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AREAS OF APPLICATION OF THE YOLOV8 DEEP LEARNING MODEL IN NON-DESTRUCTIVE TESTING

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Deep neural networks are highly capable of accurately detecting objects in images. They can even detect complex objects and perform detailed image segmentation, making them ideal for detecting anomalies or defects on the surface of objects during non-destructive testing. This is especially true for automating NDT methods that use image processing to capture detailed images of objects and analyse the data to detect defects. The use of deep learning models simplifies the inspection process, reduces labour and time costs, and helps to avoid human error.

YOLO (You Only Look Once) is one of the most well-known deep learning architectures for object detection in images and videos. The basic idea behind YOLO is to use a single network that simultaneously predicts rectangular frames and identifies classes of objects within those frames. The main advantage of YOLO is its speed, as the network performs object detection for the entire image at once, while other methods can consider each image area separately [1].

YOLO uses a main unit with fully connected layers, which has a parallel structure. This allows the network to make predictions at different image scales. In addition, YOLO uses downsampling layers to help increase computational speed and improve forecast accuracy. The overall YOLO architecture is efficient and fast, making it one of the most popular architectures for reliable real-time object detection [2].

The basic YOLO architecture has a large number of modifications. YOLOv8 is the latest iteration of the YOLO series of real-time object detectors, demonstrating the highest accuracy and performance [3]. Building on the achievements of previous versions, YOLOv8 offers new features and optimisations that make it an effective tool for solving object detection problems in a wide range of applications.

With a focus on the optimal balance between accuracy and speed, YOLOv8 is suitable for real-time object detection applications in non-destructive testing. The YOLOv8 series offers a diverse set of models, each specialised in solving specific computer vision tasks. These models are designed to meet a variety of requirements, ranging from object detection to more complex tasks such as object segmentation, position or key point detection, object orientation detection and classification.

Let us consider some examples of the successful application of the YOLOv8 network in the tasks of automating image processing in non-destructive testing. In [4], it is noted that quality assurance in additive metal manufacturing is gaining increasing recognition from scientists and industry due to its obvious advantages over traditional manufacturing methods. In this paper, authors present a method for using the YOLOv8 convolutional neural network to reliably check the quality of

metallographic images. Metallographic images contain key information about metal properties, such as structural strength, ductility, toughness, and defects.

Image segmentation based on deep learning is a reliable method for detecting microstructural defects such as cracks, inclusions, and gas porosity. Therefore, the authors propose to use the YOLOv8 model with advanced convolution mechanisms to automatically segment microstructural defects in metallographic images. In particular, for the first time, the YOLOv8 algorithm was applied to a set of metallographic data from additive manufacturing of steels to detect defects such as cracks and porosity.

The authors used 414 images from the engineering company ArcelorMittal as a training dataset. The experimental results demonstrated that the YOLOv8 model successfully detected and identified cracks and porosity in the dataset, achieving a 96 % defect detection accuracy in just 0.5 hours. According to the authors, this is an improved result compared to other existing automated defect detection methods.

It is known that the surface condition is an effective indicator for assessing the quality of industrial products. Work [5] indicates that traditional methods of automated defect detection, such as eddy current, and thermal and magnetic particle inspection, are limited to certain environments and cannot achieve satisfactory accuracy. A new and promising method is deep learning-based flaw detection. The YOLO algorithm, which is based on the analysis of visual information, is considered promising.

However, due to the complex real-world industrial environment, the direct use of existing methods still has certain limitations. To solve this problem, the authors propose an improved YOLOv8 algorithm to solve the problem of surface defect detection on aluminium plates. In this work, the authors replace the basic network loss function, which allows for a better measurement of the similarity between small defects and irregularly shaped defects, thereby improving the detection accuracy. Experimental results show a clear improvement in defect detection, with the average accuracy increasing from 98.1 % to 99.3 %. Moreover, the detection performance is superior to previous modifications of YOLO and other similar models.

The use of non-destructive testing methods is also relevant in the agricultural sector, which accounts for a large share of Ukraine's economy. This issue is addressed in [6]. As stated in the paper, current research on image recognition and detection of internal cracks in corn seeds primarily relies on visible light images.

This paper presents a method based on the use of soft X-rays that successfully detect cracks inside corn seeds using the optimised YOLOv8 model. This model effectively solves the problems associated with the limited light transmission of maize seeds, the complexity of crack localisation and the problems of algorithm generalisation. The optimised YOLOv8 model demonstrates a 3.1 % increase in the average accuracy compared to the original modification. The proposed method demonstrates an average recognition accuracy of 99.66% for undamaged and damaged seeds, and the average processing time for one image frame was 7.49 ms.

The study [7] considers the problems of non-destructive detection of diseased apples. In particular, the high complexity and low real-time performance of a machine learning model for detecting diseased fruit in apple sorting was noted. The authors investigated an improved apple defect recognition model and proposed an improved method based on the YOLOv8 network. The proposed model reduces both the network complexity and the number of parameters and uses an advanced activation function to improve the model's ability to handle nonlinear dependencies. The network uses a lightweight Efficient-Neck structure, developed using lightweight modules and supplemented with a channel shuffling strategy. Experimental results show that the improved model outperforms the baseline YOLOv8 model, achieving a 2.7 % increase in average accuracy and 8.5 % improvement in output speed. This technology offers a new, efficient method for non-destructive detection of diseased fruit during apple sorting operations.

Thus, the use of deep learning models for detecting objects in images in non-destructive testing has great potential to improve the inspection process, reduce costs, and increase production quality and safety. Deep neural networks, in particular the YOLOv8 model, demonstrate high performance in detecting objects in images in real-time, making them useful for automating image processing in non-destructive testing. The use of YOLOv8 has proven to be effective in both manufacturing and agriculture. The optimised YOLOv8 model provides increased accuracy and speed of defect detection, which helps to improve product quality and optimise production processes. The use of modern machine learning methods for non-destructive testing confirms the relevance of artificial intelligence technologies in industry and agriculture.

Keywords: non-destructive testing, deep learning, object detection.

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MEDICAL THERMAL IMAGING DIAGNOSTICS: CURRENT PROBLEMS AND SURGICAL APPLICATION

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The application of thermal imaging cameras proves to be a highly effective method for screening patients to detect inflammatory processes in the early stages of diseases. Presently, criteria for thermal imaging diagnostics cover over two hundred diseases and conditions, with continual updates to this expanding list.

Different parts of the human body exhibit distinct normal average temperatures due to variations in blood supply and innervation. While surface temperatures of symmetrical sections in the same areas typically do not vary significantly, using the opposite symmetrical region as a control site can aid in identifying pathologies [1].

Medical thermography is increasingly prevalent in multidisciplinary medical facilities, necessitating thermographers to work under variable environmental conditions. This underscores the need for medical personnel to possess a high level of expertise and adaptability to external factors, as well as patients' incomplete thermal adaptation during the diagnostic process [2]. Enhancing the information content and aligning taken indicators with the actual surface temperature of the observed object remains a critical focus. The accuracy of diagnoses relies heavily on the correct interpretation of thermograms, achievable only with clear, high-quality images obtained under specific operational conditions and considering environmental influences on thermography camera design [3]. These tasks are tackled using computer automated systems [4]. Modern systems deliver optimal outcomes by integrating artificial intelligence technologies. The reduction in computational expenses and the effectiveness of contemporary large neural networks allow for their utilization in addressing a broad spectrum of pertinent medical diagnostic tasks.

Currently, thermography diagnostics are applied in diverse medical fields such as oncology, mammalogy, otorhinolaryngology, cardiac surgery, forensic examinations, and others. In cardiac surgeries, addressing ischemic myocardial damage is crucial due to the absence of normal coronary perfusion during aorta clamping. Employing infrared cameras for precise temperature distribution control offers innovative approaches, providing detailed temperature mapping across the entire heart surface.

During hypothermia and hyperthermia under cardiopulmonary bypass, temperature fluctuations on the myocardial surface in the study area are clearly identified. Controlled cooling and heating of brain and heart tissues aim to minimize