. Joint learning between factories in different locations can maintain the privacy of data and improve the overall model. The basic model generated by training on large-scale hyperspectral data sets may need less labeled data, which is due to self-monitoring pretreatment and a small amount of shooting adaptation.

Deep learning hyperspectral imaging framework has become a fast and reliable alternative to common methods for testing food quality and safety [10]. The new architecture concept regards HSI-DL pipeline as the lowest layer of layered CPS: the original spectrum is converted into composition embedding, and the knowledge map is filled; Do causal reasoning and planning at a higher level. This hierarchical design improves performance and interpretability, and links technical capabilities with the verification and governance requirements of intelligent engineering systems.

6. CONCLUSION

Hyperspectral imaging with deep learning provides a very powerful tool to analyze food without destroying it, with high spatial and spectral accuracy and good ability to recognize shapes. When we put it in the framework of system engineering, network physical system and information theory, they are not only measured separately, but also become the layer of intelligent and adaptive food production system to help us perceive and make decisions. We have examples of fruits, grains and meat, which show that we have improved accuracy, increased speed and reduced waste. But these benefits are still limited by data efficiency, robustness in different situations, understanding of the results and how to integrate all these into CPS.

Future progress depends on the integration of food scientists, control engineers and machine learning researchers to jointly design perception models, digital twins and adaptive control strategies, while meeting physical constraints and important rules. The theoretical and architectural ideas we put forward here-especially the formulation of HSI-DL as an encoder to optimize information in closed-loop CPS-provide a solid foundation for this joint design. If we use these technologies in a responsible and proven way, they can really improve the sustainability, safety and flexibility of the global food engineering system, while maintaining strict proof and interpretation rules required by science and society.

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