

Article

International Digital System for Collective Food Security Support

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Abstract

(1) Background. Food sovereignty and local sustainability are ensured by large agro-industrial holdings and small-scale farms; this synergy forms a complementary model of the agrifood system. Maintaining this model's balance requires the creation of a unified digital ecosystem that integrates all suppliers and consumers into production chains, thereby eliminating unnecessary intermediaries. (2) Methods. This study employs a comprehensive methodological framework, including systems analysis and mathematical modeling, to develop service algorithms. Object-oriented design and software engineering methods facilitated the development and implementation of a service-oriented architecture for the digital system. (3) Results. The study presents a multi-tier architecture featuring an integration bus based on a service-oriented approach. To implement direct supply-and-demand coupling strategies, the system integrates both internal services (micro-economic indicators) and external services (macroeconomic indicators). Additionally, a recommender system based on neural networks and mathematical models was developed to personalize consumer requests and manage product sales. (4) Conclusions. The software solution is consistent with the AgTech 4.0 concept and enables the creation of a seamless environment for interstate trade. The implementation of the system enhances the transparency of the “product footprint”, facilitates the redistribution of surpluses, and, consequently, contributes to price stabilization.

Keywords: agriculture; crop production; digital transformation; food footprint; food availability; consumer basket

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1. Introduction

The task of ensuring food security at the international level is a significant and stabilizing factor in the global order [1,2]. The historical development of humanity starkly illustrates that “national security largely depends not only on human resources, military power, and spatial quantity, but also on the potential to provide the population with food” [3].

Initially, food security implied food market stability by ensuring basic food availability across all nations [4]. However, geopolitical conflicts and rising international tensions have continuously reshaped this concept. Modern frameworks define food security as matching the volume of nutritious, safe food with dietary needs for an active, healthy

lifestyle [2], expanding the concept into a social context by incorporating stable food access [5,6]. Consequently, localized food crises trigger cascading global disruptions, directly linking food security with national security [7–9].

From the viewpoint of the food security management process, key aspects include the physical availability of food in required quantities, its economic accessibility for the population, and ensuring adherence to energy and physiological consumption standards for a balanced diet, alongside guaranteeing food safety and suitability for consumption.

This can be achieved through domestic public resources based on agro-industrial activity, where agricultural transformation follows national economic development guidelines. Advancements in energy, chemistry, and information technology drive a systemic shift from extensive to intensive models of food production, processing, and marketing via technological convergence. Moreover, regional transformation rates depend not only on internal self-sufficiency but also on global market purchasing capacity [8,10,11].

This approach is typical for countries with emerging economies that direct agro-industrial resources exclusively toward cost-effective, export-oriented production. Importing products is then funded either by export proceeds or by purchasing cheaper alternatives than domestic yields [12]. From a food security perspective, such strategies entail significant logistical, political, and currency risks [9,13]. Consequently, emerging challenges in product availability and quality transform food from a basic human right into a market asset [14]. Furthermore, farmers prioritize commodities with stable demand and accessible production inputs (seeds, breeding livestock, fertilizers, feed, equipment, and spare parts). Under recessionary conditions, the constrained operation of large agricultural holdings drives the growth of small farms [15,16].

The ecological agenda serves as an increasingly important accelerator in this context [17]. At the current stage of societal development, major agricultural participants are held responsible for escalating environmental crises. Depending on their activities, agricultural holdings face criticism for soil degradation, the overuse of mineral fertilizers and pesticides, monoculture cultivation, ecosystem destruction, and carbon footprint generation. The resulting negative public sentiment has shifted consumer demand toward organic and local products, individualized nutrition, and niche commodities [18,19]. Small farms are better suited for cultivating unique varieties and performing manual quality control, which is difficult to implement in conveyor-type production. In addition, large corporations avoid such high-margin products, as they prioritize volume over uniqueness.

With intelligent technologies, small farmers are now capable of generating high profits from small plots through the implementation of various sensors, control systems, and automated solutions for managing technological and business processes [20]. Subsidies and technologies designed to prevent corporate monopolies have attracted specialists with marketing and modern management competencies to remote communities, transforming agriculture into a trendy startup [21].

Thus, the primary contemporary challenge is the capacity of small farms and large agricultural holdings to produce and market products, thereby ensuring national food security. Consequently, this paper aims to develop a conceptual model and functional mechanisms for agricultural production and marketing processes to guarantee food sustainability across a designated group of countries.

To achieve the stated objective, the following research tasks were formulated:

1. Analysis of food security mechanisms at the inter-state interaction level (Sections 2.1 and 2.2).
2. Examination of international experience in agricultural sector digital transformation within the context of control, monitoring, and data exchange during agricultural production and marketing to verify effective technological solutions (Section 2.3).

3. Development of a methodological framework and data collection for input and validation samples to test the digital system services (Sections 3.1 and 3.2).
4. Mathematical modeling of algorithms governing the digital system architectural components (Section 3.3).
5. Design of a digital system prototype providing end-to-end integration among consumers, producers, and public regulatory authorities (Sections 4.1 and 4.2).
6. Construction of baseline interaction scenarios for subjects within a unified digital space (Section 4.3).

The scientific novelty of this study lies in developing a digital food security management system that shifts the paradigm from a reactive to a predictive management model, integrating a consensus-based assessment system for internal and external threats. For end-market participants (farmers and consumers), this study establishes a unified scientific and methodological framework to engineer a transparent food footprint system at the inter-state level.

The theoretical significance of this study, grounded in its scientific novelty, lies in formalizing algorithms to manage agricultural product availability within an inter-state digital ecosystem. These algorithms enable systematic crop production planning, grant farmers collective access to shared marketing infrastructure for various crop maturity stages, and facilitate customized end-product consumption. Furthermore, these predictive models provide a baseline for research and development in yield forecasting and demand-driven adaptive cultivation planning. Ultimately, they offer a framework for designing practice-oriented educational programs to train specialists in advanced production and logistics process management.

The practical significance of this study lies in engineering a peer-to-peer (P2P) model that directly links suppliers and consumers, thereby eliminating speculative intermediaries from the end-product pricing system. The developed architecture can be utilized to deploy unified support systems for farmers or vulnerable consumer groups, particularly to mitigate the impact of sudden price surges.

2. Literature Review

2.1. Specification of Current Research in the Field of Food Security

Population food requirements dynamic change depending on the social, cultural, economic, and technological development of society [22–24]. Contemporary science proposes numerous approaches to assessing food security; however, researchers note the absence of a unified, comprehensive model capable of adaptively transforming to meet societal demands. In practice, traditional models dominate, relying on quantitative indicators of physical and economic food availability, compliance with medical nutritional standards, and baseline product quality metrics [25,26].

Within the Russian scientific discourse, the focus traditionally shifts toward developing domestic production and product distribution infrastructure, directly aligning with the provisions of the Food Security Doctrine of the Russian Federation [5,27–30]. The altering geopolitical situation in 2014 and 2022 served as a catalyst for accelerated import substitution and domestic market strengthening [31–33]. The adopted state measures enabled Russia to fully satisfy baseline population needs using internal resources, though the issue of interregional disparities in product distribution remains critical. Ensuring agribusiness sustainability under climatic and geopolitical risks is supported via breeding, genetics, precision agriculture, and logistics optimization.

A critical issue at the current stage of research is the fragmentation of digital tools and their detachment from the overarching food security strategy [11,17,20]. Most contemporary developments—including the deployment of UAVs, IoT sensors, and artificial

intelligence—are localized and aimed exclusively at addressing narrow technological tasks within individual farms, such as yield management or business process optimization [34–38].

Within the context of digitalizing accompanying workflow and operational control, researchers also highlight the limitations of end-to-end automation; for instance, the implementation of handwritten text recognition (HTR) systems enhances overall process efficiency but still requires mandatory manual data validation by a human operator due to recognition accuracy limits. This confirms that the current technological maturity and adaptability of intelligent systems do not yet permit the complete elimination of the human factor from management chains [39–41]. The resulting isolated findings are rarely considered by authors within the broader context of global food security.

Contemporary researchers enhance the traditional food security model by integrating qualitative characteristics based on medical nutritional standards and product-specific requirements. Within these frameworks, products are evaluated through the lens of consumer interaction across the following dimensions:

- Compliance with state standards and technical regulations [19,22,26];
- Accessibility, implying independence from income level, time, and location, in alignment with societal standards or established traditions [1,4,9];
- Public health preservation (e.g., dietetic nutrition, gluten-free diets) [42–44];
- Cultural preferences driven by personal beliefs (e.g., vegetarianism, pescetarianism, flexitarianism, raw food diets) [45], religious requirements (e.g., Lenten food in Christianity, Halal in Islam, Kosher in Judaism) [46–48], or local customs [49].

These characteristics exist as independent research streams that shape healthy lifestyles for both individuals and society as a whole. The objects of such studies encompass processes whose granularity is determined by the research objective—ranging from molecular levels to group human behavior. Analyzing the practical significance of these findings indicates that they align with food security under the principle of “ensuring health” rather than merely “providing food.” To standardize the assessment at this micro-level (household level), specialized metrics and indices, such as HFIAS, HDDS, HHS, and CSI, are applied in practice [50,51].

In contrast, macroeconomic and international research levels rely on dynamic partial equilibrium models (Aglink-Cosimo, PEM) and supply chain risk analysis systems (EPACIS). These methodologies theoretically substantiate the interrelations among demand, supply, pricing, and trade policy, enabling the forecasting of market shocks across state and alliance scales [52,53]. The integration of end-to-end digital solutions can bridge this gap, combining individual farm production metrics with macroeconomic market patterns to enhance regulatory efficiency.

2.2. Food Security Within the Context of Modern Economic Unions

Comprehensive approaches to assessing food security are practically reflected in the strategies of modern inter-state associations. Under global challenges, multilateral economic unions enable countries to effectively coordinate efforts to protect sovereignty, reduce import dependence, and minimize logistical costs. Below, we present an analysis of the key mechanisms and priorities for ensuring food stability applied within leading global alliances.

Within the European Union, food security is examined through the lens of the Common Agricultural Policy (CAP) and crisis response mechanisms (EFSCM). Contemporary studies focus on minimizing external shocks caused by energy price volatility and fertilizer shortages through rapid financial support for farmers [54,55]. Meanwhile, protecting

the strategic sovereignty of the EU, ensuring supply chain continuity, and accelerating the transition to environmentally sustainable agricultural practices remain top priorities [56].

Food security within the BRICS alliance is based on the principles of multilateral coordination and reducing import dependence on Western markets. Scientific publications emphasize the importance of establishing institutional platforms, such as the Digital Agriculture Network and the BRICS Grain Exchange, to ensure independent pricing and direct integration of exporters with buyers [57]. Researchers place particular emphasis on overcoming internal disparities: the bloc unites the world's largest food producers yet continues to face high rates of regional malnutrition [58,59].

Within the African Continental Free Trade Area (AfCFTA), research focuses on unlocking the potential of the intra-regional market to overcome chronic food deficits. Experts note that progressive tariff reduction enables the efficient transfer of agricultural surpluses from surplus to deficit zones, reducing the continent's reliance on costly imports [60–62]. Nevertheless, a key challenge remains striking a balance between border liberalization and protecting vulnerable local smallholders who may struggle to compete with large cross-border suppliers.

Research on food stability within the Pacific Alliance (Chile, Colombia, Mexico, Peru) is closely linked to reducing logistical costs and integrating into the global supply chains of the Asia-Pacific region. Scholars analyze the impact of climatic anomalies, such as the El Niño and La Niña phenomena, on production metrics and food inflation in Latin American countries [63]. Consequently, the focus shifts toward inter-state cooperation in agro-technology transfer and targeted subsidization to ensure the accessibility of healthy nutrition in the domestic market.

2.3. Classification of Software in Agriculture

Effective food security management at both the national level and within inter-state alliances requires the integration of end-to-end digital tools. However, a successful transition from fragmented, local software to comprehensive ecosystems is impossible without clearly structuring available IT solutions. Consequently, a detailed software classification differentiated by agricultural production scales and specific business processes becomes critically important.

The agro-industrial software market is undergoing a transformation, offering solutions differentiated by production scale and business process specifics. Agricultural enterprises are offered both specialized software products and comprehensive digital ecosystems to support sustainable development [4]. These ecosystems are based on analytical services that minimize risks in the face of volatile external factors (climate change, agronomic conditions, market conditions, etc.) [17,64,65].

The predictive potential of these systems improves production and helps identify macroeconomic patterns for national food security [13,66]. Comprehensive digital solutions enable the identification of inappropriate land use, the creation of data channels for trade forecasting, and the optimization of state regulations (preferential lending, subsidies, grants). The global pace of agricultural digitalization depends on regional specifics, including economic development, technology availability, research, climate, and government support [11,67]. The following groups of regions are distinguished:

1. Leaders (Western Europe, North America) exhibit consistently high rates of digitalization. A priority is the development and implementation of solutions for autonomous farms based on precision farming principles. The technological foundation includes sensor networks, unmanned aerial vehicles, IoT technologies, and artificial intelligence for crop yield optimization. Strict environmental standards and high labor costs further incentivize this development. Figure 1 presents a software classification with examples of relevant commercial software and their key functionalities.

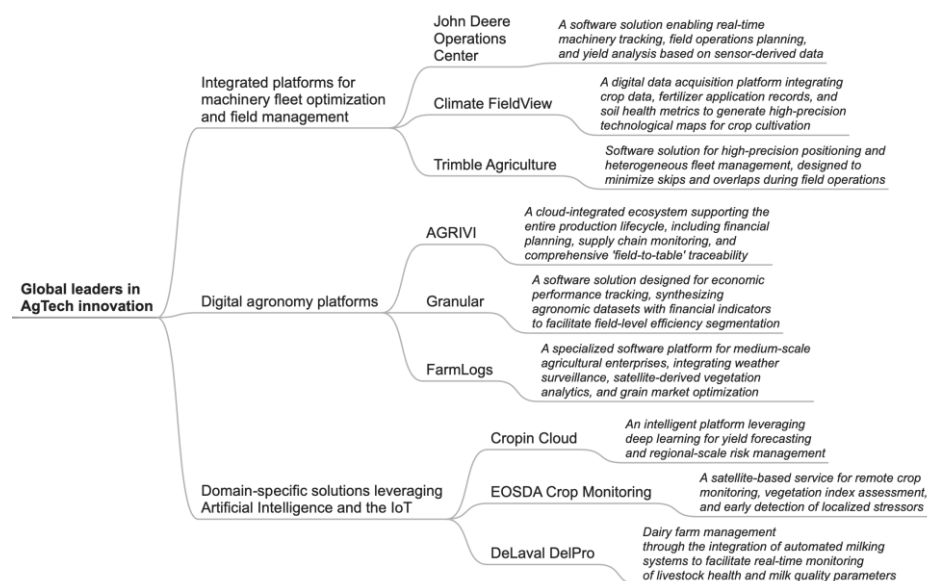


Figure 1. Classification of software used in leading countries in agricultural digitalization.

2. Dynamically developing countries (Russia, Brazil, China) exhibit accelerated transformation by customizing ready-made software for large-scale production. The main driver is government support for agricultural holdings. However, regional specifics vary: Russia and Brazil focus on smart technology, production cycle monitoring, and digital accounting, whereas China prioritizes cloud-based supply chain management. Figure 2 presents a classification of software with examples of corresponding commercial products and their main functional capabilities in dynamically developing countries.

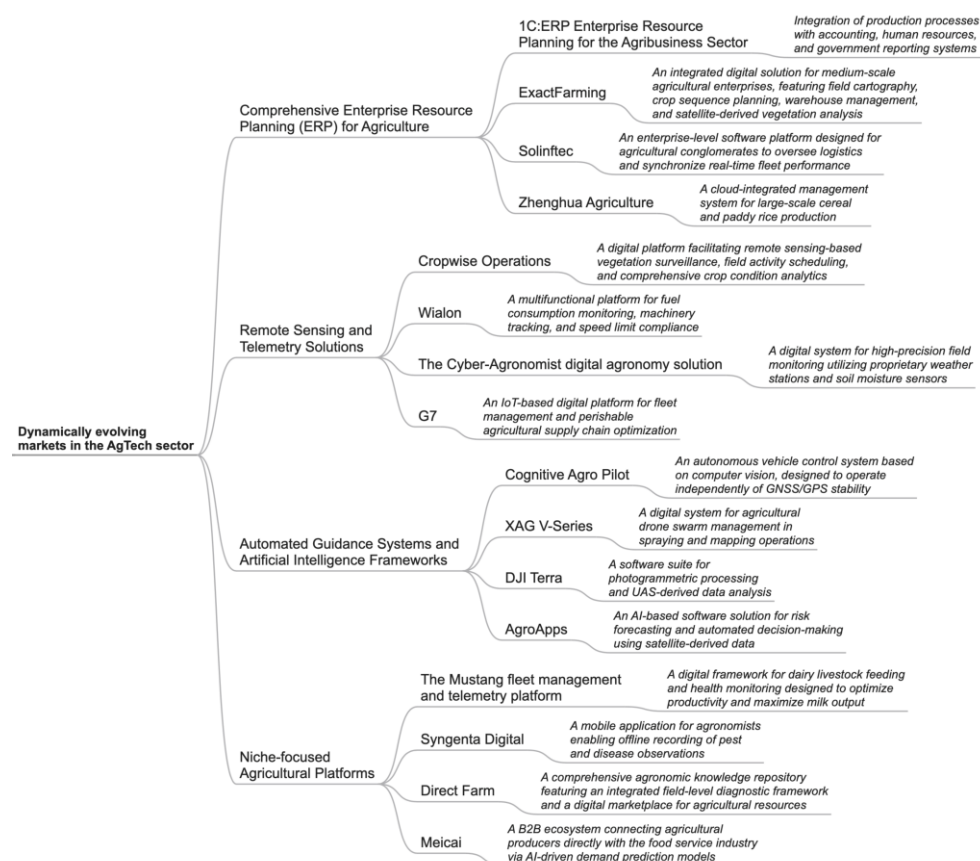


Figure 2. Classification of software used in dynamically developing countries for agricultural digitalization.

3. Developing countries with localized digitalization (India, Southeast Asian countries) exhibit moderate and fragmented transformation rates. Due to high land fragmentation, the use of specialized software adapted for small farms is prevalent. Figure 3 shows the main classification of the functional capabilities of such software products.

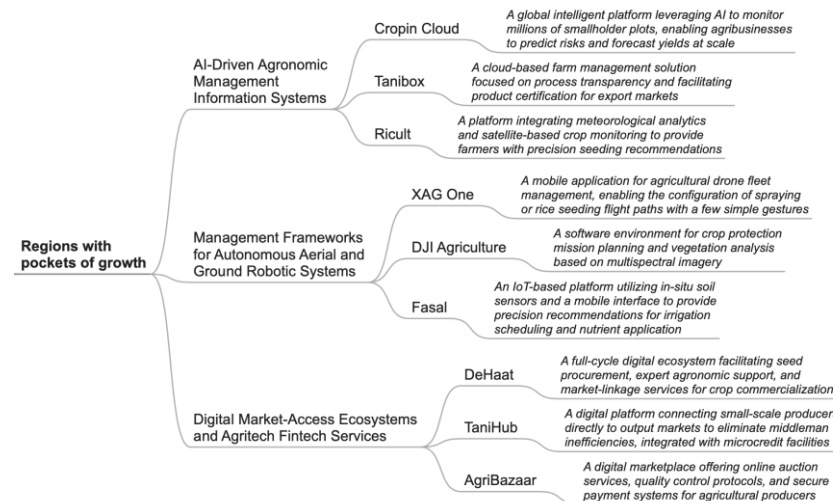


Figure 3. Classification of software for agricultural digital transformation in countries with localized digitalization.

4. Countries with low digitalization rates (most of Africa and Central Asia) face development barriers due to lacking basic infrastructure (communications, electricity). Instead of comprehensive systems, fragmented services (e.g., SMS alerts) are utilized. Technology implementation is primarily driven by international grants and humanitarian initiatives against hunger. Figure 4 shows the software solutions used according to the classification of their main functional capabilities.

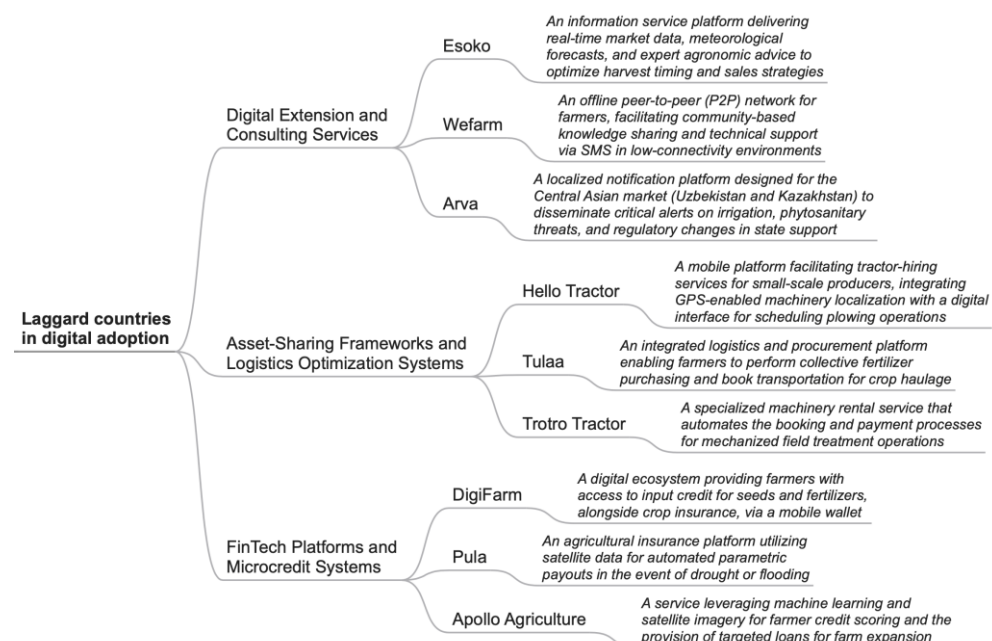


Figure 4. Classification of software for agricultural digital transformation in lagging countries.

At this stage, a distinct gap exists between modern agritech solutions and digital transformation research [30,68,69]. This is driven by the growing complexity and cost of digital systems, which integrate numerous services, equipment, and peripheral devices. Consequently, scientific research focuses on finding and justifying methods to reduce technology costs [70].

Cost reduction is achieved by improving downgrading, developing affordable analogs that retain key component properties, and optimizing, standardizing, and unifying hardware design [71,72]. Furthermore, this research aims to create fully autonomous systems, whereas current software only assists users by requiring manual operational confirmation for decision-making [73,74].

3. Materials and Methods

3.1. Area of Concern Specification

Agriculture all over the world tends to shift from large state-owned or collectively owned structures to smaller farms, specifically, family farms, individual entrepreneurs, and other types of farming, depending on the region [30,38]. This is leading to the emergence of millions of smallholders who can more quickly adapt to demand and produce unique products (organic vegetables, microgreens, meat, berries, etc.). Some of the yield may be retained for personal consumption, while the surplus can be sold, thereby becoming a part of a small business.

From a food security perspective, this approach might be seen as both beneficial and risky. For consumers, the bankruptcy or demise of a single small producer will go virtually unnoticed, which contributes to the overall stability of the market. Individual entrepreneurship allows for the creation of jobs and the development of infrastructure in remote areas, the use of organic production methods, and the effective use of available software and hardware in cultivated areas [16,21].

Conversely, institutional features expose smallholders to substantial marketing risks. Major retailers demand consistent volumes of certified commodities, thereby restricting market access for smallholders and limiting their consumer bases to immediate geographical vicinities. Furthermore, market expansion requires mitigating logistical bottlenecks in both distribution channels and input procurement, such as purchasing feed, machinery, and seeds at retail rates severely diminishes profitability compared to bulk wholesale operations.

Additionally, small-scale enterprises remain highly vulnerable to environmental or anthropogenic shocks, where sudden crop destruction frequently precipitates bankruptcy. This operational vulnerability is directly exacerbated by the lack of spare production capacity and institutional financial buffers typically maintained by large-scale agricultural conglomerates.

Based on the above, the research area of concern is the organization of farm management processes for the marketing of crop products in the context of food security.

The research focuses on the processes of organizing a digital market for farm produce.

The subject of the study covers the tools that support economic and technological relationships in a direct farmer-consumer relationship model.

Table 1 describes the input data required for system testing and neural network training.

Table 1. Input data characteristics for the digital platform.

Parameter	Access	Description	Purpose	Volume
Public Cadastral Map	https://cogisdemo.daeast.com/portal/samples/cadastre_russia (accessed on 15 June 2026) https://map.gov4c.kz/egkn (accessed on 15 June 2026) https://cadastre.kg/svc-portal/map/main.do (accessed on 15 June 2026)	Economic purpose, coordinates, and site transport accessibility	Object geopositioning for clustering, personalized consumer recommendations, and logistics optimization	Processing of 2300 cadastral records
Public Fruit Variety Catalog	https://vniispk.ru/species/cherry/alphabet (accessed on 15 June 2026)	Crop vegetation cycles, maturity stage morphology, and nutritional value	Neural network training for crop identification and maturity stage detection. Defining variety compatibility rules for product card generation and dietary recommendations	Dataset generation: 1025 images (5 crop classes) and 560 images (4 maturity classes).
Public Vegetable Variety Catalog	https://www.cnsnb.ru/AKDiL/0055/default.shtm (accessed on 15 June 2026)			Annotation of 1349 features for maturity stage identification.
State Register of Plant Varieties and Hybrids Approved for Utilization in the Russian Federation	https://gossortrf.ru/registry (accessed on 15 June 2026)			Development of 4720 logic rules for product card generation
Therapeutic Nutrition Standards	https://base.garant.ru/70412098/53f89421bbdaf741eb2d1ecc4ddb4c33/ (accessed on 15 June 2026)	Regulation of average daily dietary and specialized nutrition allowances		
Medical (Dietetic) Nutrition	https://www.bsmu.by/upload/docs/kafedri/k_obchig/2020-2/uch-mater-intern-8.pdf#page=3.17 (accessed on 15 June 2026)	Standard diet specification, clinical diet personalization for pathologies, quality control, and food distribution tracking	Parameterization of the nutrition-standard-based recommendation system	Classification of nutrition standards (16 categories) and parameter formalization (156 metrics, 2496 rules)
Nutritional Science: Fundamentals of Human Nutrition	https://www.studentlibrary.ru/en/book/ISBN9785970483794.html (accessed on 15 June 2026)	Nutriodynamics, metabolism, nutrient utilization, and human eating behavior determinants		
Nutritional Science and Clinical Dietetics	https://www.studentlibrary.ru/en/book/ISBN9785970469996.html (accessed on 15 June 2026)	Healthy nutrition concept: nutrient metabolism and age/profile-specific consumption norms		
Public procurement and tenders	https://rostender.info/category/tendery-selskoe-hozyajstvo (accessed on 15 June 2026) https://www.gov.br/conab/pt-br (accessed on 15 June 2026)	Public and commercial agribusiness procurement/tender platforms	Macro- and microeconomic parameters for agricultural product clustering and surplus prioritization	Automated analysis of 442 tenders

	https://eprocure.gov.in/eprocure/app (accessed on 15 June 2026)			
	https://www.arc.agric.za/Pages/Home.aspx (accessed on 15 June 2026)			
	https://rosstat.gov.ru/folder/13397 (accessed on 15 June 2026)			
Quality of life statistics	https://esankhyiki.mospi.gov.in/ (accessed on 15 June 2026)	Population income, expenditure, and purchasing power data sources	Agricultural product recommendation system parameters	Automated analysis of 1700 records
	https://www.statssa.gov.za/ (accessed on 15 June 2026)			
International trade data	https://www.ndrc.gov.cn/ (accessed on 15 June 2026)	Tariff quotas on agricultural products and seeds: volumes, declaration rules, and HS codes	International agricultural trade recommendation system parameters	Automated analysis of 2300 records
	https://itac.org.za/ (accessed on 15 June 2026)			

The generated input dataset is sufficiently representative and serves as a baseline for the subsequent algorithmization and digital system development phases.

3.2. Methodology Particulars

To ensure the controllability and determinism of the digital system design processes, a methodological framework comprising a system of principles, methods, and tools was developed. The structure of the developed methodological framework and the results of its application are presented in Figure 5.

The functional requirements formalization and structural decomposition of the digital system were executed using system and structural-logical analysis methods. To mathematically model the target objects and quantitatively describe processes under stochastic factors, decomposition techniques and empirical data-driven modeling were applied.

The application architecture was designed by combining microservice and layered structural patterns, separating the platform into logical data access, business logic, and controller layers. Utilizing object-oriented analysis and design isolated the software modules, ensuring overall system architectural stability.

Image recognition tasks were addressed using the deep convolutional neural network ResNet18, pretrained on the ImageNet dataset. Model training followed a two-stage layer-unfreezing (fine-tuning) strategy to optimize the balance between computational efficiency and hierarchical feature extraction accuracy.

Information asset management was structured using the relational approach and normalization theory. Integrating unique domain entities into a unified data schema eliminated data redundancy, prevented modification anomalies, and ensured database transactional integrity.

The GUI was engineered using a component-based approach, prototyping, and design systems, utilizing both declarative and imperative paradigms. GUI logic verification, task prioritization, and interaction context evaluation were executed via user scenario analysis. Heterogeneous variable synthesis, hidden dependency identification, and causal link visualization were conducted using rigorous graphical modeling methods.

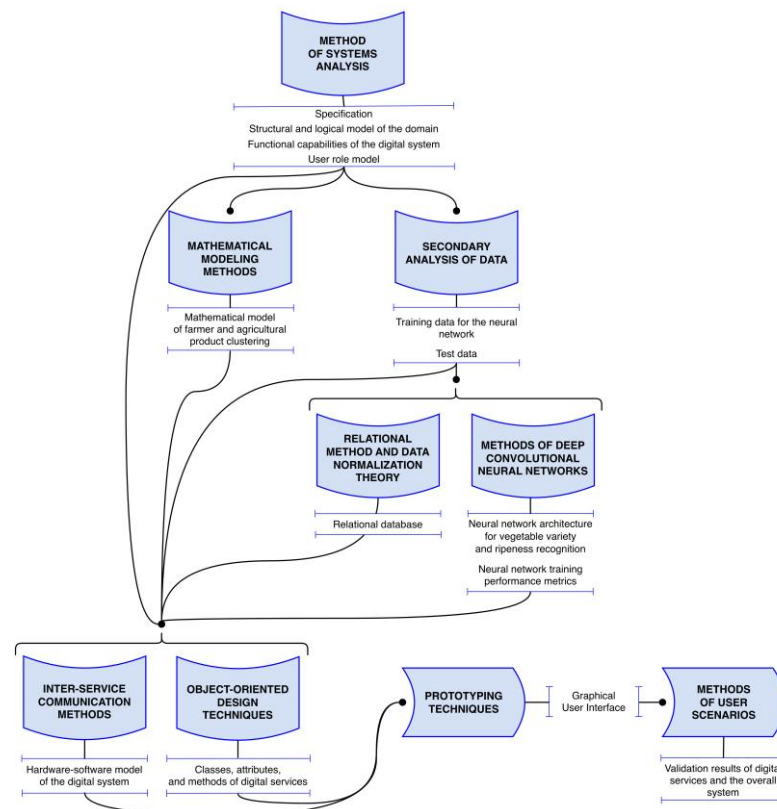


Figure 5. Model of the research methodological framework.

3.3. Specifications of Mathematical Models for Recommender Services

The operational algorithms of individual software services necessitated mathematical modeling to define core system settings, enabling automated or filter-driven recommendation generation. Based on the strict geographical stability of suppliers, proximity from the user to the farm or warehouse served as the primary parameter. Consequently, a dedicated mathematical model (Equations (1)–(4)) was developed to accurately determine the spatial distance between the agricultural site and the end user.

$$a = \sin^2 \left(\frac{\frac{\pi}{180} (lat_2 - lat_1)}{2} \right) + \cos(lat_1) \cos(lat_2) \sin^2 \left(\frac{\frac{\pi}{180} (lng_2 - lng_1)}{2} \right) \quad (1)$$

$$D = R \cdot (2 \tan^{-1} 2(\sqrt{a}, \sqrt{1-a})) \quad (2)$$

$$f_p = \{p \in places | p.D \leq D_{max}\} \quad (3)$$

$$d_{ch} = \frac{e^{\left(\frac{1}{n} \sum_{i=1}^n \ln(d_{i+1})\right)} + Med(d_1, d_2, \dots, d_n)}{2} \quad (4)$$

where lat_1 , lng_1 are the user coordinates (rad), lat_2 , lng_2 are the farm coordinates (rad), a is the haversine of the angle (square of half the chord), D is the spatial distance between the supplier and user (km), R is the mean volumetric radius of the Earth (6371 km), $places$ is the number of farms within the user-defined radius, p is the set of agricultural plots corresponding to the maximum user-supplier distance, D_{max} is the maximum supplier distance threshold defined by the user (km), f_p is the subset of farms satisfying the distance filter constraints, d_{ch} is the normalized distance for algorithm execution, and d_i is the spatial distance to the i -th farm (km).

The presented model utilizes geodata to determine user-supplier spatial proximity for result filtering. To optimize software computational efficiency given the operational

homogeneity of farms, a dedicated mathematical model (Equations (5) and (6)) was implemented to execute spatial clustering.

$$i = \left\lfloor \frac{v - v_{\min}}{v_{\max} - v_{\min}} \cdot [\log_2 n + 1] \right\rfloor \quad (5)$$

$$h_i \leftarrow h_i + 1 \quad (6)$$

where n is the number of values in the sample, v is the current value of the selected characteristic for the farm, $v_{\min}$ and $v_{\max}$ are the minimum and maximum values that the characteristic can take, respectively, i is the number of intervals, and h_i is the number of values belonging to the i -th interval.

The model is based on Sturges' rule, which determines the optimal number of intervals for normally distributed data with a moderate sample size [75]. This approach eliminates the need to analyze multiple secondary characteristics (such as area, revenue, or equipment availability) during product selection. Consequently, the system computes the farm or cluster rating based on these parameters, dynamically displaying the most suitable clusters or high-rated individual farms according to user-defined search constraints.

The baseline ranking algorithm incorporates three j -cluster metrics: the average distance to the farm $\bar{d}$ (Equation (7)), the average supplier rating $\bar{r}$ (Equation (8)), and the supplier digital service accessibility level $\bar{s}$ (Equation (9)).

$$\bar{d} = \frac{1}{k} \sum_{j=1}^k d_j \quad (7)$$

$$\bar{r} = \frac{1}{k} \sum_{j=1}^k r_j \quad (8)$$

$$\bar{s} = \frac{1}{k} \sum_{j=1}^k Sub_j \quad (9)$$

Cluster formation is executed by integrating the following methods:

- Calculating the Shannon entropy (H) for a qualitative assessment of the generated results (generalized Equation (10) across heterogeneous characteristics);

$$H = - \sum_{\frac{h_i}{n} > 0} \frac{h_i}{n} \log_2 \left(\frac{h_i}{n} \right) \quad (10)$$

- Entropy normalization (H_{norm}) to scale the results within the unit interval $[0, 1]$ (Equation (11));

$$H_{\text{norm}} = \frac{H}{\log_2 [\log_2 n + 1]} \quad (11)$$

- Calculating entropy weights (summing to unity) for an objective feature significance assessment: distance (w_d derived from distance entropy H_d , Equation (12)), rating (w_r derived from entropy H_r , Equation (13)), and digital service accessibility (w_{sub} derived from entropy H_{sub} , Equation (14));

$$w_d = \frac{H_d}{H_d + H_r + H_{\text{sub}}} \quad (12)$$

$$w_r = \frac{H_r}{H_d + H_r + H_{\text{sub}}} \quad (13)$$

$$w_{\text{sub}} = \frac{H_{\text{sub}}}{H_d + H_r + H_{\text{sub}}} \quad (14)$$

- Calculating spatial and assortment distances, estimating inter-node gaps, and determining their median values between adjacent points;
- Establishing a clustering threshold to regulate detail level and eliminate geometric distortions.

The final rating assessment of the farm (S_p) and the cluster (S_c) was based on the system of Equations (5)–(14) and formalized as objective functions 15 and 16, respectively.

$$S_p = 100 \left(w_d \frac{1}{\left(1 + \frac{d}{d_{ch}}\right)^{1.5}} + w_{ra} \left(r \left(1 - e^{-\frac{0.3d}{d_{ch}}} \right) + e^{-\frac{0.3d}{d_{ch}}} \right) + w_{sub} Sub \cdot e^{-\frac{d}{d_{ch}}} \right) \quad (15)$$

$$S_c = 100 \left(w_d \frac{1}{\left(1 + \frac{\bar{d}}{d_{ch}}\right)^{1.5}} + w_{ra} \left(\frac{\bar{r}}{5} \left(1 - e^{-\frac{0.3\bar{d}}{d_{ch}}} \right) + e^{-\frac{0.3\bar{d}}{d_{ch}}} \right) + w_{sub} \overline{Sub} \cdot e^{-\frac{\bar{d}}{d_{ch}}} \right) \quad (16)$$

The developed mathematical models account for the spatial granularity where a single farm cultivates multiple distinct plots across various crops. Consequently, the cluster rating is computed at the plot level, yielding a normalized score ranging from 0 to 100.

4. Results

4.1. Functional Architecture of the Software Package

To address the formulated objectives, a multi-tiered digital system architecture was engineered (Figure 6), wherein components across respective logical layers interact via an enterprise service bus (ESB).

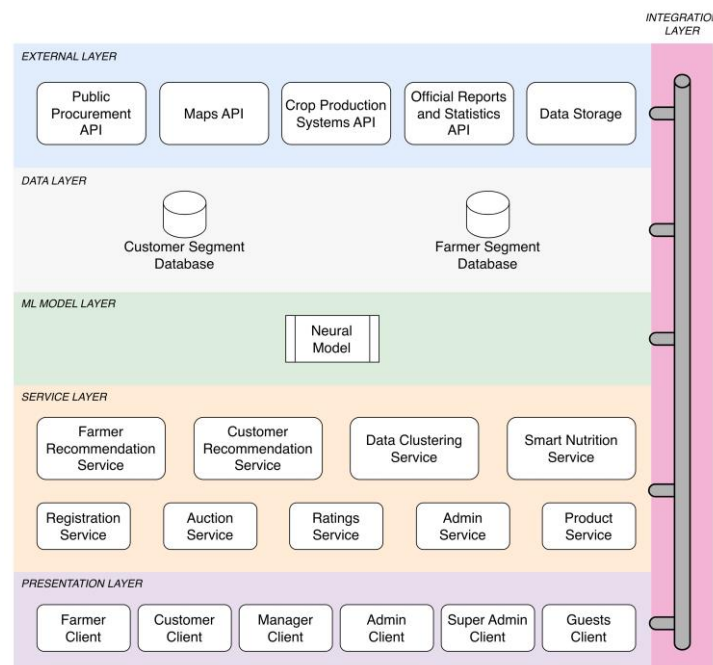


Figure 6. Architectural model of the digital food security system.

Within the engineered model, the ESB functions as the foundational backbone of the service-oriented architecture. System components interact asynchronously through a unified bus interface, thereby operationalizing logical data flow management. The digital system services are segmented into distinct architectural layers based on their functional objectives, comprising the following layers:

1. **External layer.** This layer interfaces with external systems to synchronize data via public procurement APIs and ensure service operability across adjacent architectural layers, including mapping systems and digital crop repositories. It aggregates heterogeneous data to forecast events and enhance mathematical model precision. Furthermore, it houses a data warehouse for long-term asset storage, enabling retrospective analysis and automated reporting.
2. **Data layer.** This layer incorporates segmented relational databases tailored to farmers and consumers. Appendix A illustrates the generalized relational schema, which is strictly normalized to the third normal form to guarantee data atomicity, eliminate transitive dependencies, and ensure that all non-prime attributes functionally depend exclusively on the primary key. The configured database constraints comprehensively enforce data integrity, consistency, and structural coherence.
3. **ML model layer.** This layer incorporates deep learning architectures to facilitate predictive analytics, with its performance metrics and structural characteristics described in detail in Section 4.2.
4. **Service Layer.** This layer executes the foundational business logic of the digital system via integrated analytical and operational services.
5. **Presentation Layer.** This layer comprises role-based client interfaces provisioned to users in accordance with their authorization levels regarding system functionality and resources. The interaction model for these user roles is illustrated in Figure 7.

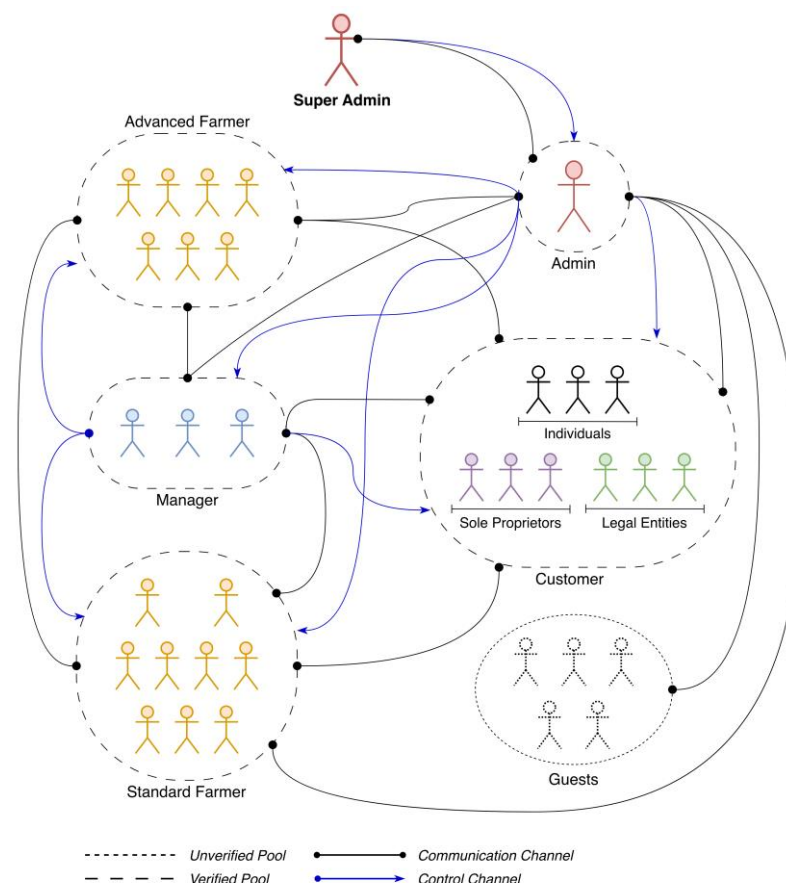


Figure 7. Functional model of user interactions within the digital food security system.

To operationalize resource and capability management, user functionalities are categorized into three core global groups:

1. Administrators: responsible for configuring functional environments across other system entities (Admin). This group subsumes Managers, who oversee content moderation, facilitate platform communications, and maintain farmer or consumer authorization privileges.
2. Consumers: encompass all actors utilizing market distribution tools (Farmer) and entities authorized to procure products (Customer).
3. Unauthorized users. This group comprises individuals who have skipped authentication (Guests). They are restricted to foundational read-only capabilities, such as accessing agronomic repositories, farm optimization frameworks, dietary guidelines, and agricultural state regulations.

The Farmer cohort is segmented into Standard Farmer and Advanced Farmer classes. Upon system onboarding, a producer pays a registration fee to unlock foundational capabilities:

- Profile engineering and modification, detailing product assortments and geographical coordinates (legal and physical addresses);
- Distribution management partitioned by crop categories, enabling manual or automated product card generation based on inventory availability, maturity stages, logistics, and delivery timelines;
- Communication frameworks, including order and product state notifications, transaction ledger reviews, and direct interaction channels with content and account managers;
- A peer-to-peer recommendation framework driven by spatial clustering and internal rating matrices.

In this scenario, the producer is designated the Standard Farmer status. To scale operational capabilities, a subscription-based model activates the Advanced Farmer tier, unlocking the following dedicated frameworks:

- Auction platform: determines final commodity pricing via transparent open bidding among buyers, where the farmer lists products within volumetric thresholds enforced by the digital food security system to mitigate systemic market and price shocks;
- Predictive production planning: a recommendation engine that forecasts regional demand by synthesizing consumer behavior, state policies, competitors' production volumes, and external environmental or climatic metrics;
- Forward ordering infrastructure: a direct interaction channel to reserve specific crop volumes across various vegetative stages (pre-season, cultivation, or harvest), enabling acreage and capacity optimization through integrated prepayments, standardized service level agreements (SLAs), and buyer rating systems, while operating as an aggregator without absolute counterparty verification guarantees;
- Interactive spatial monitoring: a tool for tracking regional agricultural output and facilitating peer-to-peer farmer communication.

Buyers within the digital system are classified by their legal and organizational frameworks into:

- Corporate entities and sole proprietors;
- Individual retail consumers.

The Manager executes user verification during registration on a voluntary basis; unverified accounts default to individual consumer status. While functional accessibility remains uniform across all buyer classes, distinct variations exist regarding order volumes and logistics frameworks. Each user maintains an internal rating and specific cluster attribution, enabling the recommendation engine to generate available buyer profiles for

Farmer entities, who can facilitate transactions via forward orders, direct sales, or integrated delivery modules.

Concurrently, the consumer-facing recommendation engine synthesizes the following parameters to generate optimized product selections:

- User-defined configurations, including delivery timelines, logistics methods, and crop maturity stages;
- Farmer metrics, tracking transaction success rates, peer reviews, production capacity, compliance certification, and system communication quality;
- Standardized principles of healthy nutrition.

All crop categories are mapped to specific dietary paradigms, including sports, therapeutic-prophylactic, clinical, and rational nutrition. Each agricultural commodity maintains a dedicated metric matrix determining its compatibility with specific dietary systems. Upon selecting a preferred nutritional framework, the engine generates an optimized selection of compatible products based on real-time market inventory.

Users can access the digital system through web browsers (PCs, tablets, or smartphones) or dedicated mobile applications across all user roles. The client-side deployment requires compliance with the minimum hardware and software specifications detailed in Table A1 of Appendix B. The system architecture minimizes client-side dependency, requiring only an updated browser environment and adequate RAM for real-time data streaming.

Conversely, ensuring the continuous operability of all architectural layers necessitates the infrastructure configuration specified in Table A2 of Appendix B. The engineered multi-tier framework establishes an architectural layout that decouples the system into modular functional layers linked via a centralized ESB, thereby providing critical advantages in scalability, fault tolerance, and data management efficiency.

4.2. Neural Network Architecture and Analysis of Its Training Results

The neural network architecture utilizes a ResNet18 baseline adapted for multi-task classification. Leveraging computer vision analysis of vegetable images, the digital system automatically triggers downstream service pipelines to execute the following processes:

- Automated product card generation (requiring producer verification) for auction or retail distribution;
- Vegetable maturity stage detection to optimize commercialization timelines and sales strategies based on real-time market demand;
- Automated order-to-product validation to verify compliance between the buyer's shipment and the farmer's initial specifications.

The underlying deep learning architecture integrates a convolutional feature extraction backbone coupled with independent, parallel multi-task heads (Figure 8).

The user-uploaded image undergoes preprocessing: it is resized to 224×224 pixels and normalized using ImageNet statistics with channel means of [0.485, 0.456, 0.406] and standard deviations of [0.229, 0.224, 0.225]. The network generates a hierarchical feature representation characterized by a progressive increase in semantic complexity and a corresponding decrease in spatial resolution. A description of these levels is provided in Table A3 of Appendix C.

To train the neural network models, two independent datasets were generated: Vegetable varieties:

- Comprised 1025 graphic objects expertly annotated across 8 target crop classes (the distribution is shown in Figure 9a).
- Vegetable maturity stages: contained 560 graphic objects classified into 4 maturity levels (the distribution is shown in Figure 9b).

Each dataset was partitioned into training and validation sets using the conventional 80% to 20% ratio, respectively. The co-occurrence of multiple vegetable instances or objects at varying maturity stages within a single image resulted in a non-linear relationship between the total sample size and the number of annotated classes. Due to this specificity, the total number of images in each dataset is not equivalent to the sum of the identified classes. This sampling approach ensured model invariance to spatial context and eliminated spurious correlations during uniform feature binding.

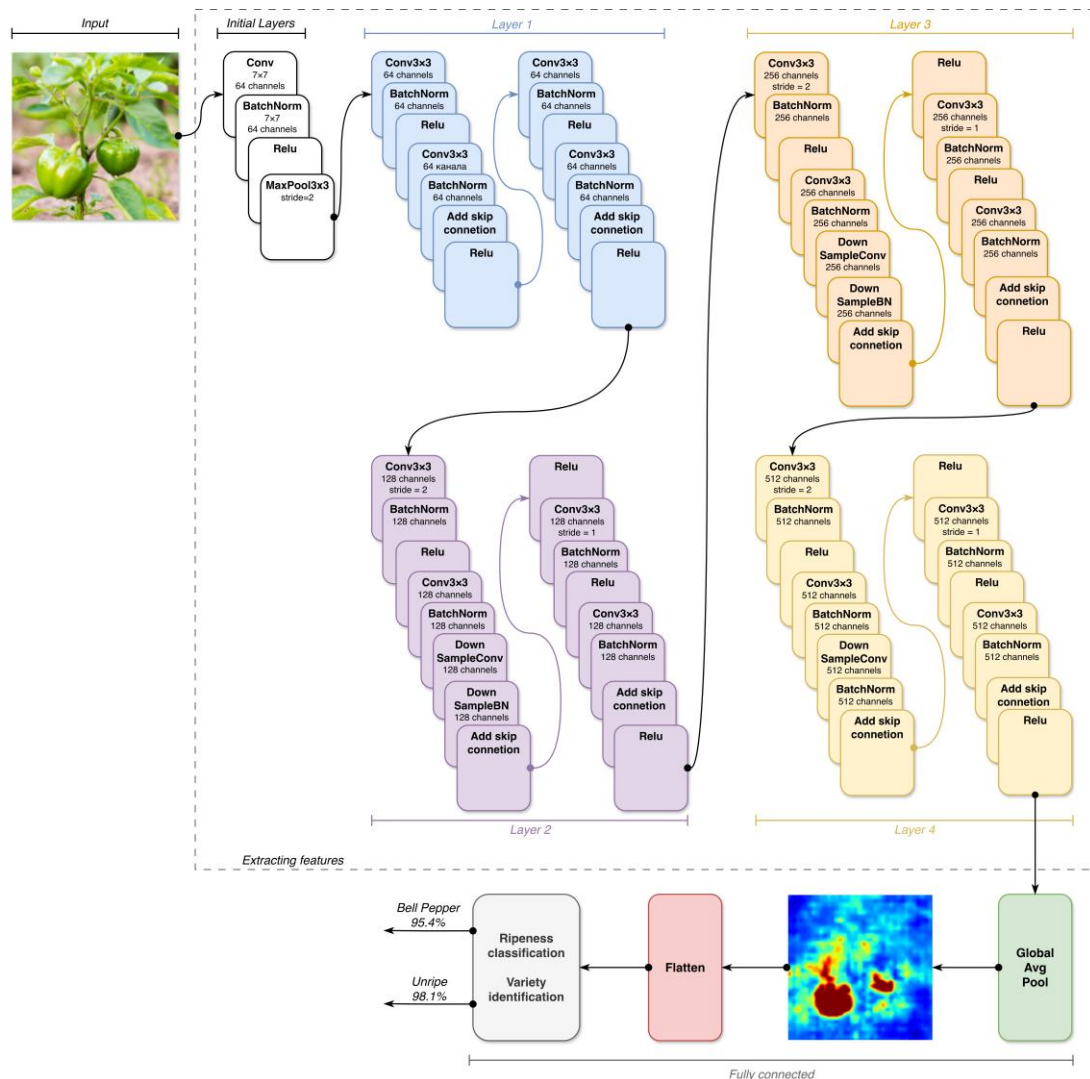


Figure 8. Neural network model for vegetable classification.

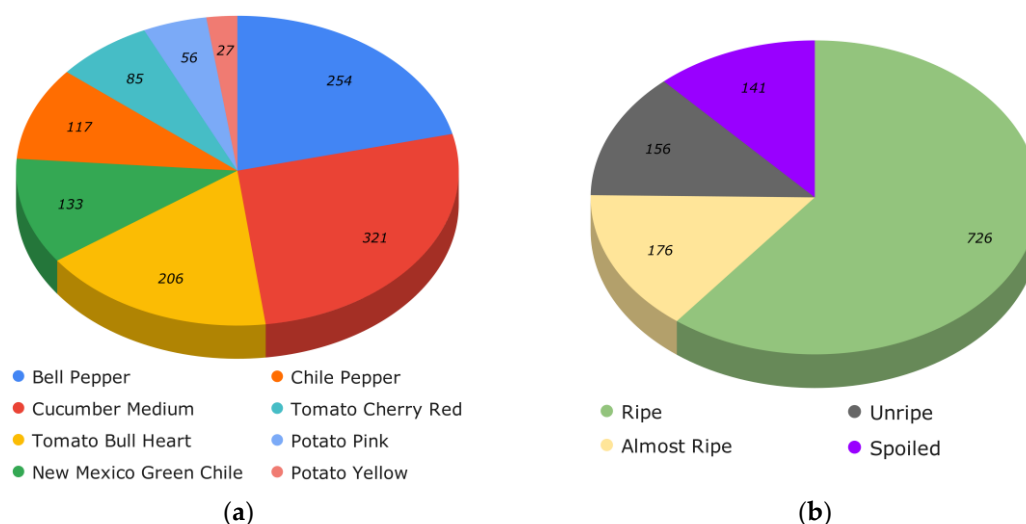


Figure 9. Quantitative characteristics of the datasets used: (a) vegetable varieties and (b) their ripeness levels.

The morphological and background structural variations in the objects within the samples were characterized by the following configurations:

1. Vegetable crop images (individual or grouped) captured directly within the vegetative environment against various natural backgrounds (on branches, soil, mulching material, or grass).
2. Harvested crops and vegetative plants depicted against heterogeneous backgrounds, including environmental artifacts and occlusions (leaves, stem fragments, soil inclusions).
3. Products packed in transparent polymer packaging (with objects captured through the film and uncovered).
4. Products placed in opaque containers (bags, sacks) with visualization through the open top of the vessel.

To enhance the robustness of the neural network models against variations in shooting conditions (exposure, background noise, spatial orientation), a suite of stochastic data augmentation methods was applied. During the preprocessing phase, a mosaic augmentation algorithm ($mosaic = 1.0$) was implemented, synthesizing four random frames into a single composite image. This approach aggregated the spatial features of the detected objects across various scales and contexts, thereby reducing the risk of overfitting and expanding the generalization capability of the algorithm.

Further stochastic modification of color and geometric characteristics was executed by the built-in module of the target architecture by optimizing the following hyperparameter vector:

1. Random variation in hue ($\pm 1\%$), saturation ($\pm 30\%$), and value/brightness ($\pm 25\%$), respectively.
2. Random spatial frame translation along the axes within $\pm 10\%$ and object geometry scaling in the range of $\pm 40\%$.
3. Horizontal axis mirroring with a 50% probability.
4. Random rotation within $\pm 15^\circ$, and dynamic adjustment of contrast and shade.

The application of the developed multicomponent transformation strategy ensured model invariance to environmental variability under real-world digital system operation.

The neural network generates a cumulative total of 2048 feature maps across distinct hierarchical levels. The structural complexity encompasses 11,182,668 parameters, 100% of which are trainable, resulting in a model footprint of 42.66 MB (FP32 format).

Model training followed a progressive layer-unfreezing fine-tuning strategy:

- Phase 1 (epochs 1–5): optimizes exclusively the multi-task heads while freezing the convolutional feature extractor, allowing the network to interpret pre-trained ImageNet representations within the domain of vegetable classification;
- Phase 2 (from epoch 6 onward): partially unfreezes upper-level blocks (Layer 3 and Layer 4) to adapt high-level features to the target domain, while maintaining frozen lower-level blocks (Layer1 and Layer2) to preserve generalized structural primitives.

The composite loss function aggregates individual cross-entropy losses computed for each objective. Optimization was driven by the AdamW algorithm (initial learning rate of 10^{-3}) coupled with a ReduceLROnPlateau learning rate scheduler, which dynamically halves the learning rate upon validation quality metric stagnation. The classification performance was evaluated via confusion matrices, with representative fragments illustrated in Figure 10.

The variety classification model (Figure 10a) demonstrates high accuracy (values on the main diagonal). The overall accuracy is 99.5%. Only a few instances of misclassification are noticeable: 98.45% for the “Bell Pepper” class and 97.62% for “Tomato Cherry Red.” This means that the model is conservative in identifying the varieties “Chile Pepper”, “Cucumber Medium”, “New Mexico Green Chile”, “Potato Pink”, “Potato Yellow”, and “Tomato Bull Heart”, and tends to predict “Bell Pepper” more often in situations of uncertainty. Figure 11a shows the dependence of the F1-score metric on the confidence threshold for the respective vegetable varieties.

The confusion matrix for the maturity stage classification exhibits a similar distribution, where the majority of values are concentrated on the main diagonal, with rare errors occurring exclusively between adjacent classes. All performance metrics exceed the 98% threshold, demonstrating the robustness of the maturity classifier. The model is well-balanced, identifying target objects with equal efficiency and minimizing inter-class misclassification. Figure 11b illustrates the F1-score metric as a function of the confidence threshold for the corresponding plant maturity stages.

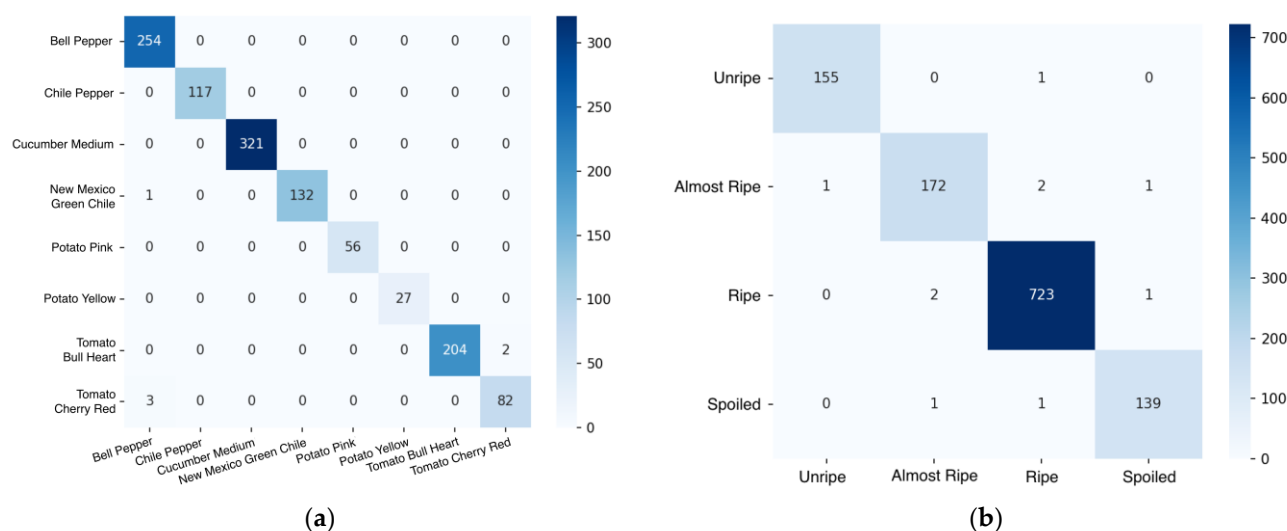


Figure 10. Confusion matrix: (a) identification of vegetable varieties; (b) assessment of vegetable ripeness.

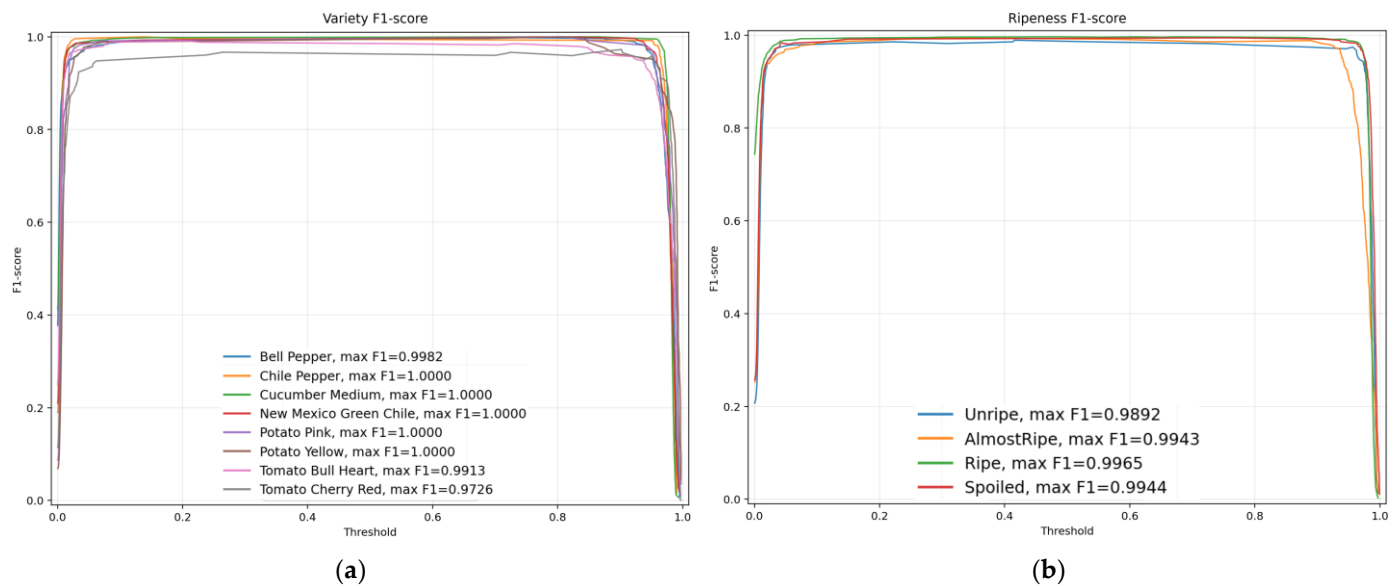


Figure 11. F1-score versus confidence threshold for the classification of (a) vegetable varieties and (b) their ripeness.

The curves for all classes exhibit a broad plateau, demonstrating that the model retains peak F1-score across a wide interval of confidence thresholds. Errors are deemed to be natural occurrence in all types of classification. Boundaries between ripeness stages and crop varieties can be unclear. From the perspective of using the results in digital system services, this accuracy is acceptable.

A comparison of the actual and predicted values revealed a high degree of correspondence with minimal local deviations. The initial class imbalance of vegetable crops in the training sample had no adverse effect on the final classification accuracy or the generalization capability of the developed model.

The class distribution generated by the neural network was statistically indistinguishable from the empirical distribution. This conclusion is supported by Pearson's chi-squared goodness-of-fit test results: the empirical value $\chi^2 = 0.1907$ is significantly below the critical threshold of 14.067 for 7 degrees of freedom at the specified significance level ($p = 0.05$).

The model was trained over 25 epochs, the results of which are shown in Figure 12.

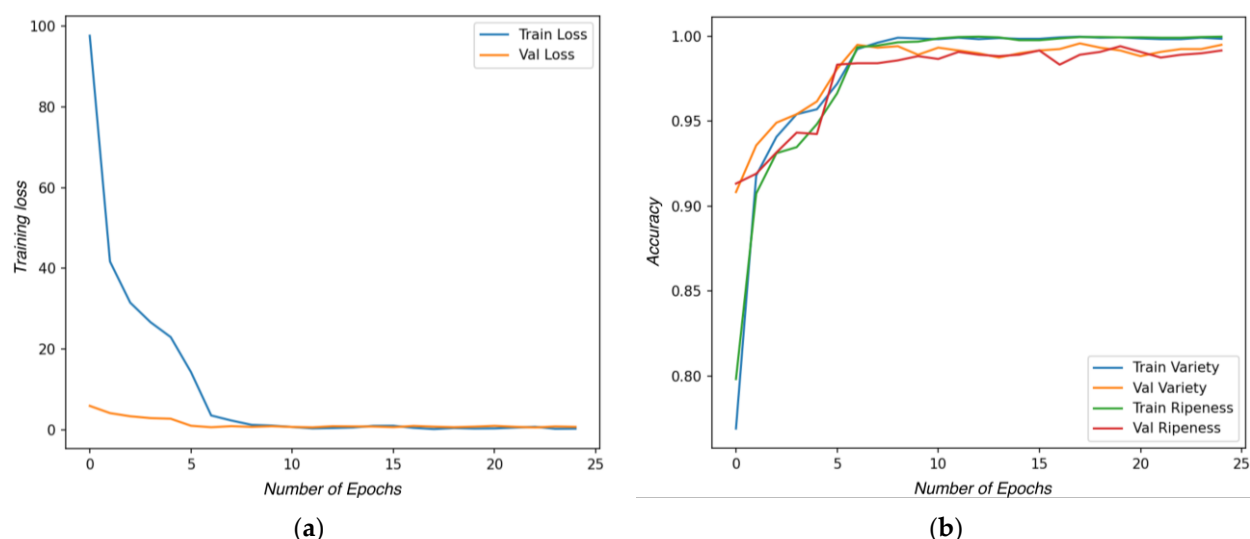


Figure 12. Graphs of training results: (a) loss function and (b) classification accuracy.

Figure 12a illustrates the trajectory of the loss function. Within the training subset, the model captured generalized structural primitives by approximately the 7th epoch, precipitating an error reduction to near-zero values. Concurrently, validation losses remained consistently low, progressively asymptotic to zero. The convergence and subsequent stabilization of both training and validation trajectories near the origin confirm the total absence of overfitting.

Figure 12b demonstrates the accuracy optimization curves for the variety and maturity classification tasks. The trajectories for variety classification rapidly plateau at 1.0 by approximately the 10th epoch, validating the empirical evidence derived from the confusion matrix (Figure 11a). Conversely, while the training trajectory for the maturity detection task reaches 100%, the corresponding validation curve exhibits stochastic fluctuations (“noise”) and stabilizes marginally below the other trajectories—a behavior directly attributable to the isolated classification errors documented in the corresponding matrix (Figure 11b).

The rapid convergence of the validation and training trajectories within the 10–12 epoch interval verifies the high generalization capability, spatial invariance, and efficiency of the engineered neural network model when processing independent, previously unseen datasets (Figure 13).

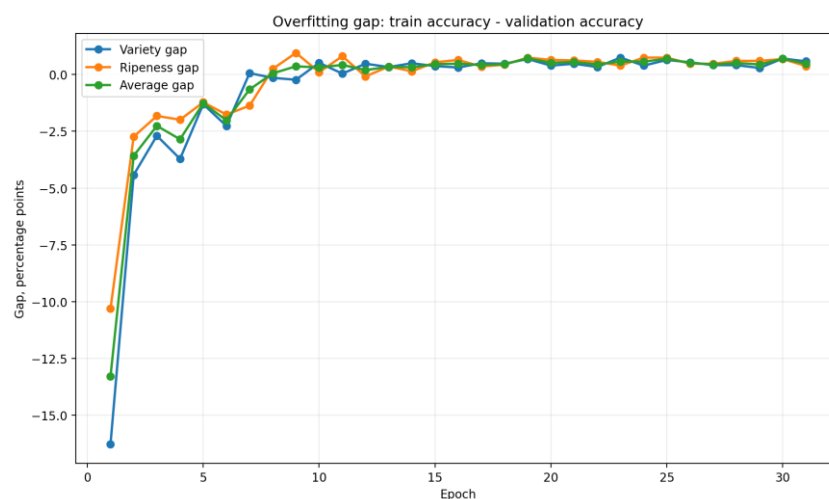


Figure 13. Dynamics of the overfitting gap.

The amplitude fluctuations of the target metrics during the initial training phase were caused by the application of intensive data augmentation procedures. The subsequent convergence of the curves indicates the stabilization of the optimization process, proves the absence of overfitting, and verifies the high generalization capability of the developed model.

To verify that the model did not overfit to artifacts (spurious features) and to explicate the regions of interest determining the final prediction, feature maps were visualized using Occlusion Sensitivity. A masking algorithm was iteratively applied to a 224×224 pixel inference image: 8×8 pixel patches were occluded with zero values (black color), followed by a re-evaluation of the target class posterior probability. The decrease in network confidence is directly proportional to the significance of the masked region for decision-making.

Upon completing the iterative process, the resulting relevance matrix was spatially smoothed using a Gaussian filter $\sigma = 2.0$ and normalized by the 99th percentile. For final detection, the output was converted to the JET color space and superimposed onto the original image. When interpreting the localization map, maximum gradient values (high

feature significance) are verified in red, while minimum values (zero contribution) appear in blue.

4.3. Verification of Results Based on a User Case

A comprehensive assessment of the functional capabilities, architectural solutions, and user interfaces of the engineered digital system was conducted via use-case modeling. This methodology operationalizes the verification of interaction logic between distinct user roles and the software environment. Representative use-case fragments implementing core workflows for the Buyer and Farmer entities are detailed below.

Upon user authorization under the “Buyer” role, the main page is initialized, displaying a list of farms available for ordering (Figure 14). If the user grants geolocation access, spatial proximity serves as the baseline ranking criterion. The distance is calculated based on a mathematical model (Equations (1)–(4)) utilizing the farm site geotags extracted from the cadastral map and the current coordinates of the buyer. In the absence of geopositioning access, the user’s location is determined at the country level via their IP address.

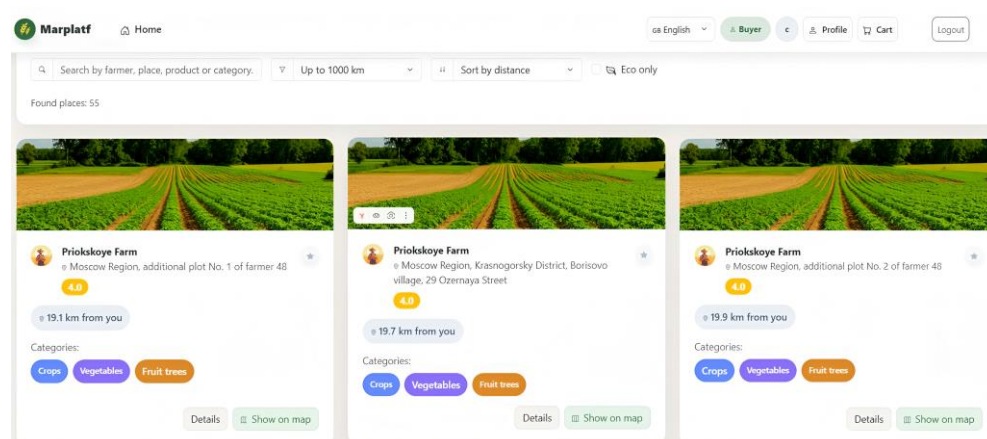


Figure 14. Interface main page with a list of farms available to the user in the “Buyer” role.

Regardless of the positioning method, the developed interface implements global search and data filtering tools. A search bar allows users to filter farms by all card attributes.

Result output management is provided through dynamic filters. The algorithm supports sorting and selecting objects based on three key parameters: distance radius (in kilometers), internal farm rating, and categories of commercial agricultural products.

During farm visualization on the interactive map, automated clustering was performed, determined by the spatial distribution of the objects and the current level of map detail (zoom level) (Figure 15).

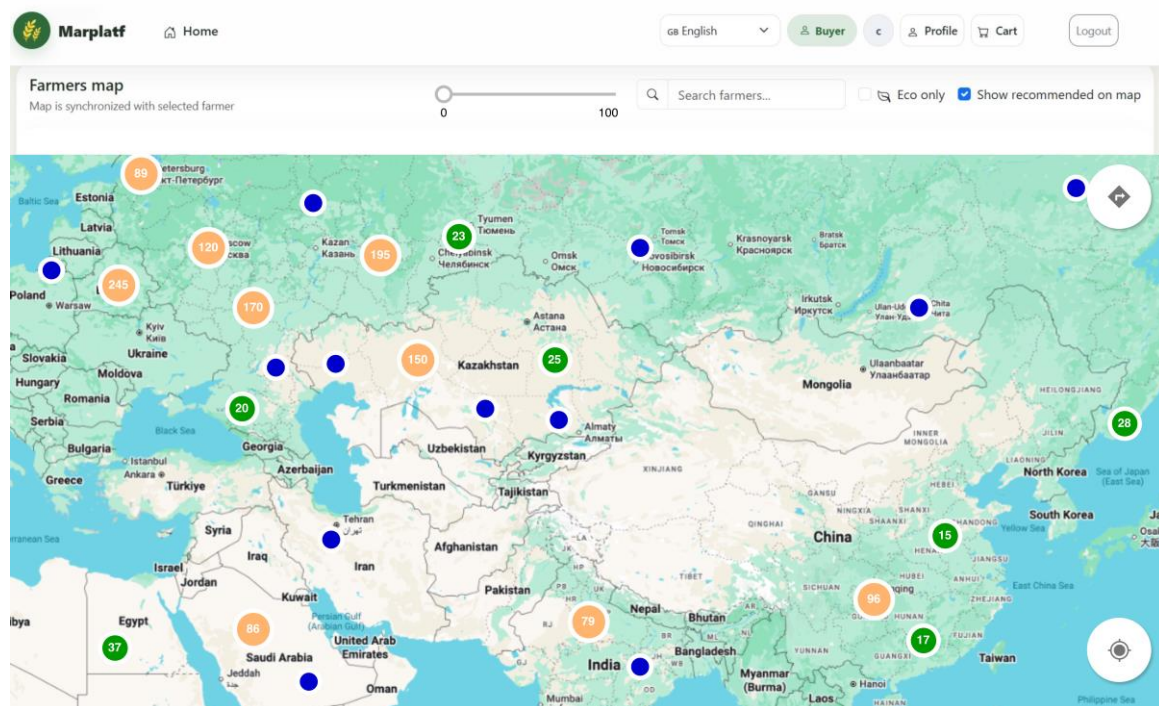


Figure 15. Display of farm clusters at the initial zoom level.

When user filtration parameters were initialized or the map scale was increased, the level of detail was progressively enhanced. Concurrently, the recalculation and regrouping of farm clusters were executed in accordance with the mathematical model defined by Equations (15) and (16). The digital system administrator interface displaying the dynamic object clustering results is shown in Figure 16.

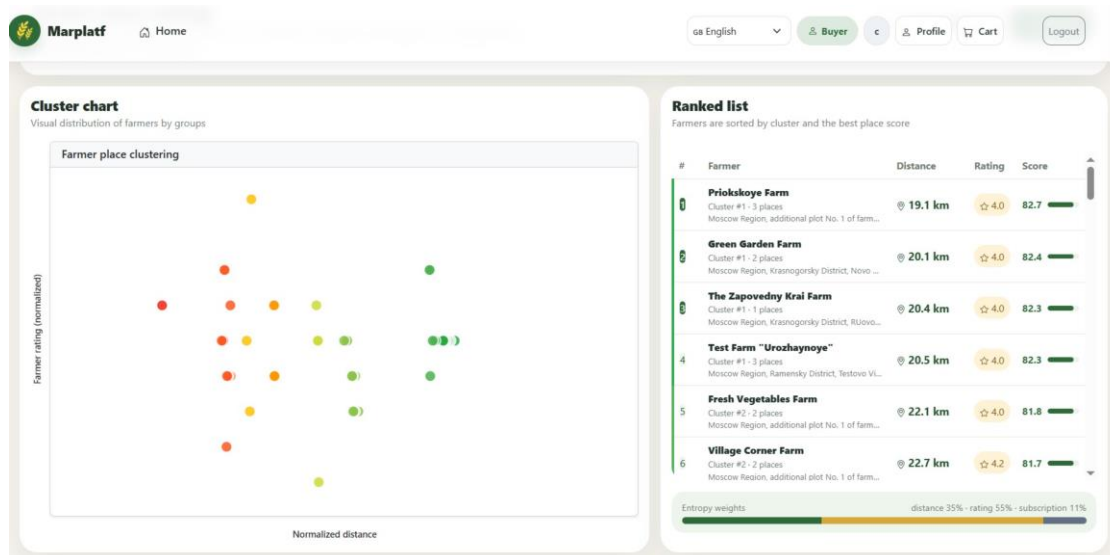


Figure 16. Visualization of farm site clustering within the administrator interface.

An alternative approach to locating a farm is searching by the type of agricultural product it yields. In the digital system, this functionality is implemented by integrating dynamic filters, a search bar, and a computer vision crop image recognition tool. The user can upload a photograph or an external image of a crop to find the most suitable producer for the corresponding product. Figure 17 illustrates the software implementation model for this scenario.

The buyer may utilize this functionality not only for product searching and ordering, but also for the following purposes:

- Verifying delivered orders to confirm compliance between the received and declared goods;
- Identifying agricultural products during retail purchases;
- Generating customized diets and selecting appropriate products.

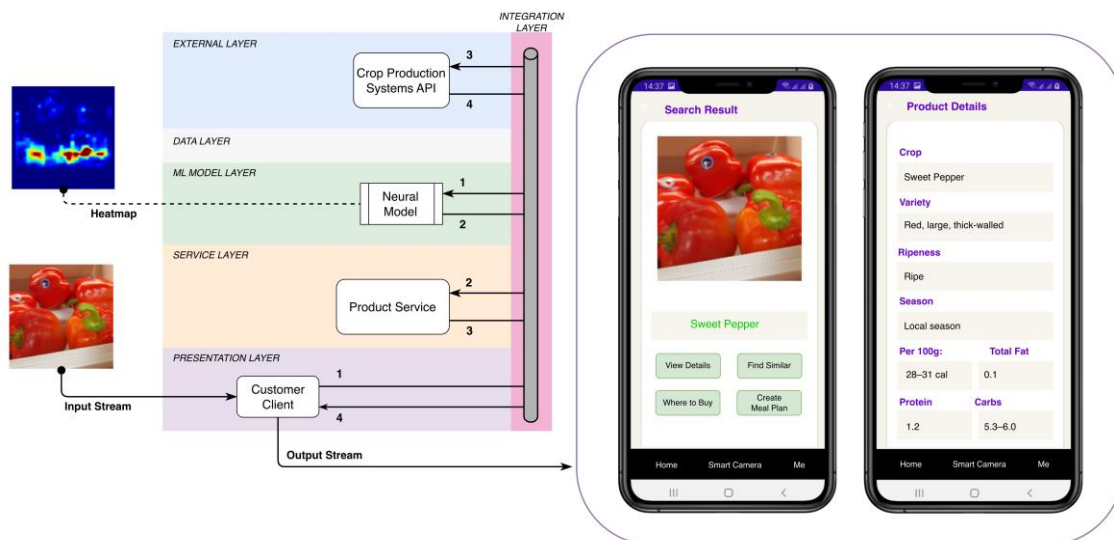


Figure 17. Model of customer-system interaction when searching for products by image.

These features are available to the user both in the mobile application and in the mobile browser. The workflow involves uploading an image of an agricultural crop (Input Stream), which is sent to the ML MODEL LAYER (Stream 1) for recognition. Based on the classification result (Stream 2), reference metadata on the product are imported from the external Crop Production System API service, where Stream 3 denotes the data request, and Stream 4 transfers product profiles, including variety descriptions, caloric values, macronutrient matrices, cultivation periods, and associated agronomic data. Based on the retrieved metrics, the user can activate the recommendation engine to find producers selling similar products or construct a customized diet.

To enter product information into the system, users with the “Farmer” function must configure a dedicated profile for their farm. This is accomplished by importing a cadastral map delineating land parcels or a location corresponding to the legal address. To ensure accurate logistics calculations, the location of the warehouse responsible for final consumer delivery must be specified. Moreover, for each allocated plot, the digital system enables selection of commodities cultivated directly within the area. Figure 18 presents the farmer’s personal dashboard interface, which operationalizes the generation of these product cards based on boundaries extracted from the cadastral map.

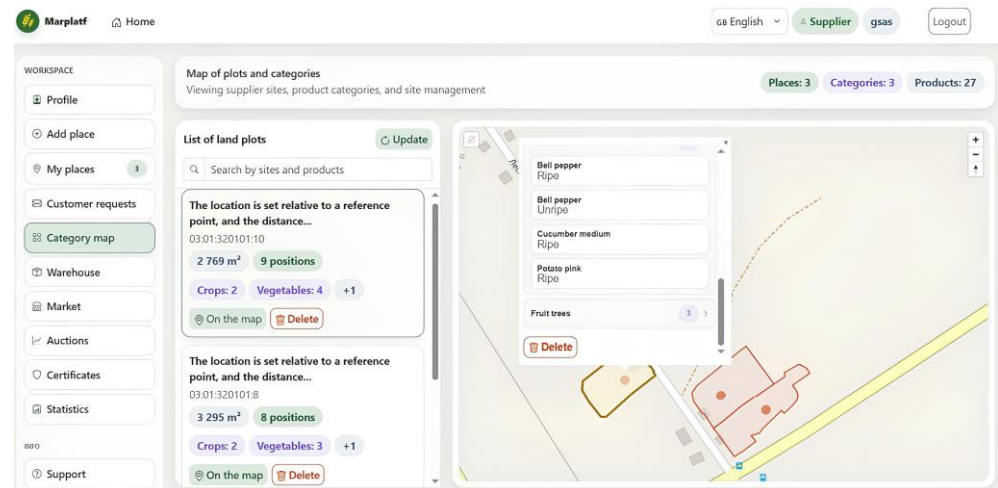


Figure 18. The page for generating farm profiles in the farmer's personal account.

The next step is defining a list of products cultivated or stored in the warehouse for each allocated plot. With the completed digital profile, the digital system generates an interactive map to visualize agricultural production by region, automatically updating the spatial clustering metrics.

Product data can be entered via several modes: manual; automated.

When entering data manually, the farmer must fill out a form within the mobile application or the mobile version of the website. In the automated mode, specific fields are populated utilizing metadata obtained by analyzing crop images via the neural network. To initiate this process, the farmer must upload an image of the seed packaging or the fruit at various vegetative stages. After the system determines the variety, maturity stage, and estimated growing season, the farmer determines the marketing method. This is necessary to ensure the correct operation of the recommendation engine, as products can be sold through forward order, auction, or immediate availability at a negotiated price. Figure 19 illustrates the model of farmer interaction with the product card generation system.

When implementing the product card use case, two Input Streams are generated: the actual vegetable image and metadata added by the farmer after verifying the performance of the integrated systems (Product Service, Neural Model, and Crop Procurement API). Stream A transmits the image to determine the variety and maturity level (Stream B), which is compared with reference agronomic metadata. The generated Stream C (transformed into Output Stream 1) is transmitted to the farmer to verify product characteristics, which include the timeline, volume, methods, and cost of sale (Input Stream 2).

The retrieved metrics (Stream D) are transmitted to the food security forecasting service. The analysis results (acceptable sales volume and recommended cost) are routed to the Product Service as Stream E to prepare the data imported into related services. These mechanisms operationalize cluster metric updates, recommendation generation, active product card storage, and analytical report archiving (Stream G). Similar information is transmitted to the farmer: Stream G is transformed for rendering within the application interface as Output Stream 2. Any adjustments by the farmer trigger Stream F, which is transmitted to the Product Service to update the data associated with Stream G.

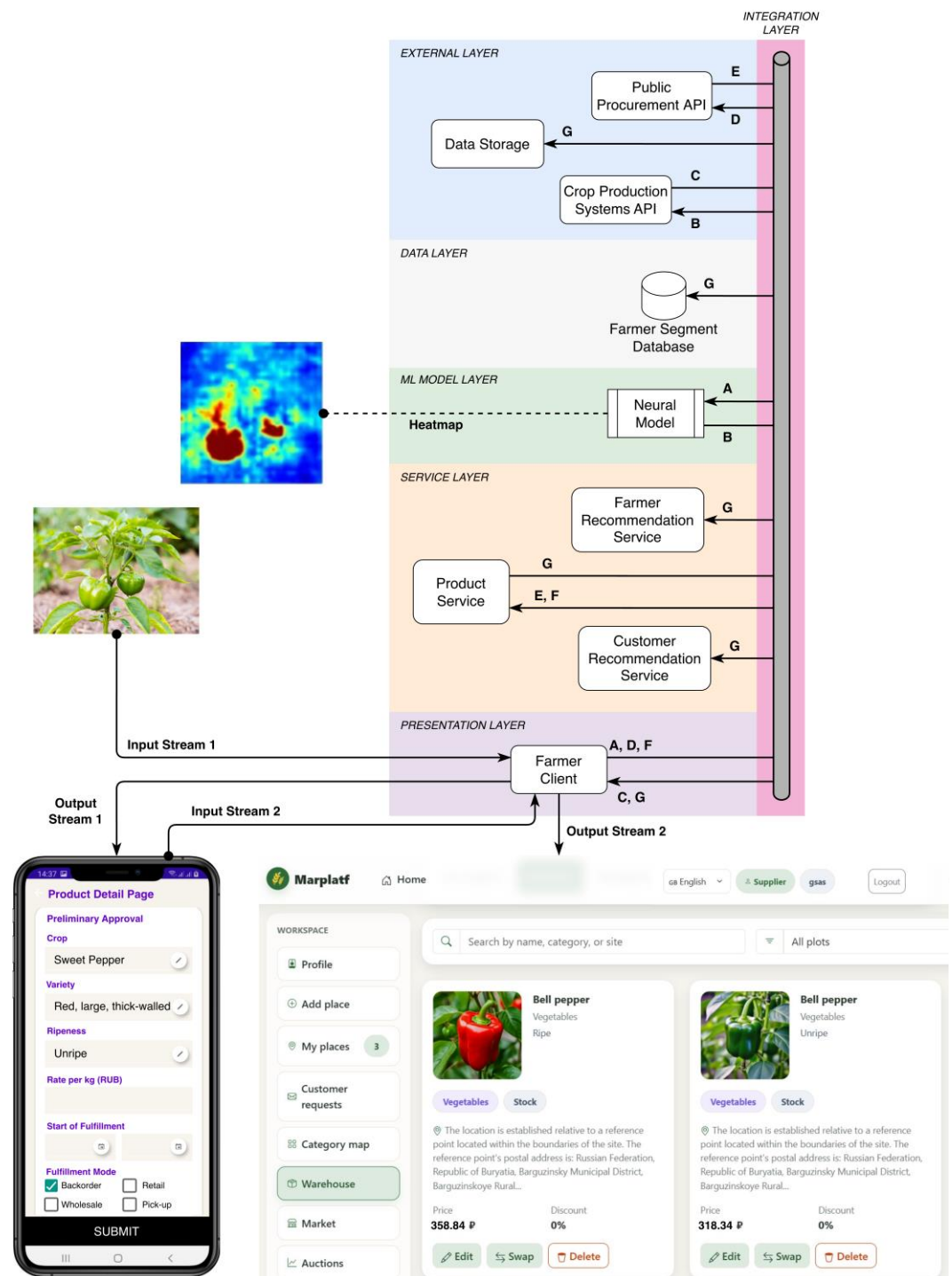


Figure 19. Model of the digital system-farmer interaction when generating product cards.

In the automatic mode, the system dynamically updates vegetable maturity matrices based on standard growing seasons, optimizing buyer-facing recommendations. Furthermore, the farmer can diversify product distribution mechanisms:

- Retail or wholesale distribution: via forward orders (allowing buyers to reserve specific yield volumes at any vegetative phase, from pre-season initialization to harvest) or based on real-time volumetric inventory at a fixed unit price;
- Auctions, which operationalize competitive wholesale distribution (Figure 20).

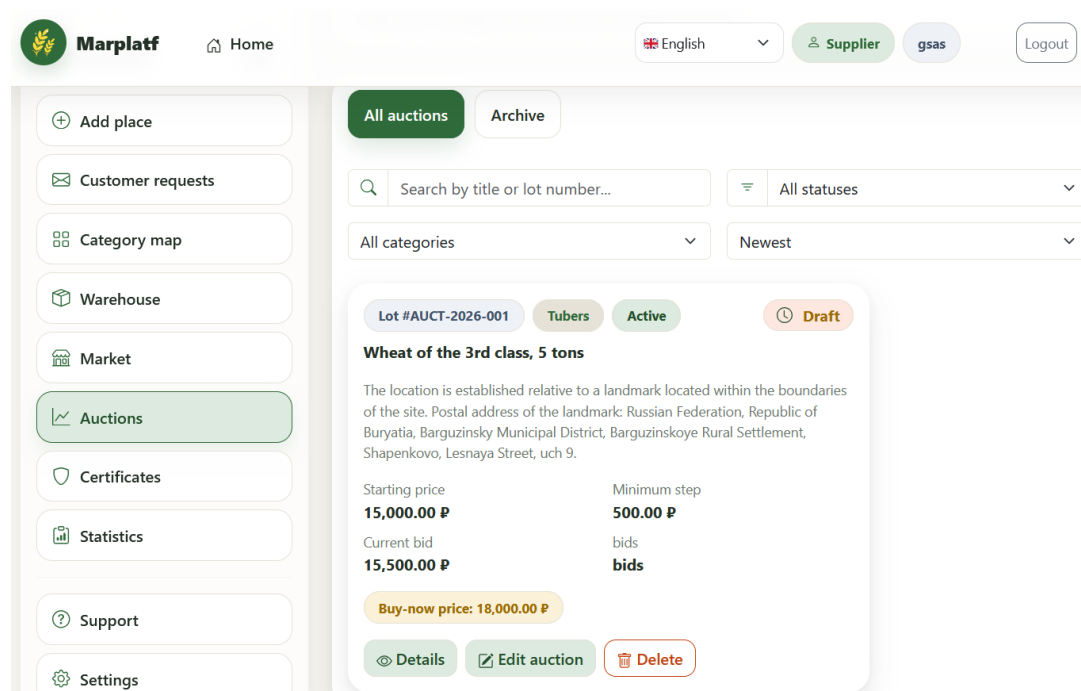


Figure 20. Auction organization interface in the personal account of a user with the “Farmer” function.

The recommendation engine, factoring in commercial volumes and real-time market dynamics, proposes optimized sales strategies to the farmer:

- Bulk wholesale distribution of the entire crop volume via integrated auctions or direct transactions with the customer;
- Segmenting the yield into distinct batches for subsequent commercialization through forward order systems or upon availability.

The developed recommendation system performed a multifactorial analysis of macro- and microeconomic indicators, accounting for the spatial distribution of agricultural producers relative to end consumers. The algorithm automatically verified the product volume available for export and calculated farm ratings within the cluster based on the following criteria and constraints:

- Foreign trade and regulatory barriers: when embargoes or sanitary import restrictions were imposed on a target region, prohibited products were excluded from the search results for potential orders.
- Quotas: current tariff quota volumes of importing countries were integrated to minimize the risk of incurring elevated out-of-quota duties.
- Supply–demand balance: production deficits were analyzed across specific commodity nomenclature groups.
- Logistics profitability: the minimum shipment volume was calculated based on covering cross-border logistics costs, with model scalability achieved through exchange rate and freight risk monitoring.

When calculating object ratings at the national and regional levels, the algorithm performed real-time distribution management based on the following priorities:

- Spatial priority: local products were assigned the highest rank in the recommendation system, while products from adjacent regions were ranked based on production costs, logistical losses, and the self-sufficiency ratio of the supplying region.

- Surplus management: if a producer lacked storage infrastructure during a seasonal surplus, the system redirected offers to large retailers, processing plants, or wholesale distribution center operators to ensure year-round sales.
- Subsidization: the availability of state transportation subsidies to specific federal subjects was integrated into the ranking logic.
- Purchasing power differentiation: the product assortment matrix was adapted to the regional profile, prioritizing high-margin and organic products in high-income regions, and mass-market goods in low-income regions.
- Institutional demand: public procurement plans and tendering procedures were factored into the distribution model.

In the developed digital platform prototype, a data import module was implemented via bulk file uploads from relevant institutional repositories, executed by a user with administrator privileges. Figure 21 illustrates the administrator dashboard interface, displaying current regional indicators based on the specified configurations.

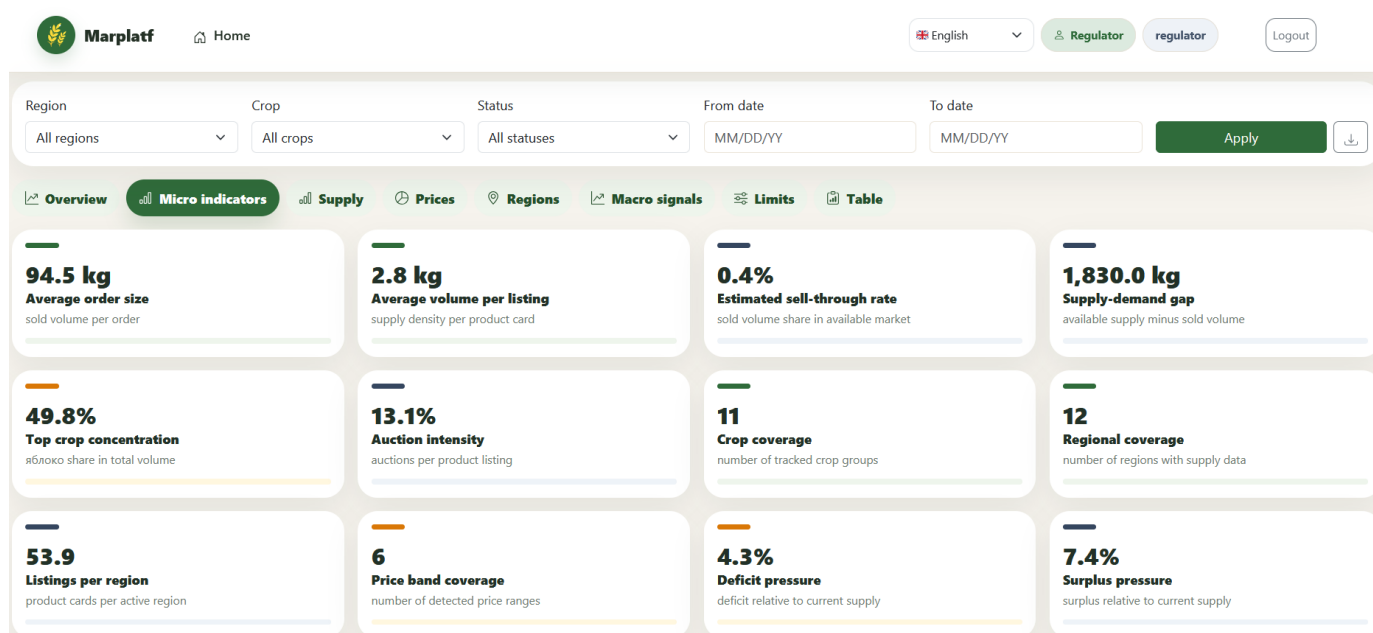


Figure 21. System administrator interface featuring regulatory functions.

The architecture of the developed digital system supports scalability regarding automated data collection from external sources. Upon transitioning to automated data harvesting, the regulatory representatives' functions will be confined to monitoring verified metrics and exporting analytical reports.

5. Discussion

5.1. Analysis of Results in the Context of Theoretical Significance

The empirical findings align with established principles of digital transformation within the agricultural sector, spanning both conceptual and technical perspectives.

The engineered digital system model facilitates a paradigm shift from reactive to predictive food security management. The scalability frameworks for such systems remain directly contingent upon the availability of valid and reproducible methodological tools for assessment and forecasting. These frameworks must incorporate heterogeneous data integration from disparate sources, account for spatial and territorial specifics, and enable proactive risk communication [5,7,14].

The developed model balances agrifood complex economic efficiency, social accessibility, nutritional adequacy, and ecological equilibrium. Based on the “one-to-one” principle, the model enables direct farmer-buyer interactions, addressing critical small agribusiness challenges such as reliance on speculative intermediaries and retail market monopolization. By removing redundant links from the pricing chain increases farmers’ economic resilience while rendering finished products more accessible and diverse. Consequently, a transformation of market relations occurs along the social development vector, a conclusion validated by studies investigating negative social trends in regional food accessibility [19,41].

The implementation of clustering algorithms based on entropy analysis enables automatic segmentation of producers and consumers, facilitating the determination of the actual balance of supply and demand. This allows government agencies to quickly identify surplus products and redirect them to deficit regions, as well as organize exports or imports, stabilizing prices and the product market.

Farmers thus gain a tool for planning and adjusting their cropping structure based on actual market conditions, such as the volume of advanced orders and production levels in their own and neighboring regions. Buyers, meanwhile, can manage their food consumption levels over the long term, creating a unified system for monitoring food security at various levels.

This methodology also addresses the fundamental problem noted in domestic studies regarding the dominance of models based solely on comparing regional production and self-sufficiency indicators with national averages [52,56,68].

The results of this study present new challenges in food security, as deploying a digital system may intensify market volatility, introduce novel forms of resource and information inequality, and alter consumer behavior. These risks align with conclusions from studies on digital economic transformation [37,67,76].

Conversely, digital systems offer emerging opportunities for real-time data analysis, supply chain optimization, and personalized consumer and farmer assistance. Furthermore, this framework enables early crisis warnings through simulation models that replicate process logic to identify causal relationships and test management strategies [27,77,78].

To operationalize these functions, this paper outlines a digital system architecture for data collection and processing. The underlying services leverage microeconomic indicators while integrating macroeconomic fluctuations.

Economic research demonstrates that a comprehensive food security assessment is multidimensional, and integrating its aspects yields a synergistic effect [7,15]. A systemic analysis of both indicator groups reveals structural imbalances: for example, high rates of agricultural production at the macro level may coexist with a declining quality of the population’s diet at the micro level.

Timely identification of these dynamics helps determine underlying causes, such as inefficient income distribution or low consumer demand. While digital system’s services do not predict macroeconomic changes, they enable real-time microeconomic data acquisition and export to the external environment for external system analysis.

The integration of microeconomic indicators in the developed system focuses attention on specific farmers, households, and consumers, reflecting the physical and economic availability of food. Researchers note that consumption patterns may deteriorate even amid favorable macroeconomic indicators [12,79].

For example, the population may consume food depleted in vitamins and protein, while the corresponding products remain in warehouses, unclaimed. Using predictive models in the system’s services allows for analyzing current indicators and forecasting how the composition and quality of the consumer basket will change.

5.2. Result Analysis Within the Context of Practical Significance

From a technical perspective, the developed software meets digital transformation requirements. It represents not only a tool for supporting existing processes, but also a digital platform that fosters a new economic model.

The system's architecture integrates key Industry 4.0 technologies, including neural networks for product quality decision-making and routine document management. It also leverages predictive analytics and big data to generate microeconomic statistics and forecast food balance changes. Furthermore, cloud services provide scalability and cross-border technology integration, while mathematical models enable automatic clustering and real-time recommendations rather than relying on retrospective statistics.

Finally, this unified digital ecosystem establishes a seamless environment for food security stakeholders, ensuring a transparent "product footprint" through customization and client-centric principles that create personalized product offers based on quality and origin.

Existing market software solutions can be divided into government monitoring systems, marketplaces, and analytical models [52]. Table 2 presents a comparative analysis between the developed software solution and existing market alternatives.

Table 2. Comparative analysis of existing agricultural platform classes and the developed digital system.

Criterion	Farmer Marketplaces	State Agribusiness Monitoring Systems	Developed Digital System
Target scale and integration	Primarily local or national level	Country-level macroeconomic assessment	Inter-state level (economic union integration)
Content processing	Manual entry	Manual entry and automated document import	Automated variety and maturity recognition with manual editing support
Recommendation and search algorithm deployment	Combined search bar and filter utilization	Not supported	Intelligent clustering and query-based recommendation system
Sales models	Retail or wholesale sales	Not supported	Crop forward pre-orders, direct retail/wholesale sales, and wholesale auctions
Production planning	None	Directive or retrospective	Recommendation system based on regional demand and competitor behavior
Food security	Commercial focus (profit maximization)	Statistical accounting and subsidization	Predictive supply-demand balance management to eliminate deficits
Pricing	Free-market pricing (high risk of speculation)	Regulated and statutory pricing	Intermediary-free optimization with regulatory compliance constraints

Most existing platforms target large-scale enterprises due to high deployment complexity and prolonged payback periods. These systems address localized tasks, including enterprise management, specific operational processes, sales, logistics, and regulatory compliance. Conversely, the developed system establishes a unified digital ecosystem for food sustainability, accommodating all domestic and international agricultural market participants.

The selected architectural solution ensures stable system operation with indicators corresponding to the stated problem. Research by domestic and international scientists

notes that dividing the architecture into layers with abstraction of communication channels allows for modifying the internal logic of the service without transforming other components [11,35,66,72].

This ensures semantic compatibility across different layers, guaranteeing transaction integrity and maintaining fault tolerance during peak loads or temporary unavailability of individual services. Furthermore, the architectural model is scalable to integrate new functional modules without compromising the structural integrity of the entire system.

5.3. Limitations

The study exhibits technical, economic, consumer, and social limitations.

Some regions face infrastructure shortages, including uneven high-speed internet access and limited availability of modern mobile devices, complicating full system implementation and accurate food security transformation assessments.

Furthermore, long-term system performance testing has not been conducted under macroeconomic shocks, such as abrupt customs duty alterations or global climatic and technological disasters. These unpredictable factors can disrupt individual service algorithms, including clustering and recommender systems.

Finally, countries outside economic unions may encounter difficulties due to unharmonized trade legislation, which poses risks to final product pricing, volume accounting, transaction conclusion, and forecasting.

The main societal problem may be the conservatism of small farmers, who distrust software that makes autonomous decisions, as well as their personal connections to local resellers for selling their yield. Accordingly, further research is needed to estimate what happens when the most vulnerable participants go underground from the digital market since they are unable to ensure the required quality of digital interaction.

The operation of the developed neural network classifier under real-world conditions is subject to several fundamental limitations stemming from external environmental factors and training sample specificities. A key adverse factor is extreme illumination levels (insufficient insolation in storage warehouses or intense artificial glare), which can distort the agricultural product color feature maps. To mitigate this risk during the digital system prototype design phase, images captured under varying natural and artificial lighting scenarios, as well as across different vegetation phases and crop storage periods, were preemptively integrated into the dataset.

An additional source of input tensor errors is associated with the technical parameters and aberrations of the optical systems of mobile devices used for image capture. Variability in smartphone camera resolutions, focal lengths, automatic white balance, and motion blur can degrade recognition accuracy. The current graphic dataset volume and stochastic augmentation procedures do not entirely eliminate this issue; its definitive resolution is planned through digital platform scaling and continuous input dataset expansion.

The spatial–geographic factor presents another significant limitation capable of inducing dataset class imbalance due to user-generated content characteristics. Depending on farm geographic locations and consumer density, a statistical shift toward dominant local market crops (driven by seasonality, affordability, or regional priorities) is projected within the uploaded image structure. This trend could degrade the recognition quality for rare agricultural product species. Within the developed architecture, this issue is addressed via periodic fine-tuning of the neural network modules.

6. Conclusions

The establishment of an international digital system for interaction between agricultural producers and end consumers aligns with AgTech 4.0. Technological advancements

have enabled the transition to “smart” production while reshaping peripheral agricultural processes.

Although globalization has enhanced food accessibility, it introduces uncertainty in national food security. Furthermore, global food production has increased, yet its uneven distribution exacerbates vulnerability to market fluctuations.

Consequently, food security depends not only on agricultural production volumes but also on the stability of international relations. Simultaneously, domestic sectors become vulnerable to global prices, rendering smallholder farmers unable to compete with cheap imports.

The developed digital system serves as a tool for optimizing transaction costs, minimizing intermediaries in the food supply chain, and establishing direct market connections between supply and demand. Integrating farm performance big data provides high pricing transparency, safeguarding the interests of small- and medium-sized agribusinesses regarding fair market value. Furthermore, economic entities gain instruments to plan operations based on current demand and forecast microeconomic indicators.

On an interstate scale, digital coordination integrates macroeconomic indicators to address planning, logistics, and pricing efficiently. This framework enhances product lifecycle traceability, facilitates resource redistribution, and minimizes logistical losses, which is critical for perishable products, while monitoring phytosanitary standards. Consequently, these mechanisms guarantee product quality and bolster consumer confidence, particularly for imported goods.

Ultimately, the developed digital system strengthens interstate agricultural marketing ties. Beyond supporting agro-industrial and farm growth, it fosters institutional resilience in international trade relations amid volatile global markets.

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Institutional Review Board Statement: The study did not use personal data. The work was carried out without experimental studies of plants (cultivated and wild) and collection of plant material, without the participation of animals and animal materials. Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements.

Data Availability Statement: Commercial restrictions apply to the provision of full access to the source code and test data. Data not subject to such restrictions are available in an open repository at the following link: <https://github.com/SymplysoF/Marplatf> (accessed on 15 June 2026). Use of these materials in research and publications requires mandatory attribution and a citation of the original source. Any additional information is available from the author upon request.

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Abbreviations

The following abbreviations are used in this manuscript:

P2P	Peer-to-peer
UAV	Unmanned Aerial Vehicle

AgTech	Agricultural Technology
IoT	Internet of Things
HTR	Handwritten Text Recognition
HFIAS	Household Food Insecurity Access Scale
HDDS	Household Dietary Diversity Score
HHS	Household Hunger Scale
CSI	Coping Strategies Index
GUI	Graphical user interface
PEM	Policy Evaluation Model
EPACIS	Econometric Partial Aquilibrium Computational Information System
CAP	Common Agricultural Policy
EFSCM	European Food Security Crisis preparedness and response Mechanism
BRICS	Brazil, Russia, India, China, South Africa
AfCFTA	African Continental Free Trade Area
IT	Information Technology
SMS	Short Message Service
HS codes	Harmonized System codes
ESB	Enterprise Service Bus
rad	Radian
km	Kilometer
API	Application Programming Interface
ML model layer	Machine Learning model layer
SLA	Service Level Agreement
PC	Personal Computer
RAM	Random Access Memory
GPS	Global Positioning System
Mbps	Megabits per second
JET	Jet colormap
MB	Megabyte
FP32	32-bit Floating Point

Appendix A

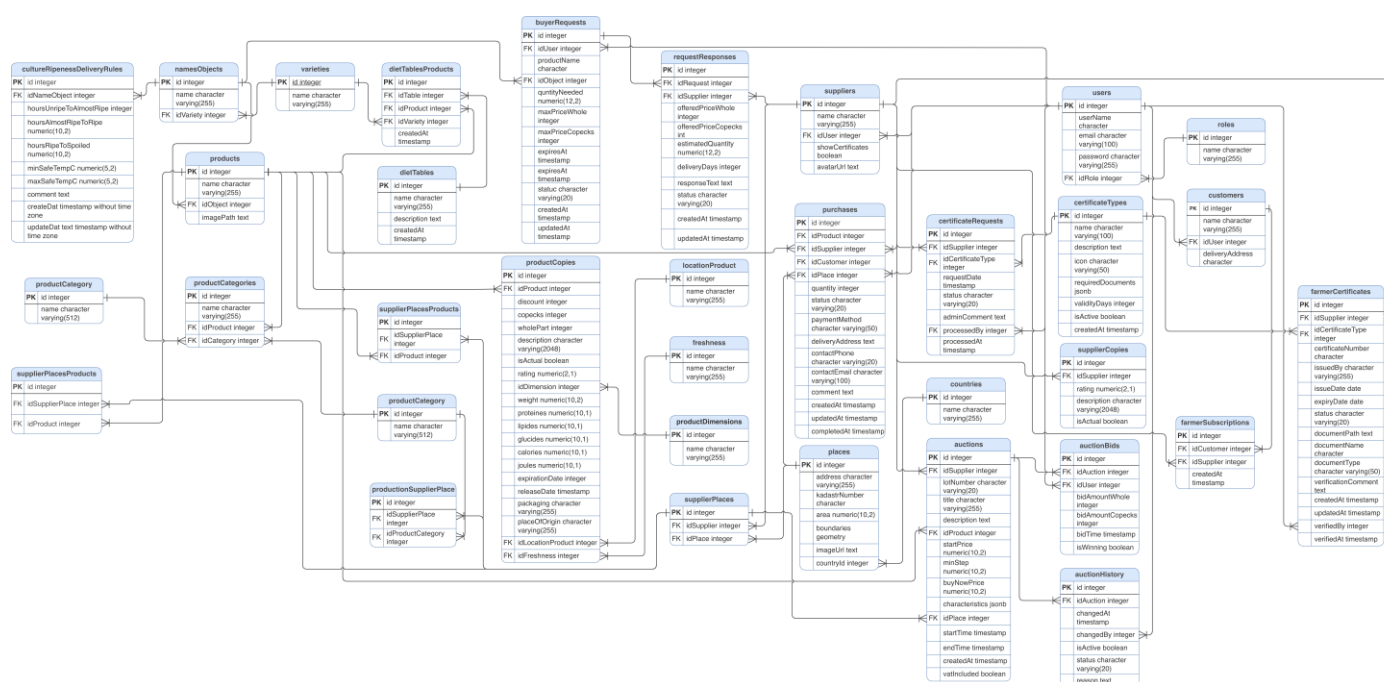


Figure A1. Data Model.

Appendix B

Table A1. Characteristics of the user's software and hardware in a digital system.

Characteristics	Minimum Requirements	
	Mobile Application or Mobile Version	Browser on a Personal Computer
RAM	2 GB. 4 GB For interactive maps.	8 GB
Processor	Quad-core processor with a frequency of at least 1.5 GHz.	Dual-core processor (e.g., Intel Core i3 (Intel Corporation, Santa Clara, CA, USA) or AMD Ryzen 3 (Advanced Micro Devices Inc., Santa Clara, CA, USA)) with a frequency of at least 2.0 GHz
Screen resolution	1280 × 720	1366 × 768 (1920 × 1080 Full HD recommended)
Internet connection	3G/4G (LTE) or Wi-Fi. GPS/GLONASS module preferred.	Stable internet connection with a speed of 5–10 Mbps
Storage	500 MB	2–5 GB of available disk space
Operating system	Android: 8.0 (Oreo) and up (Google LLC, Mountain View, CA, USA).	Windows: 10 or 11 (64-bit) (Microsoft Corporation, Redmond, WA, USA). MacOS: 11.0 (Big Sur) (Apple Inc., Cupertino, CA, USA).
	iOS: 13.0 and up (Apple Inc., Cupertino, CA, USA).	Linux: Current Ubuntu (Canonical Ltd., London, UK) or Astra Linux (RusBITech-Astra LLC, Moscow, Russia) distributions with a graphical shell.
Browser	Up-to-date versions of Chrome (Google LLC, Mountain View, CA, USA), Safari (Apple Inc., Cupertino, CA, USA), or Yandex Browser (Yandex LLC, Moscow, Russia) with JavaScript and HTML5 support (for mobile version).	Up-to-date versions of Google Chrome, Yandex Browser, Microsoft Edge (Microsoft Corporation, Redmond, WA, USA) or Mozilla Firefox (Mozilla Corporation, San Francisco, CA, USA)
Additional (optional) conditions	A camera for identifying product grade and quality.	CryptoPro EDS Browser plug-in (Crypto-Pro LLC, Moscow, Russia) for electronic signing of contracts.
	PDF reader for viewing downloaded reports and certificates.	Adobe Acrobat Reader (Adobe Inc., San Jose, CA, USA) or built-in browser tools for viewing documents. A spreadsheet and document management package (Microsoft Office (Microsoft Corporation, Redmond, WA, USA), LibreOffice (The Document Foundation, Berlin, Germany), or MyOffice (New Cloud Technologies Ltd., Moscow, Russia)) for analyzing downloaded data.

Table A2. Specification of the software and hardware complex of the digital system in the minimum configuration.

Component	Technical Requirement	Purpose
Server	x86-64 architecture, at least 2 processors (16 cores/32 threads total), base frequency from 2.5 GHz (Intel Corporation/Advanced Micro Devices Inc., Santa Clara, CA, USA)	Service Layer and Business Logic Support
RAM	64 GB DDR4/DDR5 ECC with error correction (Micron Technology Inc./Samsung Electronics/SK Hynix, Boise, ID/San Jose, CA, USA)	Integration Layer Operation and Caching
Storage	2 × 960 GB NVMe SSDs in RAID 1 (Mirror) (Samsung Electronics/Kioxia/Solidigm, San Jose, CA, USA)	High-Speed Access to the Data Layer
GPU	NVIDIA A2 or T4 (16 GB VRAM) with CUDA/Tensor core support (NVIDIA Corporation, Santa Clara, CA, USA)	ML Model Layer Inference and Operation

Network Interface	2 × 10 GbE SFP+ (channel redundancy) (Intel Corporation/Cisco Systems/Broadcom, Santa Clara, CA, USA)	Data Exchange with the External Layer and High Bus Throughput
System Software	Linux 64-bit (Ubuntu Server 22.04 LTS) (Canonical Ltd., London, UK) or Linux 64-bit (RHEL 9) (Red Hat Inc./IBM, Raleigh, NC, USA)	Base Operating Environment
Virtualization Environment	Docker Engine 24.0+ (Docker Inc., Palo Alto, CA, USA), Kubernetes (K8s) (Cloud Native Computing Foundation, San Francisco, CA, USA) or K3s (Rancher Labs/SUSE, Cupertino, CA, USA)	Isolation and Deployment of System Micro-services
DBMS and Brokers	PostgreSQL 15+ (PostgreSQL Global Development Group, Berkeley, CA/New York, NY, USA), Redis 7+ (Redis Inc., Mountain View, CA, USA), Apache Kafka (Apache Software Foundation, Forest Hill, MD, USA)/RabbitMQ (Broadcom Inc., Palo Alto, CA, USA)	Implementation of Data Layers and the Service bus
Power Supply	Two independent power supplies (hot-plug) with a minimum capacity of 750W each (Delta Electronics/Lite-On Technology/Artesyn Embedded Power, Plano, TX, USA/San Jose, CA, USA)	Security

Appendix C

Table A3. Characteristics of the layers of the neural network model.

Level	Number of Layers	Features by Type	Characteristics
Initial Layers	4	Low-level (edges, corners, color)	Primary processing for dimensionality reduction and feature extraction: convolution with a large kernel to cover large regions (Conv7×7); data normalization to speed up training (BatchNorm); activation to introduce nonlinearity (Relu); reduction in the spatial dimension of the feature map (MaxPool3×3). 64 different feature maps are created to preserve image detail.
Layer1	14	Basic textures	Convolutional layers (Conv3×3) capture local textures and shapes. After each convolution, batch normalization (BatchNorm) and negative value zeroing are performed to model complex nonlinear dependencies (Relu). The use of skip connections ensures that the original pixel and gradient data is preserved for deep learning without training loss. The channel scale is reduced and the channel depth is doubled. The feature map resolution is halved vertically and horizontally. Increasing the number of channels is used to recognize complex image elements (roundness, curves, textures, etc.).
Layer2	16	Complex patterns	A special convolution adjusts the size and number of channels of the input signal to the output (Down SampleConv) and normalizes it (Down SampleBN) for subsequent summation (Add skip connection). To refine and consolidate the obtained features, a series of 3 × 3, BatchNorm, and Relu convolutions are run. The spatial size of the feature map is halved to increase the receptive field of subsequent filters on the original image.
Layer3	16	Partial objects	A chain of convolutions and a parallel path convert the 128 input channels to 256 output channels for subsequent summation. Preparation and refinement for final processing occur. Isolated features are assembled into unified concepts.

			Maximum level of abstraction.
Layer4	16	Whole objects	Data is transformed from 256 channels to 512, scaled down, and features are re-fined before being passed to the classifier.
Fully connected	2	Aggregated features	Global average pooling transforms $7 \times 7 \times 512$ spatial feature maps into a 512-dimensional feature vector. The Flatten operation creates a one-dimensional representation.

References

- Melnikov, A.B.; Mikhaylushkin, P.V.; Kotok, N.Y. Assessment of the level of food security in the world. *Mezhdunarodnyi Sel'skokhozyaistvennyi Zhurnal* **2021**, *1*, 4–6. <https://doi.org/10.24412/2587-6740-2021-1-4-6>.
- Drynochkin, A. Some aspects of food security in the countries of Central and South-Eastern Europe. *Contemp. Eur.* **2023**, *1*, 88–99. <https://doi.org/10.31857/S0201708323010072>.
- Stolyarova, A.N.; Shamray-kurbanova, L.V.; Darelina, O.V.; Chumakova, E.A. Food security as an element of state's national security. *Food Policy Secur.* **2023**, *10*, 219–236. <https://doi.org/10.18334/ppib.10.2.117818>.
- Lu, Y.; Zhang, Y.; Hong, Y.; He, L.; Chen, Y. Experiences and lessons from Agri-Food system transformation for sustainable food security: A review of China's practices. *Foods* **2022**, *11*, 137. <https://doi.org/10.3390/foods11020137>.
- Kamalian, A.K. Food security in the Eurasian economic union: Problems and solutions. *Econ. Agric. Russ.* **2022**, *4*, 12–20. <https://doi.org/10.32651/224-12>.
- Arghiroiu, G.A.; Bobeică, M.; Silviu, B.; Mann, S. From Crisis to Resilience: A Bibliometric Analysis of Food Security and Sustainability Amid Geopolitical Challenges. *Sustainability* **2025**, *17*, 8423. <https://doi.org/10.3390/su17188423>.
- Oluwole, O.; Ibidapo, O.; Arowosola, T.; Raji, F.; Zandonadi, R.P.; Alasqah, I.; Lho, L.H.; Han, H.; Raposo, A. Sustainable transformation agenda for enhanced global food and nutrition security: A narrative review. *Front. Nutr.* **2023**, *10*, 1226538. <https://doi.org/10.3389/fnut.2023.1226538>.
- Nekmahmud, M. Food consumption behavior, food supply chain disruption, and food security crisis during the COVID-19: The mediating effect of food price and food stress. *J. Foodserv. Bus. Res.* **2024**, *27*, 227–253. <https://doi.org/10.1080/15378020.2022.2090802>.
- Abdullahi, A.M.; Kalengyo, R.B.; Warsame, A.A. The unmet demand of food security in East Africa: Review of the triple challenges of climate change, economic crises, and conflicts. *Discov. Sustain.* **2024**, *5*, 244. <https://doi.org/10.1007/s43621-024-00381-5>.
- Mumah, E.; Hong, Y.; Chen, Y. Exploring the reality of global food insecurity and policy gaps. *Humanit. Soc. Sci. Commun.* **2025**, *12*, 1241. <https://doi.org/10.1057/s41599-025-05315-8>.
- Karpov, A.; Dorofeev, O.; Smirnova, Y.; Kulibaba, I.; Beresneva, Y. Hardware and software system for adaptive precision agriculture management within the consolidation of modern agrotechnologies in the crop production sector of the Kyrgyz Republic. *Front. Comput. Sci.* **2026**, *8*, 1763420. <https://doi.org/10.3389/fcomp.2026.1763420>.
- Varzakas, T.; Smaoui, S. Global food security and sustainability issues: The road to 2030 from nutrition and sustainable healthy diets to food systems change. *Foods* **2024**, *13*, 306. <https://doi.org/10.3390/foods13020306>.
- Krykavskyy, Y.; Shandrivska, O.; Pawłyszyn, I. A study of macroeconomic and geopolitical influences and security risks in supply chains in times of disruptions. *LogForum* **2023**, *19*, 423–441. <https://doi.org/10.17270/J.LOG.2023.855>.
- Campomanes, F.; Marshall, M.; Nelson, A. A method for estimating physical and economic food access at high spatial resolution. *Food Secur.* **2024**, *16*, 47–64. <https://doi.org/10.1007/s12571-023-01404-1>.
- Adukov, R.K. Functions of the state in the development of small businesses and contracting in the agricultural sector. *Econ. Labor Manag. Agric.* **2025**, *12*, 140–150. Available online: <http://xn----8sberiaeye3ai0ax4i.xn--p1ai/eng/article/1776> (accessed on 15 June 2026).
- Rodnina, N.V. On the role of farming in food security. *AIC Econ. Manag.* **2022**, *8*, 3–10. <https://doi.org/10.33305/228-3>.
- Rudnicki, R.; Biczowski, M.; Wiśniewski, Ł.; Wiśniewski, P.; Bielski, S.; Marks-Bielska, R. Towards green agriculture and sustainable development: Pro-environmental activity of farms under the common agricultural policy. *Energies* **2023**, *16*, 1770. <https://doi.org/10.3390/en16041770>.
- Khachatryan, A.; Sakhbieva, A.; Kirpicheva, M.; Dolgova, M.; Chernov, S. Consumer Demand for Environmental Friendliness as a New Round of Modern Marketing Development. *Pol. J. Environ. Stud.* **2023**, *32*, 4095–4111. <https://doi.org/10.15244/pjoes/166350>.

19. Snimshchikova, I.V. The trend of consumer demand in the current economic realities of Russia. *Work. Kuban State Agrar. Univ.* **2022**, *100*, 70–73. Available online: <https://proceedings.kubsau.ru/eng/issue/2022/100/70-73> (accessed on 15 June 2026).
20. Garg, D.; Alam, M. Smart agriculture: A literature review. *J. Manag. Anal.* **2023**, *10*, 359–415. <https://doi.org/10.1080/23270012.2023.2207184>.
21. Champia, M.N. Agricultural Startups: Innovation, Challenges, and Future Prospects. *Int. J. Sci. Res. Technol.* **2025**, *2*, 175–176. <https://doi.org/10.5281/zenodo.14983885>.
22. Kurepina, N.L.; Pavlova, N.T.S.; Sarunova, M.P.; Krasnokutskii, N.A. Providing the population with quality food—Strategic food security rural areas: Risk assessment, development models. *AIC Econ. Manag.* **2024**, *12*, 3–11. <https://doi.org/10.33305/2412-3>.
23. Korolkova, A.P.; Shatilov, M.V. Analysis of the state of production and consumption of vegetables in the Russian Federation. *Mach. Equip. Rural Area* **2021**, *6*, 40–50. <https://doi.org/10.33267/2072-9642-2021-6-40-46>.
24. Evdokimova, O.; Evdokimov, N.; Goncharova, I.; Butenko, I.; Pyanikova, E.; Kovaleva, A. Actual problems of production of functional and specialized food products in the food industry. *E3S Web Conf.* **2024**, *486*, 02005. <https://doi.org/10.1051/e3sconf/202448602005>.
25. Loginov, D.A. Food security as a factor of sustainable national economic development. *E3S Web Conf.* **2024**, *537*, 04002. <https://doi.org/10.1051/e3sconf/202453704002>.
26. Bondarenko, L.V.; Iakovleva, O.A.; Simanovskii, N.A. Food consumption in Russia: Regulatory approach to regulation. *AIC Econ. Manag.* **2021**, *12*, 13–27. <https://doi.org/10.33305/2112-13>.
27. Krasnikov, A.; Nikishina, I.; Mudrakova, O.; Krasilnikov, I. Simulation modelling of traffic flow of the east-west latitudinal corridor for socio-economic development of the Novosibirsk region. *BIO Web Conf.* **2024**, *83*, 05003. <https://doi.org/10.1051/bioconf/20248305003>.
28. Avarskii, N.D.; Alpatov, A.V.; Khashir, A.A.; Overchuk, L.A. Methodological aspects of structuring the infrastructure of the agri-food market in the context of global transformations. *Econ. Labor Manag. Agric.* **2025**, *1*, 7–19. <https://doi.org/10.33938/251-7>.
29. Altukhov, A.I. Priority development of agriculture—The basis for ensuring food security of Russia. *Vestn. Ross. Akad. Nauk* **2025**, *6*, 9–19. <https://doi.org/10.7868/S3034520025060025>.
30. Migunov, R.A.; Syutkina, A.A. Research of challenges of the agro-industrial complex as the basis of strategic goal-setting of the development of the agricultural sector. *Izv. Timiryazev Agric. Acad.* **2022**, *4*, 135–145. <https://doi.org/10.26897/0021-342X-2022-4-135-145>.
31. Osenniy, V.V.; Shevkunenko, M.Y. State mechanisms to support import-substituted and export-oriented production in the Agro-Industrial complex of the Russian Federation. *Work. Kuban State Agrar. Univ.* **2024**, *112*, 70–74. <https://doi.org/10.21515/1999-1703-112-70-74>.
32. Ushachev, I.; Serkov, A.; Chekalin, V.; Kharina, M. Long-term agrarian policy of Russia: Challenges and strategic priorities. *AIC Econ. Manag.* **2021**, *1*, 3–17. <https://doi.org/10.33305/211-3>.
33. Sandu, I.S.; Nechaev, V.I.; Ryzhenkova, N.E. On the development of a new strategy for innovative development of the agro-industrial complex: Prerequisites and priorities. *Econ. Agric. Russ.* **2022**, *8*, 2–12. <https://doi.org/10.32651/228-2>.
34. Kushwah, N.; Billore, V.; Sharma, O.P.; Singh, D.; Chauhan, A.P.S. Integrated Nutrient management for optimal plant health and crop yield. *Plant Sci. Arch.* **2024**, *8*, 10–12. <https://doi.org/10.51470/PSA.2023.8.2.10>.
35. Liu, R.; Sun, Y.; Li, M.; Zhang, M.; Zhang, Z.; Li, H.; Yang, W. Development and application experiments of a grain yield monitoring system. *Comput. Electron. Agric.* **2022**, *195*, 106851. <https://doi.org/10.1016/j.compag.2022.106851>.
36. Krasnikova, I.; Mudrakova, O. Simulation modeling of transport and socioeconomic development of megapolis districts (on the example of Moscow city). *E3S Web Conf.* **2024**, *515*, 02024. <https://doi.org/10.1051/e3sconf/202451502024>.
37. Simonov, V.; Karpov, A. Process modeling of unmanned aerial vehicles using intelligent systems in forestry. *BIO Web Conf.* **2024**, *145*, 04023. <https://doi.org/10.1051/bioconf/202414504023>.
38. Simonović, Z.; Ilić, B. Complex business system management in an agro-industrial complex. In *IV international Scientific Conference “Sustainable Agriculture and Rural Development”*; Institute of Agricultural Economics: Belgrade, Serbia, 2024; pp. 265–274.
39. Martuscelli, L.; Fantozzi, I.C.; Mancusi, F.; Schiraldi, M.M. Evaluating the suitability of handwritten text recognition for industrial operations: A practical case study on acceptance sampling inspection workflow. *Int. J. Interact. Des. Manuf.* **2026**, *20*, 2621–2639. <https://doi.org/10.1007/s12008-026-02513-9>.
40. Avarskii, N.D.; Kolesnikov, A.V.; Seregin, S.N. The quality as a factor in ensuring the safety of food products. *Econ. Labor Manag. Agric.* **2025**, *4*, 4–13. <https://doi.org/10.33938/254-4>.

41. Lisitsyn, A.B.; Chernukha, I.M.; Lunina, O.I. From food security to food safety and quality. *Food Ind.* **2021**, *2*, 8–14. <https://doi.org/10.24412/0235-2486-2021-2-0010>.
42. De Queiroz, F.L.N.; Raposo, A.; Han, H.; Nader, M.; Ariza-Montes, A.; Zandonadi, R.P. Eating competence, food consumption and health outcomes: An overview. *Int. J. Environ. Res. Public Health* **2022**, *19*, 4484. <https://doi.org/10.3390/ijerph19084484>.
43. Odoms-Young, A.; Brown, A.G.; Agurs-Collins, T.; Glanz, K. Food insecurity, neighborhood food environment, and health disparities: State of the science, research gaps and opportunities. *Am. J. Clin. Nutr.* **2024**, *119*, 850–861. <https://doi.org/10.1016/j.ajcnut.2023.12.019>.
44. Silva, P.; Araújo, R.; Lopes, F.; Ray, S. Nutrition and food literacy: Framing the challenges to health communication. *Nutrients* **2023**, *15*, 4708. <https://doi.org/10.3390/nu15224708>.
45. Moreno, L.A.; Meyer, R.; Donovan, S.M.; Goulet, O.; Haines, J.; Kok, F.J.; Veer, P.V. Perspective: Striking a balance between planetary and human health—is there a path forward? *Adv. Nutr.* **2022**, *13*, 355–375. <https://doi.org/10.1093/advances/nmab139>.
46. Biesbroek, S.; Kok, F.J.; Tufford, A.R.; Bloem, M.W.; Darmon, N.; Drewnowski, A.; Fan, S.; Fanzo, J.; Gordon, L.J.; Hu, F.B.; et al. Toward healthy and sustainable diets for the 21st century: Importance of sociocultural and economic considerations. *Proc. Natl. Acad. Sci. USA* **2023**, *120*, e2219272120. <https://doi.org/10.1073/pnas.2219272120>.
47. Dahiya, A.; Duggal, S.; Kumar, N. Religious and cultural perspectives on food selection. In *Food Chemistry, Function and Analysis Functional Foods of the Future*; Gupta, V.K., Sharma, M., Gaur, S., Kuhad, R.C., Eds.; Royal Society of Chemistry: London, UK, 2025; pp. 277–292. <https://doi.org/10.1039/9781837673292-00277>.
48. Ovsianynkov, Y. The impact of religious food standards on the formation of a quality control system in the food industry. *Three Seas Econ. J.* **2025**, *6*, 51–56. <https://doi.org/10.30525/2661-5150/2025-4-7>.
49. Turgunova, G.; Djumaeva, M.; Aitbaeva, A. Preserving health through traditions: How folk customs form a healthy lifestyle. *BIO Web Conf.* **2024**, *120*, 01059. <https://doi.org/10.1051/bioconf/202412001059>.
50. Tegegne, G.E.; Berlie, A.B.; Mengistie, D.; Yigzaw, A. Determinants of food security indicators in Bahir Dar City, Ethiopia: A focus on female-headed households. *Discov. Sustain.* **2025**, *6*, 48. <https://doi.org/10.1007/s43621-024-00732-2>.
51. Fadol, A.A.; Tong, G.; Akram, M.W.; Andleeb, S.; Akram, N.; Rehman, K.U. The role of coping strategies in food consumption assessment: Evidence from Sudan using FCS and HDDS. *Cogent Food Agric.* **2025**, *11*, 2514291. <https://doi.org/10.1080/23311932.2025.2514291>.
52. Kanojia, M.; Kamani, P.; Kashyap, G.S.; Naz, S.; Wazir, S.; Chauhan, A. Alternative agriculture land-use transformation pathways by partial-equilibrium agricultural sector model: A mathematical approach. *Int. J. Inf. Technol.* **2025**, *17*, 2533–2552. <https://doi.org/10.1007/s41870-024-02158-5>.
53. Kato, K.Y.M.; Delgado, N.G.; Romano, J.O. Territorial approach and rural development challenges: Governance, state and territorial markets. *Sustainability* **2022**, *14*, 7105. <https://doi.org/10.3390/su14127105>.
54. Pieralli, S.; Chatzopoulos, T.; Elleby, C.; Domínguez, I.P. *Documentation of the European Commission's EU Module of the Aglink-Cosimo Model: 2021 Version*; Publications Office of the European Union: Luxembourg, 2022. <https://doi.org/10.2760/222318>.
55. Mancusi, F.; Fruggiero, F.; Pham, D.T. The Remanu-Leasing Model Towards a Convenient and Sustainable Product Circularity. In *Advances in Remanufacturing. IWAR 2023; Lecture Notes in Mechanical Engineering*; Fera, M., Caterino, M., Macchiaroli, R., Pham, D.T., Eds.; Springer: Cham, Switzerland, 2024; pp. 377–387. https://doi.org/10.1007/978-3-031-52649-7_30.
56. Matejková, E.; Májek, M.; Qineti, A.; Sojková, Z. Comparative analysis of European Union countries based on selected aspects of food security. *Agric. Econ./Zemědělská Ekon.* **2024**, *70*, 265–278. <https://doi.org/10.17221/16/2024-AGRICECON>.
57. Moch, E. The economic and geopolitical significance of the BRICS nations: A comparative analysis of their global influence in the 21st century. *E. Afr. J. Bus. Econ.* **2024**, *7*, 86–100. <https://doi.org/10.37284/eajbe.7.2.2310>.
58. Laamarti, Y.; Dorofeev, A.; Botokanova, G.; Murzakhmedova, G.; Kashirin, S.; Usmanova, M.; Kadirov, R.; Alybaev, A. Role of BRICS in global food security: Econometric panel modeling of Food Security Index, 2009–2024. *Front. Sustain. Food Syst.* **2026**, *10*, 1748543. <https://doi.org/10.3389/fsufs.2026.1748543>.
59. Swatson, H.; Alabi, D.; Naidoo, K.; Cooposamy, R.; Arthur, G. BRICS Agricultural Food System and Innovations: Hope for Global Food Security. In *Innovation and Development of Agricultural Systems. Sustainable Development Goals Series*; Maponya, P., Tshikovihi, N., Netswera, F., Eds.; Palgrave Macmillan: Singapore, 2024; pp. 183–209. https://doi.org/10.1007/978-981-97-2926-5_9.
60. Reed, C.; Anderson, W.; Kruczkiewicz, A.; Nakamura, J.; Gallo, D.; Seager, R.; McDermid, S.S. The impact of flooding on food security across Africa. *Proc. Natl. Acad. Sci. USA* **2022**, *119*, e2119399119. <https://doi.org/10.1073/pnas.2119399119>.

61. Wudil, A.H.; Usman, M.; Rosak-Szyrocka, J.; Pilař, L.; Boye, M. Reversing years for global food security: A review of the food security situation in Sub-Saharan Africa (SSA). *Int. J. Environ. Res. Public Health* **2022**, *19*, 14836. <https://doi.org/10.3390/ijerph192214836>.
62. Onyeaka, H.; Nwauzoma, U.M.; Akinsemolu, A.A.; Tamasiga, P.; Duan, K.; Al-Sharify, Z.T.; Siyanbola, K.F. The ripple effects of climate change on agricultural sustainability and food security in Africa. *Food Energy Secur.* **2024**, *13*, e567. <https://doi.org/10.1002/fes3.567>.
63. Hernández-Vásquez, A.; Visconti-Lopez, F.J.; Vargas-Fernández, R. Factors associated with food insecurity in Latin America and the Caribbean countries: A cross-sectional analysis of 13 countries. *Nutrients* **2022**, *14*, 3190. <https://doi.org/10.3390/nu14153190>.
64. Gulizahra, T. Forecasting Gross Yield in Agriculture Using The Arima Model: The Case of Cereal Crops. *Cent. Asian J. Innov. Tour. Manag. Financ.* **2026**, *7*, 235–241. <https://doi.org/10.51699/cajitmf.v7i1.1096>.
65. Zhao, X.; Wise, M.A.; Waldhoff, S.T.; Kyle, G.P.; Huster, J.E.; Ramig, C.W.; Rafelski, L.E.; Patel, P.L.; Calvin, K.V. The impact of agricultural trade approaches on global economic modeling. *Glob. Environ. Change* **2022**, *73*, 102413. <https://doi.org/10.1016/j.gloenvcha.2021.102413>.
66. Hernández Hernández, G.C.; Gómez Gómez, J.; Jiménez-Cabas, J. Predictive models based on artificial intelligence to estimate crop yield: A literature review. *Agriculture* **2025**, *15*, 2438. <https://doi.org/10.3390/agriculture15232438>.
67. Suci, E.Ş.; Kalender, M.A. Digital Transformation in Agricultural Structures: Evaluation in Terms of Technological Developments, Practices and Sustainability. *Turk. J. Agric.-Food Sci. Technol.* **2025**, *13*, 3708–3717. <https://doi.org/10.24925/tur-jaf.v13is2.3708-3717.8158>.
68. Kasemi, R.; Lammer, L.; Vincze, M. The gap between technology and agriculture, barrier identification and potential solution analysis. *IFAC-Paper* **2022**, *55*, 314–318. <https://doi.org/10.1016/j.ifacol.2022.12.042>.
69. Sarkar, A.; Wang, H.; Rahman, A.; Memon, W.H.; Qian, L. A bibliometric analysis of sustainable agriculture: Based on the Web of Science (WOS) platform. *Environ. Sci. Pollut. Res.* **2022**, *29*, 38928–38949. <https://doi.org/10.1007/s11356-022-19632-x>.
70. Afzal, A.; Bell, M. 2023 Precision agriculture: Making agriculture sustainable. In *Precision Agriculture*; Zaman, Q., Ed.; Academic Press: London, UK, 2023; pp. 187–210. <https://doi.org/10.1016/B978-0-443-18953-1.00006-4>.
71. Panfilov, V.A. Synergistic Foundations of Future Agro-Industrial Technologies. *Vestn. Russ. Agric. Sci.* **2025**, *1*, 47–50. <https://doi.org/10.7868/S3034519725010101>.
72. Asiminari, G.; Benos, L.; Kateris, D.; Busato, P.; Achillas, C.; Grøn Sørensen, C.; Pearson, S.; Bochtis, D. Simplifying field traversing efficiency estimation using machine learning and geometric field indices. *AgriEngineering* **2025**, *7*, 75. <https://doi.org/10.3390/agriengineering7030075>.
73. Pak, J.; Kim, J.; Park, Y.; Son, H.I. Field evaluation of path-planning algorithms for autonomous mobile robot in smart farms. *IEEE Access* **2022**, *10*, 60253–60266. <https://doi.org/10.1109/ACCESS.2022.3181131>.
74. Gackstetter, D.; Von Bloh, M.; Hannus, V.; Meyer, S.T.; Weisser, W.; Luksch, C.; Asseng, S. Autonomous field management—an enabler of sustainable future in agriculture. *Agric. Syst.* **2023**, *206*, 103607. <https://doi.org/10.1016/j.agsy.2023.103607>.
75. Erokhin, V.I.; Krasnikov, A.S.; Khvostov, M.N. Matrix corrections minimal with respect to the Euclidean norm for linear programming problems. *Autom. Remote Control* **2012**, *73*, 219–231. <https://doi.org/10.1134/S0005117912020026>.
76. Vatutina, L.A.; Grankina, V.L.; Suetin, A.N.; Khomenko, E.B. Big Data Analytics in Stock Exchange Practice. In *Management of Digital Technologies in the Innovative Economy. Advances in Science, Technology & Innovation*; Popkova, E.G., Ed.; Springer: Cham, Switzerland, 2025; pp. 13–18. https://doi.org/10.1007/978-3-031-83331-1_3.
77. Kulibaba, I.; Kuchmezov, K.; Laamarti, Y.; Shamshurina, N.; Shamshurin, V. Managing traffic and pedestrian flows at an intersection: Simulation model parameters. *E3S Web Conf.* **2022**, *363*, 02040. <https://doi.org/10.1051/e3sconf/202236302040>.
78. Altunina, Y.; Korotun, O.; Polevshchikov, I. Simulation model of a queuing system in the service of state registration, cadastre and cartography. *E3S Web Conf.* **2024**, *535*, 05003. <https://doi.org/10.1051/e3sconf/202453505003>.
79. Kozlova, S.A.; Feroova, I.S. Regional Food Security in the Era of Digital Transformation: Theoretical and Methodological Analysis of Assessment Approaches. *J. Sib. Fed. Univ. Humanit. Soc. Sci.* **2025**, *18*, 2478–2489.

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