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IMPLEMENTATION OF ARTIFICIAL INTELLIGENCE AND IOT TECHNOLOGIES IN INTELLIGENT MEASURING SENSOR SYSTEMS FOR VEGETABLE OIL PRODUCTION

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Abstract. The article presents a systematic overview of modern approaches to integrating artificial intelligence (AI) and the Internet of Things (IoT) technologies into intelligent measuring sensor systems, with a focused application in vegetable oil production. Architectural models, data processing methods, machine learning algorithms, energy efficiency, security, and scalability issues are examined in detail. Applications in industry, energy, transport, medicine, and smart city systems are analyzed for broader context, while special attention is devoted to the unique requirements of vegetable oil processing stages, including raw material reception and quality assessment, seed cleaning and conditioning, mechanical pressing or solvent extraction, refining (degumming, neutralization, bleaching, deodorization), quality control (acidity, peroxide value, color, clarity, oxidative stability), and final storage and packaging. Particular emphasis is placed on the Edge AI and TinyML concepts, which ensure the transfer of intelligent processing directly to the sensor level, enabling real-time decision-making with minimal latency. The prospects for the development of neuromorphic computing, self-sustaining sensory nodes, and seamless integration with 5G/6G infrastructure are thoroughly substantiated, highlighting their potential to enhance sustainability, product quality, and operational efficiency in the vegetable oil industry.

Keywords: artificial intelligence, Internet of Things, intelligent sensors, industrial IoT, vegetable oil production, Edge AI, TinyML.

INTRODUCTION

Digitalization has given rise to new types of cyber-physical systems, where measuring instruments are transformed from simple passive sensors into intelligent data processing centers that actively participate in the information process and contribute to autonomous decision-making.

The popularity of the Internet of Things (IoT) concept has increased dramatically due to the emergence of numerous publications dedicated to expanding network capabilities and the widespread deployment of advanced sensory devices across diverse sectors. This growth was also facilitated by the International Telecommunication Union's initiatives aimed at unifying digital platforms and establishing global standards for interconnected systems.

Simultaneously with rapid advancements in artificial intelligence, particularly in the field of deep learning, a new interdisciplinary direction emerged – AIoT (Artificial Intelligence of Things). The popularity of neural networks has significantly increased thanks to the groundbreaking work of researchers such as Geoffrey Hinton, Yann LeCun, and Yoshua Bengio [1], whose research laid the foundation for modern algorithms capable of efficiently processing large volumes of heterogeneous information in real time.

Intelligent measurement systems have become an indispensable tool in various fields, such as industrial process automation within the Industry 4.0 framework, smart energy networks, medical diagnostics and continuous patient monitoring, intelligent transport systems, agricultural innovations, and environmental monitoring. In the specific context of vegetable oil production, these systems are critical for ensuring consistent product quality, optimizing resource utilization,

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minimizing waste, and maintaining strict compliance with food safety standards throughout the entire production chain – from raw oilseed intake to final bottled product.

Industry 4.0 represents a new era in industrial development, where automation reaches a qualitatively new level due to the deep implementation of digital technologies. Within this concept, production processes are closely interconnected with information systems and intelligent management mechanisms. Industry 4.0, often referred to as the fourth industrial revolution, is characterized by the profound integration of digital technologies into physical production chains. This integration enables achieving higher levels of autonomy, flexibility, and unprecedented efficiency in manufacturing operations. The central element of Industry 4.0 is the "smart factory" concept, where equipment, sensors, software platforms, and the human factor collectively form a single, interconnected digital ecosystem. In vegetable oil production facilities, modern equipment such as screw presses, centrifuges, bleaching earth filters, deodorizers, and packaging lines is equipped with arrays of sensors and robust communication systems. These allow continuous collection, processing, and transmission of data on key parameters including temperature, pressure, moisture content, free fatty acid levels, peroxide value, color indices, and oxidative stability indicators in real time [2-6].

Industrial automation of the future is closely linked to the Industrial Internet of Things (IIoT). IIoT creates a unified information platform that unites machines, robots, conveyors, storage tanks, and other production assets into a cohesive network. Gathering data from numerous sensors that record temperature profiles during pressing, vibration patterns in centrifuges, chemical composition during refining, and environmental conditions in storage areas allows for deep, multidimensional analysis and informed decision-making in managing the entire production process. Such an approach shifts operations from reactive problem-solving (responding to breakdowns or quality defects after they occur) to predictive and prescriptive maintenance, where potential malfunctions, quality deviations, or oxidation onset are detected well in advance through advanced processing of large data volumes.

Machine learning and AI are opening new horizons for automating production processes in vegetable oil manufacturing. With the help of sophisticated algorithms capable of recognizing hidden patterns and complex nonlinear relationships in vast data arrays, it is possible to optimize critical parameters such as pressing pressure and temperature, bleaching earth dosage, deodorization vacuum levels and steam injection rates, and cooling profiles. As a result, systems can independently make fine adjustments to technological processes, significantly reducing the number of defective batches, lowering energy and raw material consumption, and improving the oxidative stability and shelf life of the final edible oil product. This allows not only to automate control but also to make it truly intelligent and adaptive to variations in raw material quality (e.g., differences between sunflower, soybean, rapeseed, or palm oilseeds).

Industry 4.0 is characterized by the integration of cyber-physical systems that seamlessly connect physical objects with their digital representations or "digital twins." Among the most promising tools in this concept, special attention is paid to digital twins – virtual analogues of individual equipment units (such as a screw press or deodorizer) or even entire production lines. Digital twins provide the ability to simulate various operating modes under different raw material conditions, conduct virtual testing of process modifications, and analyze the potential impact of parameter changes without risking disruption to actual production or product quality.

Industrial automation is traditionally built on a hierarchical structure consisting of several distinct levels. At the basic field level, sensors and actuators are responsible for collecting accurate data and executing physical actions. At the control level, programmable logic controllers (PLC) implement real-time control algorithms. At the supervisory level, SCADA systems provide comprehensive monitoring and oversight of technological processes. Production management is handled through MES systems, while corporate-level integration is achieved via ERP systems that combine production data with commercial and supply chain operations. Within the Industry 4.0 paradigm, the traditional boundaries between these hierarchical levels are

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increasingly blurred, enabling direct interaction between field devices and cloud-based analytics platforms for enhanced flexibility.

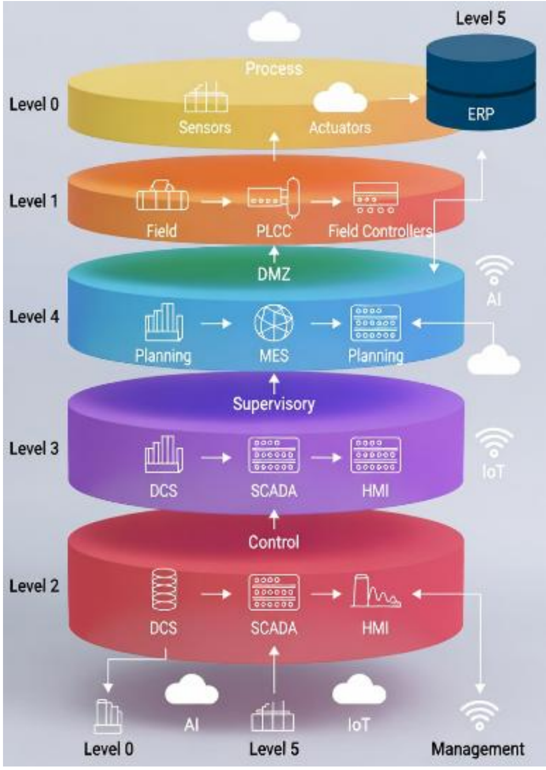

Fig.1. Architecture of industrial automation adapted for vegetable oil production facilities.

The new generation of automation opens up a wide range of advantages for industrial enterprises engaged in vegetable oil production, including substantially increased productivity, reduced operating costs, consistently improved product quality, and enhanced flexibility to handle varying raw material batches or produce specialized oil grades. Thanks to advanced automation and intelligent systems, companies can rapidly respond to fluctuations in raw seed quality, market demands for different oil specifications, and regulatory requirements, all while minimizing the influence of the human factor and significantly improving overall safety in the production environment.

Intelligent energy networks, or Smart Grid, represent an innovative approach to electric power organization that relies on digital technologies, automation, and bidirectional flow of both energy and information. In energy-intensive vegetable oil plants – where pressing, heating, vacuum distillation, and refining processes consume considerable electricity and thermal energy – Smart Grid enables dynamic load balancing, integration of on-site renewable sources (such as solar or biomass), and precise optimization of energy consumption patterns [7,8].

Similar digital transformations have profoundly impacted other sectors. In medicine, intelligent sensors enable continuous patient monitoring. In transport, they support traffic optimization and autonomous systems. In agriculture (the source of oilseeds), sensors monitor soil moisture, temperature, and crop health, directly influencing downstream oil quality. In environmental monitoring, sensor networks track pollution levels. These cross-domain insights provide valuable lessons for adapting AIoT solutions to the specific challenges of vegetable oil production, such as maintaining strict temperature control to prevent oxidation or real-time detection of impurities during refining.

Modern information, communication, and intelligent technologies are widely applied across these key areas. Sensors, big data processing capabilities, and automated control systems collectively ensure higher efficiency, elevated safety standards, and sustainable development of industries – principles that are particularly relevant for the environmentally sensitive and resource-intensive vegetable oil sector.

MATERIALS AND METHODS

The study of IoT architectures involves a comprehensive comparative analysis of different approaches to system creation, where key aspects include overall structure, functionality, scalability, security mechanisms, and the specific scope of intended use. IoT architectural solutions define the fundamental principles of interaction between physical devices, communication networks, information processing platforms, and end-user applications [9,10].

In IoT ecosystems, the classical three-layer architecture remains the most commonly adopted model. It consists of the perception layer (where sensors and actuators collect raw environmental data such as temperature, moisture, pressure, pH, color, and chemical indicators), the network layer (responsible for reliable data transmission using wired or wireless protocols), and the application layer (where advanced data processing, visualization, and decision-making occur). This architecture is valued for its simplicity and intuitive design. However, it encounters significant difficulties in scaling to large industrial facilities and is not always optimal for highly complex, time-critical tasks typical in vegetable oil refining lines, where delays in parameter adjustment can lead to product spoilage or safety issues.

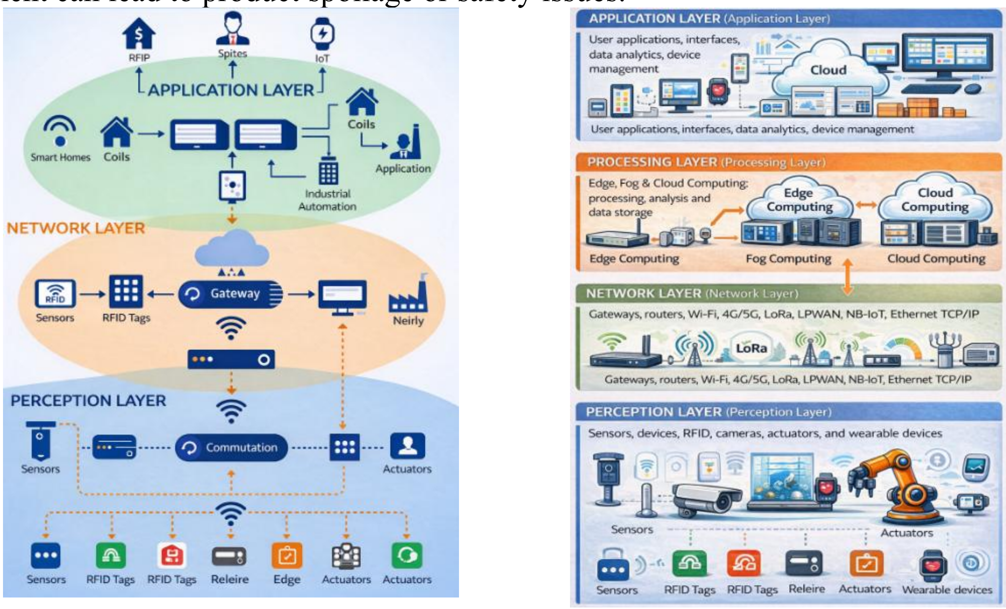

Fig.2. Comparative analysis of IoT (Internet of Things) architectures and their suitability for vegetable oil production.

Four-layer architectures introduce an additional dedicated data processing layer that performs preliminary cleaning, aggregation, and basic analysis of information before forwarding it to higher-level applications. This significantly improves overall system performance, reduces load on central servers, and is especially valuable in industrial settings and Smart Grid applications. In vegetable oil production, such layers can locally filter noise from sensor readings during high-speed pressing or bleaching processes.

Modern distributed IoT systems frequently employ a five-level structure that includes devices, transport network, edge/fog data processing, application level, and a business/strategic level responsible for long-term planning, reporting, and integration with corporate ERP systems. This architecture greatly enhances scalability and manageability but requires more sophisticated infrastructure and higher initial investments [11-13].

Cloud-based IoT architecture centralizes data storage and heavy computational tasks in remote data centers, offering excellent scalability and flexibility while reducing the need for powerful on-site hardware. However, it remains vulnerable to internet connectivity issues and

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raises important cybersecurity concerns, which are critical in food production where data integrity affects product safety.

Complementary models such as Fog Computing and Edge Computing partially shift processing tasks closer to the data generation points – either at peripheral devices or local servers. These approaches drastically reduce response times, lower network bandwidth requirements, and improve overall system reliability. Edge architectures are particularly advantageous in critical applications demanding immediate reactions, such as real-time adjustment of pressing parameters, detection of early oxidation signals via peroxide value sensors, or automatic diversion of off-spec oil batches in vegetable oil lines. IoT systems may also adopt service-oriented architecture (SOA), which promotes modularity, reusability of components, and easier integration, though it demands high standardization of protocols and data formats.

When selecting or designing IoT architectures for vegetable oil production, multiple evaluation criteria must be considered: scalability for expanding production capacity, information transmission latency (critical during continuous refining), security level against cyber threats, energy consumption of sensor nodes, implementation complexity, and long-term operating costs. Simple three-layer models suit smaller-scale or pilot installations, while five-layer and service-oriented architectures prove more effective in large corporate or industrial contexts. Cloud solutions excel in globally distributed operations, whereas Edge and Fog approaches demonstrate clear superiority for latency-sensitive tasks. A growing trend involves hybrid integration of cloud and edge paradigms, achieving an optimal balance of speed, adaptability, and reliability.

Structuring machine learning algorithms aims to provide an orderly classification of diverse methods and strategies. Classification is based on multiple criteria, including the learning mechanism, type of data processed, specific tasks addressed, and underlying mathematical principles. This systematic approach deepens understanding of the machine learning domain, facilitates optimal method selection for particular industrial challenges, and accelerates the development of intelligent sensor systems. Machine learning is traditionally categorized by the type of supervision used. Supervised learning trains models on labeled datasets with known outcomes, enabling prediction or classification tasks. It includes regression techniques for forecasting continuous variables (e.g., predicting peroxide value trends or energy consumption during deodorization) and classification algorithms for categorizing oil quality grades or detecting impurities. Unsupervised learning explores unlabeled data to uncover hidden structures, patterns, or clusters – useful for anomaly detection in sensor streams or grouping similar raw material batches. Reinforcement learning operates through interaction with an environment, receiving rewards or penalties, and is applied in optimizing control policies for robotic packaging or autonomous adjustment of process parameters.

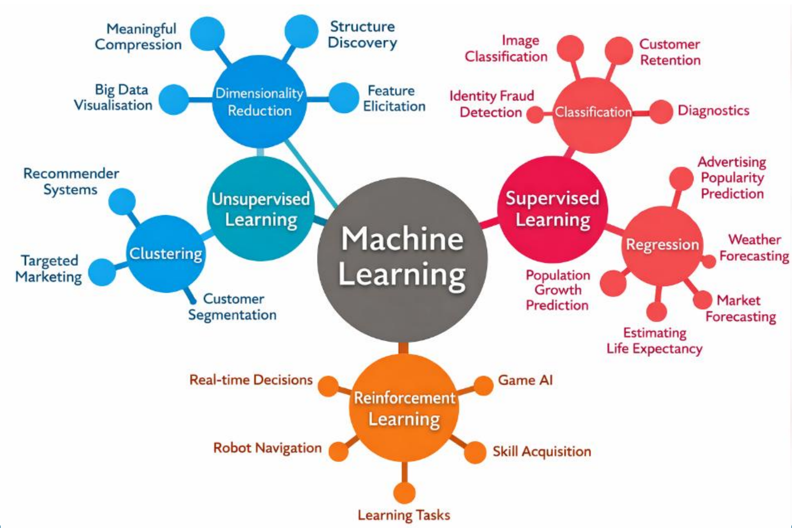

Fig.3. Systematization of machine learning algorithms and their applications in vegetable oil sensor systems.

Algorithms can also be grouped by the problems they solve: forecasting (remaining shelf life or equipment failure), classification (good/medium/unfit oil), clustering (raw material variability), optimization (resource allocation), anomaly detection (early oxidation or contamination), and recommendation systems (process parameter suggestions).

From a mathematical perspective, algorithms fall into statistical methods (based on probability distributions), linear algebra and optimization techniques (gradient descent, matrix operations), and neural network approaches that mimic biological systems for handling nonlinear, high-dimensional data. Knowledge representation varies from explicit parameters/weights in linear or neural models to rule-based or tree-structured formats that offer better interpretability.

The degree of automation in the learning process further differentiates methods – from classical algorithms requiring manual feature engineering to deep learning models that automatically extract hierarchical features from raw multisensor data.

Creating a typical architecture for an intelligent sensor node provides a structured model of its components, functional roles, interrelationships, and collaborative principles. This node serves as the foundational building block in modern cyber-physical systems, IoT networks, and automated control environments for vegetable oil production [14-16].

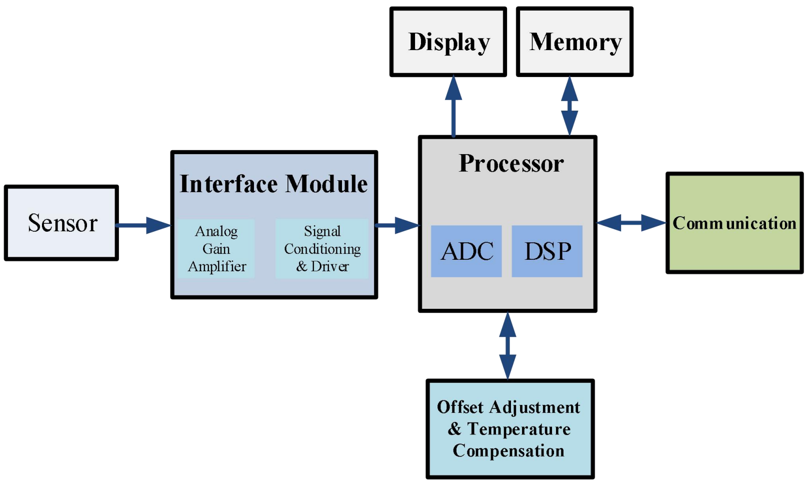

Fig.4. Typical architecture of the intelligent measuring sensor node deployed in vegetable oil production lines.

The intelligent sensor node follows a modular design with several interconnected functional blocks. The sensing layer contains primary transducers that convert physical and chemical parameters (temperature, pressure, vibration, humidity, acidity, peroxide value, color, clarity, and gas composition) into electrical signals. Modern nodes support multisensor arrays for simultaneous monitoring of multiple indicators critical to oil quality.

The analog interface module performs initial signal conditioning: amplification, filtering, noise suppression, and compensation for nonlinearities or temperature drifts. The analog-to-digital conversion module transforms continuous signals into high-resolution digital data with adjustable sampling rates.

The computing (intelligent) module, powered by microprocessors or microcontrollers, executes advanced algorithms for data filtering, feature extraction, anomaly detection, predictive modeling, and local decision-making. Embedded machine learning or TinyML models allow on-device classification of oil quality or prediction of oxidation risks without constant cloud dependency.

The communication module supports multiple protocols (wired industrial buses, wireless Wi-Fi, LoRaWAN, Bluetooth, or 5G) for interaction with local networks or remote systems. The

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energy management module ensures efficient power supply, incorporating harvesting from vibration or thermal sources and dynamic sleep modes. The software layer includes drivers, processing routines, algorithmic logic, and over-the-air update capabilities.

This architecture enables distributed intelligence, self-diagnostics, adaptive control, and autonomous operation – essential for reliable performance in harsh industrial environments of vegetable oil plants.

Various AI approaches, including classical machine learning, deep learning, and TinyML, are employed. Regression models predict continuous parameters such as future peroxide values. Support Vector Machines (SVM) excel in classification and regression with nonlinear kernels. k-Nearest Neighbors (kNN) offers simple instance-based learning, while Random Forest ensembles provide robust, interpretable predictions resistant to overfitting. Deep learning architectures like Convolutional Neural Networks (CNN) process image data for visual inspection of oil color and clarity or impurity detection. Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks handle time-series data from continuous sensor streams during refining. Autoencoders enable unsupervised dimensionality reduction and anomaly detection in multisensor data [17].

TinyML brings machine learning to highly constrained microcontrollers with limited memory and power. It enables on-device intelligence for real-time anomaly detection, local filtering, and low-latency responses in remote or battery-powered sensors monitoring storage tanks or transport conditions, drastically reducing cloud dependency and enhancing data privacy.

RESULTS

AIoT, the integrated “Artificial Intelligence of Things” model, combines AI and IoT capabilities into a single powerful intelligent platform. In vegetable oil production, this model creates fully automated workflows where data is collected from sensors, intelligently processed in real time, and used for decision-making at every production stage.

The model operates through synergistic layers. The sensory layer deploys intelligent sensors at critical points: raw seed intake (moisture and impurity detection), pressing (pressure and temperature), refining (acidity, color, peroxide monitoring), and storage (oxidative stability via gas sensors). The communication layer ensures secure, reliable data exchange. The Edge layer performs local analytics – for example, using TinyML to detect early oxidation or adjust bleaching parameters instantly. The cloud layer handles large-scale model training, long-term trend analysis, predictive maintenance scheduling, and global optimization. The application layer provides dashboards, alerts, and decision-support tools for operators and managers.

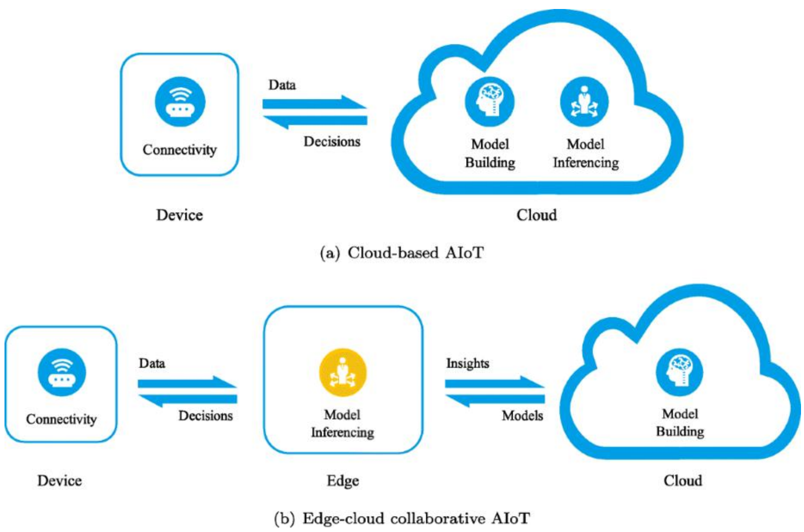

Fig.5. AIoT Integration Model tailored for vegetable oil production processes.

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Energy efficiency is achieved through low-power hardware, dynamic mode switching, energy harvesting, and local processing that minimizes data transmission. Security is implemented via encryption, authentication, secure boot, intrusion detection, and anomaly monitoring. These measures ensure autonomous, reliable, and safe operation of sensor networks in food production environments.

Practical implementation of AIoT in vegetable oil production yields measurable benefits: predictive maintenance reduces unplanned downtime of presses and deodorizers; computer vision with CNNs automates quality inspection for defects or contaminants; optimization algorithms lower energy use during refining; and real-time monitoring prevents oxidative degradation, improving yield and product shelf life.

DISCUSSION

AIoT combines the strengths of AI and IoT to create smart, flexible, and largely self-sufficient systems for vegetable oil production. It enables autonomous decision-making, accurate forecasting of quality parameters and equipment failures, resource optimization, enhanced safety, reduced cloud dependency, and personalized process adjustments. However, implementation faces notable challenges: limited on-device computing power and energy resources, difficulties in standardization and system integration, information security and privacy concerns, the critical impact of data quality on model performance, and complexities in developing and maintaining hybrid edge-cloud architectures [18-20].

Despite these obstacles, AIoT offers substantial advantages, including offline operation in remote facilities, predictive capabilities that shift from reactive to proactive management, efficient resource utilization that supports sustainability goals, and improved overall security of both equipment and data. Successful deployment requires careful balancing between technological potential and the practical constraints of hardware, software, and operational environments. AIoT and intelligent sensory systems continue to advance rapidly, with ongoing innovations in hardware and software platforms. Promising directions include neuromorphic processors that mimic biological neural efficiency for ultra-low-power edge computing, 6G networks offering near-instantaneous data exchange and massive device connectivity, self-learning sensors capable of autonomous adaptation to changing raw material or environmental conditions, and quantum-inspired optimization algorithms for solving complex scheduling and resource allocation problems in large-scale refineries [21,22].

The synergy of these technologies promises higher autonomy, superior energy efficiency, enhanced intelligence, and seamless scalability – paving the way for the next generation of intelligent systems in vegetable oil manufacturing, as well as broader industrial, transport, and urban applications.

CONCLUSION

The convergence of artificial intelligence and the Internet of Things is giving birth to a new generation of intelligent measuring systems that transcend traditional data collection roles. In vegetable oil production, these systems actively process multisensor information, predict future quality deviations or equipment issues, optimize complex technological processes, and execute autonomous decisions in dynamically changing production environments.

Innovative methodologies grounded in machine learning, deep learning architectures, intelligent sensor nodes, and distributed data processing frameworks open promising avenues for elevating accuracy, reliability, and cybersecurity in industrial and infrastructure systems. The adoption of predictive analytics, robotic automation, and adaptive control algorithms contributes to substantial cost reductions, consistent improvement in edible oil quality, and uninterrupted operational stability across the production chain. Looking ahead, the continued development of neuromorphic chips, 6G communication infrastructure, self-learning sensory nodes, and quantum-enhanced optimization methods will drive the creation of systems that are not only more intelligent and energy-efficient but also capable of continuous self-improvement and adaptation. This technological progress will unlock extensive opportunities for AIoT deployment across the vegetable oil industry and related sectors, fostering sustainable, efficient, and intelligent interaction between physical processes and digital intelligence.

As a result of the deep integration between artificial intelligence and IoT, a transformative generation of intelligent measurement systems is emerging. These systems possess the capacity to optimize intricate production workflows, respond flexibly to varying conditions, and deliver high performance while consuming minimal resources – ultimately supporting higher-quality vegetable oil products and more sustainable manufacturing practices.

REFERENCES

1. Hinton G., LeCun Y., & Bengio Y. (2015). Deep learning. Nature, 521, 436–444. https://doi.org/10.1038/nature14539
2. L. Atzori, A. Iera, G. Morabito. "The Internet of Things: A Survey" // Computer Networks, vol. 54, no. 15, pp. 2787–2805, 2010. DOI: 10.1016/j.comnet.2010.05.010
3. A. Zanella et al. "Internet of Things for Smart Cities" // IEEE Internet of Things Journal, vol. 1, no. 1, pp. 22–32, 2014. DOI: 10.1109/JIOT.2014.2306328
4. H. Ning, Z. Wang. "Future Internet of Things Architecture" // IEEE Communications Magazine, vol. 49, no. 11, pp. 104–110, 2011. DOI: 10.1109/MCOM.2011.6069719
5. D. Evans. "The Internet of Things: How the Next Evolution of the Internet Is Changing Everything" // Cisco White Paper, 2011.
6. K. Ashton. "That 'Internet of Things' Thing" RFID Journal, 2009.
7. X. Fang et al. "Smart Grid – The New and Improved Power Grid" // IEEE Communications Surveys & Tutorials, 2012. DOI: 10.1109/SURV.2011.101911.00087
8. A. Ghasempour, "Internet of Things in Smart Grid," IEEE Internet of Things Journal, 2019. DOI: 10.1109/JIOT.2018.2872777
9. J. Fraden, Handbook of Modern Sensors, Springer, 2016.
10. R. Isermann, "Model-Based Fault Detection," Control Engineering Practice, 2005. DOI: 10.1016/j.conengprac.2004.12.005
11. A. Mahmood et al., "Reliability in IoT," IEEE Access, 2018. DOI: 10.1109/ACCESS.2018.2834119
12. S. Li et al., "Industrial Internet," IEEE Transactions on Industrial Informatics, 2017. DOI: 10.1109/TII.2017.2786779
13. H. Boyes et al., "Industrial IoT Security Framework," Computer Law & Security Review, 2018. DOI: 10.1016/j.clsr.2017.12.005
14. Y. LeCun, Y. Bengio, G. Hinton. "Deep Learning" // Nature, vol. 521, pp. 436–444, 2015. DOI: 10.1038/nature14539
15. G. Hinton et al. "Deep Neural Networks for Acoustic Modeling" // IEEE Signal Processing Magazine, vol. 29, no. 6, 2012. DOI: 10.1109/MSP.2012.2205597
16. F. Adelantado et al. "Understanding the Limits of LoRaWAN" // IEEE Communications Magazine, 2017. DOI: 10.1109/MCOM.2017.1600613
17. J. G. Andrews et al. "What Will 5G Be?" // IEEE JSAC, 2014. DOI: 10.1109/JSAC.2014.2328098
18. M. Zorzi et al. "From Today's INTRAnet to the Internet of Things" // IEEE Wireless Communications, 2010. DOI: 10.1109/MWC.2010.5675772
19. Y. Mao et al. "Mobile Edge Computing: Survey" // IEEE Communications Surveys & Tutorials, 2017. DOI: 10.1109/COMST.2017.2682318
20. S. Deng et al. "Edge Intelligence: The Confluence of Edge Computing and AI" // IEEE Internet of Things Journal, 2020. DOI: 10.1109/JIOT.2020.2984887
21. N. D. Lane et al. "DeepX: A Software Accelerator for Low-Power Deep Learning" // IPSN, 2016. DOI: 10.1145/2883817.2883822

pISSN:2349-5707 Volume:13,Issue 4, April -2026 eISSN:2349-5715

22. Q. Yang et al. “Federated Machine Learning” // ACM TIST, 2019. DOI: 10.1145/3298981