

AI-Assisted Prediction of Polysaccharide–Gluten Interactions for Optimizing Frozen Dough Quality

Hermann-Josef Zahn

School of Electrical Engineering and Computer Science, Oregon State University, Corvallis,
OR, USA.

hermannjosefmail@oregonstate.edu

Iona McGahey

Department of Electrical Engineering and Computer Science, University of Missouri,
Columbia, MO, USA.

iona.work@missouri.edu

Abstract

Frozen dough quality depends on coupled biochemical, colloidal, thermal, and logistical processes that are difficult to optimize through empirical formulation alone. Polysaccharides can stabilize gluten networks, modulate ice recrystallization, and alter water distribution, but their effects are strongly nonlinear and depend on molecular structure, concentration, freezing rate, storage history, and baking conditions. This paper examines artificial intelligence assisted prediction of polysaccharide–gluten interactions as a system-level infrastructure problem rather than a narrow modeling task. It argues that predictive accuracy must be embedded within data architectures, sensing modalities, model governance, deployment pathways, and sustainability constraints. The discussion first frames frozen dough as a socio-technical infrastructure in which formulation decisions interact with cold-chain operations, supplier variability, and consumer expectations. It then analyzes multimodal data acquisition, including rheological, thermal, spectroscopic, imaging, and textual sources, and considers the trade-offs among deep learning, physics-informed learning, and hybrid modeling. The paper emphasizes robustness, interpretability, fairness across suppliers and regions, and policy mechanisms for validation and audit. It further evaluates how AI-assisted formulation can reduce waste and energy use while avoiding rebound effects and inequitable access. A central claim is that polysaccharide–gluten prediction systems should be designed as governed decision-support infrastructures that connect laboratory discovery, industrial production, and regulatory oversight. The conclusion proposes that long-term value depends less on isolated predictive benchmarks and more on interoperable data, transparent uncertainty, lifecycle accountability, and adaptive deployment in real bakery supply chains.

Keywords

AI-assisted prediction; polysaccharide–gluten interactions; frozen dough; cryoprotection; food systems; multimodal sensing; governance; sustainability.

1. Introduction

Frozen dough technology occupies a critical position in modern bakery supply chains because it enables centralized production, long-distance distribution, retail baking, and household convenience. However, freezing and frozen storage impose mechanical and biochemical stresses on the gluten network, yeast viability, and water distribution. These stresses can lead to reduced proofing capacity, weaker gas retention, undesirable crumb structure, and

inconsistent volume after baking. Polysaccharides have therefore attracted attention as cryoprotective and rheology-modifying agents because they can influence ice formation, water mobility, and macromolecular crowding. Yet the relationship between polysaccharide structure and gluten functionality is not easily reduced to a single formulation rule. The same hydrocolloid may improve one dough system while destabilizing another, depending on molecular weight, branching, charge density, concentration, and interaction with other ingredients. This complexity creates a strong motivation for artificial intelligence assisted prediction, but it also exposes the limits of purely data-driven approaches when data are sparse, heterogeneous, and tied to specific processing conditions [1], [2].

The central premise of this paper is that AI-assisted prediction of polysaccharide–gluten interactions should be understood as an infrastructure problem. A model that predicts dough quality in a laboratory setting may fail in an industrial bakery if sensor drift, batch variation, or supply-chain discontinuities are not addressed. Similarly, a highly accurate black-box model may be rejected by quality assurance teams if it cannot explain why a formulation change is recommended. The relevant system therefore includes not only machine learning architectures but also data provenance, laboratory protocols, cloud-edge deployment, digital twins, regulatory standards, and organizational incentives [3], [6], [7]. The quality of frozen dough is also a socio-technical outcome because it depends on farmer practices, flour milling, hydrocolloid extraction, cold-chain reliability, retail handling, and consumer baking behavior. Predictive systems that ignore these dependencies risk optimizing a narrow objective while shifting costs elsewhere.

Recent advances in food science and machine learning suggest that hybrid approaches can combine mechanistic insight with pattern recognition. For example, rheological measurements, differential scanning calorimetry, nuclear magnetic resonance, near-infrared spectroscopy, and imaging can provide complementary views of dough state [14], [18]. Deep learning can integrate these modalities, while physics-informed regularization can constrain predictions with known thermodynamic and polymer principles [1], [3]. The practical challenge is to design architectures that remain robust under distribution shift and interpretable enough for regulatory and commercial decision-making. This paper contributes a system-level analysis of those trade-offs. It first characterizes frozen dough as a socio-technical infrastructure, then examines data and sensing architectures, model design, governance, sustainability, validation, and industrial translation. Throughout, the discussion emphasizes that polysaccharide–gluten prediction is not merely a computational problem but a governance and deployment problem that shapes who benefits from improved frozen dough quality [4], [5], [20].

2. Frozen Dough Quality as a Socio-Technical Infrastructure

Frozen dough quality emerges from a sequence of coupled transformations. During mixing, gluten proteins hydrate and form a viscoelastic network. During freezing, ice crystals nucleate and grow, potentially damaging gas cells and redistributing water. During frozen storage, recrystallization and molecular rearrangement continue, often altering dough strength and extensibility [8], [9]. During thawing, proofing, and baking, the accumulated structural history determines gas retention, crumb texture, and sensory properties. Polysaccharides intervene at multiple points in this sequence. They can bind water, increase viscosity, retard ice crystal growth, and modify the effective concentration of gluten proteins. Some hydrocolloids also participate in gelation or sol-gel transitions that stabilize the system during thermal cycling. The structural basis of such cryoprotective transitions has been studied in

specific polysaccharide fractions, including a *Phyllanthus emblica* L. polysaccharide fraction for frozen dough applications [15]. Such findings are valuable, but they also illustrate the specificity problem: a mechanism identified in one fraction may not transfer directly to another botanical source or industrial extraction process.

From a systems perspective, frozen dough quality is produced across organizational boundaries. A flour mill may vary protein content and starch damage; a hydrocolloid supplier may vary molecular weight and impurity profile; a frozen dough manufacturer may vary mixing energy, freezing rate, and storage temperature; a retailer may vary display case conditions; and a consumer may vary thawing and baking practices. Each boundary creates information loss and uncertainty. AI-assisted prediction can help only if it accounts for this distributed production of quality. A model trained only on controlled laboratory data may learn relationships that are not stable in commercial environments. Conversely, a model trained on plant data may capture operational correlations but lack mechanistic interpretability. The most promising systems are therefore likely to be layered, combining mechanistic priors, laboratory characterization, and operational feedback [3], [6].

The socio-technical dimension also includes economic and regulatory pressures. Frozen dough is attractive because it reduces labor costs, extends shelf life, and supports product consistency, but it also depends on energy-intensive cold chains. Formulation changes that improve freeze tolerance may increase ingredient costs, alter labeling requirements, or raise allergen and consumer acceptance concerns. Predictive systems that recommend polysaccharide addition must therefore be evaluated not only for predicted quality but also for cost, sustainability, and regulatory compliance. This expands the objective function beyond single-point accuracy. It requires multi-objective optimization under uncertainty, with explicit treatment of trade-offs among texture, processability, cost, and environmental impact. Such trade-offs are common in complex engineered systems, where optimization in one dimension can degrade another [6], [7], [8].

Finally, frozen dough quality is connected to broader questions of resilience. A supply chain that depends on a narrow set of hydrocolloids or a single predictive model may become fragile under climate disruption, trade restrictions, or ingredient shortages. AI-assisted systems can support diversification by rapidly screening alternative polysaccharides and predicting their interactions with gluten under different conditions. However, this benefit depends on data diversity and model transferability. If training data are concentrated in a few wheat varieties or processing regimes, the system may fail precisely when alternative sources are most needed. Thus, robustness and fairness are not secondary ethical add-ons; they are functional requirements for infrastructure-scale deployment [4], [5], [20].

3. Data Architectures and Multimodal Sensing for Polysaccharide–Gluten Prediction

Predicting polysaccharide–gluten interactions requires data that capture molecular structure, colloidal behavior, thermal history, and final product quality. Molecular structure can be represented through sugar composition, linkage analysis, molecular weight distribution, branching, charge, and conformational features. Colloidal and rheological behavior can be measured through oscillatory rheology, creep tests, extensional viscosity, and mixing curves. Thermal behavior can be observed through differential scanning calorimetry, while water mobility can be probed through nuclear magnetic resonance and dielectric spectroscopy. Spectroscopic methods such as near-infrared and Raman spectroscopy can provide rapid, non-destructive fingerprints of dough state. Imaging and computer vision can capture bubble distribution, surface texture, and crumb structure after baking [14], [18]. Each modality has

different sampling frequency, cost, noise structure, and spatial resolution, creating a heterogeneous data architecture problem.

The value of these modalities depends on metadata and provenance. A rheological measurement without information about flour specification, water absorption, mixing protocol, freezing rate, and storage duration is of limited use for generalization. Similarly, a spectroscopic measurement without calibration conditions may not transfer across instruments or factories. AI-assisted prediction therefore requires disciplined data engineering: standardized ontologies, controlled vocabularies, time-stamped records, instrument calibration logs, and clear linkage between samples and process conditions. These requirements are familiar from cyber-physical systems and smart manufacturing, where interoperability and traceability determine whether data can support real-time control and long-term learning [6], [7]. In food systems, the challenge is compounded by biological variability and by the fact that many relevant variables are expensive or destructive to measure.

Multimodal fusion offers a way to compensate for sparse and noisy measurements. Early fusion combines raw or feature-level data before prediction, while late fusion combines separate model outputs. Intermediate fusion can learn shared representations across modalities. The choice among these strategies affects robustness, interpretability, and deployment complexity. For example, a model that relies on hyperspectral imaging may achieve high accuracy in a pilot plant but fail in a small bakery that lacks such sensors. A model that uses only mixing torque and temperature may be less accurate but more widely deployable. This is a structural trade-off between predictive richness and infrastructural fit. The appropriate architecture depends on the decision context. High-stakes formulation changes may justify laboratory-grade multimodal characterization, while routine quality monitoring may require low-cost proxies [14], [19].

Data governance is equally important. Frozen dough data often include proprietary formulations, supplier information, and process parameters that firms may not wish to share. Federated learning and privacy-preserving analytics can allow multiple actors to contribute to model improvement without centralizing raw data. However, these approaches introduce new risks, including uneven participation, free-riding, and difficulty in auditing model behavior. Governance must therefore specify data rights, model ownership, update protocols, and liability when predictions contribute to product failure. Without such arrangements, the infrastructure may remain fragmented, with isolated models that cannot learn across the supply chain. The alternative is a tiered data commons in which pre-competitive data, such as generic polysaccharide properties and standard rheological curves, are shared, while commercially sensitive formulation data remain protected [20]. Such a commons could accelerate scientific progress while preserving competitive incentives, but it requires institutional design rather than purely technical solutions.

4. Model Architectures and Structural Trade-offs

Model design for polysaccharide–gluten prediction must balance accuracy, interpretability, computational cost, and data efficiency. Deep neural networks can approximate complex nonlinear relationships and integrate heterogeneous inputs, but they often require large labeled datasets and can be sensitive to distribution shift [1], [2]. Tree-based ensembles and Gaussian processes can perform well on tabular data and provide uncertainty estimates, but they may struggle with high-dimensional spectral or imaging inputs. Physics-informed neural networks and hybrid models can embed thermodynamic constraints, mass balance, or polymer scaling relationships, potentially improving extrapolation and interpretability [3]. The most

appropriate architecture is not universal; it depends on the maturity of mechanistic knowledge, the availability of labeled data, and the cost of prediction errors.

Interpretability is a central trade-off. In a research setting, a complex model may be acceptable if it reveals new hypotheses through feature attribution or latent representations. In a manufacturing setting, quality assurance personnel may need to understand why a formulation is predicted to fail under a specific storage condition. Interpretability can be achieved through inherently transparent models, post hoc explanations, or hybrid designs that separate mechanistic and learned components. However, explanations can be unstable or misleading if the model is poorly calibrated. The system therefore needs both explanation mechanisms and validation procedures that test whether explanations correspond to causal mechanisms. This is particularly important when predictions inform changes to polysaccharide type or concentration, because incorrect causal inference could lead to costly or unsafe formulation decisions [3], [4].

Scalability introduces another structural trade-off. Cloud-based training can leverage large datasets and powerful accelerators, but cloud inference may be unsuitable for real-time control in bakeries with limited connectivity or strict data residency requirements. Edge deployment can reduce latency and preserve privacy, but it constrains model size and energy use. A hybrid architecture may train centrally and deploy compact models at the edge, with periodic updates and fallback modes. Such architectures are common in smart manufacturing and cyber-physical systems, where resilience depends on graceful degradation when network or sensor failures occur [6], [7]. For frozen dough, a fallback mode might use conservative formulation rules when the model's uncertainty exceeds a threshold, ensuring that automation does not override human judgment in ambiguous situations.

Data efficiency is especially relevant because experimental characterization of polysaccharide–gluten interactions is expensive. Active learning can prioritize experiments that are expected to reduce model uncertainty or improve decision quality. Transfer learning can leverage models pretrained on related food systems, such as starch–hydrocolloid mixtures or gluten-free doughs, and fine-tune them on frozen dough data. However, transfer learning can also propagate biases if the source and target systems differ in important ways. A model pretrained on high-protein wheat flour may not transfer well to ancient grains or composite flours. The design challenge is to encode enough domain knowledge to guide transfer while retaining the flexibility to learn new interactions. This favors modular architectures in which polysaccharide properties, gluten network features, and process conditions are represented separately before being combined in a prediction layer [14], [19].

5. Governance, Robustness, Fairness, and Deployment

Deploying AI-assisted prediction in frozen dough supply chains requires governance that addresses accountability, transparency, and fairness. Accountability means that someone is responsible when a prediction contributes to product failure, food waste, or consumer harm. Transparency means that relevant stakeholders can understand the basis of recommendations, the uncertainty around them, and the limits of the training data. Fairness means that the benefits and risks of the system are distributed equitably across large manufacturers, small bakeries, ingredient suppliers, and consumers. These principles are widely discussed in AI ethics and policy, but they must be operationalized in food-specific terms [20]. For example, a model that performs well for large firms with extensive sensors may systematically disadvantage small bakeries that cannot afford the same instrumentation.

Robustness is both a technical and organizational property. Technical robustness includes resistance to sensor noise, missing data, adversarial manipulation, and distribution shift. Organizational robustness includes clear escalation paths, human oversight, and contingency plans when the model is unavailable or unreliable. In frozen dough production, distribution shift can arise from seasonal flour variation, changes in hydrocolloid extraction, new freezing equipment, or altered storage conditions. A model that was validated under one set of conditions may silently degrade under another. Continuous monitoring, drift detection, and periodic revalidation are therefore necessary. These practices resemble those used in safety-critical manufacturing and healthcare AI, where post-deployment surveillance is essential because pre-deployment testing cannot anticipate all failure modes [4], [5].

Fairness also has a supply-chain dimension. If predictive models favor certain polysaccharides because they are well represented in training data, they may marginalize underutilized or regionally important crops. This can reduce biodiversity and create dependency on a narrow ingredient base. Conversely, if models are designed to explore diverse polysaccharide sources, they can support regional food systems and circular bioeconomy goals. Achieving this requires deliberate data collection from underrepresented raw materials and transparent reporting of model performance across categories. It also requires participation from suppliers and producers in model design, so that local knowledge is not excluded. Governance bodies should therefore include not only data scientists and food engineers but also farmers, processors, regulators, and consumer representatives [20].

Deployment architecture must reflect these governance commitments. A centralized model with opaque updates may be efficient but difficult to audit. A federated or tiered architecture may distribute control but complicate consistency. A practical compromise is a modular system with shared core models for polysaccharide properties, localized calibration for specific plants, and explicit versioning of both data and models. Each prediction should carry a provenance record indicating which data, model version, and assumptions produced it. This record enables traceability during recalls or quality investigations. It also allows regulators to assess whether a system meets standards for safety, labeling, and fair competition. In this sense, the governance layer is not separate from the AI architecture; it is part of the architecture [6], [7], [20].

6. Sustainability and Circularity Implications

Frozen dough systems have significant environmental footprints because they depend on refrigeration, transportation, and packaging. AI-assisted prediction can improve sustainability by reducing formulation trial-and-error, lowering waste from failed batches, and optimizing freezing and storage conditions. If predictive models can identify polysaccharide blends that preserve quality under less energy-intensive freezing, they may reduce peak energy demand and greenhouse gas emissions. They can also help extend the usable life of dough, reducing retail and household waste. However, these benefits are not automatic. Improved efficiency can lead to rebound effects if lower costs increase production and consumption. Sustainability assessment must therefore consider lifecycle impacts rather than assuming that optimization for quality or cost automatically improves environmental outcomes [8], [11].

Polysaccharides used in frozen dough may be derived from grains, legumes, fruits, seaweeds, or processing byproducts. Some sources have favorable environmental profiles because they valorize waste streams, while others may compete with food production or require intensive processing. AI-assisted prediction can support circularity by screening underutilized polysaccharides for cryoprotective function. For example, pectin-rich fruit residues, beta-

glucan fractions, and seed gums could be evaluated for their interactions with gluten and their effects on frozen storage stability. The system could rank candidates not only by predicted quality but also by availability, extraction energy, and social impact. This requires integrating lifecycle inventory data with predictive models, a task that is methodologically challenging because environmental data are often uncertain and geographically variable [11], [12], [13].

Starch retrogradation and water redistribution are also central to frozen dough quality and waste. Predictive models that anticipate retrogradation under different storage regimes can help processors adjust formulation or logistics to avoid stale or structurally compromised products [16]. Hydrocolloids can slow retrogradation and improve freeze-thaw stability, but overdosing may negatively affect texture or processing. The sustainability optimum may therefore differ from the quality optimum. For instance, a slightly lower predicted loaf volume might be acceptable if it allows a shorter freezing time or a more sustainable ingredient source. Multi-objective optimization can make these trade-offs explicit, but it requires governance mechanisms to decide which objectives matter and how they are weighted. These are not purely technical choices; they reflect organizational priorities and public values [17].

Finally, sustainability includes social dimensions. Small producers may lack the capital to adopt sensor-rich AI systems, while large firms may consolidate data and market power. If predictive tools become proprietary bottlenecks, the benefits of improved frozen dough quality may accrue unevenly. Public research institutions, open standards, and pre-competitive data commons can help counter this tendency. They can also ensure that sustainability metrics are independently audited rather than self-reported. The long-term viability of AI-assisted formulation depends on whether it supports a more resilient and inclusive food system, not merely a more efficient one [13], [20].

7. Validation, Policy, and Industrial Translation

Validation is the bridge between laboratory prediction and industrial trust. A model that predicts polysaccharide–gluten interactions must be tested across multiple scales: molecular characterization, dough rheology, pilot-scale freezing, commercial storage, and consumer baking. Each scale introduces new variables and potential failure modes. Validation should therefore include not only average accuracy but also calibration, uncertainty quantification, subgroup performance, and stress testing under extreme conditions. For example, a model may perform well at standard frozen storage temperatures but fail during temperature abuse. It may predict quality for a common wheat flour but not for whole grain or composite flours. These failures may be invisible in aggregate metrics but consequential in practice [14], [18].

Policy can support validation by establishing standards for data quality, model documentation, and post-market surveillance. In food systems, regulators already require traceability, labeling, and safety assurance. AI-assisted formulation could be incorporated into these frameworks through model cards, audit trails, and mandatory reporting of significant deviations. However, overly prescriptive rules may stifle innovation, especially for small firms. A tiered approach may be more effective: low-risk decision support could follow voluntary standards, while high-risk automated formulation changes could require independent validation. The appropriate level of regulation depends on the consequences of error, the degree of automation, and the vulnerability of affected populations [4], [5], [20].

Industrial translation also depends on human factors. Bakers and quality managers may trust or distrust AI recommendations based on past experience, organizational culture, and

perceived usability. A model that provides accurate predictions but unclear explanations may be ignored. A model that is too conservative may be seen as unnecessary. Successful deployment therefore requires participatory design, training, and clear communication of uncertainty. It also requires integration with existing workflows, such as formulation software, batch records, and quality control systems. The goal is not to replace human expertise but to augment it with predictions that are timely, contextual, and accountable [6], [7].

Cross-domain comparisons offer useful lessons. In agriculture, machine learning has been used for yield prediction, disease detection, and precision irrigation, with many of the same challenges around data scarcity, transferability, and equity [19]. In manufacturing, cyber-physical systems and digital twins have demonstrated the value of closed-loop feedback between models and operations [6], [7]. In healthcare, AI deployment has highlighted the importance of prospective validation, bias monitoring, and human oversight [4], [5]. Frozen dough prediction can learn from these domains by treating deployment as a continuous learning process rather than a one-time installation. The most successful systems will likely be those that combine mechanistic understanding, multimodal data, and governance arrangements that enable trust and adaptation over time [3], [14].

8. Conclusion

AI-assisted prediction of polysaccharide–gluten interactions has the potential to improve frozen dough quality by reducing empirical trial-and-error, guiding formulation under uncertainty, and supporting more sustainable cold-chain operations. However, the value of such systems depends on how they are embedded in infrastructure. Predictive models must be supported by interoperable data architectures, calibrated sensors, transparent uncertainty, robust deployment, and governance that addresses accountability and fairness. Polysaccharide–gluten interactions are biologically and physically complex, and no single model or dataset can capture all relevant variation. The realistic goal is not perfect prediction but better decision-making under uncertainty, with clear boundaries around when to trust the model and when to rely on human judgment. The structural basis of cryoprotective transitions and the specific behavior of polysaccharide fractions in frozen dough illustrate both the promise and the specificity of this field [15]. Future progress will require collaboration among food scientists, computer scientists, engineers, regulators, and supply-chain actors. It will also require metrics that go beyond accuracy to include robustness, interpretability, sustainability, and equitable access. If designed as a governed socio-technical infrastructure, AI-assisted prediction can help create frozen dough systems that are more resilient, less wasteful, and more responsive to diverse consumer and producer needs [20].

References

1. LeCun, Y., Bengio, Y., & Hinton, G. (2015). Deep learning. *Nature*, 521(7553), 436–444.
2. Jordan, M. I., & Mitchell, T. M. (2015). Machine learning: Trends, perspectives, and prospects. *Science*, 349(6245), 255–260.
3. Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., & Prabhat. (2019). Deep learning and process understanding for data-driven Earth system science. *Nature*, 566(7743), 195–204.
4. Topol, E. J. (2019). High-performance medicine: The convergence of human and artificial intelligence. *Nature Medicine*, 25(1), 44–56.

5. Rajpurkar, P., Chen, E., Banerjee, O., & Topol, E. J. (2022). AI in health and medicine. *Nature Medicine*, 28(1), 31–38.
6. Kusiak, A. (2018). Smart manufacturing. *International Journal of Production Research*, 56(1-2), 508–517.
7. Lee, J., Bagheri, B., & Kao, H. A. (2015). A cyber-physical systems architecture for Industry 4.0-based manufacturing systems. *Manufacturing Letters*, 3, 18–23.
8. Selomulyo, V. O., & Zhou, W. (2007). Frozen bread dough: Effects of freezing storage and dough improvers. *Journal of Cereal Science*, 45(1), 1–17.
9. Ribotta, P. D., León, A. E., & Añón, M. C. (2001). Effect of freezing and frozen storage of doughs on bread quality. *Journal of Agricultural and Food Chemistry*, 49(2), 913–918.
10. Matuda, T. G., Chevallier, S., Filho, P. A., LeBail, A., & Tadini, C. C. (2008). Impact of guar and xanthan gums on proofing and calorimetric parameters of frozen bread dough. *Journal of Cereal Science*, 48(3), 741–746.
11. Lazaridou, A., & Biliaderis, C. G. (2007). Molecular aspects of cereal β -glucan functionality: Physical properties, technological applications and physiological effects. *Journal of Cereal Science*, 46(2), 101–118.
12. Mudgil, D., Barak, S., & Khatkar, B. S. (2014). Guar gum: Processing, properties and food applications—A review. *Journal of Food Science and Technology*, 51(3), 409–418.
13. Li, J. M., & Nie, S. P. (2016). The functional and nutritional aspects of hydrocolloids in foods. *Food Hydrocolloids*, 53, 46–61.
14. Zhou, L., Zhang, C., Liu, F., Qiu, Z., & He, Y. (2019). Application of deep learning in food: A review. *Comprehensive Reviews in Food Science and Food Safety*, 18(6), 1793–1811.
15. Zhang, T., Fang, J. Q., Wang, P. P., & Chen, C. (2026). Structural basis of the cryoprotective sol-gel transition in a *Phyllanthus emblica* L. polysaccharide fraction for frozen dough applications. *Food Hydrocolloids*, 112842.
16. Wang, S., Li, C., Copeland, L., Niu, Q., & Wang, S. (2015). Starch retrogradation: A comprehensive review. *Comprehensive Reviews in Food Science and Food Safety*, 14(5), 568–585.
17. Rosell, C. M., Rojas, J. A., & Benedito de Barber, C. (2001). Influence of hydrocolloids on dough rheology and bread quality. *Food Hydrocolloids*, 15(1), 75–81.
18. Sun, D. W. (Ed.). (2016). *Computer vision technology for food quality evaluation* (2nd ed.). Academic Press.
19. Kamilaris, A., & Prenafeta-Boldú, F. X. (2018). Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, 147, 70–90.
20. Floridi, L., Cows, J., Beltrametti, M., Chatila, R., Chazerand, P., Dignum, V., Luetge, C., Madelin, R., Pagallo, U., Rossi, F., Schafer, B., Valcke, P., & Vayena, E. (2018). AI4People—An ethical framework for a good AI society: Opportunities, risks, principles, and recommendations. *Minds and Machines*, 28(4), 689–707.