UDC 655.344:004

MACHINE LEARNING-BASED QUALITY CONTROL SYSTEMS IN PRINT PRODUCTION

V. V. Bernatsek[1], T. V. Vladyka[2], N. V. Vladyka[3], R. P. Marchuk[4]

[1] *Lviv Polytechnic National University, 19, Pid Holoskom St., Lviv, 79020, Ukraine,* https://orcid.org/0000-0001-8955-1762*,*
*e-mail:*volodymyr.v.bernatsek@lpnu.ua
[2] *Lviv Polytechnic National University, 19, Pid Holoskom St., Lviv, 79020, Ukraine,* https://orcid.org/0009-0006-4769-0303*,*
*e-mail:*taras.v.vladyka@lpnu.ua
[3] *Lviv Polytechnic National University, 19, Pid Holoskom St., Lviv, 79020, Ukraine,* https://orcid.org/0009-0002-4808-9836*,*
*e-mail:*nazar.v.vladyka@lpnu.ua
[4] *Lviv Polytechnic National University, 19, Pid Holoskom St., Lviv, 79020, Ukraine,* https://orcid.org/0009-0008-1777-7488*,*
*e-mail:*ruslan.p.marchuk@lpnu.ua

Creative Commons Attribution 4.0 (CC BY 4.0) License

The integration of machine learning technologies into print quality control systems represents a significant advancement in modern printing production. This article examines the application of artificial intelligence methods and computer vision algorithms for automated defect detection, colour consistency monitoring, and real-time quality assessment in printing processes. The study analyses current approaches to implementing neural networks, particularly convolutional neural networks (CNNs), for identifying various types of printing defects including misregistration, colour deviation, streaking, and substrate irregularities. Special attention is given to the development of information models that describe the interaction between quality control subsystems, production workflow, and decision-making mechanisms. The research demonstrates that machine learning-based systems can achieve defect detection accuracy exceeding 95%, significantly reducing material waste and improving overall production efficiency. The article presents a comprehensive analysis of existing solutions, identifies key challenges in implementing intelligent quality control systems, and proposes directions for future research. The findings indicate that hybrid approaches combining traditional image processing techniques with deep learning methods show the most promising results for industrial applications. The practical significance of this work lies in providing a systematic framework for developing and implementing automated quality control systems in printing enterprises.

Keywords: *machine learning, print quality control, computer vision, convolutional neural networks, defect detection, information technologies, automated inspection systems, deep learning.*

Problem statement. The modern printing industry is characterised by high quality requirements, reduced print runs, and increasing diversity of orders. Traditional quality control methods based on visual inspection by operators cannot provide the necessary speed, accuracy, and objectivity of assessment, especially in high-speed printing conditions.

The problem lies in the necessity to develop effective information systems capable of automatically detecting a wide range of printing defects in real-time, adapting to different types of products and technological processes, and making informed decisions regarding corrective actions. The application of machine learning methods opens new possibilities for solving these tasks; however, it requires in-depth analysis of the specifics of their implementation in printing production.

The relevance of the research is determined by the need to minimise waste, reduce material costs, increase productivity, and ensure stable quality of printed products in conditions of growing competition in the printing services market [1-5].

Analysis of recent research and publications. Issues concerning the application of computer vision, machine learning, and deep learning for print quality control have been actively studied by the international scientific community in recent years.

A fundamental overview of artificial intelligence applications in the printing industry is presented in the work by bin Masod and Zakaria [1], which systematises industrial applications, challenges, and benefits of implementing AI technologies. The authors identify quality control as one of the priority directions for digitalisation of printing production, emphasising the potential of machine learning for automating inspection processes.

Research by Villalba-Diez et al. [2] demonstrates practical application of deep learning for quality control in Industry 4.0 conditions. The authors developed a system based on convolutional neural networks for real-time detection of print defects, utilising sensor technologies and integration with production systems. The results showed significant improvement in detection accuracy compared to traditional computer vision methods.

An important contribution to the development of printing defect classification methods was made by authors in work [3], who proposed a deep learning-based classification method for working with imbalanced samples. This work is particularly relevant, as in real production some types of defects occur significantly less frequently than others, creating a class imbalance problem when training models. The authors applied augmentation and resampling techniques to improve the classification quality of rare defects. For the sphere of personalised and variable data printing, researches [4] presented an innovative inspection system based on deep learning, capable of controlling the quality of products with variable data (variable data printing). The system demonstrates the ability to adapt to constantly changing content, which is critical for modern digital printing technologies.

Hybrid approaches to automating industrial quality control were investigated by Vinod et al. in [5], who proposed a combined deep learning method integrating the advantages of different neural network architectures. Their approach showed improved generalisation ability and robustness to variations in production conditions.

Whilst the main body of research concerns traditional printing technologies, significant progress is also observed in related fields. Bhandarkar et al. [6] developed a system for detecting defects in 3D printing in real-time with layer-by-layer analysis, which can be adapted for web and sheet-fed printing. In [7] it was conducted a comprehensive review of image processing and computer vision methods for defect detection in 3D printing, systematising machine learning approaches that can be extrapolated to printing applications. Additionally, Selot and Dwivedi [8] presented a review of machine learning and sensor technology approaches for additive manufacturing, highlighting common methodological principles with traditional print quality control. Authors in the work [9] conducted a comprehensive review of printed circuit board defect detection methods based on image processing, machine learning, and deep learning. Despite the specificity of PCB production, many of the described approaches (edge detection, texture analysis, pattern classification) are directly applicable to printing product quality control, especially for printing with high detail and registration accuracy.

Analysis of scientific literature indicates significant progress in applying deep learning methods for automating print quality control. However, issues remain insufficiently researched regarding the creation of universal information models of quality control systems, adaptation of algorithms to the specifics of different printing technologies (offset, flexographic, digital), optimisation of neural network architectures for operation under limited computational resources, and integration of systems into existing production processes with minimal equipment modifications.

The aim of the research. The aim of the research is to develop an information model of a print quality control system based on machine learning methods, analyse the effectiveness of different neural network architectures for detecting typical printing defects, and determine optimal approaches to integrating intelligent control systems into printing production.

Presentation of the main research material. An automated print quality control system based on machine learning represents a complex multi-component structure that can be presented as an information model (Fig. 1).

The main functional blocks of the system include:

- The image capture module performs scanning of printed sheets or web in real-time with high resolution (typically 600-1200 dpi). Linear or matrix CCD/CMOS sensors with specialised illumination are used to ensure stable shooting conditions.
- The preprocessing module performs image normalisation, geometric distortion correction, contrast enhancement, and segmentation of regions of interest. These operations are critically important for increasing the effectiveness of subsequent analysis stages.
- The machine learning module is the core of the system and includes trained neural networks for defect detection and classification. The typical architecture is based on convolutional neural networks (CNNs) adapted for specific types of printing defects.

– The decision-making module analyses detection results, assesses the criticality of detected defects according to specified tolerances, and forms commands for the printing process control system or signals for the operator.

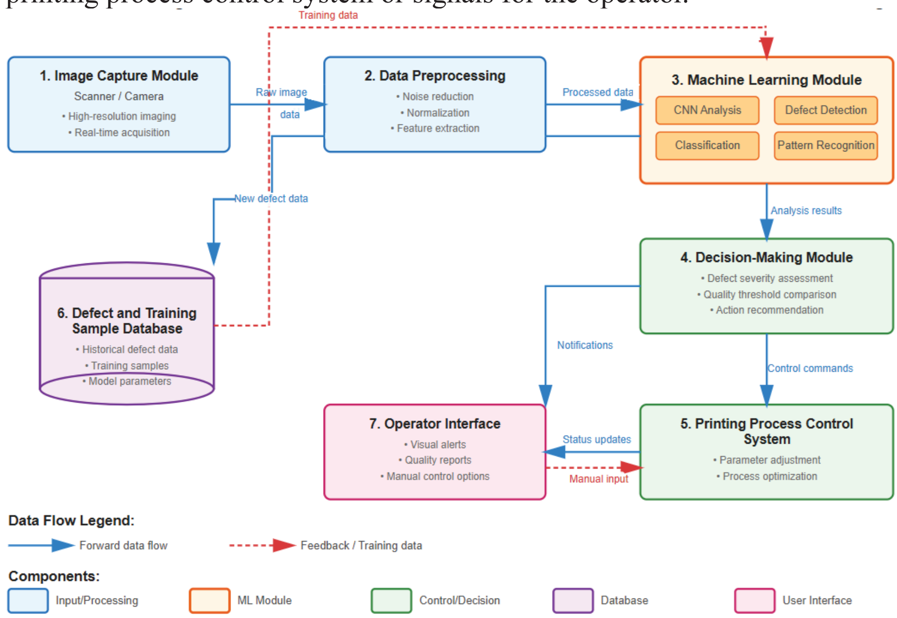

Fig. 1. Information model of a print quality control system based on machine learning

Systematisation of printing defects is an important stage in developing a quality control system. Table 1 presents a classification of main defect types and corresponding machine learning methods for their detection.

Table 1

Classification of printing defects and methods for their detection

Defect Type	Characteristics	Detection Method	Accuracy, % [3-5]
Misregistration	Colour layer shift	CNN + edge detection	97.2
Colour deviations	Non-compliance with reference values	CNN + colour analysis	95.8
Streaking	Periodic streaks on print	Frequency analysis + ML	94.5
Hickeys	Random ink spots	Object detection (YOLO)	96.3
Over/under-inking	Excessive or insufficient ink density	Regression models + CNN	93.7
Substrate scratches	Mechanical paper damage	Semantic segmentation	91.2
Dot gain	Change in halftone element size	CNN + morphological analysis	95.1

For print quality control tasks, the following convolutional neural network architectures have proven most effective:

- ResNet (Residual Networks) demonstrates high efficiency due to the skip connections mechanism, which allows training deep networks without gradient degradation. For printing defect classification tasks, ResNet-50 or ResNet-101 modifications are typically used [10].
- EfficientNet provides an optimal balance between accuracy and computational efficiency, which is critically important for real-time systems. Scaling the network by depth, width, and input resolution allows adapting the architecture to specific requirements [11].
- YOLO (You Only Look Once) and its modifications (YOLOv5, YOLOv8) are ideally suited for detecting local defects (hickeys, scratches, foreign inclusions) due to processing speed and the ability to detect multiple objects in a single image [12].
- U-Net is applied for semantic segmentation tasks when it is necessary to precisely determine the boundaries of defective zones, for example, for analysing under-inking zones or detecting gradient distortions [13].
- VGG16 can be used for quality control of printing processes as a computer vision tool for automated classification and analysis of imprints defects, including uneven ink application, banding, halftone dot distortion, and general print quality deviations. The architecture is effective as a feature extractor in hybrid control systems, where convolutional layers form informative image descriptors, and further decision-making is carried out by classical or ML algorithms. Thanks to transfer learning, VGG16 provides stable results even on limited samples, which makes it suitable for experimental and industrial quality control systems of various printing technologies [14].

Comparative analysis of different architecture performance is presented in Figure 2. A critical factor in the success of machine learning systems is the quality and volume of training data. For print quality control tasks, forming a representative sample has its own peculiarities:

- Data collection is carried out by scanning real printed samples with different types of defects. The recommended dataset size for a basic system is at least 10,000 annotated images for each defect class.
- Data annotation is conducted by expert technologists using specialised software. Cross-validation by multiple experts is applied to improve annotation quality.
- Data augmentation includes the following transformations:
  - geometric transformations (rotations, reflections, scaling);
  - colour corrections (brightness, contrast, saturation changes);
  - noise addition to simulate different scanning conditions;
  - synthetic defect generation on defect-free images.

Application of augmentation allows increasing the effective training sample size by 15-20 times and significantly improving model generalisation ability.

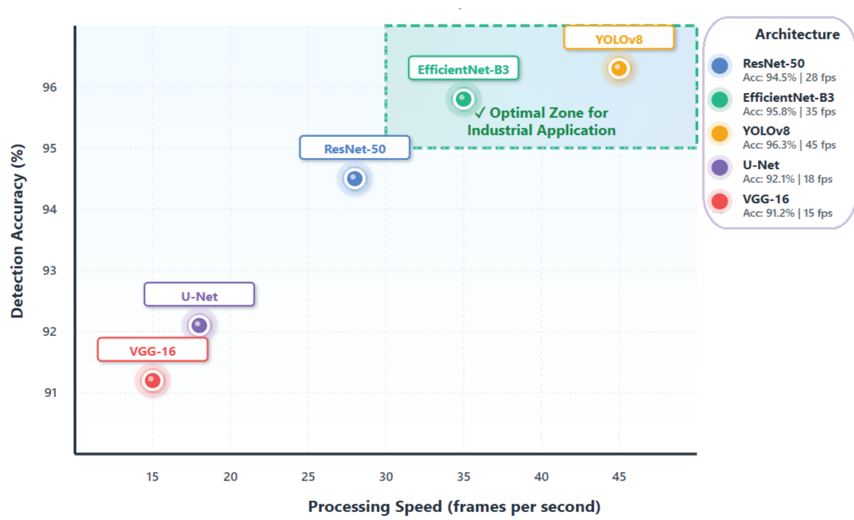

Fig. 2. Comparison of neural network architecture effectiveness for print quality control

Successful implementation of a machine learning-based quality control system requires consideration of technological specifics of particular production (Fig. 3).

Key integration aspects:

– Hardware integration involves installing scanning modules directly on the printing press (inline systems) or on separate inspection tables (offline systems). Inline systems provide real-time control but have higher cost.
– Software integration includes connection with MIS (Management Information System), colour management systems, and production databases for automatic receipt of reference samples and quality specifications.
– Feedback is implemented through automatic adjustment of printing press parameters (ink feed, pressure, registration) based on defect analysis results, which minimises waste.

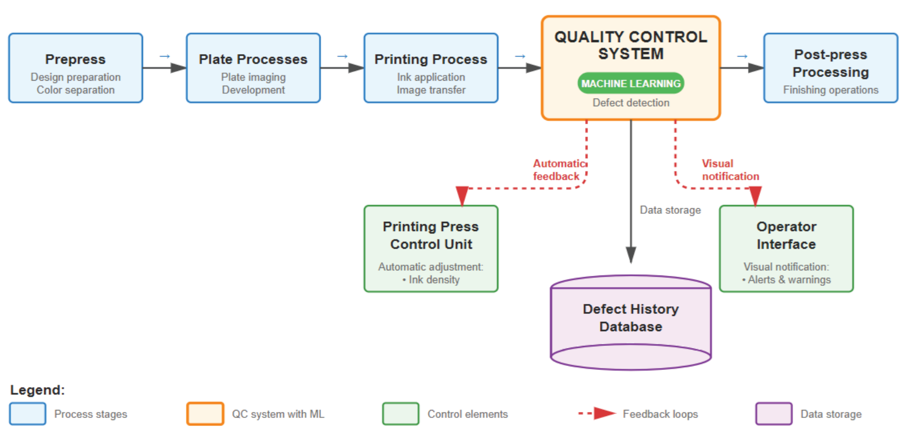

Fig. 3. Scheme of quality control system integration into the printing process

For comprehensive assessment of quality control system effectiveness, the following metrics are used:

- Detection precision – the ratio of correctly detected defects to the total number of system triggers. High precision minimises false positives.
- Detection recall – the ratio of detected defects to the actual number of defects. High recall ensures a minimal number of missed defects.
- F1-score – harmonic mean of precision and recall, providing a balanced assessment.
- Processing speed – the number of sheets or metres of web analysed per unit time. For high-speed printing, critical processing speed is 150+ m/min.
- Economic efficiency – reduction in waste quantity, material savings, and productivity increase in monetary equivalent.

Table 2 presents typical performance indicators of modern systems.

Table 2

Performance indicators of ML-based quality control systems

Parameter	Traditional Methods	ML-based Systems	Improvement
Detection accuracy, %	78-85	94-97	+15-19%
Processing speed, m/min	80-100	150-200	+75-100%
Waste reduction, %	-	40-60	-
Setup time, min	45-60	10-15	-70-75%
ROI period, months	-	18-24	-

Conclusions. Information technologies based on machine learning demonstrate significant potential for automating quality control in printing production, ensuring defect detection accuracy at the level of 94-97%, which is 15-19% higher than traditional methods. The developed information model of the quality control system describes the interaction of key components: image capture modules, preprocessing, machine learning, decision-making, and integration with the production process. The most effective neural network architectures for print quality control tasks are EfficientNet for general classification, YOLOv8 for local defect detection, and U-Net for defective zone segmentation.

Successful implementation of machine learning-based quality control systems requires a comprehensive approach including formation of representative training samples, application of data augmentation, and deep integration with existing production systems.

Prospects for further research include development of self-learning systems that adapt to new defect types without retraining, application of federated learning methods for experience exchange between different productions without transferring confidential data, and integration with Industry 4.0 technologies for creating fully automated smart printing facilities.

СПИСОК ВИКОРИСТАНИХ ДЖЕРЕЛ

1. Masod M. Y., Zakaria S. F. Artificial Intelligence in the Printing Industry: A Systematic Review of Industrial Applications, Challenges and Benefits. *International Journal of Research and Innovation in Social Science*. 2024. P. 1713–1732.
2. Deep learning for industrial computer vision quality control in the printing industry 4.0 / J. Villalba-Diez et al. *Sensors*. 2019. Vol. 19, No. 18. Art. No. 3987. DOI: https://doi.org/10.3390/s19183987.
3. A deep learning based printing defect classification method with imbalanced samples / E. Zhang et al. *Symmetry*. 2019. Vol. 11, No. 12. Art. No. 1440. DOI: https://doi.org/10.3390/sym11121440.
4. A novel inspection system for variable data printing using deep learning / O. Haik et al. *Proceedings of the IEEE/CVF winter conference on applications of computer vision*. 2020. P. 3541–3550.
5. A hybrid deep learning approach to automate industrial quality control / K. Vinod et al. *International Journal of Computer Integrated Manufacturing*. 2025. P. 1–21. DOI: https://doi.org/10.1080/0951192X.2024.2449886.
6. Bhandarkar V. V., Karnati M., Tandon P. Real-time layer-by-layer defects detection in 3D-printed multi-geometry polymer components using deep learning. *Measurement*. 2026. Art. No. 120332. DOI: https://doi.org/10.1016/j.measurement.2024.120332.
7. Defect detection in 3D printing: A review of image processing and machine vision techniques / E. Armin et al. *The International Journal of Advanced Manufacturing Technology*. 2025. Vol. 140, No. 3. P. 2103–2128. DOI: https://doi.org/10.1007/s00170-025-14958-1.
8. Selot A., Dwivedi R. K. Machine learning and sensor-based approach for defect detection in MEX additive manufacturing process-A Review. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*. 2023. Vol. 45, No. 10. Art. No. 535. DOI: https://doi.org/10.1007/s40430-023-04444-2.
9. Ling Q., Isa N. A. M. Printed circuit board defect detection methods based on image processing, machine learning and deep learning: A survey. *IEEE Access*. 2023. Vol. 11. P. 15921–15944. DOI: https://doi.org/10.1109/ACCESS.2023.3245093.
10. Deep residual learning for image recognition / K. He et al. *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016. P. 770–778. DOI: https://doi.org/10.1109/CVPR.2016.90.
11. Tan M., Le Q. EfficientNet: Rethinking model scaling for convolutional neural networks. *International conference on machine learning*. 2019. P. 6105–6114.
12. You only look once: Unified, real-time object detection / J. Redmon et al. *Proceedings of the IEEE conference on computer vision and pattern recognition*. 2016. P. 779–788. DOI: https://doi.org/10.1109/CVPR.2016.91.
13. Ronneberger O., Fischer P., Brox T. U-net: Convolutional networks for biomedical image segmentation. *Medical image computing and computer-assisted intervention*. 2015. P. 234–241. DOI: https://doi.org/10.1007/978-3-319-24574-4_28.
14. VGG-16 | CNN model. *GeeksforGeeks*. 2025. URL: https://www.geeksforgeeks.org/computer-vision/vgg-16-cnn-model/ (дата звернення: 19.01.2026).

REFERENCES

1. Masod, M. Y., & Zakaria, S. F. (2024). Artificial intelligence in the printing industry: A systematic review of industrial applications, challenges and benefits. *International Journal of Research and Innovation in Social Science*, 1713–1732.
2. Villalba-Diez, J., Schmidt, D., Gevers, R., Ordieres-Meré, J., Buchwitz, M., & Wellbrock, W. (2019). Deep learning for industrial computer vision quality control in the printing industry 4.0. *Sensors*, *19*(18), 3987. https://doi.org/10.3390/s19183987.
3. Zhang, E., Li, B., Li, P., & Chen, Y. (2019). A deep learning based printing defect classification method with imbalanced samples. *Symmetry*, *11*(12), 1440. https://doi.org/10.3390/sym11121440.
4. Haik, O., Perry, O., Chen, E., & Klammer, P. (2020). A novel inspection system for variable data printing using deep learning. In *Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision* (pp. 3541–3550).
5. Vinod, K., Sasinthiran, A., Thangaraj, N., & Gnanasekaran, S. (2025). A hybrid deep learning approach to automate industrial quality control. *International Journal of Computer Integrated Manufacturing*, 1–21. https://doi.org/10.1080/0951192X.2024.2449886.
6. Bhandarkar, V. V., Karnati, M., & Tandon, P. (2026). Real-time layer-by-layer defects detection in 3D-printed multi-geometry polymer components using deep learning. *Measurement*, Article 120332. https://doi.org/10.1016/j.measurement.2024.120332.
7. Armin, E., Ebrahimian, S., Sanjari, M., Saidi, P., & Pourreza, H. R. (2025). Defect detection in 3D printing: A review of image processing and machine vision techniques. *The International Journal of Advanced Manufacturing Technology*, *140*(3), 2103–2128. https://doi.org/10.1007/s00170-025-14958-1.
8. Selot, A., & Dwivedi, R. K. (2023). Machine learning and sensor-based approach for defect detection in MEX additive manufacturing process-A review. *Journal of the Brazilian Society of Mechanical Sciences and Engineering*, *45*(10), 535. https://doi.org/10.1007/s40430-023-04444-2.
9. Ling, Q., & Isa, N. A. M. (2023). Printed circuit board defect detection methods based on image processing, machine learning and deep learning: A survey. *IEEE Access*, *11*, 15921–15944. https://doi.org/10.1109/ACCESS.2023.3245093.
10. He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 770–778). https://doi.org/10.1109/CVPR.2016.90.
11. Tan, M., & Le, Q. (2019). EfficientNet: Rethinking model scaling for convolutional neural networks. In *International Conference on Machine Learning* (pp. 6105–6114).
12. Redmon, J., Divvala, S., Girshick, R., & Farhadi, A. (2016). You only look once: Unified, real-time object detection. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 779–788). https://doi.org/10.1109/CVPR.2016.91.
13. Ronneberger, O., Fischer, P., & Brox, T. (2015). U-net: Convolutional networks for biomedical image segmentation. In *Medical Image Computing and Computer-Assisted Intervention* (pp. 234–241). https://doi.org/10.1007/978-3-319-24574-4_28.
14. VGG-16 | CNN model. (2025). *GeeksforGeeks*. https://www.geeksforgeeks.org/computer-vision/vgg-16-cnn-model/.

doi: 10.32403/2411-3611-2026-1-49-121-131

СИСТЕМИ КОНТРОЛЮ ЯКОСТІ ПОЛІГРАФІЧНОГО ВИРОБНИЦТВА НА ОСНОВІ МАШИННОГО НАВЧАННЯ

В. В. Бернацек[1], Т. В. Владика[2], Н. В. Владика[3], Р. П. Марчук[4]

[1] НУ «Львівська Політехніка», вул. Під Голоском, 19, Львів, 79020, Україна, https://orcid.org/0000-0001-8955-1762, e-mail:volodymyr.v.bernatsek@lpnu.ua
[2] НУ «Львівська Політехніка», вул. Під Голоском, 19, Львів, 79020, Україна, https://orcid.org/0009-0006-4769-0303, e-mail: taras.v.vladyka@lpnu.ua
[3] НУ «Львівська Політехніка», вул. Під Голоском, 19, Львів, 79020, Україна, https://orcid.org/0009-0002-4808-9836, e-mail: nazar.v.vladyka@lpnu.ua
[4] НУ «Львівська Політехніка», вул. Під Голоском, 19, Львів, 79020, Україна, https://orcid.org/0009-0008-1777-7488, e-mail: ruslan.p.marchuk@lpnu.ua

Стаття присвячена дослідженню застосування методів машинного навчання та штучного інтелекту для автоматизації контролю якості в поліграфічному виробництві. Актуальність дослідження зумовлена зростаючими вимогами до якості друкованої продукції, скороченням накладів, збільшенням різноманітності замовлень та необхідністю мінімізації браку в умовах високошвидкісного друку. Традиційні методи візуального контролю операторами не забезпечують необхідної точності, швидкості та об›єктивності оцінювання, що робить актуальним впровадження інтелектуальних систем автоматизованої інспекції.

У роботі представлено аналіз сучасних підходів до застосування згорткових нейронних мереж (CNN) для виявлення різноманітних типів друкарських дефектів, включаючи несуміщення фарб, колірні відхилення, смугастість, марашки, подряпини субстрату, розтискування растрової крапки. Розроблено інформаційну модель системи контролю якості, яка описує взаємодію між підсистемами захоплення зображення, попередньої обробки даних, машинного навчання, прийняття рішень, управління виробничим процесом та інтерфейсом оператора.

Проаналізовано особливості формування навчальних вибірок, методи аугментації даних для підвищення узагальнюючої здатності моделей, а також аспекти апаратної та програмної інтеграції систем у існуючі виробничі процеси. Представлено метрики оцінювання ефективності систем, включаючи точність детекції, повноту виявлення дефектів, швидкість обробки та економічну ефективність.

Результати дослідження можуть бути використані технологами, інженерами та керівниками поліграфічних підприємств для обґрунтованого прийняття рішень щодо впровадження інтелектуальних систем контролю якості. Визначено перспективні напрямки подальших досліджень, включаючи розробку самонавчальних адаптивних систем, застосування методів федеративного навчання та

інтеграцію з технологіями Індустрії 4.0 для створення повністю автоматизованих розумних друкарень майбутнього.

Ключові слова: *машинне навчання, контроль якості друку, комп›ютерний зір, згорткові нейронні мережі, виявлення дефектів, інформаційні технології, автоматизовані системи контролю, глибоке навчання.*

Стаття надійшла до редакції: 01.03.2026.
Submitted: 01.03.2026.
Прийнято до друку: 14.05.2026.
Accepted: 14.05.2026.
Опубліковано: 20.05.2026.
Published: 20.05.2026.