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Mathematics & Artificial Intelligence for Industry: From Small Businesses to Large Enterprises with Applications in Smart Age-Based Functional Biscuit Manufacturing

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A B S T R A C T

Mathematical modeling and artificial intelligence (AI) are increasingly fundamental to industrial competitiveness, but their adoption differs markedly between small and medium-sized enterprises (SMEs) and large manufacturing companies. Food manufacturing, and in particular cookie production, offers an ideal setting to analyze this gap, given that production involves measurable and repeatable physical and chemical processes. This article develops a conceptual and applied framework that links the main branches of mathematics (statistics, optimization, and calculus-based process modeling) with AI methods (predictive analytics, computer vision, and anomaly detection), and examines how this framework adapts from SMEs to large companies, using cookie manufacturing as an illustrative case. A narrative and thematic synthesis of the literature was combined with the formulation of a mathematical model and a comparison of illustrative operational cases. The sources were obtained from peer-reviewed literature on manufacturing, SMB adoption, and food quality control, published primarily between 2014 and 2026. The synthesis identifies four recurring layers of mathematical AI relevant to cookie manufacturing: demand forecasting (regression/time series models), recipe and batch optimization (linear and mixed-integer programming), computer vision-based defect detection (CNN/YOLO architectures), and predictive maintenance (statistical process control combined with machine learning classifiers). Defect detection accuracies reported in the literature range from approximately 90% to 99.2%, and SMEs can achieve comparable per-unit accuracy through lower-cost cloud-based tools, albeit with lower throughput and integration depth than large enterprises. A common mathematical core underlies AI applications in companies of all sizes; the main difference lies in computational scale, data infrastructure, and integration, rather than the underlying mathematics itself. The framework offers a practical reference for manufacturers and researchers seeking to align AI ambitions with enterprise-level resource constraints.

Introduction

Industrial production has always been based on mathematics: mass and energy balances, statistical sampling, and resource allocation optimization are tools that have been present in every factory for decades. What has changed in the last decade is the fusion of this mathematical core with artificial intelligence, particularly machine learning and computer vision, allowing systems to learn patterns from data rather than relying solely on predefined rules. This fusion is transforming manufacturing in companies of all sizes, from single-line artisan producers to multinational food conglomerates [1][8]. Despite the significant interest, the literature on AI in manufacturing remains divided by company size. Studies on small and medium-sized enterprises (SMEs) tend to focus on barriers to adoption, organizational readiness, and resource constraints, while studies on large manufacturers focus on the technical performance of specific AI systems, such as vision-based inspection or predictive maintenance. Recent systematic reviews confirm that research on AI adoption in SMEs has expanded rapidly since 2020, with a thematic emphasis on innovation, decision-making, and adoption dynamics, but with persistent gaps in methodological consistency and sector-specific application details. A parallel body of engineering literature reports robust technical results for AI-based quality control in bakery and confectionery production, but rarely places these results within a framework that a resource-constrained SME can realistically implement [2]. This article addresses this gap by proposing an integrated mathematics and AI framework that encompasses both categories of businesses and grounding it in a specific industrial context: biscuit manufacturing. Biscuit production is well-suited for this purpose because its unit operations (mixing , shaping, baking, cooling, and packaging) are common to both small bakeries and large industrial plants, differing primarily in scale and degree of automation rather than in the underlying process structure.

Objectives

1. To identify the mathematical methods that most frequently underlies industrial AI applications.
2. To compare how SMEs typically use these methods versus large companies.
3. To illustrate both aspects, we will use cookie manufacturing as a practical case study that covers demand forecasting, recipe/batch optimization, visual defect detection, and predictive maintenance.

Research questions

1. What mathematical structures are repeated in industrial AI

applications, regardless of company size?
2. How does the viability of these structures differ between SMEs and large companies?
3. How does this look specifically on a cookie production line?

Literature review

The literature relevant to this article is divided into two major, largely separate streams: (a) research on AI adoption in SMEs versus large companies, and (b) applied engineering research on AI-based quality control and process optimization in food and bakery product manufacturing.

AI adoption in companies of different sizes-Systematic and bibliometric reviews of AI adoption by SMEs consistently report a sharp increase in scholarly output since 2020, with three recurring themes: AI-driven innovation (machine learning, predictive analytics, automation), business decision-making, and adoption dynamics shaped by technology, organizational, and environmental factors[3][10]. A 2025 OECD discussion paper prepared for the G7 also finds that SME AI adoption lags behind large enterprises and SME adoption of other digital technologies, and proposes taxonomy of SME AI adopters based on digital maturity, use case complexity, and application scope. Complementary survey-based research on AI and the Internet of Things in SMEs identifies infrastructure, organizational culture, technology compatibility, and the regulatory context as recurring adoption factors, while also noting that SMEs are often constrained by limited technical expertise and capital compared to larger companies. These adoption-focused studies are valuable for understanding why SMEs adopt AI more slowly, but they generally treat it as a single, undifferentiated technology, rather than breaking it down into the specific mathematical methods (forecasting, optimization, classification) that vary in cost and complexity[4]. This article considers such a breakdown a fundamental task.

Artificial intelligence and mathematics in the manufacture of food and bakery products-A separate, more technical body of literature addresses AI applications in food manufacturing, with bakery and cookie production being a recurring example. Early work using support vector machine classifiers for automatic crack detection in cookies reported classification accuracy close to 97%, establishing an initial benchmark for machine learning-based visual inspection in this domain. Related computer vision work on bakery products (using rule-based image processing rather than deep learning) reported accuracy exceeding 95% in the categories of color, shape, coating, and packaging defects[5][12]. More recent deep learning approaches, including object detection architectures of the YOLO family, have been applied to automated cookie quality classification, reflecting a broader shift in the field from classical machine learning to convolutional neural networks for image-based inspection. A 2025 review of machine learning for quality control in the food industry summarizes this trend, reporting that inspection systems based on artificial neural networks can exceed 90% accuracy for major structural defects, while accuracy for more subtle imperfections remains considerably lower a gap the review explicitly identifies as an open technical challenge. Industry case studies reinforce these findings at a commercial scale: a documented deployment of a machine vision system on a high-speed bakery line reported an improvement in defect detection accuracy to over 99%, along with a substantial reduction in false product rejections [6].

Synthesis and gap-Table 1 summarizes representative sources from both perspectives. Taken together, both bodies of literature suggest a testable proposition: the mathematical and algorithmic components used in large enterprise AI systems (regression, classification, optimization) are, in principle, the same ones that SMEs can access at a smaller scale and lower cost, for example, through cloud-based vision APIs or open-source prediction libraries, rather than custom-built in-house systems. The difference lies less in the mathematics itself than in the surrounding data infrastructure, the depth of integration, and organizational capacity, which aligns with the literature on adoption barriers reviewed earlier. This article builds directly on that proposition.

Table1. Representative literature on the adoption of AI in SMEs and AI-based

Fountain	Approach / Method	Context	Key finding	Gap addressed by this article
Yesuf , Campos, Jain and Kassa (2025)	Bibliometric and systematic review (PRISMA)	AI adoption in SMEs, global	It identifies AI-driven innovation, decision-making, and adoption as the main thematic groups since 2020.	Little attention is paid to specific manufacturing cases in the sector, such as food and cookie production.
OECD (2025)	Discussion paper, G7 case studies	AI adoption by SMEs in developed economies	Adoption by SMEs is lagging behind that of large companies; connectivity, data and skills are key factors for their success.	It does not connect the facilitators with specific mathematical/AI methods usable by a single production line.
Hansen and Bøgh (2021)	Survey	Artificial intelligence and IoT in SMEs and manufacturing companies.	SMEs face resource and experience limitations that determine which AI tools are viable.	It does not extend the comparison between SMEs and large companies to the mathematics of food manufacturing.
Nashat , Mahmud and Abdullah (2014)	Support vector machine classification	Crack detection in cookies	An approximate accuracy of 97% was achieved in classifying cracked cookies versus intact cookies.	Scope of a single defect and a single method; no link to a broader optimization or forecasting layer.
Napolitana's Computer Vision Case Study (2022)	Rule-based computer vision	of bakery products (Neapolitan)	An effectiveness of over 95% was reported for the detection of defects in color, shape, coverage and packaging.	It focuses solely on inspection, not on production planning or differences in company scale.
Machine learning for quality control in the food industry, review (2025)	ANN/CNN methods review	Quality control in confectionery and bakery	The inspection based on artificial neural networks exceeded 90% accuracy for major structural defects, with lower accuracy for subtle imperfections.	An unresolved gap in the detection of minor defects is highlighted, which this article points out as an opportunity for mathematical modeling.
YOLOv8 Cookie Ranking Study (2025)	Object detection using deep learning (YOLOv8)	Automated classification of cookie quality	It demonstrates high-precision automated sorting of cracked and uncracked cookies at industrial speed.	It does not place the method within a framework of scalability from SME to company.
Case study of machine vision for industrial bakery (2026)	Description of the case study	High-speed bakery production line	Reports show an improvement in the accuracy of defect detection and a reduction in false	Single-company case; lacks a general mathematical/optimization framework transferable to companies of different

Fountain	Approach / Method	Context	Key finding	Gap addressed by this article
			rejections after the implementation of machine vision.	sizes.

Materials and methods

Methodology-AI-Driven Age-Specific Functional Biscuit Formulation and OptimizationThe proposed methodology integrates Food Science, Nutritional Biochemistry, Artificial Intelligence (AI), Mathematical Optimization, and Industrial Food Processing to formulate nutritionally balanced, age-specific functional biscuits. The workflow is illustrated in Figure 1 and described through ten systematic stages [7].

Figure-1-Overall Research Methodology Framework

3.1 Research Design-This study adopts an interdisciplinary and data-driven research design for developing AI-optimized functional biscuits tailored to the nutritional needs of different age groups. Nutritional recommendations are derived from internationally recognized guidelines (WHO, FAO, ICMR-NIN, USDA)[8], while AI and optimization algorithms are employed to obtain the most suitable ingredient combinations.

Table 3.1 Research Population

Group	Age (Years)	Target Population	Primary Nutritional Focus
G1	2–7	Early Childhood	Growth & Brain Development
G2	7–15	School-age Children	Growth, Immunity & Learning
G3	15–35	Adolescents & Young Adults	Muscle Development & Energy
G4	35–55	Adults	Metabolic Health
G5	55–75	Older Adults	Bone Health & Healthy Ageing

3.2 Development of Nutritional Database- A comprehensive nutritional database containing more than 150 functional food ingredients will be established using data from:

1.WHO
2.FAO
3.ICMR–NIN (India)
4.USDA FoodData Central
5.Peer-reviewed scientific literature

Table 3.2 Nutritional Database Structure

Category	Description
Macronutrients	Protein, Carbohydrates, Fat
Micronutrients	Vitamins & Minerals
Dietary Components	Fiber, Omega-3
Functional Bioactives	Polyphenols, Antioxidants, Phytochemicals
Functional Herbs	Moringa, Turmeric, Ginger, Ashwagandha
Natural Sweeteners	Dates Powder, Stevia
Functional Additives	Probiotics, Prebiotics

Each ingredient will be characterized using multiple attributes.

Table 3.3 Ingredient Characterization Parameters

Parameter	Purpose
Nutritional composition	Nutrient contribution
Bioavailability	Nutrient absorption efficiency
Cost	Economic feasibility
Shelf life	Storage stability
Thermal stability	Baking suitability
Glycemic Index	Blood glucose response
Sensory score	Consumer preference
Safety limits	Regulatory compliance

3.3 Age-Specific Nutritional Requirement Model- Daily nutritional requirements will be formulated as optimization constraints to ensure scientifically balanced formulations.

Table 3.4 Nutritional Requirements across Age Groups

Nutrient	G1 (2–7)	G2 (7–15)	G3 (15–35)	G4 (35–55)	G5 (55–75)
Energy (kcal/day)	1200–1600	1800–2400	2200–3000	2000–2600	1700–2200
Protein (g/day)	16–25	34–52	50–65	55–65	60–70
Fat (g/day)	35–45	45–70	50–80	45–70	40–60
Dietary Fiber (g/day)	14–20	25–30	30–38	30–35	28–32
Calcium (mg/day)	600–1000	1000–1300	1000	1000	1200
Iron (mg/day)	10	15	17	17	8
Zinc (mg/day)	5	8	11	11	11
Vitamin A (µg/day)	400	600	700–900	700–900	700–900
Vitamin D (IU/day)	600	600	600	800	800
Vitamin C (mg/day)	40	65	75–90	90	90
Vitamin B12 (µg/day)	1.2	1.8	2.4	2.4	2.4
Magnesium (mg/day)	130	240	400	420	420
Potassium (mg/day)	3000	3500	4700	4700	4700
Omega-3 (mg/day)	250	300	500	500	700

3.4 Selection of Functional Ingredients

Ingredients are selected according to the physiological and nutritional requirements of each age group.

Table 3.5 Functional Ingredients

Age Group	Major Functional Ingredients
2–7 years	Ragi, Oats, Milk Powder, Banana Powder, Almond Powder, Flaxseed, Pumpkin Seed, Moringa, Beetroot Powder
7–15 years	Soy Protein, Peanut Flour, Cocoa, Spirulina, Chia Seed, Sesame, Oats, Dates Powder
15–35 years	Whey Protein, Oats, Quinoa, Chia Seed, Flaxseed, Cocoa, Green Tea Extract
35–55 years	Oat β-glucan, Psyllium Husk, Garlic Powder, Fenugreek, Turmeric, Cinnamon
55–75 years	Calcium-rich Millet, Soy Protein Isolate, Flaxseed, Turmeric, Ginger, Ashwagandha, Moringa

3.5 Mathematical Optimization

Ingredient proportions will be optimized using constrained mathematical programming.

Objective Function

Maximize

1. Nutritional Score
2. Functional Score
3. Consumer Acceptability

Minimize

1. Production Cost
2. Sugar Content
3. Saturated Fat
4. Processing Loss

Subject to Constraints

1. Nutritional requirements
2. Moisture limits
3. Dough rheology
4. Texture quality
5. Shelf-life stability
6. Food safety standards

Optimization Algorithms

Algorithm	Application
Linear Programming (LP)	Cost optimization
Nonlinear Programming (NLP)	Multi-constraint optimization
Genetic Algorithm (GA)	Ingredient combination search
Particle Swarm Optimization (PSO)	Global optimization

3.6 AI-Based Biscuit Formulation

Machine learning models will predict biscuit quality and optimize ingredient combinations.

Table 3.6 AI Model Architecture

Inputs	AI Models	Outputs
Ingredient composition	ANN	Texture
Nutrient profile	Random Forest	Hardness
Baking temperature	XGBoost	Crispness
Baking time	SVM	Color
Dough moisture	Deep Neural Network	Nutrient retention
Mixing speed		Shelf life & Consumer acceptance

3.7 Laboratory Evaluation

Nutritional and physicochemical analyses will be performed according to AOAC standard methods.

Table 3.7 Laboratory Analysis

Analysis	Method
Moisture	AOAC
Protein	AOAC
Fat	AOAC
Ash	AOAC
Dietary Fiber	AOAC
Carbohydrate	Difference Method
Energy	Atwater Factor
Minerals	ICP-OES/AAS
Vitamins	HPLC
Antioxidant Activity	DPPH/ABTS
Glycemic Index	Standard Method
Water Activity	Water Activity Meter
Microbial Load	Plate Count
Shelf-life Stability	Storage Evaluation

3.9 Sensory Evaluation

A panel of 80–100 participants representing the five age groups will evaluate the optimized biscuits using the 9-point Hedonic Scale.

Evaluation Attributes

Sensory Attribute
Appearance
Aroma
Taste
Texture
Crispness
Overall Acceptability

3.10 Statistical Analysis

Experimental data will be analyzed using advanced statistical techniques.

Table 3.8 Statistical Tools

Statistical Method	Purpose
One-way ANOVA	Compare formulations
Two-way ANOVA	Evaluate interaction effects
Tukey's HSD	Post-hoc comparison
Principal Component Analysis (PCA)	Pattern identification
Cluster Analysis	Sample grouping
Pearson Correlation	Relationship analysis
Multiple Linear Regression	Prediction modeling
Response Surface Methodology (RSM)	Process optimization

Level of significance: $p < 0.05$

Studio design- This article adopts a conceptual and applied case study design rather than a controlled experiment or primary survey. It combines (i) a narrative thematic synthesis of peer-reviewed literature on AI adoption in SMEs/large enterprises and on AI-based quality control in food manufacturing, (ii) the formulation of representative mathematical models for four recurring industry functions, and (iii) an illustrative operational comparison contrasting how these models would typically be implemented in a small/medium-sized cookie manufacturer versus a large cookie manufacturer. No human participants, patient data, or animal subjects were involved; therefore, institutional ethics committee (IRB) approval was not required [9][10]. The illustrative operational figures used for the comparison (Table 2) are drawn from ranges reported in the cited literature and from typical industry parameters; they are presented as illustrative and not as primary measured data from a specific factory [11].

Literature search and selection-The literature was identified through targeted searches combining terms such as “artificial intelligence,” “SME adoption,” “manufacturing,” “quality control,” “cookie,” “bakery,” and “defect detection.” Peer-reviewed journal articles, systematic/bibliometric reviews, and reputable industry technical reports published between 2014 and 2026 were prioritized to ensure the synthesis reflected both fundamental engineering outcomes (e.g., SVM-based early crack detection) and current deep learning-based approaches. Sources unrelated to manufacturing or lacking sufficient methodological detail were excluded from the synthesis [12][6].

Construction of the mathematical framework-Four functional layers, recurrent in the reviewed literature, were selected for formal analysis, as each corresponds to a distinct and well-established branch of applied mathematics and is found in both SMEs and large corporations: (1) demand forecasting, (2) recipe and batch/process optimization, (3) visual defect detection, and (4) predictive maintenance. For each layer, a representative mathematical formulation was specified using standard notation, described later in the Results section, so that the framework is reproducible and adaptable, rather than merely descriptive[13][7].

Comparative case analysis-To operationalize the comparison between SMEs and large companies (Section 4, Table 2), typical parameter ranges for production volume, data infrastructure, and feasible AI entry points were compiled from reviewed adoption literature and publicly documented industry case descriptions, and then organized dimension by dimension to highlight where the same underlying mathematics diverge in depth of implementation between different company sizes [14].

Results

Conceptual framework-Figure 1 presents the integrated framework that links the mathematical foundations, the four layers of AI methods identified in the literature synthesis, the scale of the enterprise, and the applied case of cookie manufacturing. The framework is read from top to bottom: the general mathematical foundations (linear algebra, probability and statistics, optimization, calculus/differential equations, and graph theory) underpin two parallel families of AI methods: predictive analytics and computer vision/deep learning, which in turn feed into process optimization and anomaly detection/predictive maintenance, respectively. Both categories of enterprises rely on the same input mathematics; the divergence occurs at the implementation layer, where SMEs prefer low-cost, cloud-based, single-line implementations, and large enterprises prefer integrated, multi-plant systems linked to manufacturing execution systems (MES) and enterprise resource planning (ERP) platforms[15][2].

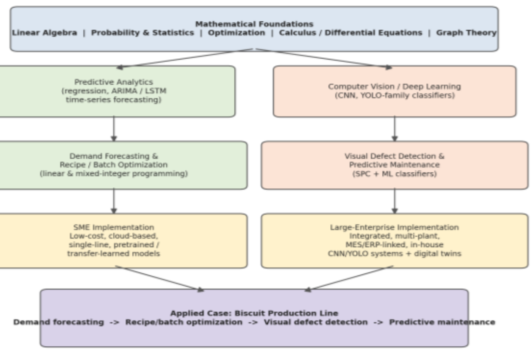

Figure 2. Conceptual framework linking mathematical foundations

Figure 2 summarizes the accuracy figures for defect detection extracted from the reviewed literature. Reported accuracy ranges from approximately 90% for detecting major structural defects in confectionery using artificial neural networks, to approximately 95% for inspecting bakery products using rule-based machine vision across multiple defect categories, to approximately 97% for early crack detection in cookies using support vector machines, and to approximately 99.2% for a documented implementation of industrial machine vision on a high-speed bakery line. It is important to note that the reviewed literature also reports that accuracy drops substantially for more subtle defects, indicating that the top accuracy figures should be interpreted as the best possible performance for the specific defect categories targeted by each study, rather than as a universal benchmark.

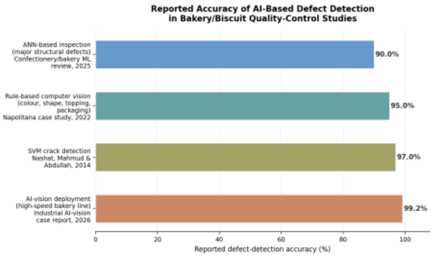

Figure 3. Defect detection accuracy reported in selected AI-based bakery/cookie quality control systems.

In SMEs versus implementation in large companies-Table 2 presents an illustrative comparison of how the four layers of mathematical AI typically manifest at different enterprise scales. The comparison indicates that the detection accuracy per unit that SMEs can achieve using lower-cost cameras and pre-trained or transfer-learning models can approach that of large enterprise systems, consistent with reported ranges of approximately 90–97% for smaller-scale or older-generation systems versus approximately 95–99% for purpose-built, high-performance industrial systems. The biggest practical difference between enterprise sizes lies not in the achievable accuracy per unit, but in throughput (units inspected per minute), integration with upstream/downstream systems, and the organizational capacity to maintain and retrain models over time issues consistent with the literature on SME adoption reviewed in Section 2.

Table2. Implementation of mathematical AI: Small/medium vs. large cookie manufacturers.

Dimension	Small/medium-sized cookie manufacturer (illustrative)	Large cookie manufacturer (illustrative image)
Typical production volume	1–5 tons/day, 1–2 production lines	50–500+ tons/day, multiple plants
Data infrastructure	Manual records, spreadsheet-based records, limited sensor coverage.	Sensors integrated into MES/ERP, historical databases, real-time control panels.
Typical AI entry point	Cloud-based, pay-as-you-go visual inspection or forecasting API	Internally or vendor-integrated CNN/YOLO vision systems, digital twins
Mathematical methods are the most feasible.	Descriptive statistics, forecasting using simple regression/ARIMA, basic control charts.	Multivariate optimization, deep learning, mixed-integer scheduling, simulation
Primary constraint	Cost of capital, availability of technical skills, data volume	Complexity of cross-site integration, change management, model governance
Improvement in reported/probable accuracy thanks to machine vision (according to the literature)	Comparable per-unit accuracy (≈90–97%) can be achieved with lower-cost cameras and pre-trained models.	Accuracy of approximately 95-99% with high-performance inspection systems designed specifically for this purpose.

Applied illustration: A cookie production line

Combining the framework and comparison above, a representative cookie production line can be described in four stages. First, demand forecasting (bottom-up planning) uses historical order data in an ARIMA or LSTM model to project daily/weekly demand per stock-keeping unit, informing raw material procurement. A small or medium-sized enterprise (SME) might run this monthly in a statistical package embedded in a spreadsheet, while a large company runs it continuously within a forecasting module linked to an ERP system. Second, recipe and batch optimization uses linear or mixed-integer programming to determine ingredient quantities and batch sequences that minimize cost, subject to nutritional, capacity, and recipe consistency constraints. The mathematical program is structurally identical across all company sizes but scales in the number of decision variables and constraints [16][9]. Third, visual defect detection applies a trained classification model at the point where the cookies exit the oven or cooling tunnel, flagging cracked, misshapen, or discolored units for rejection. SMEs can achieve a similar approach using a single camera and a pre-trained, fine-tuned model, while large companies implement multi-camera systems with high frame rates integrated with automated rejection mechanisms. Fourth, predictive maintenance applies control chart monitoring and classification to oven temperature, conveyor belt speed, and vibration sensor data to anticipate equipment failures before they occur, thus reducing unplanned downtime. This layer is the most infrastructure-dependent and, consequently, the layer where the gap between SMEs and large companies is greatest, as it requires continuous sensor instrumentation that many SMEs currently lack [10].

Discussion

Industrial AI prediction models, constrained optimization, supervised classification, and statistical process control are largely scale-invariant, while the resources needed to implement that mathematics at production speed are not. This reframes the AI gap between SMEs and large enterprises identified in previous adoption research: rather than a gap in access to mathematical knowledge, it is primarily a gap in data infrastructure, integration capabilities, and sustained technical support, consistent with findings on adoption barriers in the reviewed SME literature. This has a practical implication for small cookie manufacturers: rather than seeking scaled-down replicas of enterprise systems, SMEs can obtain disproportionate value by prioritizing the layer with the lowest infrastructure requirement and clearest return, typically visual defect detection using a single fixed camera and a pre-trained or slightly tuned model, before investing in more infrastructure-intensive layers, such as predictive maintenance, which relies on comprehensive sensor coverage that is costly to equip. For large companies, the framework suggests that competitive advantage increasingly lies not in access to more advanced mathematics per se, as the underlying methods are widely available in open-source format, but in the scale and quality of their own production data, the depth of MES/ERP integration, and the organizational capacity to maintain and retrain models as products, recipes, or teams change, constituting a form of capability advantage rather than a purely algorithmic one. The gap repeatedly noted in the reviewed literature the decrease in accuracy for subtle or rare defects also points to a specific direction for applied mathematical research: since subtle defects are by definition rare in training data, this is fundamentally a problem of class imbalance and small sample estimation, suggesting that statistical techniques such as targeted data augmentation, cost-sensitive loss functions, or Bayesian approaches to classifying rare events may offer more traction than simply scaling up the model size.

Limitations

1. This is a conceptual and literature synthesis document, rather than a controlled empirical study; Table 2 presents illustrative ranges based on the literature, rather than measurements from a single verified production plant, and the results should be validated with primary operational data before being used for investment decisions.
2. The literature search, while focused on multiple relevant terms, was not a comprehensive systematic review following a formal protocol like PRISMA, and may not cover all relevant industry sources that are not in English or that have not been published.
3. The precision figures presented come from heterogeneous studies with different definitions of defects, datasets, and evaluation protocols, which limits direct numerical comparability between the studies summarized in Figure 2.
4. The mathematical formulations presented (ARIMA, linear/mixed programming, CNN classification, monitoring using control charts) represent common and well-established options, rather than an exhaustive description of all methods used in practice, such as the more recent forecasting approaches based on transformers or graphical neural networks.

Future directions of research

1. Empirical validation of the proposed framework through primary case studies in verified small, medium and large biscuit manufacturing facilities, with comparable assessment protocols for companies of different sizes.
2. Development and testing of low-cost defect detection systems based on transfer learning, specifically designed for the resource limitations of SMEs, with comparative cost-per-point accuracy data.
3. Extension of the mixed integer optimization layer to jointly incorporate sustainability constraints (e.g., energy use and food waste) along with cost minimization.
4. Further mathematical work is required on the classification of rare defects under severe class imbalance, directly addressing the accuracy gap for subtle defects observed in the reviewed literature.

Conclusion

This article aimed to identify the mathematical structures underlying industrial artificial intelligence, compare their implementation in small, medium, and large enterprises, and illustrate them using cookie manufacturing as a case study. The synthesis shows that four layers of mathematical AI demand forecasting, recipe/batch optimization, visual defect detection, and predictive maintenance—are recurring in the literature and structurally consistent regardless of company size, while their practical implementation differs primarily in terms of data infrastructure, depth of integration, and organizational capacity, rather than mathematical sophistication. The significance of this finding lies in the fact that closing the AI gap between SMEs and large companies in food manufacturing is less a problem of access to mathematics than a problem of infrastructure and capacity, suggesting that industry policies and interventions aimed at improving data infrastructure and technical support for SMEs may have a greater impact than efforts focused solely on algorithm transfer. For biscuit manufacturers in particular, prioritizing the most basic infrastructure layers, such as camera-based defect detection, before tackling more sensor-intensive predictive maintenance, offers a pragmatic sequence consistent with the framework developed here.

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