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ARTIFICIAL INTELLIGENCE MODELS FOR QUALITY CONTROL OF TOROID TRANSFORMER WINDINGS

The paper presents a review and comparative analysis of modern artificial intelligence models suitable for real-time quality control of toroidal transformer winding. It is shown that existing AI solutions for transformer diagnostics and electronic product quality control are mainly focused on post-production (offline) analysis and do not address the specifics of the winding process. More than 25 neural network architectures were evaluated according to model size (≤ 200 MB), accuracy, computational load, and relative efficiency metrics. The most promising models were identified: EfficientNetV2-S and YOLOv11l as primary options for classification and object detection respectively, and EfficientNetB0 with YOLOv8n as lightweight alternatives. A universal four-stage scheme for integrating AI into a winding quality control system is defined and analyzed. The obtained results provide a scientific basis for developing low-cost intelligent monitoring systems for toroidal transformer winding machines, suitable for laboratory, educational, and small-batch production.

Keywords: *artificial intelligence; quality control; toroidal transformer winding; convolutional neural networks; EfficientNet; YOLO; real-time; embedded systems.*
Fig.: 5. Table: 7. References: 18.

Relevance of the research topic. In the modern world, the influence of artificial intelligence (AI) is growing rapidly. Due to the significant potential and great flexibility of AI as a data processing tool, more and more companies are implementing the use of AI in their work. Between 2017 and 2025, the percentage of companies using AI increased from 20 % to 78 %[1].

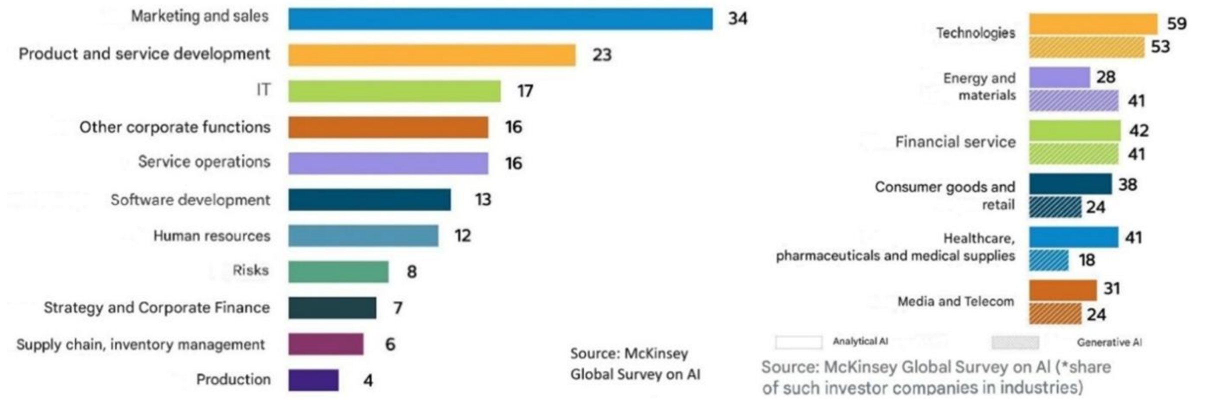
The growing demand for the AI use stimulates an increase in the number of studies conducted to investigate its working principles [2], [3], rules and methods of application [2], [4], improvement of its accuracy [2], [5], or new areas of application [6].

According to [7], the percentage of manufacturing companies that use generative AI is 4% (see Fig. 1, *a*).

This indicator can be explained by the fact that in manufacturing companies, the need for generative AI appears at the initial stages of establishing the manufacture.

Once production begins, the need for this AI decreases sharply, and instead, there is a need for analytical AI, which allows for analysis of the course of production processes and their precise control. This explains the large share of technology companies investing in the development and use of analytical AI (see Fig. 1.b).

These statistics confirm the relevance of the topic of this study, as the demand for the use of AI in production processes, in particular in quality control of final products, encourages the study of new and additional analysis of existing solutions. The analysis of existing solutions will allow us to examine current AI models from a different perspective and identify unconventional and creative approaches to their application.



a) *b)*

Fig. 1. Statistics data:
a – the direction of activity of companies using generative AI in 2024, by function, %;
b – shares of companies investing more than 10% of technologies in AI by industry, % [7]

Problem Statement. The absence of ready-made AI solutions for specialized manufacturing problems is driving the current trend of investing in the development of corresponding AI systems. In modern production of toroidal transformers, quality control of the winding process remains one of the key challenges that affects the efficiency and reliability of the final products. Currently, the accuracy of the control process depends to a significant extent on monitoring systems, human factors (operator errors, psychological characteristics of individuals, visual acuity, and others), winding process parameters (wire tension, angle of the applied turn, winding speed, and others), and the quality of the final product (uniformity of turn distribution, quality of turn overlay, number of detected defects, number of turns, and others).

This problem is accompanied by the following objectives: the aspiration for real-time control, the desire to increase the number of acquired parameters, and the aim to determine parameters that would be difficult to measure without the use of AI. These objectives indicate potential avenues for improving the quality control system for the winding of toroidal transformers on the machine.

Furthermore, in winding machines similar to those described in the previous work [8], it is proposed to integrate artificial intelligence models for automated real-time quality control. Fig. 2 presents an example of this machine manufactured by us, in which the implementation of AI will significantly reduce the influence of the human factor and improve the accuracy of monitoring winding parameters.

Real-time control enables the timely detection of defects and the implementation of corrective measures, sometimes without interrupting the winding process itself. It also allows for the proactive halting of the production process to prevent significant losses associated with the failure of involved equipment.

Increasing the number and complexity of monitored parameters makes it possible to substantially reduce the amount of defective output in the manufacturing process. This reduction in defects is achieved through enhanced adaptability of the manufacturing process, facilitated by the increased volume of information obtained about the product.

The simultaneous achievement of all these objectives is ensured by the appropriate selection of an AI model and the properly conducted process of its training. As a result, the AI becomes capable of processing large volumes of data, which enables the monitoring of the required number of parameters that are complex to detect. It is also capable of flexibly and accurately processing visual information, thereby significantly reducing the influence of the human factor on the winding process.

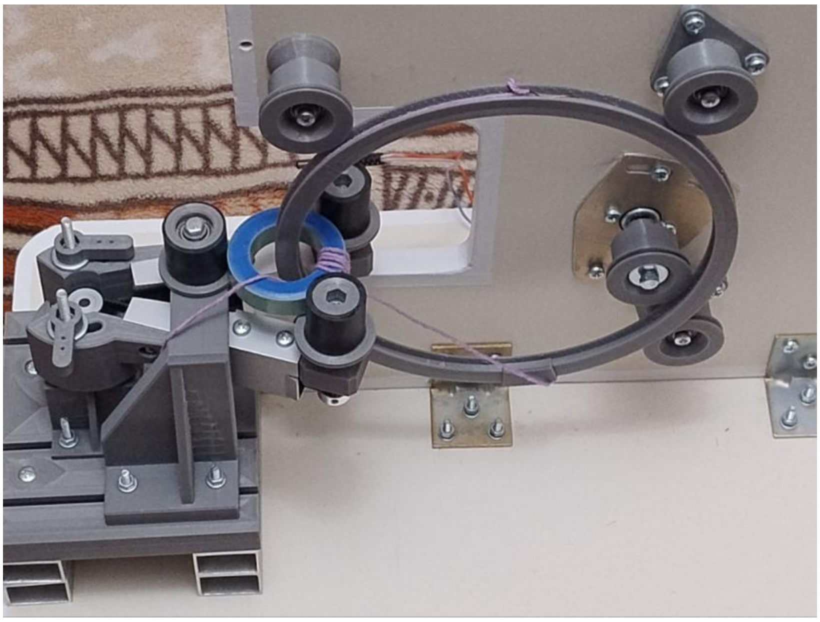


Fig. 2. Image of manufactured machine

Source: created by the authors.

Review of Recent Research and Publications. Recent studies in the field of artificial intelligence (AI) and its applications in transformer diagnostics demonstrate significant progress in improving the accuracy and automation of quality control. However, their focus remains limited with respect to real-time monitoring of the winding process for toroidal transformers, as evidenced by the following:

• In [5], deep learning (DL) techniques (CNN, RNN, Autoencoders, GAN) are described, achieving accuracies of 90–99% for multimodal data, but the emphasis is on IoT and medical applications rather than manufacturing, with noted dependence on GPU resources.

• In [9], the integration of Frequency Response Analysis (FRA) with ML/DL models (SVM, CNN, ANN) is investigated, achieving accuracies of 90–99 % in detecting winding defects (axial displacement, short circuits). The focus is on offline analysis, without adaptation for real-time application on winding machines.

• In [10], DL models (ResNet, AlexNet) are examined for visual inspection, with accuracies of 91–98 %, but without specific application to transformers or online monitoring.

• In [11], CNN-based approaches are proposed for inspecting cast products (accuracy up to 99%), yet they concentrate on offline analysis.

• In [12], traditional methods (88–91%), ML (92–94 %), and DL (up to 98 %) are compared for detection, but without emphasis on real-time operation or transformers.

• In [13], a comparison is presented between CNN-based AI models for defect detection and classification (87 %) in semiconductor manufacturing processes and traditional methods (77 %). However, there are no mentions of potential applications in the winding process of toroidal transformers.

The sources reviewed above provide the following examples of AI applications in electronics:

1. AI as an analyzer of data obtained from Frequency Response Analysis (FRA) diagnostics of transformers [9].
2. AI as a component for quality control of soldered components on PCB boards [10], [12].
3. AI as a classifier of defects during semiconductor manufacturing [13].
4. AI as a regulating element in quasi-resonant and switching converters [6].
5. AI as a classifier of defects in finished rapid-response radio stations [14].

In the first example, AI serves as a component of the transformer diagnostic process. Its task is to interpret data obtained from FRA testing of an assembled transformer. Specialized equipment designed for conducting and capturing the transformer's transient response is used as the data acquisition means (DAM).

In this example, AI does not participate directly in measuring characteristics, as time is required to obtain the complete transient response graph for subsequent analysis and interpretation. Here, AI operates in a post-processing mode. The implementation of AI demonstrated high accuracy—ranging from 90 % to 100 % in detecting and classifying defects—compared to 80–85 % accuracy achieved by traditional methods without AI. The best results were obtained using SVM (up to 100 %), ANN (up to 99.3 %), CNN (up to 98.27 %), and hybrid models with optimization (up to 99.75 %).

In the second example, AI is a component of the visual inspection process for defects in manufactured printed circuit boards. Its task is to identify incorrectly placed components on the board. A camera installed and configured on the production line conveyor serves as the DAM.

In this example, AI participates directly in measurement and defect detection, as the frame captured by the camera contains the entire defect and does not require prolonged measurements. This enables AI operation in real time. The introduction of AI in printed circuit board production increased defect detection accuracy to 99.5%, reduced inspection time from 20 to 5 seconds, and boosted production speed by 30%.

In the third example, AI is a component of the visual inspection process for the surface of manufactured semiconductors. Its task is to identify defects (see Fig. 3) on the semiconductor surface. A Scanning Electron Microscope (SEM), which provides high resolution, is used as the DAM for capturing the surface of the manufactured semiconductors.

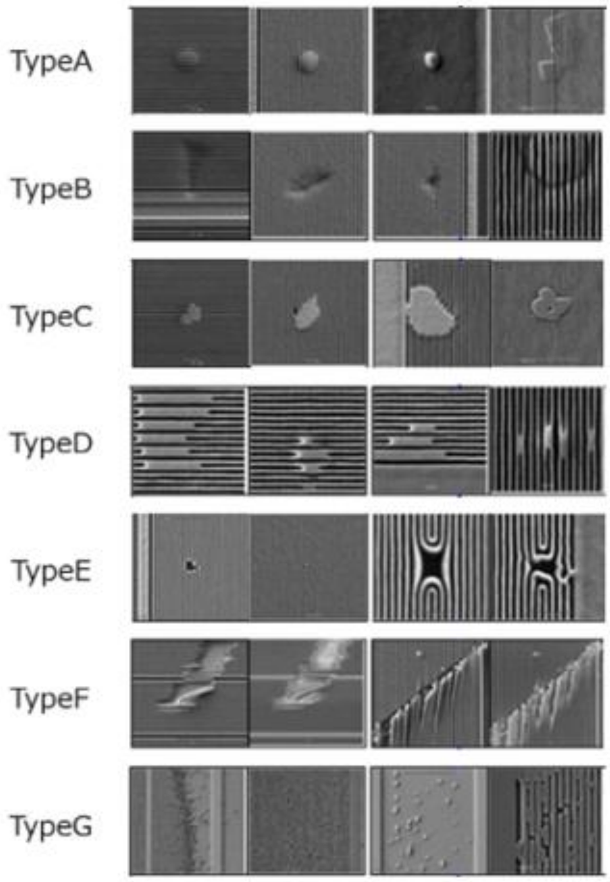


Fig. 3. Types of defects on the surface of semi-conductor [12]

In this example, AI participates directly in measurement and defect detection, as the frame obtained from the SEM contains the entire defect and does not require prolonged measurements. Here, AI operates in real-time mode. The implementation of CNN-based AI improved the average defect detection accuracy (87.26%) compared to traditional methods (77.23 %). It also reduced manual inspection labor costs by two-thirds relative to traditional approaches.

In the fourth example, the use of AI is proposed for controlling the energy conversion process in quasi-resonant and switching converters. Its task involves continuous and flexible monitoring of the system's control inputs to maintain the specified output voltage. Voltage and current transformers equipped with sensors, which generate voltage and current signals to provide data for the AI, are used as the data acquisition means (DAM).

In this example, AI directly participates in detecting deviations of output values from the setpoints, as the signals formed by the DAM clearly reflect discrepancies between actual and desired values. Here, AI operates in real-time mode. The implementation of AI is expected to enhance the device's energy efficiency, increase adaptability and robustness, and improve dynamic performance.

In the fifth example, AI is employed for visual inspection of finished rapid-response radio stations. Its task consists of the final product verification and detection of defects (e.g., misplaced buttons, missing labels). A system comprising multiple configured cameras, which provide images of the entire product surface, serves as the DAM.

In this example, AI directly participates in measurement and defect detection, as the frames obtained from the DAM contain the complete defect and do not require prolonged measurements. The introduction of AI reduced the time required for instrument evaluation from 30 seconds to 0.8 seconds. AI-based quality control systems achieve defect detection accuracy of up to 99 %, surpassing the human level of 80%. A pilot study on 1,000 units demonstrated payback on the investment within one month, owing to reduced inspection time and operator staffing.

Highlighting Previously Unresolved Aspects of the General Problem. The conducted analysis of key sources allows us to assess the current state of research and identify significant gaps that justify the necessity of the present study. In summary, the reviewed literature demonstrates that publications addressing transformer diagnostics are predominantly focused on post-production (offline) analysis, primarily using Frequency Response Analysis (FRA) combined with machine learning and deep learning methods [9]. No approaches have been proposed for implementing artificial intelligence directly during the toroidal transformer winding process on winding machines.

Other sources describe successful applications of AI in various manufacturing quality control processes (PCB inspection [10, 12], semiconductor surface defect detection [13], etc.), yet none of them mention or adapt these techniques specifically to the real-time monitoring of the toroidal transformer winding process.

Thus, to date, there are no ready-made artificial intelligence solutions adapted for real-time quality control during the winding of toroidal transformers on winding machines or suggestions on which artificial neural network to use. It is precisely this research gap that the present study aims to address.

Aim of the Article. The aim of this article is to examine variants of existing AI models for quality control of manufactured products and to assess their potential applicability to monitoring the winding process of toroidal transformers. It involves analyzing the advantages and disadvantages of each considered type. Additionally, key model parameters will be determined, such as prediction accuracy, computational load for inference, and model size. These parameters provide initial information regarding the capabilities of the selected AI model and enable forecasting of future training costs based on these values.

Relative metrics will be calculated, including the ratio of prediction accuracy to computational load and the ratio of prediction accuracy to model size. These metrics facilitate the selection of an appropriate model depending on available resources and time constraints.

Based on the obtained information about the AI models, variants of the most effective ones will be proposed for implementing quality control in the winding process of toroidal transformers.

Main Body. The overall analysis of the preceding examples revealed four main stages in the diagnostic process using a trained AI model, namely:

1. Preparatory stage – deployment of the DAM and the AI model takes place.
2. Measurement stage – initial data about the product are obtained using the DAM.
3. Information processing stage – the acquired initial data are transmitted to the AI for processing and interpretation. At this stage, the AI identifies the presence of defects for which it has been trained.
4. Completion stage – based on the AI's conclusions, appropriate measures are taken to correct the defect or dispose of the defective item.

Having analyzed the sources, all mentioned methods of information processing and defect detection were identified and systematized. Results of analysis and arrangement are shown in Table 1 and Table 2.

Table 1 – Learning based classifiers

Type of artifitial neural network	Examples
Feedforward	Multilayer Perceptron (MLP) Deep Belief Networks (DBN) Autoencoders
Convolutional neural network (CNN)	VGG-Net (Visual Geometry Group Network) ResNet (Residual Network) DenseNet EfficientNetB0
Object Detection	YOLO (You Only Look Once) SSD (Single Shot MultiBox Detector)
Transformers	Vision Transformer (ViT)
Recurrent neural networks (RNN)	Recurrent Neural Networks (RNN)
Hybrids	Deep Ensemble Learning

Source: created by the authors

Table 2 – Classical machine learning methods

Type of artifitial neural network	Examples
Core methods	Support Vector Machines (SVM) Support Vector Regression (SVR)
Tree type methods	Decision Trees Random Forest
Rule-based classifiers	Fuzzy Logic Control (FLC) Sliding Mode Control (SMC)

Source: created by the authors

To initially reduce the potential AI variants, only the types of AI models would be retained from the list of classifiers.

The next stage of reduction will be based on model size, as a larger model size results in longer training and inference times, as well as greater consumption of available resources and energy. It should be noted that, for comparison purposes, priority will be given to variations of AI models that process images of 224×224 pixels. In this case, the model architecture directly influences its size and performance speed.

The search results, based on data from sources [15], [16], are summarized in Table 3.

Table 3 – AI models sizes

Architecture	Input tensor size	Model size (MB)	Notes
Multilayer Perceptron (MLP)	224×224×3 = 150.528	Varying	Size depends on number of layers
Deep Belief Networks (DBN)	224×224×3 = 150.528	Varying	Size depends on number of layers
Autoencoders	224×224×3	Varying	Size depends on number of layers
VGG-16	224×224×3	528 [15]	138M parameters × 4 bytes = 552 МБ → ~528 МБ (optimized).
ResNet-50	224×224×3	98 [15]	25.6M × 4 = 102.4 → ~98 MB
ResNet-101	224×224×3	170 [15]	44.5M parameters.
DenseNet-121	224×224×3	31 [15]	8M parameters.
DenseNet-201	224×224×3	77.4 [15]	20M parameters
EfficientNetB0	224×224×3	20 [15]	5.3M parameters.
EfficientNetB7	600×600×3	253 [15]	66.3M parameters.
EfficientnetV2-s	384×384×3	82.7 [15]	21.5M parameters.
YOLOv8n (nano)	224×224×3	6.53 [16]	2.7M parameters. Has object detection version
YOLOv8l (large)	224×224×3	87 [16]	37.5M parameters. Has object detection version
YOLOv11l (large)	224×224×3	51.4 [16]	14.1M parameters. Has object detection version
SSD300 (with VGG-16 backbone)	300×300×3	136 [15]	35.6M parameters.
Vision Transformer (ViT-B/16)	224×224×3	330 [15]	86.5M parameters.
ViT-L/16	224×224×3	1100 [15]	304.3M parameters.

Source: created by the authors.

Models with a defined architecture and a size of less than 200 MB were selected. A predefined architecture saves time during training by eliminating the need for stages involving the adjustment of the number of layers or their dimensions, ensuring that the AI can effectively detect objects (defects) in images. A size limit of less than 200 MB simplifies the process of selecting the appropriate AI model by excluding excessively large models, thereby saving time on training in the future and retaining compact, high-performance models capable of operating in real-time mode on the machine.

For the next selection stage, initial accuracy and computational load values were identified for each model that met the previous criteria [15], [16]. These parameters help mitigate the influence of the deployment device's specifications on the AI model and provide a realistic representation of its capabilities.

The models were also divided into classifiers (those that determine what is depicted in the image) and detectors (those that identify the location of the target in the image). This distinction is justified by the possibility of implementing defect detection systems at different levels of complexity. For instance, if the system only needs to determine whether a defect is present in the image, it is advisable to use an AI classifier, as its objective is to categorize images into those containing a defect and those that do not.

If the system needs to determine whether a defect is present in the image while simultaneously indicating to the user the exact location of the detected defect, object detection models must be employed, as they are capable of marking the location of the defect in the image (most commonly with a bounding box).

The search results and classification are presented in Tables 4 and 5.

Table 4 – Accuracy and speed of AI classifier models

Architecture	Accuracy, %	Computational load, GFLOP/s	Size, MB
ResNet-50	80.9	4.1	98.0
ResNet-101	81.9	7.8	170.0
DenseNet-121	74.4	2.8	31.0
DenseNet-201	76.9	4.3	77.4
EfficientNetB0	77.7	0.4	20.0
EfficientNetV2-s	84.3	8.4	82.7
YOLOv8n	69.0	0.5	6.5
YOLOv8l	73.8	12.3	87.8
YOLOv11l	78.3	6.2	51.4

Source: created by the authors

Table 5 – Accuracy and speed of object detection models

Architecture	Accuracy, %	Computational load, GFLOP/s	Size, MB
YOLOv8n (nano)	37.3	8.7	6.5
YOLOv8s	52.9	165.2	87.8
YOLOv11l	53.4	86.9	51.4
SSD300 (with VGG-16 backbone)	25.1	34.9	136.0

Source: created by the authors

For the final step in model selection, in addition to the established prediction accuracy, relative metrics were calculated: the ratio of prediction accuracy to computational load and the ratio of prediction accuracy to model size. These metrics indicate the amount of resources utilized to achieve 1% of the model's accuracy; the higher the value of this metric, the more efficient the AI model.

The formulas for calculating these metrics are presented as (1) and (2).

$$P_{load} = \frac{A_{acc}}{R_{load}}, \quad (1)$$

where:

P_{load} – ratio of prediction accuracy to computational load (s);
A_{acc} – prediction accuracy (%);
R_{load} – computational load (1/s).

$$P_{size} = \frac{A_{acc}}{N_{size}}, \quad (2)$$

where:

P_{size} –ratio of prediction accuracy to model size (MB^{-1});
A_{acc} – prediction accuracy (%);
N_{size} – model size (MB).

The results of the searches and calculations are given in Table 6 and Table 7.

Table 6 – Efficiency of classification AI models

Architecture	Accuracy, %	P_{load}, s	P_{size}, MB^{-1}
EfficientnetV2-s	84.2	10.1	1.0185
ResNet-101	81.9	10.5	0.4817
ResNet-50	80.9	19.8	0.8251
YOLOv11l	78.3	12.6	1.5233
EfficientNetB0	77.7	199.2	3.8846
DenseNet-201	76.9	17.9	0.9935
DenseNet-121	74.4	26.3	2.4011
YOLOv8l	73.8	6.0	0.8405
YOLOv8n	69.0	138.0	10.5666

Source: created by the authors.

Table 7 – Efficiency of object detection AI models

Architecture	Accuracy, %	P_{load} , s	P_{size} , MB^{-1}
YOLOv11l	53.4	0.61	1.0389
YOLOv8s	52.9	0.32	0.6025
YOLOv8n (nano)	37.3	4.29	5.7120
SSD300 (with VGG-16 backbone)	25.1	0.72	0.1846

Source: created by the authors.

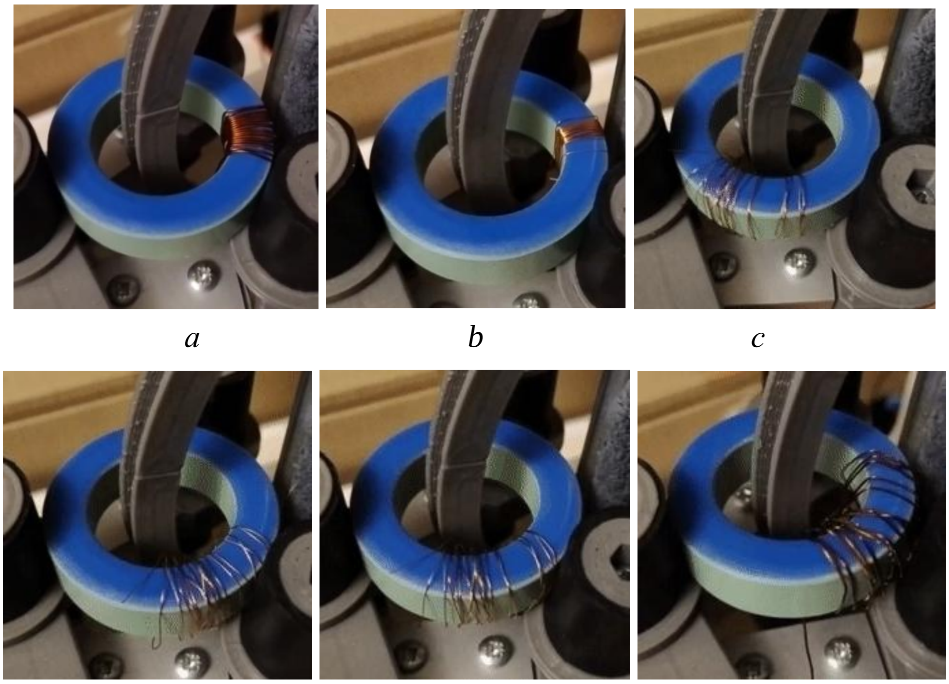
As a result of the analysis, two AI models were selected for each category: image classification and object detection. The first model in each pair prioritizes maximum prediction accuracy, with only minor differences in metrics compared to other models. The second serves as a backup, emphasizing maximum resource efficiency in case the primary model proves to be too demanding.

For image classification, it is advisable to use the EfficientNetV2-S model, as it achieves the highest prediction accuracy while being more efficient than ResNet-101, the next most accurate model. As a backup option, EfficientNetB0 is recommended, given its moderate accuracy among the considered AI models and its superior resource efficiency.

For object detection in images, the YOLOv11l model is recommended, as it offers higher accuracy and greater resource efficiency than YOLOv8s, the next most accurate model. As a backup, YOLOv8n is appropriate, as it provides the best optimization, although its accuracy is significantly lower.

The objective of training the selected AI model is to enable clear identification of four types of defects (gap, protrusion, conductor break, and conductor crossover). To achieve this objective, a specialized dataset was created containing images with clearly expressed defects. Examples of correct conductor winding and examples of defects are shown in Fig. 4.

A dataset containing correctly classified images with clearly expressed defects enables the training of an AI model capable of accurately and precisely classifying the specified types.



a *b* *c*

d *e* *f*

Fig. 4. Examples of winding:

a, b – correct conductor winding; c– defects conductor break;
d – defects conductor crossover; e – defects gap; f – defects protrusion

Source: created by the authors.

Experience with AI applications has shown a trend whereby the larger the dataset, the more accurate the trained AI model becomes. However, manually creating and classifying a large volume of data is highly time-consuming. Therefore, to artificially increase the dataset size, data augmentation algorithms are employed [17], [18]. Their operating principle involves applying various transformation methods to existing images (geometric transformations, color adjustments, sharpness modifications, random erasing, etc.) and saving the results of these transformations as new classified data. Examples of these transformations are illustrated in Fig. 5.

Fig. 5. Examples of data augmentation

Source: created by the authors.

Conclutions. The systematic analysis of contemporary research in the application of artificial intelligence for quality control of electronic products and transformer diagnostics has revealed that, to date, there are no ready-made AI solutions adapted for real-time monitoring of the winding process in toroidal transformers.

A comparative analysis of more than 25 neural network architectures (convolutional, transformer-based, object detectors, and classical methods) was conducted based on four key criteria: model size (≤ 200 MB), classification/detection accuracy, computational load, and relative efficiency (accuracy-to-load ratio and accuracy-to-size ratio).

Based on the analysis and calculations, the most promising models for implementation on cost-effective embedded platforms such as Raspberry Pi 5 or STM32 + NPU (Neural Processing Unit) were identified as follows:

• for classifying the presence of winding defects — EfficientNetV2-S (highest accuracy with acceptable resource requirements);

• for localizing and marking defects — YOLOv11l (optimal accuracy-to-performance ratio);

• as lightweight backup options — EfficientNetB0 and YOLOv8n, for classification and localization of defects, respectively.

A four-stage scheme for integrating AI into the quality control system for toroidal transformer winding was defined (preparatory, measurement, information processing, and completion stages), which enables real-time operation and minimizes the influence of the human factor.

The obtained results provide a scientifically substantiated foundation for the further practical implementation of intelligent quality control systems for toroidal core winding in laboratory, educational, and small-scale production environments.

In the future, it will be necessary to perform fine-tuning of the selected models and to carry out hardware implementation of the system on a winding machine.

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МОДЕЛІ ШТУЧНОГО ІНТЕЛЕКТУ ДЛЯ КОНТРОЛЮ ЯКОСТІ НАМОТУВАННЯ ТОРОЇДНИХ ТРАНСФОРМАТОРІВ

Вплив штучного інтелекту (ШІ) у сучасній промисловості стрімко зростає. З 2017 по 2025 рік частка компаній, що використовують ШІ, зросла з 20% до 78%. Попит на аналітичний ШІ у виробництві збільшується для точного контролю процесів, тоді як генеративний ШІ застосовується переважно на початкових етапах (лише 4% виробничих компаній). Це підтверджує актуальність застосування ШІ для контролю якості у виробництві, зокрема намотування тороїдних трансформаторів, для зменшення впливу людського фактора та підвищення точності моніторингу.

Контроль якості намотування тороїдних трансформаторів залишається ключовою проблемою, що впливає на надійність виробів. Точність залежить від систем моніторингу, людського фактора, параметрів намотування та якості кінцевого виробу. Цілі: контроль у реальному часі, збільшення кількості параметрів та виявлення складних дефектів. Інтеграція ШІ у намотувальні верстати (як у розробленому авторами прототипі) дозволяє вчасно виявляти дефекти, підвищувати адаптивність процесу та зменшувати брак без зупинки виробництва.

Дослідження демонструють прогрес ШІ у діагностиці трансформаторів та виявленні дефектів (точність 90–99% за допомогою CNN, SVM тощо), але фокус на offline пост-виробничому аналізі (FRA, інспекція PCB, напівпровідники). Відсутні рішення для моніторингу у реальному часі під час намотування тороїдних трансформаторів, що вказує на прогалину.

В статті розглянути існуючі моделі ШІ, оцінити їх придатність для контролю якості намотування тороїдних трансформаторів, проаналізувати переваги/недоліки, ключові параметри (точність, навантаження, розмір) та відносну ефективність, запропонувати оптимальні варіанти для впровадження.

Приклади застосування ШІ в електроніці: аналіз даних FRA, виявлення дефектів на PCB (99,5% точність, реальний час), інспекція напівпровідників (87% точність) та керування перетворювачами. Визначено чотириетапну схему інтеграції ШІ: підготовчий, вимірювальний, обробки та завершальний. Проаналізовано понад 25 архітектур нейронних мереж за розміром, точністю, навантаженням та ефективністю. Відібрано: EfficientNetV2-S та YOLOv11l як основні (класифікація/детекція); EfficientNetB0 та YOLOv8n як легкі резервні. Створено датасет з чотирма типами дефектів (зазор, протрузія, обрив, перехрещення), доповнений для тренування.

Готові рішення ШІ для контролю намотування тороїдних трансформаторів у реальному часі відсутні. Аналіз виділяє перспективні моделі для вбудованих платформ (Raspberry Pi 5, STM32+NPU). Пропонована схема мінімізує людський фактор. Результати створюють базу для інтелектуальних систем у лабораторному та малосерійному виробництві. Подальше дослідження: тонке навчання моделей та апаратна реалізація.

Ключові слова: *штучний інтелект; контроль якості; намотування тороїдальних трансформаторів; згорткові нейронні мережі; EfficientNet; YOLO; реальний час; вбудовані системи.*

Рис.: 5. Табл.: 7. Бібл.: 18.

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