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APPLICATION OF NEURAL NETWORKS FOR DETECTING DEFECTS AND DAMAGE IN METAL STRUCTURES

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Abstract. The rapid development of neural networks has led to the integration of these technologies into various industrial sectors. At the same time, improving the accuracy and efficiency of detecting defects and damages, including in real-time, remains a critical task. By combining neural networks with the Internet of Things (IoT) and technologies for data collection, storage and protection, it is possible to create a comprehensive and effective information-measurement system for surface defect detection. In this context, the present work highlights recent advances in the application of artificial intelligence for quality control, as well as the detection of defects and damages in structures. The focus is on the development and training of neural networks capable of effectively identifying and classifying various types of defects. The study demonstrates how these technologies significantly improve the speed and accuracy of diagnostics compared to traditional visual and instrumental inspection methods. The results of model testing on real industrial data confirm the high efficiency of the proposed approach. Additionally, the authors have developed an algorithm and implemented software for the automatic annotation of images in a format suitable for modern architectures such as YOLO. This approach enables the effective application of the model for detecting damages on the surfaces of structures and systems using widely available types of datasets.

Keywords: defect detection, neural networks, YOLO architecture, structural integrity monitoring, infrared thermography, automated defect analysis, machine learning for defectoscopy

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ПРИМЕНЕНИЕ НЕЙРОННЫХ СЕТЕЙ ДЛЯ ВЫЯВЛЕНИЯ ДЕФЕКТОВ И ПОВРЕЖДЕНИЙ МЕТАЛЛИЧЕСКИХ КОНСТРУКЦИЙ

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Аннотация. Бурное развитие нейронных сетей привело к интеграции этих технологий в различные отрасли промышленности. В то же время повышение точности и эффективности выявления дефектов и повреждений, в том числе в реальном времени, остается актуальной задачей. Комбинируя нейронные сети с Интернетом вещей (IoT), а также технологиями сбора, хранения и защиты данных, возможно создать комплексную и эффективную информационно-измерительную систему для обнаружения поверхностных дефектов. В этом контексте данная работа освещает современные достижения в применении искусственного интеллекта для контроля качества, а также выявления дефектов и повреждений в конструкциях. Основное внимание уделяется разработке и обучению нейронных сетей, способных эффективно идентифицировать и классифицировать различные типы дефектов. Исследование демонстрирует, как эти технологии значительно повышают скорость и точность диагностики по сравнению с традиционными методами визуального и инструментального контроля. Результаты тестирования моделей на реальных промышленных данных подтверждают высокую эффективность предложенного подхода. Кроме того, авторами разработан алгоритм и реализовано программное обеспечение для автоматической аннотации изображений в формате, подходящем для современных архитектур, таких как YOLO. Данный подход позволяет эффективно применять модель для обнаружения повреждений на поверхностях конструкций и систем, используя широкодоступные типы наборов данных.

Ключевые слова: обнаружение дефектов, нейронные сети, архитектура YOLO, мониторинг целостности конструкций, инфракрасная термография, автоматизированный анализ дефектов, машинное обучение для дефектоскопии

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Introduction

In the design and operation of engineering products, special attention is given to methods for detecting macrocrack-type defects in critical structural elements, as these significantly impact the reliability and lifespan of complex technical systems. This is particularly relevant for structures operating under variable loads in aviation, railway and automotive transport, such as bridge structures, road surfaces etc.

Defects of this type can occur on the surfaces of load-bearing structural elements and lead to product failures with potentially catastrophic consequences, especially in aviation. The causes of surface defects include both objective factors, such as structural heterogeneity of construction materials, maximum surface stresses during deformation and characteristics of surface material layers, and subjective factors, including deviations in the shape and dimensions of products, dents, scratches, other manufacturing defects and operational errors like hard aircraft landings.

The development and creation of artificial intelligence (AI) devices and systems aimed at addressing this problem is a highly relevant task. A critical requirement in this process is the transformation of raw photo and video data obtained from devices into annotated data structures suitable for processing by neural networks (NNs).

In this work, the authors have developed an information-measurement system for detecting surface defects. This includes the design and software implementation of an algorithm for automatic annotation of images into a format compatible with the state-of-the-art YOLO architecture. The algorithm processes widely used dataset types, such as run length encoded (RLE) masks on images. This solution enables the application of the model for efficient defectoscopic inspection of engineering structures and products.

Before implementation, it is essential to examine existing approaches and solutions for detecting defects in metal structures. The study [1] explores intriguing NN training methods based on various YOLO versions and other types of NNs. It also evaluates multiple methods for assessing detection efficiency across different spectra. The results demonstrate that for visible spectrum, the most effective methods are: GVN, HOG + SVM, SSD, GrabCut, cascading CNN, LBPHF + SVM, DMNN, VGG-19, LBP + ULBP, YOLO v3, DELM + LRF, SVM, Faster R-CNN, CNN, stereovision + PLAMEC. The most significant achievement was solving the key issue of inspecting power line structures (PLS) using unmanned aerial vehicles (UAV) by introducing mobility and flexibility to the process, enabling effective investigation of hard-to-reach areas.

The study [2] outlines the primary shortcomings and causes of defects in massive metal structures. It further demonstrates how infrared thermography provides a clear assessment of technical conditions, which is critical for the safe operation of structures. Infrared thermography is based on surface temperature monitoring using thermal imaging in the infrared range. Unfortunately, a suitable sensor for these studies has not yet been identified, making this method currently impractical.

In the study [3], a fiber-optic sensor was utilized to evaluate load on load-bearing elements of bridge structures. The sensor's key feature is its use of Bragg gratings and an interrogator, allowing precise measurement of relative deformation and temperature. While this method is excellent for continuous monitoring and structural reinforcement, it is not suitable for emergency integrity assessments of bridge structures.

Method

NNs and defect detection

NNs, particularly convolutional NNs (CNNs), have proven highly effective in image classification and detection tasks. In the context of structural analysis, NNs can process images and videos captured by drones or stationary cameras, automatically identifying signs of damage, such as cracks, corrosion, deformations and other defects.

YOLO (You Only Look Once) – a NN architecture designed for object detection in images [4–8].

The YOLO model employs a fully CNN that predicts bounding boxes and object classes in a single process. The input image is divided into a grid, with each grid cell predicting:

- the bounding box;
- the confidence that the bounding box contains an object;
- the probabilities of the object's belonging to specific class.

CNNs can extract and interpret complex visual features, making them an effective tool for automatic detection of defects on the surface of structures [9–14].

AI-based methods enhance defect detection across various domains. Studies have improved PCB inspection using YOLO v8 and AOI technology [15, 16]. A hybrid AI approach has been proposed for defect control [17]. Deep learning aids material classification and real-time road defect detection [18, 19].

CNN architecture

The architecture of CNNs includes several key components, each of which plays a crucial role in image analysis:

- **Convolutional layers.** These layers apply filters to the input images, extracting important features such as edges, corners and textures. For example, in the context of bridge diagnostics, convolutional layers can identify cracks, signs of corrosion and other defects.
- **Activation function.** Rectified Linear Unit (ReLU) adds non-linearity to the model, allowing it to learn more complex and abstract features of the images.
- **Pooling layers.** These layers reduce the dimensionality of feature maps while preserving the most significant information. This helps decrease the amount of data to process and makes the model less sensitive to the exact location of features.
- **Fully connected layers.** These layers combine the extracted features and use them for classification or regression, allowing the determination of the extent and type of damage in the bridge structure.

CNN-based models, particularly YOLO, have significantly advanced defect detection across industries. Studies highlight improvements in solar panel and metal surface inspection [20–22], road defect segmentation [23] and steel strip analysis [24]. The evolution from YOLO v1 to YOLO v8 further enhances CNN-driven industrial defect detection [25].

Problem of data heterogeneity

Different research groups and companies use various datasets to train their models. This can make it difficult to apply existing data for training a new NN. Different projects may require different NNs, each with specific data and annotation requirements for training. In such cases, data transformation mechanisms can be used, but in some situations, finding an acceptable solution may not be possible. For example, an RLE dataset is not directly compatible with the YOLO NN.

In this work, the authors have developed a data converter from RLE format to a format compatible with YOLO[1] [26]. RLE is a mask on the image that can label an object of any shape or type, but YOLO requires the coordinates of the top-left and bottom-right corners of a rectangle containing the object. In Fig. 1, on the right, the yellow-purple image is the mask on the picture, provided from the training data set of Severstal[2] [27, 28], while on the left is the original photo from Severstal's dataset, to which the authors applied the developed program that determines the coordinates of the defect marking squares for use in the YOLO NN.

YOLO accepts annotations in the form of a separate file with coordinates in the format: <class_label> <x_center> <y_center> <width> <height>. In the original Severstal dataset, defect annotations (labels) are stored in a separate .csv file as a string containing the pixel number and the count of subsequent pixels. As a result of applying the program developed by the authors, by referencing the image mask and using the cv2 library[3], with the parameters "CV_RETR_EXTERNAL" and "CV_CHAIN_APPROX_SIMPLE", we obtain the contours of adjacent mask pixels.

The mask (on the right in Fig. 1) is a new layer overlaid on the original image, showing only the damaged area (yellow) and the image area (purple).

[1] See the guide on working with YOLO in Python on the website https://docs.ultralytics.com/ru/usage/python and the source code together with instructions for running the software implementation by the authors of automatic image annotation for YOLO on the website https://github.com/Nosikmov/Kaggle-Dataset-to-YOLO.

[2] The dataset of images and defect annotations of Severstal steel sheets: https://www.kaggle.com/competitions/severstal-steel-defect-detection/data, a software implementation of defect detection on steel sheets using convolutional neural networks by a prizewinner of competitions on the Kaggle platform: https://www.kaggle.com/code/lightforever/severstal-mlcomp-catalyst-infer-0-90672.

[3] An open-source library for computer vision, machine learning, and image processing; for details see https://docs.opencv.org/4.x/d1/dfb/intro.html.

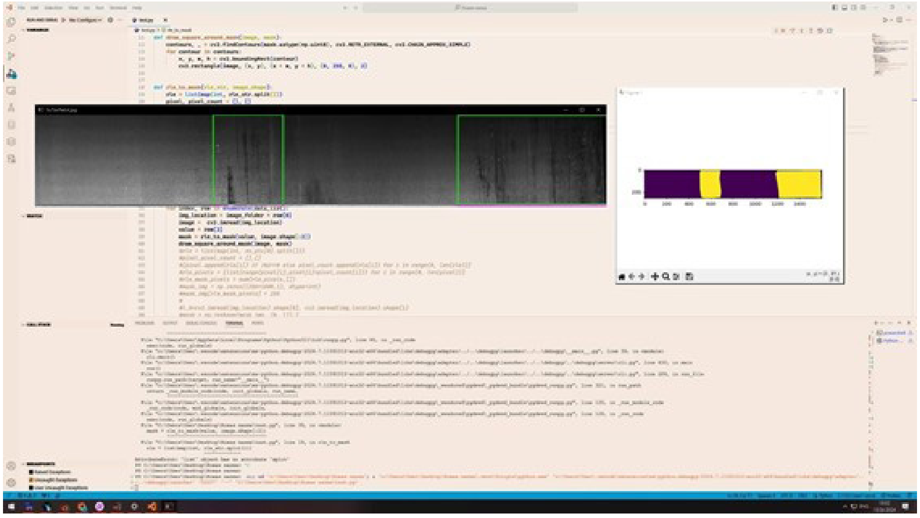

Fig. 1. The result of the data preparation program for training the YOLO v8 model

The contours (on the left in Fig. 1, green) represent the edges of the damage area in the mask. Since the damage area can have an arbitrary shape and YOLO works with rectangles, it is necessary to find the edges of the damage area in the mask to obtain the bounding rectangle.

Adjacent contour pixels are first converted into lines, using the pixel coordinates and their count in the line. If the lines are located next to each other, they are considered adjacent, and in this case, they need to be grouped into a single bounding rectangle annotation for YOLO.

The obtained contours can be converted into values suitable for the YOLO annotation format. Since the annotation requires rectangle coordinates, it is necessary to determine the center of the rectangle by averaging the corresponding values. The width and height of the rectangle are calculated as the difference between the relevant coordinates. The center, width and height are then normalized by dividing by the image dimensions. This process forms a defect annotation string, which is compatible with YOLO[4] (Figs. 2, 3).

An example of the result from the trained model on the converted data is shown in Fig. 4.

Advantages of CNN

- **Superior processing of visual data.** CNNs are capable of identifying complex visual patterns, which is especially important for detecting cracks and other structural anomalies in images and videos.
- **Generalization to new data.** After training on a large dataset, CNNs can successfully apply their knowledge to new, previously unseen images, providing high accuracy under various conditions.
- **Automation.** The use of CNNs for structural monitoring reduces the need for frequent physical inspections, which lowers costs and enhances safety.

Recent advancements in CNN-based YOLO models have significantly improved defect detection across multiple domains. Enhanced architectures have been applied to surface, packaging and PCB defect detection [29–32], as well as to steel, weld and pavement inspections [33–35]. Additionally, specialized adaptations have optimized insulator defect analysis [36].

Training NNs

To achieve high accuracy in defect detection, NNs must be trained on large datasets containing images of various types of defects. These datasets were sourced from open datasets. It is important to ensure the protection of training data using modern encryption methods and blockchain technologies, which guarantee the integrity and security of the data.

[4] See https://github.com/Nosikmov/Kaggle-Dataset-to-YOLO for details on how to transform the Severstal dataset into a suitable dataset for YOLO.

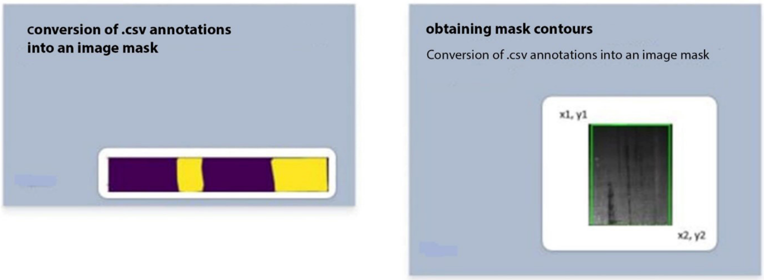

Fig. 2. Process of programmatically converting defect annotations into YOLO format

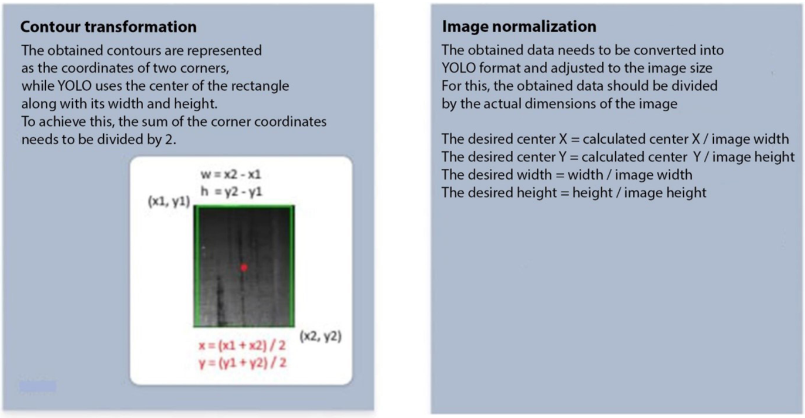

Fig. 3. Obtained data needs to be converted into YOLO format and adjusted to the image size, therefore, it should be divided by the actual dimensions of the image

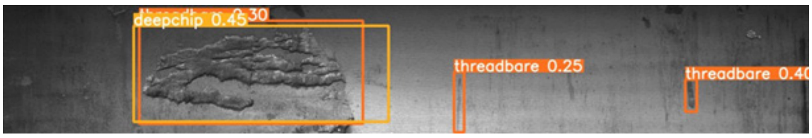

Fig. 4. Results of the YOLO model evaluation

Application of IoT for data collection

The Internet of Things (IoT) devices, such as vibration, temperature and deformation sensors, are installed on bridge structures for continuous monitoring of their condition. These sensors transmit real-time data to servers or cloud platforms, where it is analyzed by NNs to detect anomalies and assess risk.

Sensor types

- Vibration sensors detect changes in vibrations caused by cracks or other structural alterations.
- Strain sensors detect changes in shape or deformation of structural elements.
- Thermal sensors monitor temperature changes that may indicate internal issues, such as material strength degradation.
- Acoustic sensors are used to detect sounds caused by cracks or delaminations in the material.

Dash cameras, road cameras, drones

Modern technologies provide a variety of tools for monitoring road surface conditions. Among them, road cameras, dash cameras and drones stand out. These devices enable the collection of visual information about the roads, which helps improve their condition and enhance road traffic safety.

The use of drones to capture images of road surfaces offers several advantages, including the ability to inspect hard-to-reach sections of roads.

Dash cameras are installed in vehicles and record the road conditions in real time.

Advantages of IoT are as follows:

- **Continuous monitoring**: Continuous data collection allows for quick response to changes in the condition of the structure.
- **Process automation**: The exclusion of the human factor from the data collection process reduces the likelihood of errors.
- **Wide availability**: IoT devices can be installed even in hard-to-reach places, providing more comprehensive monitoring coverage.

Mobile devices for data collection and analysis

Mobile devices, such as smartphones and tablets, can be used to collect data from sensors and cameras, as well as for preliminary processing. With specialized applications, primary diagnostics of the condition of structures can be performed and data can be transmitted to central servers, utilizing blockchain technologies for more detailed analysis by NNs.

Advantages of mobile devices are as follows:

- **Convenience of use**: Mobile devices are always at hand and allow for quick collection of the necessary information.
- **Mobility**: The ability to work anywhere and anytime.
- **Interactivity**: Applications can provide users with instant feedback and recommendations.

Blockchain

Blockchain is a distributed ledger in which data is stored in the form of a chain of blocks. Each record is protected by cryptographic methods and is linked to previous records, which prevents unauthorized data alteration.

Key features of blockchain technologies are as follows:

- **Data integrity**: The data recorded in the blockchain cannot be altered without a corresponding entry in the blockchain, which prevents falsification.
- **Transparency**: Each participant in the network can verify the authenticity of the data, which increases trust in the system.
- **Security**: The use of cryptography protects data from unauthorized access.
- **Decentralization**: The absence of a central controlling authority eliminates single points of failure and enhances the system's resilience.

Let us consider the process of integrating blockchain technologies to ensure the reliability of data storage used for training NNs, using the example of bridge structure monitoring.

- **Data collection**: IoT sensors installed on bridges collect data on the condition of the structures, such as vibrations, deformations and temperature changes.
- **Data recording in blockchain**: The collected data is sent to the blockchain, where it is recorded as immutable blocks. Each block contains the hash of the previous block, creating a data chain.
- **Data analysis**: NNs access the data from the blockchain for analysis and model training. Due to the high reliability and integrity of the data, NNs are trained more accurately and efficiently.
- **Monitoring and updating**: Data is continuously updated and added to the blockchain, ensuring the relevance of the information for analysis and decision-making.

Example of usage

Let us assume that vibration sensors on the bridge detect anomalies that could indicate the beginning of a crack. The vibration data is recorded in the blockchain, where it can be verified and analyzed by NNs to determine the severity of the defect and the need for repair.

Data collection from satellites

Satellites equipped with high-resolution cameras regularly capture Earth's surfaces, including road networks. These images cover large areas and provide up-to-date information.

Defect detection from defectogram images

NNs can be trained using images from defectograms, which are graphical representations of structural defects. Such images can be obtained through various non-destructive testing methods, such as ultrasonic, radiographic and thermographic diagnostics.

Deep CNNs (DCNNs) play a crucial role in defect detection across multiple domains. Advanced models enhance glass insulator inspection and electron microscopy diagnostics [37, 38], while DCNN-based approaches improve defect identification in industrial manufacturing [39–41]. Additionally, NNs optimize defect depth estimation and automated surface analysis [42–44].

Process of image analysis

- **Image collection**: Defectograms are collected from various diagnostic methods.
- **Preprocessing**: The images are processed to improve quality and remove noise.
- **Model training**: The NN is trained on pre-labeled images, where the types and locations of defects are marked.
- **Analysis and detection**: The trained model analyzes new images and identifies defects, specifying their type and location.

In the context of the study, the following NNs were used:

- NNs trained for crack and defect recognition in steel;
- NNs trained for tuberculosis detection from fluorography images.
- The YOLO NN designed for fast and accurate detection and classification of objects in real-time image processing.

These networks were retrained to recognize cracks and defects on bridges using specialized datasets with images of bridge structure damage.

For training the NNs, datasets containing images of various bridge damages were used, including cracks, corrosion, deformations and other defects, as well as images from dash cameras and road cameras showing potholes and clean road surfaces. These images were meticulously labeled to accurately indicate the defects.

Results

After retraining, the NNs demonstrated successful defect detection on objects that needed to be identified. The accuracy of detection was high, ranging from 70 to 90%, which confirms the effectiveness of the method. The NNs were able to adapt to new conditions and deliver good results in the assigned tasks.

The application of NNs, initially trained for other tasks, and their retraining for specific defect monitoring conditions, demonstrates high efficiency and potential for real-world applications.

Use of NNs in conjunction with the IoT

The IoT and NNs, when used together, are convenient for processing real-time data, allowing for continuous receipt of up-to-date information in a processed form.

The process consists of a 3-step algorithm:

1. Acquiring information from IoT sensors.
2. Processing data through an intermediate operating system or other real-time processing system.
3. Transfer of the previously processed data to the NN.

This configuration allows for automatic data transmission without noticeable losses and adds several debugging tools to optimize and increase the accuracy of the NN model.

Implementation of a damage and defect detector on Raspberry Pi

For mobility and compactness, single-board computers with sufficient computing power, such as the Raspberry Pi Model 4B, were chosen. The board supports Linux operating systems, which allows using the Python programming language without significant limitations. The IoT sensor used is the OV5647 camera, which supports Full HD and infrared lighting for night-time recording.

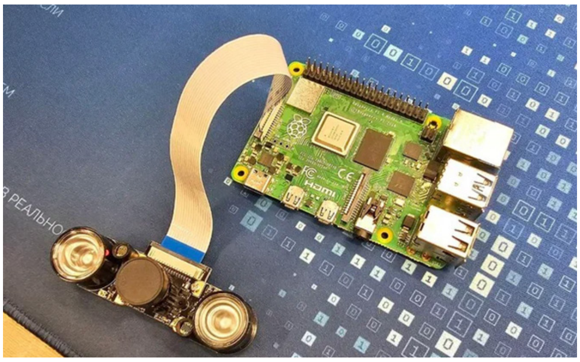

Fig. 5. Minimal configuration

Fig. 6. Assembled detector

Fig. 5 shows the minimal setup required for the detector to work, consisting of a single-board computer, a compatible camera and an SD card that stores our program code in auto-start mode, as well as the Linux operating system (Raspberry Pi OS). Additionally, a keyboard, mouse and monitor can be added for convenient use of debugging tools. If peripheral devices are unavailable for viewing results, wired or wireless (Bluetooth) headphones are recommended for listening to audio signals during defect detection, allowing for mobile operation with the device.

Fig. 6 shows the fully assembled detector, ready for operation.

The design is suitable for continuous operation in a fixed location or for mobile use in various areas. This implementation of the detector enables solving a wide range of tasks, such as automating the assessment of metal quality for various industries and evaluating the integrity of structures in hard-to-reach and poorly lit areas.

Architecture of the hardware-software complex

The architecture of the hardware-software complex of the detector is described in Fig. 7[5].

The entire architecture is hosted on a Raspberry Pi running a Linux operating system, which facilitates interaction with the camera through libraries and drivers. After receiving the image from the camera, the operating system passes the data to the virtual Python environment, specially configured for the detector. Using the picamera2 library, the image is converted to JPG format in the main thread of our program code. The image is then transformed into a matrix and passed to the NN for processing and defect detection. In the child thread, created upon launching the program, a monitoring window is available to track the image and camera angle, which will allow for optimization and improvement of the defect detection accuracy by the NN in the future.

[5] See Raspberry Pi documentation: https://www.raspberrypi.com/documentation/.

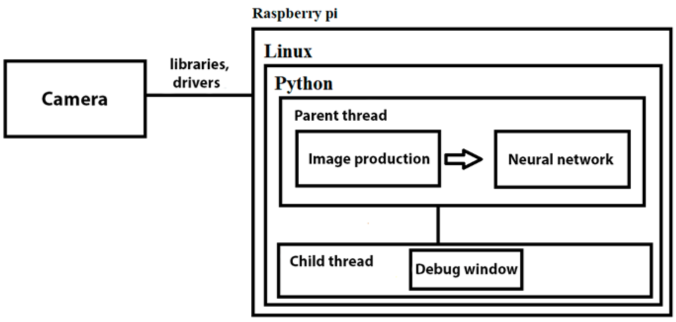

Fig. 7. Architecture of the hardware-software complex

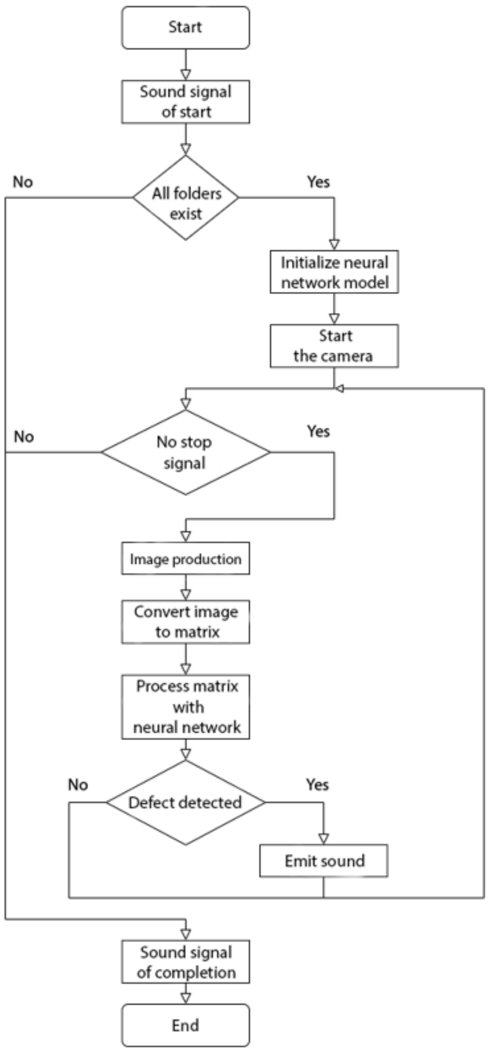

Fig. 8. Flowchart of the program code

Block diagram of the program code

The listing of the program that uses a camera to capture images and send them to the NN for processing, with added debugging tools such as a camera window and the display of NN results in the console, is available on the website https://github.com/ikly323/raspberry_metal. Fig. 8 shows the flowchart of this program code.

When the program is launched, an initial sound signal is emitted to notify the user that the detector has started. After the sound, the program checks the integrity of the project and the presence of all necessary files, which ensures the initialization of the NN model and the activation of the camera for further interaction. After all checks and service launches are completed, an infinite loop starts, responsible for defect detection and notifying the user. To do this, a frame is captured, saved as a file in the operating system, and then passed to the NN as a matrix. Based on the NN's prediction, a decision is made whether to emit an audio notification or not. The program completes its life cycle when the Ctrl + C command (kill signal) is issued or when the Raspberry Pi is powered off.

Conclusion

The use of NNs in combination with IoT, blockchain technologies and mobile devices represents a powerful tool for monitoring and assessing the process of detecting surface defects in structural elements and technical systems, ensuring high accuracy and prompt detection. The implementation of this development will contribute to improving the safety, resilience, reliability and lifespan of mechanical engineering products, road and railway surfaces. Additionally, based on the conducted research, a defect detection process for metals during the production preparation phase can be implemented in autonomous mode.

The architecture of the developed detector allows for a versatile expansion of defect detection capabilities by adding advanced analysis methods. In the future, ultrasound may be used to study macrocracks, as well as a more detailed surface analysis using time-of-flight sensors.

REFERENCES

1. **Astapova M.A., Lebedev I.V.** Review of approaches to the detection of defects in power transmission line elements in images in the infrared, ultraviolet and visible spectra. *Modeling, optimization and information technology*, 2020, Vol. 8, No. 4, Pp. 1–34. DOI: 10.26102/2310-6018/2020.31.4.036

2. **Glushkov S.P., Solovyev L.U., Borisovskaya N.E.** The detection of defects in the structures reinforced with composites by infrared thermography. *Siberian Transport University Bulletin*, 2015, Vol. 35, No. 4, Pp. 36–42.

3. **Fedotov M.Yu., Loskutov M.L., Shelemba I.S., Kolesnikov A.V., Ovchinnikov I.G.** To the issue of monitoring of metal-bearing bridges supporting fiber optic sensors. *Russian journal of transport engineering*, 2018, Vol. 5, No. 3, Art. no. 11SATS318. DOI: 10.15862/11SATS318

4. **Bao H., Wu W., Yu J., Cao Y., Liu Y., Zhang H., Li X., Shi W.** Application of YOLO model in road defect detection. *2024 5th International Seminar on Artificial Intelligence, Networking and Information Technology* (*AINIT*), 2024, Pp. 2280–2284. DOI: 10.1109/AINIT61980.2024.10581746

5. **Pei J., Wu X., Liu X.** YOLO-RDD: A road defect detection algorithm based on YOLO. *2024 27th International Conference on Computer Supported Cooperative Work in Design* (*CSCW*D), 2024, Pp. 1695–1703. DOI: 10.1109/CSCWD61410.2024.10580137

6. **Kumar A., Kalia A., Verma K., Sharma A., Kaushal M.** Scaling up face masks detection with YOLO on a novel dataset. *Optik*, 2021, Vol. 239, Art. no. 166744. DOI: 10.1016/j.ijleo.2021.166744

7. **Shi R., Li T., Yamaguchi Y.** An attribution-based pruning method for real-time mango detection with YOLO network. *Computers and Electronics in Agriculture*, 2020, Vol. 169, Art. no. 105214. DOI: 10.1016/j.compag.2020.105214

8. **Ali-Gombe A., Elyan E., Moreno-García C.F., Zwiegelaar J.** Face Detection with YOLO on edge. *Proceedings of the 22nd Engineering Applications of Neural Networks Conference. EANN 2021* (eds. L. Iliadis, J. Macintyre, C. Jayne, E. Pimenidis), 2021, Vol. 3, Pp. 284–292. DOI: 10.1007/978-3-030-80568-5_24

9. **Zanevych Yu.** Traffic light detection with YOLO models. *Grail of Science*, 2024, No. 38, Pp. 194–199. DOI: 10.36074/grail-of-science.12.04.2024.033

10. **Xu H., He J., Liang Y., Liu Y., He Y.** Detection of nectarines on trees with YOLO models. *2023 35th Chinese Control and Decision Conference* (*CCDC*), 2023, Pp. 1789–1794. DOI: 10.1109/CCDC58219.2023.10326846

11. **Viswanatha V., Chandana R.K., Ramachandra A.C.** Real time object detection system with YOLO and CNN models: A review. arXiv:2208.00773, 2022. DOI: 10.48550/arXiv.2208.00773

12. **Yu J., Ye X., Tu Q.** Traffic sign detection and recognition in multiimages using a fusion model with YOLO and VGG network. *IEEE Transactions on Intelligent Transportation Systems*, 2022, Vol. 23, No. 9, Pp. 16632–16642. DOI: 10.1109/TITS.2022.3170354

13. **Maleki P., Ramazani A., Khotanlou H., Ojaghi S., Mousavi M., Kalinin A., Mosavi A.** Object detection for vehicles with YOLO. *2024 IEEE 22nd World Symposium on Applied Machine Intelligence and Informatics* (*SAMI*), 2024, Pp. 000343–000350. DOI: 10.1109/SAMI60510.2024.10432884

14. **Sadhin A.H., Hashim S.Z.M., Samma H., Khamis N.** YOLO: A competitive analysis of modern object detection algorithms for road defects detection using drone images. *Baghdad Science Journal*, 2023, Vol. 21, No. 6, Art. no. 24. DOI: 10.21123/bsj.2023.9027

15. **Inyutin A.V., Lukashevich M.M.** PCB defect detection based on YOLOv8 architecture. *System Analysis and Applied Information Science*, 2024, No. 2, Pp. 16–24. DOI: 10.21122/2309-4923-2024-2-16-24

16. **Khodataeva T.S., Kashirin N.V., Averina A.I., Guryanov A.E.** Approaches to the development of a printed circuit board defect detection system based on AOI technology. *Trudy ISP RAN/Proc. ISP RAS*, 2023, Vol. 35, No. 4, Pp. 109–120. DOI: 10.15514/ISPRAS-2023-35(4)-5

17. **Vengerenko V.V., Inyutin A.V.** Hybrid inspection of printed board defects. *Informatics*, 2024, Vol. 21, No. 3, Pp. 63–79. DOI: 10.37661/1816-0301-2024-21-3-63-79

18. **Kuzevanov V.O., Tikhomirova D.V.** Deep learning for effective visualization and classification of recyclable material labels. *Scientific Visualization*, 2024, Vol. 16, No. 5, Pp. 179–196. DOI: 10.26583/sv.16.5.12

19. **Antonov M.O., Temkin I.O.** Real-time recognition and tracking of road surface defects based on complex using of standard computational procedures and deep neural networks. *Software & Systems*, 2024, Vol. 37, No. 3, Pp. 421–430. DOI: 10.15827/0236-235X.142.421-430

20. **Sobolev A.S.** Development of a system for detecting defects in solar panel based on the YOLO v5 algorithm. *Izvestiya Tula State University*, 2023, No. 12, Pp. 480–483. DOI: 10.24412/2071-6168-2023-12-480-481

21. **Xu Y., Zhang K., Wang L.** Metal surface defect detection using modified YOLO. *Algorithms*, 2021, Vol. 14, No. 9, Art. no. 257. DOI: 10.3390/a14090257

22. **Zhang M., Yin L.** Solar cell surface defect detection based on improved YOLO v5. *IEEE Access*, 2022, Vol. 10, Pp. 80804–80815. DOI: 10.1109/ACCESS.2022.3195901

23. **Kanaeva I.A., Spitsyn V.G.** Road damage defects segmentation based on convolutional neural network ensemble. *Tomsk State University Journal of Control and Computer Science*, 2024, Vol. 68, Pp. 75–85. DOI: 10.17223/19988605/68/8

24. **Li J., Su Z., Geng J., Yin Y.** Real-time detection of steel strip surface defects based on improved YOLO detection network. *IFAC-PapersOnLine*, 2018, Vol. 51, No. 21, Pp. 76–81. DOI: 10.1016/j.ifacol.2018.09.412

25. **Hussain M.** YOLO-v1 to YOLO-v8, the rise of YOLO and its complementary nature toward digital manufacturing and industrial defect detection. *Machines*, 2023, Vol. 11, No. 7, Art. no. 677. DOI: 10.3390/machines11070677

26. **Agamirov L.V., Agamirov V.L., Los V.S., Nosikov M., Toutova N.V.** Dataset annotation converter for training neural networks to detect defects on various surfaces. *2024 Intelligent Technologies and Electronic Devices in Vehicle and Road Transport Complex* (*TIRVED*), 2024, Pp. 1–4. DOI: 10.1109/TIRVED63561.2024.10769786

27. **Agamirov L.V., Agamirov V.L., Gaeva A.P., Vestyak K.V.** Ispol'zovanie neyronnykh setey dlya vyyavleniya defektov i povrezhdeniy v konstruktsiyakh mostov [The use of neural networks for detecting defects and damages in bridge structures]. *Tezisy dokladov XXX Mezhdunarodnogo simpoziuma im. A.G. Gorshkova.*

Dinamicheskie i tekhnologicheskie problemy mekhaniki konstruktsiy i sploshnykh sred [*Abstracts of the XXX International Symposium named after A.G. Gorshakov. Dynamic and Technological Problems of Mechanics of Structures and Continuous Media*], 2024, Vol. 1, Pp. 6–9.

28. **Khaush A.** Primenenie neyrosetey dlya resheniya zadach obnaruzheniya treshchin [Application of neural networks for crack detection]. *XV Molodezhnyy nauchnyy forum "Telekommunikatsii i informatsionnye tekhnologii – realii, vozmozhnosti, perspektivy". Sektsiya "Tsifrovaya ekonomika, upravlenie i biznes-tekhnologii"* [*XV Youth Scientific Forum "Telecommunications and Information Technologies - Realities, Possibilities, Prospects". Section "Digital Economy, Management and Business Technologies"*], 2024.

29. **Hatab M., Malekmohamadi H., Amira A.** Surface defect detection using YOLO network. *Intelligent Systems and Applications* (*IntelliSys 2020*), 2020, Vol. 1250, Pp. 505–515. DOI: 10.1007/978-3-030-55180-3_37

30. **Xie Y., Hu W., Xie S., He L.** Surface defect detection algorithm based on feature-enhanced YOLO. *Cognitive Computation*, 2023, Vol. 15, Pp. 565–579. DOI: 10.1007/s12559-022-10061-z

31. **Vu T.-T.-H., Pham D.-L., Chang T.-W.** A YOLO-based real-time packaging defect detection system. *Procedia Computer Science*, 2023, Vol. 217, Pp. 886–894. DOI: 10.1016/j.procs.2022.12.285

32. **Chen W., Huang Z., Mu Q., Sun Y.** PCB defect detection method based on Transformer-YOLO. *IEEE Access*, 2022, Vol. 10, Pp. 129480–129489. DOI: 10.1109/ACCESS.2022.3228206

33. **Zhao C., Shu X., Yan X., Zuo X., Zhu F.** RDD-YOLO: A modified YOLO for detection of steel surface defects. *Measurement*, 2023, Vol. 214, Art. no. 112776. DOI: 10.1016/j.measurement.2023.112776

34. **Liu M., Chen Y., Xie J., He L., Zhang Y.** LF-YOLO: A lighter and faster YOLO for weld defect detection of X-ray images. *IEEE Sensors Journal*, 2023, Vol. 23, No. 7, Pp. 7430–7439. DOI: 10.1109/JSEN.2023.3247006

35. **Du F.-J., Jiao S.-J.** Improvement of lightweight convolutional neural network model based on YOLO algorithm and its research in pavement defect detection. *Sensors*, 2022, Vol. 22, No. 9, Art. no. 3537. DOI: 10.3390/s22093537

36. **Yi W., Ma S., Li R.** Insulator and defect detection model based on improved YOLO-S. *IEEE Access*, 2023, Vol. 11, Pp. 93215–93226. DOI: 10.1109/ACCESS.2023.3309693

37. **Korzhov A.V., Surin V.A., Cheskidova M.A., Lonzinger P.V., Safonov V.I., Belov K.N.** Development of an algorithm for detecting defects in glass insulators based on computer vision using a neural network approach. *Bulletin of the South Ural State University. Series "Mathematics. Mechanics. Physics"*, 2024, Vol. 16, No. 4, Pp. 35–42. DOI: 10.14529/mmph240405

38. **Mukhamadiyarov R.A., Klyshnikov K.Yu., Koshelev V.A., Kutikhin A.G.** Potential of diagnostic electron microscopy of calcification, pathological neovascularization and elastolysis in combination with phenotyping of cell populations in large arteries. *Russian Journal of Cardiology*, 2024, Vol. 29, No. 8, Art. no. 5909. DOI: 10.15829/1560-4071-2024-5909

39. **Tulbure A.-A., Tulbure A.-A., Dulf E.-H.** A review on modern defect detection models using DCNNs – Deep convolutional neural networks. *Journal of Advanced Research*, 2022, Vol. 35, Pp. 33–48. DOI: 10.1016/j.jare.2021.03.015

40. **Wang T., Chen Y., Qiao M., Snoussi H.** A fast and robust convolutional neural network-based defect detection model in product quality control. *The International Journal of Advanced Manufacturing Technology*, 2018, Vol. 94, Pp. 3465–3471. DOI: 10.1007/s00170-017-0882-0

41. **Khanam R., Hussain M., Hill R., Allen P.** A comprehensive review of convolutional neural networks for defect detection in industrial applications. *IEEE Access*, 2024, Vol. 12, Pp. 94250–94295. DOI: 10.1109/ACCESS.2024.3425166

42. **Darabi A., Maldague X.** Neural network based defect detection and depth estimation in TNDE. *NDT & E International*, 2002, Vol. 35, No. 3, Pp. 165–175. DOI: 10.1016/S0963-8695(01)00041-X

43. **Singh S.A., Desai K.A.** Automated surface defect detection framework using machine vision and convolutional neural networks. *Journal of Intelligent Manufacturing*, 2023, Vol. 34, pp. 1995–2011. DOI: 10.1007/s10845-021-01878-w

44. **Xing J., Jia M.** A convolutional neural network-based method for workpiece surface defect detection. *Measurement*, 2021, Vol. 176, Art. no. 109185. DOI: 10.1016/j.measurement.2021.109185

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