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IMPLEMENTATION OF INTELLIGENT QUALITY CONTROL SYSTEMS AT FLOUR MILLS IN UKRAINE

The article is devoted to the urgent problem of modernization of the agro-industrial complex through the transition to automated monitoring of product quality in real time. The author justifies the need to abandon traditional laboratory methods, which have significant time delays (from 2 to 4 hours), which creates risks of producing defective products in the event of technological failures. The proposed solution is based on the development of a cyber-physical system (CPS) based on the Edge Computing architecture. This allows you to transfer the decision-making process directly to the production line, eliminating delays in data transmission to the cloud and eliminating the impact of electromagnetic interference typical of industrial zones. Special attention is paid to safety: the system hardware is designed taking into account the explosive hazard of flour dust (zones 20–22 according to the ATEX classification), which requires the use of sealed housings of the IP65/IP67 standard and limiting the surface temperature of the devices. The technical implementation includes the use of industrial cameras with a global shutter (Global Shutter), which prevent distortion of the image of the moving flour flow. For quality analysis, the MobileNetV2 neural network architecture is used, optimized using TensorRT INT8 quantization, which allows achieving classification accuracy of over 98% with minimal computational costs. The mathematical model of the system is based on the analysis of the CIE Lab color space and hybrid processing of visual and parametric data from sensors. The scientific novelty of the work lies in the implementation of a dual approach to analysis: in parallel with the classification of varieties, an algorithm based on unsupervised learning (autoencoders) works. This allows you to detect previously unknown types of defects or foreign impurities (insects, metal particles, etc.) by analyzing deviations from the mathematical model of the "ideal product". The proposed system provides stable operation with a response delay within 15–45 ms, which is critically important for the automatic operation of the defect cutters. The implementation of such a CFS contributes to the harmonization of Ukrainian standards with EU requirements for food safety.*

Keywords: cyber-physical systems, intelligent quality control, edge computing, machine learning, computer vision, deep learning, Convolutional Neural Networks (CNN), MobileNetV2, Internet of Things.

Introduction

The modern agro-industrial complex is currently undergoing a strategic macroeconomic reorientation, systematically transitioning from a traditional raw material export model to advanced production of high-value-added processed goods [1]. Within the context of the gradual harmonization of domestic production standards with the stringent regulatory frameworks and technical requirements of the European Union, the demand for absolute stability, continuous traceability, and uncompromising safety of flour quality indicators has increased exponentially.

This paradigm shift necessitates a fundamental modernization of metrological support and quality control infrastructures deployed at flour milling enterprises[2]. Historically, the global milling industry has relied heavily on classical laboratory methods, which are inherently discrete, often destructive, and characterized by significant time delays. Standard laboratory sampling and chemical analyses typically require intervals of two to four hours, creating critical operational "blind spots" in the production cycle [3]. During these unmonitored periods, critical technological failures—such as sifter screen ruptures or the ingress of foreign impurities—may go undetected, resulting in the production of substantial volumes of defective output.

Despite the rapid development of artificial intelligence and computer vision technologies, a significant gap remains between theoretical advancements and their practical application in harsh industrial environments. Most commercial in-line analyzers available on the market are prohibitively expensive and difficult to integrate into the legacy architecture of domestic enterprises. This creates an urgent need for the development of affordable and efficient solutions capable of operating directly at the Edge of the technological line.

The objective of this work is to enhance the efficiency of flour quality control by developing a cyber-physical system that ensures automated data collection and intelligent analysis based on machine learning.

The research tasks required to achieve the stated objective include:

1. Analysis of modern methods and tools for automated quality control;
2. Substantiation of the system architecture and selection of machine learning models;
3. Development of the data collection subsystem and selection of sensor hardware;
4. Software implementation of quality analysis and classification algorithms.

Architecture and Safe Deployment of a CPS in the Flour Milling Industry

The transition from conceptual mathematical models to the physical implementation of a cyber-physical system in an industrial flour milling environment requires absolute adherence to strict operational constraints, safety requirements, and timeframes. The architectural foundation of the proposed system is stratified into a hierarchical three-tier vertical integration model, compliant with the ISO/IEC 30141:2024 Internet of Things reference architecture [4] and further structured by the ISA-95 standard semantic framework [5].

The base perception layer interacts directly with the physical environment, encompassing optical modules, environmental sensors, and high-speed pneumatic drive mechanisms. The intermediate layer is the edge computing node, functioning as a localized intelligent core where real-time inference and deterministic control logic are executed autonomously. The upper cloud or local analytical level processes long-term data aggregation, complex relational database management, and asynchronous model updates for the entire equipment fleet, effectively creating a unified digital twin of the flour milling production.

Operating within a flour milling facility introduces critical hardware constraints, primarily driven by the extreme volatility and explosiveness of organic flour dust. During the transport, milling, and packaging of flour, fine-dispersed aerosols are inevitably generated, which form highly reactive and explosive environments when suspended in oxygen. The accumulation of this dust on the surfaces of technological equipment further creates flammable aerogels.

In accordance with the European ATEX Directive (2014/34/EU) [6], which strictly regulates the placement of electrical and mechanical equipment in potentially explosive atmospheres, the internal volumes of bins and transport pipelines are classified as Zone 20, where an explosive dust atmosphere is continuously present. The immediate external environment surrounding sifters, conveyors, and observation windows is classified as Zone 21 or Zone 22.

Consequently, every electronic component, edge computing device, optical sensor, and lighting module deployed at the perception level must be hermetically sealed in specialized enclosures that meet or exceed IP65/IP67 ingress protection standards. Furthermore, the hardware design must absolutely preclude the accumulation of static electricity, and the maximum operating surface temperature of the equipment under peak computational load must remain strictly below the minimum ignition temperature of the specific flour dust cloud.

Quality Determination

The primary analytical mechanism operating on this edge equipment relies on a rigorous mathematical formalization of the quality control process. From a systems analysis perspective, this task is defined as a multiclass pattern recognition problem under conditions of stochastic uncertainty.

Let Ω denote the set of all possible states of the technological flour stream. At any discrete time step t, the sensor array generates an observation vector $X(t)$, which includes both visual and parametric properties. The target set is a discrete set of quality classes $Y = \{y_1, y_2, \dots, y_K\}$, corresponding to standardized industrial grades.

The fundamental objective of the machine learning model is to find an optimal decision function F, that maps the input vector X to a predicted class $y \in \mathrm{Y}$ while minimizing the probability of misclassification [7]. From a probability theory standpoint, this is expressed as maximizing the posterior probability $P(y_K|X,\Theta)$ for a given set of model parameters Θ. The optimal class y^* is determined by the Maximum A Posteriori (MAP) decision rule:

$$y^* = \underset{y_k \in Y}{\arg\max}\, P(y_k|X,\Theta)$$

This ensures the minimization of empirical classification error within the continuous stream.

The input feature space processed by the system is inherently hybrid. The visual component is mathematically represented as a three-dimensional tensor:

$$X_y = \mathbb{R}^{H\times W\times C}$$

Where H and W denote the spatial resolution in pixels, and C represents the color depth channels.

Since standard RGB color spaces are perceptually non-uniform and highly sensitive to fluctuations in external lighting, the system performs a mathematical transformation of the input tensor into the CIE Lab* color space. This transformation separates the intrinsic lightness (L^*) from the chromaticity coordinates (a^* та b^*). The L^* coordinate serves as a direct indicator with a high correlation to flour whiteness and its overall degree of refinement. The perceived color difference is mathematically defined using the Euclidean distance metric ΔE:

$$\Delta E = \sqrt{(\Delta L^*)^2 + (\Delta a^*)^2 + (\Delta b^*)^2}$$

Simultaneously, the system processes a parametric vector $X_{sens} = [s_1, s_2, \ldots, s_M]^T \in \mathbb{R}^M$ that captures high-frequency telemetry from environmental sensors. This vector undergoes min-max normalization to constrain all values within the interval [0, 1], preventing variables with larger numerical ranges from exerting a disproportionate influence on the gradient descent process.

To integrate these disparate data modalities, the system employs a hybrid late-fusion architecture. The visual tensor X_{img} is processed by a convolutional backbone to extract a dense latent feature vector V_{img}, which is subsequently concatenated with the normalized parametric vector X_{sens} to form a unified representation:

$$X_{final} = V_{img} \oplus X_{sens}$$

In the fully connected layers, the final predicted probability output generated by each neuron is calculated as a weighted sum of multimodal inputs, activated by a non-linear function, defined mathematically as:

$$f(x) = \sigma(w_0 + \sum_{i=1}^{n} w_i x_i)$$

Deep Learning Architecture and Inference Optimization

For effective processing of the visual tensor, classical deterministic computer vision algorithms were carefully evaluated and subsequently rejected. The microstructure of bulk flour is extremely complex; visual differences between various grades often manifest as low-contrast spatial anomalies that deterministic algorithms are unable to reliably isolate under varying industrial lighting conditions[8].

Instead, deep convolutional neural networks are deployed due to their unparalleled capacity for hierarchical, automated feature extraction. A convolutional neural network applies localized convolution operations to learn highly abstract spatial hierarchies directly from raw pixel data. However, the deployment of massive architectures, such as VGG-16, is mathematically and computationally impermissible on edge devices constrained by strict thermal budgets.

To meet this requirement, the MobileNetV2 architecture is implemented. The ingenuity of MobileNetV2 lies in the mathematical factorization of the standard convolution operation into depthwise separable convolutions. This structural decomposition bifurcates the process into a spatial depthwise convolution followed immediately by a pointwise convolution. The mathematical reduction factor for computational costs is defined as:

$$Reduction\ Ratio = \frac{1}{N} + \frac{1}{D_K^2}$$

where N is the total number of output channels (filters) in the convolutional layer, and D_k is the spatial size of the convolutional kernel.

For a standard 3×3 kernel, this formula theoretically proves a reduction factor of 8–9 times[9]. This structural decomposition radically accelerates inference speed while maintaining an F1-score and classification accuracy that often exceed 98–99%.

The optimization of the model parameters Θ is formulated as empirical risk minimization. The chosen objective function is Categorical Cross-Entropy, which is mathematically defined as:

$$\mathrm{L}(\Theta) = -\frac{1}{N}\sum_{\mathrm{i}=1}^{\mathrm{N}}\sum_{\mathrm{k}=1}^{\mathrm{K}} \mathrm{I}(\mathrm{y_i} = \mathrm{k}) * \log(p_{i,k})$$

where:

N is the training sample size;

K is the number of classes;

$\mathrm{I}(\cdot)$ - is the indicator function, which equals 1 if the true class of sample i is k, and 0 otherwise;

$p_{i,k}$ - is the probability predicted by the model that sample i belongs to class k.

The raw logit outputs z_k of the final neural network layer are transformed into a normalized probability distribution using the Softmax activation function:

$$p_k = Softmax(z)_k = \frac{e^{z_k}}{\sum_{j=1}^{K} e^{z_j}}$$

The objective function L is minimized iteratively using the Adam optimization algorithm[10].

Edge Computing Paradigm and Network Constraints

The primary functional philosophy of the proposed intelligent system is the complete transfer of computational intelligence and decision-making authority from remote centralized data centers directly to the production floor—a paradigm widely recognized as edge computing[11]. In a high-performance industrial flour milling environment, the physical flow of the milled product is continuous, highly turbulent, and extremely rapid.

A complex computer vision system tasked with analyzing this continuous stream at high frame rates inevitably generates gigabytes of raw, uncompressed video data every minute. Attempting to transmit this colossal volume of uncompressed data over standard industrial local area networks—which are often already congested with existing SCADA traffic—to a centralized cloud server creates an insurmountable bandwidth bottleneck and operationally unacceptable latency.

Cloud-based predictive analytics and machine vision systems regularly encounter unpredictable round-trip data transmission latency ranging from 800 to 2,400 milliseconds. Within this seemingly brief multi-second window, a high-speed pneumatic or gravity transport system can easily move significant volumes of heavily contaminated flour beyond the point of feasible mechanical diversion, leading to irreversible product loss, contamination of large storage bins in subsequent stages, and severe financial penalties.

Furthermore, operating flour milling plants are inherently high-electromagnetic interference (EMI) environments. The dense concentration of massive high-voltage asynchronous motors, complex variable frequency drives (VFDs), and heavy switching gear generates intense, continuous EMI[12]. These interferences regularly disrupt sensitive wireless protocols and can even degrade communication quality across heavily shielded wired Ethernet networks.

Consequently, relying on a constant, uninterrupted internet connection to a remote server for mission-critical quality control—which necessitates instantaneous response—represents a significant and unacceptable operational vulnerability that no plant manager can afford. By processing raw sensor data, executing complex AI inference matrices, and initiating immediate mechanical control responses entirely locally on a dedicated edge device, the proposed architecture completely bypasses the need for external network data transmission.

This localized architecture mathematically reduces decision latency from seconds to a calculated, highly stable 15–45 milliseconds, ensuring true real-time reactive intervention at the operating speed of the machinery itself. The edge node effectively functions as an autonomous, highly intelligent agent on the production floor; it processes raw visual data, extracts relevant quality metrics or critical anomaly flags, and transmits only lightweight, highly aggregated textual metadata (e.g., "Timestamp: 14:02:01, Ash content estimated at 0.55%, Status: Normal") to the plant's central SCADA system or Enterprise Resource Planning (ERP) software via standard protocols such as MQTT or OPC UA[13].

This architectural solution not only preserves critical factory network bandwidth but also provides an absolute guarantee that the localized quality control loop remains fully functional and protective, even in the event of a total failure of the external network infrastructure or cloud connectivity.

Optical Equipment and Edge Computing Platforms

The physical interface of the cyber-physical system for interaction with the real world requires a highly specialized sensor module that can be mechanically integrated directly into existing gravity pipes, chutes, or pneumatic transport lines with minimal physical intervention in the existing plant architecture. Visual evaluation of flour—a complex, micro-textured, dynamically changing, and highly reflective particulate medium—demands exceptionally stringent optical parameters that standard consumer cameras fail to meet.

A non-negotiable critical engineering requirement for this system is the use of industrial machine vision cameras specifically equipped with a global shutter. In stark contrast to budget-friendly and common rolling shutter sensors (which expose the image sensor sequentially, row by row), a global shutter exposes the entire multi-megapixel pixel array simultaneously in a single instant[14].

When capturing high-resolution images of flour cascading down a vertical pipe at speeds exceeding several meters per second, a rolling shutter will inevitably induce severe geometric distortions (known as the "jello effect"). This temporal distortion physically warps the visible shape of particles in the image and artificially, destructively alters the perceived texture and spatial frequency. Such distortion completely annihilates the precise visual features and subtle gradients upon which the deep neural network relies for accurate classification[15].

The global shutter, being tightly electronically synchronized with a high-intensity LED or stroboscopic lighting system using microsecond pulses, effectively "freezes" the turbulent motion of the product stream, ensuring a sharp, absolutely undistorted image regardless of the external, often poor ambient lighting typical of old factory ceilings. To successfully perform highly complex deep learning inferences on these high-resolution, high-frame-rate input video streams without frame dropping, the system requires an exceptionally robust and energy-efficient computational engine installed locally.

A comprehensive comparative analysis of modern commercially available Edge AI platforms reveals a broad spectrum of computational options, ranging from basic general-purpose CPUs to highly specialized tensor processors and sophisticated field-programmable gate arrays[16] (see Table 1).

Technical analysis demonstrates that platforms utilizing massively parallel GPU architectures, such as the widely adopted NVIDIA Jetson Orin Nano, offer an optimal balance of high tensor performance, rigorous power efficiency, and rapid developer accessibility. The Orin Nano module, capable of reliably delivering up to 67 trillion operations per second (TOPS), represents a massive, revolutionary computational leap compared to previous generations of embedded systems.

Table 1

Comparative Analysis of Computing Platforms for Industrial Edge AI Deployment

Platform	Base Computing Architecture	Peak AI Performance	Typical Power Consumption	Software Ecosystem Integration and Ease of Development
Industrial Microcontroller (e.g., STM32)	ARM MCU + Integrated NPU	< 2 TOPS	< 3 W	Extremely limited; requires low-level, vendor-specific C code.
TPU Coprocessor (e.g., Google Coral)	Base CPU + Edge TPU ASIC	4 TOPS	5–10 W	Limited to TFLite; restricted support for complex custom operators.
NVIDIA Jetson Orin Nano	ARM CPU + Ampere GPU Architecture	Up to 67 TOPS	7–15 W	Comprehensive; full support for CUDA, TensorRT, PyTorch, and extensive community libraries.
Industrial FPGA (e.g., Xilinx/Intel)	Programmable Logic Gates	Highly variable / Specialized	High / Variable	Extremely complex; requires highly specialized VHDL/Verilog hardware engineers.

It provides sufficient high-speed memory bandwidth (102 GB/s utilizing LPDDR5) to process complex vision transformers and deep convolutional networks in real-time without incurring bottlenecks. This immense computational density allows the local edge system to easily maintain inference speeds of 30 to 60 frames per second on high-resolution data, fully satisfying the stringent timing constraints required to trigger automated mechanical diversion devices or critical safety signals [17].

Post-training Quantization and Model Optimization

To further aggressively optimize the deployment of these deep neural networks on constrained edge hardware, it is necessary to carefully apply rigorous software optimization techniques. The most critical and influential of these processes is post-training quantization. Standard neural networks are typically trained on massive cloud GPU clusters using high-precision 32-bit floating-point (FP32) numbers to capture minute gradient updates.

However, executing vast volumes of mathematical operations in FP32 format on embedded edge devices consumes excessive amounts of RAM and generates significant thermal dissipation. By employing specialized optimization frameworks such as NVIDIA TensorRT, the dense weights of the trained model and mathematical activations can be artificially and systematically compressed into lightweight 8-bit integers (INT8).

This advanced mathematical quantization radically reduces the overall model memory footprint fourfold and accelerates inference execution time by an impressive 2–3 times. Importantly, empirical data and large-scale testing demonstrate that the resulting decrease in classification accuracy from this compression is statistically insignificant, typically remaining well below a 1% loss [18].

This vital optimization step is precisely what makes the robust deployment of extremely complex, incredibly deep AI architectures practically feasible on a computational module, thereby radically and permanently lowering the financial barrier to entry for small and medium-sized enterprises.

Unsupervised Anomaly Detection using Advanced Autoencoders

While convolutional neural networks excel at classifying known, previously encountered variables, they demonstrate a fundamental and hazardous vulnerability when deployed in mission-critical quality control systems: a total inability to reliably manage the unknown. In an active flour milling facility, the dataset generated through daily production is catastrophically and severely imbalanced.

Millions of captured frames will consist of entirely normal, high-grade flour, while a critical defect necessitating a line stoppage—such as a detached fragment of blue polyurethane from a compromised sifter, a stray migrating insect (e.g., Tribolium or Sitophilus), or a charred, discolored clump from an overheated bearing—might occur as rarely as once a month.

Training a traditional supervised CNN on such highly skewed data inevitably leads to model collapse, wherein the model becomes mathematically biased and persistently predicts a "normal" status to artificially minimize its loss function. Furthermore, a supervised model is incapable of detecting a specific class of defects it has never been trained on. For a visual comparison of various algorithmic approaches and their efficacy in real-world production environments, the primary characteristics of machine learning paradigms are summarized in Table 2. to create a truly robust safety system, a parallel algorithmic pipeline based entirely on unsupervised machine learning—specifically utilizing deep autoencoders—is meticulously integrated. The mathematical shift here is fundamental: instead of attempting to train the AI on what every possible defect looks like, the model is intensively trained exclusively on what absolute perfection looks like [8].

An autoencoder elegantly consists of two symmetrical, coupled neural networks: the Encoder and the Decoder. During the extensive training phase, the model is fed exclusively with high-quality images of clean flour, validated by laboratory standards. The sole mathematical objective of the Encoder is to ruthlessly compress the high-dimensional input image into a narrow mathematical "bottleneck"—a low-dimensional tensor known as the latent space representation.

Table 2

Comparative Analysis of Algorithmic Approaches to Industrial Food Quality Inspection

Learning Paradigm	Typical Model Architecture	Primary Industrial Application	Handling of New/Unknown Defects	Data Annotation Requirements
Supervised Classification	ResNet, MobileNet (CNN)	Grade classification, identification of known impurities	**Low** (Will force misclassification or completely ignore novel input data)	**Massive**; requires exhaustive, perfectly balanced, manually labeled datasets.
Supervised Object Detection	YOLO, SSD, Mask R-CNN	Precise localization and counting of specific, known particles (e.g., counting known insects)	**Low**	**Extremely high**; requires tens of thousands of manually drawn bounding boxes.
Unsupervised Anomaly Detection	Autoencoders (AE, VAE), PatchCore	Universal, agnostic anomaly detection and creation of the system's "safety net"	**Excellent** (Naturally detects any mathematical deviation from the learned "normal" baseline)	**Zero manual labeling**; requires only a clean baseline of normal (acceptable) production data.

This intensive compression forces the network to completely discard random noise and learn only the most essential, intrinsic underlying features of the unique texture and color distribution of the flour. The Decoder then attempts to reproduce and reconstruct the original high-resolution image solely from this compressed, constrained latent vector.

The internal weights of the model are iteratively optimized over thousands of epochs by minimizing the mathematical reconstruction loss (e.g., Mean Squared Error or Mean Absolute Error), measured strictly between the original input image and the reconstructed output. In the harsh conditions of real-world production, when the edge camera captures a frame containing a sudden anomaly (e.g., an entirely unknown foreign object or a strange, irregular clump formation), the image is rapidly passed through the autoencoder.

Since the network has learned only the strict mathematical rules for reconstructing normal, clean flour, the Encoder proves completely incapable of accurately mapping the strange, anomalous geometry into its learned latent space. Consequently, the Decoder subsequently generates a highly distorted, erroneous reconstruction of the foreign object.

By rapidly calculating the pixel-wise mathematical difference between the live input image and the AI's erroneous reconstruction, the system instantaneously generates a highly discernible anomaly map. A strictly defined, statistically validated error threshold is applied; if the total reconstruction error spikes and exceeds this critical threshold, the system immediately and autonomously signals the SCADA system regarding the presence of a critical anomaly.

Conclusions

The comprehensive design and implementation of the proposed cyber-physical system represent a paradigm shift in quality control methodologies for the flour milling industry. By transitioning from retrospective laboratory testing to continuous, real-time in-line monitoring, milling enterprises can drastically reduce production "blind spots" and prevent the large-scale release of defective product batches.

The application of an Edge Computing architecture fully addresses the critical constraints associated with cloud-based inference, specifically by eliminating high network latency and neutralizing the risks of electromagnetic interference (EMI) inherent in industrial environments. The utilization of industrial CMOS sensors with a global shutter, synchronized with high-intensity LED lighting, ensures the acquisition of morphologically accurate, undistorted images of the high-speed flour stream.

Furthermore, the integration of deep convolutional neural networks, specifically the MobileNetV2 architecture optimized via TensorRT INT8 quantization, provides unparalleled classification accuracy while remaining within the strict computational and thermal envelopes of edge devices. This ensures that the system response time ($t_{response}$) remains strictly less than the physical transport time ($t_{transport}$), enabling deterministic pneumatic actuator triggering perfectly synchronized with the material flow.

The critical vulnerability of supervised learning models to dataset imbalance is effectively neutralized through the implementation of unsupervised Convolutional Autoencoders. This dual-pipeline approach ensures the robust detection of "zero-day" anomalies, creating comprehensive protection against unforeseen contamination. Ultimately, this scalable architecture, which integrates seamlessly into legacy equipment, offers a financially viable path for small and medium-sized enterprises to achieve Industry 4.0 compliance, guaranteeing absolute product traceability and uncompromising food safety.

ADDITIONAL INFORMATION

DECLARATION ON THE USE OF GENERATIVE ARTIFICIAL INTELLIGENCE TOOLS

In preparing this work, the author used DeepL Translate and Grammarly for: grammar and spelling checks, paraphrasing, and rephrasing. After using these tools/services, the author reviewed and edited the content and takes full responsibility for the content of this publication.

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ВПРОВАДЖЕННЯ ІНТЕЛЕКТУАЛЬНИХ СИСТЕМ КОНТРОЛЮ ЯКОСТІ НА БОРОШНОМЛИНАХ В УКРАЇНІ

Стаття присвячена актуальній проблемі модернізації агропромислового комплексу через перехід до автоматизованого моніторингу якості продукції в режимі реального часу. Автор обґрунтовує необхідність відмови від традиційних лабораторних методів, які мають значні часові затримки (від 2 до 4 годин), що створює ризики випуску бракованої продукції при виникненні технологічних збоїв. В основі запропонованого рішення лежить розробка кіберфізичної системи (КФС) на базі архітектури Edge Computing (периферійних обчислень). Це дозволяє перенести процес прийняття рішень безпосередньо на виробничу лінію, усуваючи затримки передачі даних у хмару та нівелюючи вплив електромагнітних завад, характерних для промислових зон. Особлива увага приділяється безпеці: апаратне забезпечення системи розроблене з урахуванням вибухонебезпечності борошняного пилу (зони 20–22 за класифікацією ATEX), що вимагає використання герметичних корпусів стандарту IP65/IP67 та обмеження температури поверхні пристроїв. Технічна реалізація включає використання промислових камер із глобальним затвором (Global Shutter), які запобігають спотворенню зображення рухомого потоку борошна. Для аналізу якості застосовується нейромережева архітектура MobileNetV2, оптимізована за допомогою квантування TensorRT INT8, що дозволяє досягти точності класифікації понад 98% при мінімальних обчислювальних витратах. Математична модель системи базується на аналізі колірного простору CIE Lab та гібридній обробці візуальних і параметричних даних від сенсорів. Наукова новизна роботи полягає у впровадженні дуального підходу до аналізу: паралельно з класифікацією сортів працює алгоритм на основі некерованого навчання (автоенкодери). Це дозволяє виявляти невідомі раніше типи дефектів або сторонні домішки (комах, металеві частинки тощо) за рахунок аналізу відхилень від математичної моделі «ідеального продукту». Запропонована система забезпечує стабільну роботу з затримкою реакції в межах 15–45 мс, що є критично важливим для автоматичного спрацювання відсікачів браку. Впровадження такої КФС сприяє гармонізації українських стандартів із вимогами ЄС щодо безпеки харчових продуктів.*

Ключові слова: кіберфізичні системи, інтелектуальний контроль якості, периферійні обчислення (Edge Computing), машинне навчання, комп'ютерний зір, глибоке навчання, Convolutional Neural Networks (CNN), MobileNetV2, Інтернет речей.