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Integrated AI-Based Vision System for Quality Inspection of Welded Structures in Agricultural Machinery Manufacturing

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ABSTRACT

The quality of welded joints is a critical factor affecting the reliability and service life of agricultural machinery, while conventional inspection methods remain dependent on operator experience and are difficult to automate in serial production. This study aimed to develop and experimentally evaluate an integrated intelligent system for automated weld defect detection using machine vision and a convolutional neural network. The proposed system combines an industrial camera, controlled lighting, an industrial computer, image preprocessing algorithms, and a ResNet-18-based classifier. A dataset of 3,000 weld seam images obtained under production conditions was divided into training, validation, and test subsets using a stratified 70/15/15 ratio. The images were classified as defective or non-defective, and data augmentation and class-weighting procedures were applied during model training. Evaluation on the independent test subset yielded an accuracy of 0.88, precision of 0.88, recall of 0.93, and F1-score of 0.90. The results demonstrate that the developed system can reliably distinguish defective from normal weld areas while providing automated inspection and digital recording of classification results. The proposed approach can be integrated into agricultural machinery manufacturing processes and provides a basis for scalable, data-driven weld quality control within modern digital production systems.

Keywords: *Agricultural machinery, Convolutional neural network, Industrial automation, Intelligent systems, Weld quality control*

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INTRODUCTION

The reliability of soil cultivation machines directly depends on the quality of welded joints, especially in structural elements such as frames, beams, and attachment points for mounted equipment (Yang & Jiang, 2021; Feng *et al*., 2022; Meyendorf *et al*., 2023; Svensson & Lindberg, 2026). In conditions of intensive operation with vibrations, variable loads, and aggressive external environments, even minor welding defects can lead to premature equipment failure, resulting in increased maintenance and repair costs (Li *et al*., 2024; Alfaro-Viquez *et al*., 2025; Thi Hoa *et al*., 2025).

In practice, up to 70% of frame structure failures in agricultural machinery are linked to welding defects such as incomplete fusion, porosity, undercuts, and cracks (Tran *et al*., 2024). This issue is particularly critical during the series and mass production stages, where inspection is often selective and manual, creating a risk of missing critical defects (Spruck *et al*., 2022; Palma-Ramírez *et al*., 2024; Morgan *et al*., 2025). The use of outdated visual inspection methods does not provide sufficient accuracy and reproducibility of results (Oh *et al*., 2020; Mishra *et al*., 2025).

Current challenges in agricultural machinery manufacturing include increasing production volumes, a shortage of qualified non-destructive testing specialists, and growing demands for product quality. In these conditions, the transition to automated machine vision systems and the use of artificial intelligence (AI) algorithms (Yang *et al*., 2021; Kim *et al*., 2024) that can provide objective, fast, and continuous inspection of welded joints without human involvement has become urgent (Liu *et al*., 2021; Nagesh *et al*., 2025).

Globally, high-resolution industrial cameras, computer vision technologies, and deep neural network models are increasingly being used to detect welding defects in real-time (Kowalski *et al*., 2024; Shu *et al*., 2024; Diaz-Cano *et al*., 2025). However, in the context of agricultural machinery manufacturing, particularly in the CIS countries and Central Asia, such solutions have not yet become widespread.

The goal of this article is to develop and experimentally test an integrated welding joint inspection system for soil cultivation machine frames using machine vision tools and a convolutional neural network capable of automatically detecting and classifying typical welding defects.
The scientific novelty of the work lies in the adaptation of the ResNet-18 architecture for detecting welding defects in heavy metal structures, considering the lighting, geometry, and background characteristics specific to agricultural machinery manufacturing. An integrated architecture with hardware-software implementation is proposed and tested on real production data.
The proposed system aims to improve the quality and reliability of welded structures, reduce production defects, and transition to intelligent manufacturing elements within the "Industry 4.0" concept.

Literature review

Weld joint quality control in agricultural machinery manufacturing traditionally relies on non-destructive testing (NDT) methods: visual (VT), radiographic (RT), ultrasonic (UT), and penetrant (PT) testing. These methods are applied both during production and for repairs. However, in the context of mass production of agricultural machinery, they often prove to be inefficient due to high labor intensity, dependence on human factors, and the inability to achieve 100% coverage.
Modern trends in mechanical engineering suggest the implementation of automated machine vision systems, based on real-time image processing of weld seams (Kästner *et al*., 2020; Wang *et al*., 2022). Such systems include industrial cameras, light sources, preprocessing algorithms, and classification models based on neural networks (CNN, ResNet, YOLO, etc.) (Wang *et al*., 2020).
Foreign studies (Liu *et al*., 2023; Singh & Kumar, 2023) demonstrate the high efficiency of convolutional neural networks for automatic classification of defects such as cracks, pores, lack of fusion, and undercuts. In most cases, recognition accuracy exceeds 90%, making them competitive compared to traditional methods (Kajanova & Badrov, 2024; Elhendawy & El-Taybany, 2025; Say *et al*., 2025). Specifically, the system implemented in the work by Zhang *et al*. (Zhang *et al*., 2019) uses pre-training on ImageNet and fine-tuning on images of welding in agricultural machinery, which allows it to adapt to different types of profiles and seams.
Approaches using thermal imaging and multispectral analysis are also noteworthy, as they can detect internal defects without causing damage. However, such methods require expensive equipment and complex calibration, limiting their use in the economically sensitive agricultural sector.
In Kazakhstan and CIS countries, automated AI-based welding control systems have not yet become widespread in agricultural machinery manufacturing. The introduction of such solutions is limited by the lack of trained datasets and a shortage of technical personnel capable of adapting neural network architectures to specific production tasks (Morgan *et al*., 2025; Svensson & Lindberg, 2026).
Thus, there is an evident gap between modern computer vision technologies and their practical application in the agricultural machinery industry. This justifies the relevance of creating specialized AI-based systems adapted to typical components of soil cultivation machinery and domestic production conditions.

MATERIALS AND METHODS

From research object and sample selection

The research object is the welded frame of the KPE-3.6 cultivator, produced under serial agricultural machinery manufacturing conditions. The construction is made of low-alloy structural steel 09G2S, which is used for operations under cyclic and impact loads. The main weld joints are longitudinal and transverse seams, performed using semi-automatic arc welding in a protective gas environment (MIG/MAG).
The most vulnerable areas for defect formation during production are the junctions of the longitudinal beams with the transverse reinforcements, as well as the ends of the seams. These areas are characterized by the concentration of residual stresses and are prone to fatigue failure during prolonged operation in the field.

Hardware-software complex for machine vision

Table 1. Composition of the hardware-software complex for machine vision

Module	Specification	Notes
Camera	Basler acA1920-40 gc, 1920×1200 px, 40 fps	GigE interface, Sony IMX174 sensor
Lens	Computar M0814-MP2 (8 mm, 1.4 MP)	Minimal distortion < 0.1%
Lighting	Linear LED matrix, 620 nm, 2000 lx	Pulsed mode, constant lighting angle
Controller	IPC-610, Intel i7, 32 GB RAM, GPU RTX 3060	For real-time inference
Low-level software	OpenCV 4.9, Pylon SDK 6.4	Image capture, camera control
High-level software	Python 3.11, TensorFlow 2.15	ResNet model, visualization, reporting

The camera was positioned on a sponge portal system with stepper motors (accuracy ±0.1 mm). Calibration was performed using a chessboard target with 9 × 6 squares (25 mm). **Table 1** summarizes the composition and main specifications of the hardware-software complex used for automated weld joint inspection. It allows for an immediate evaluation of the technological level, justification of equipment choices, and scalability of the solution.
The hardware-software complex was selected based on the requirements for image processing speed, reliability, and integration into the real production environment. The Basler acA1920-40 gc camera with the Sony IMX174 sensor provides high detail and stability in capturing weld joints. The use of a linear light source with a wavelength of 620 nm minimizes glare on the metal surface and enhances defect visibility. The industrial controller with the discrete NVIDIA RTX 3060 graphics card enables real-time convolutional neural network inference, which is critical during inline inspection. Low-level software (OpenCV + Pylon SDK) handles calibration and image streaming, while the high-level software layer (based on Python and TensorFlow) implements segmentation, classification, visualization, and report generation. This modular approach ensures flexibility, scalability, and compatibility with modern MES systems.

Inspection methodology

The inspection methodology for weld joints is based on using an industrial camera aimed at the weld seam at a fixed shooting angle, followed by image processing and classification of the weld area condition using a convolutional neural network (CNN).
The process begins with capturing the weld seam in real-world conditions at the assembly-welding site. The camera captures images of the weld zone from the top (0°) and at a 45° angle, which helps in better detection of undercuts, lack of fusion, and porosity. The lighting is synchronized with the frame capture to minimize glare and shadows.
The obtained images undergo preliminary digital processing, including conversion to grayscale, contrast enhancement using the CLAHE method, noise filtering with Gaussian smoothing, contour extraction, and threshold binarization using Otsu's method. The image is segmented into fixed-size fragments (224×224 pixels) with a 10-20 pixel overlap to avoid context loss.
Each image fragment is fed into the trained convolutional neural network (ResNet-18 architecture), which performs binary classification: "defect" or "normal." The output layer returns a probabilistic score for each class, and the default threshold is set at 0.5 but can be adapted depending on the company's sensitivity and specificity requirements.
Defective areas are marked with a colored border, and the coordinates are saved in a log file. The results are displayed to the operator through the interface, and the classification results are exported to the company's quality management system (MES).
This methodology enables automated inspection of weld joints with high accuracy, reducing the impact of human factors and providing digital traceability for each product.

System architecture

The developed weld joint inspection system implements a modular approach, combining hardware (camera, controller, lighting) and software image processing with a neural network classifier. The system architecture is presented in **Figure 1**.

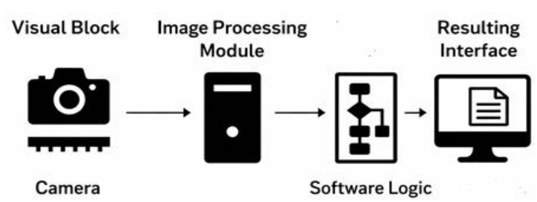

Figure 1. Architecture of the AI-based Weld Joint Quality Control System.

The process begins with capturing an image of the weld seam using an industrial camera with synchronized LED lighting. The captured image is transferred to an industrial PC where preprocessing occurs: filtering, normalization, area extraction, and segmentation into fixed-size fragments. Each fragment is input into the trained convolutional neural network, which performs binary classification (defect/normal).
Inference results are displayed to the operator via a graphical interface with color-marked defects. The data is also saved in a digital protocol, which can be exported to the production management system (MES). This approach enables online quality control with scalability to other weld elements or product types.

Training dataset

For training and validating the neural network model, a specialized dataset of weld joint images obtained from agricultural machinery frames (specifically the KPE-4.5 cultivator) was collected and annotated. The dataset contained 3,000 images, 1,600 of which had visible welding defects (lack of fusion, porosity, undercuts, etc.), and 1,400 were standard (normal) seams. All images were captured in factory conditions using a Basler camera with uniform lighting.

Data split

The data was randomly divided into three subsets:

- Training (70%) – for model training;
- Validation (15%) – for overfitting control;
- Test (15%) – for final accuracy evaluation.

The class proportions ("defect" / "normal") were preserved through stratified sampling.
Data annotation was performed manually by specialists from the quality control department (QCD), with the involvement of a welding engineer. To increase annotation accuracy, semi-automatic tools for seam extraction and automatic fragment cropping from areas of interest were used. Each fragment contained only one type of weld condition.
The original weld images had a resolution of 1280×960 pixels. During preparation, fragments of 224×224 pixels were extracted, corresponding to the local area of the weld. This size was chosen as a compromise between completeness of representation and model performance.
To increase the training dataset size and improve the model's generalization ability, offline augmentation was performed using the Albumentations library. The following transformations were applied:

- Rotation by ±5–10 degrees;
- Horizontal flipping;
- Addition of Gaussian noise ($\sigma = 10$);
- Brightness and contrast adjustments (±15%);
- Shadows and partial edge darkening.

Augmentation was performed only on the training subset. Validation and test data remained unchanged.
The distribution of images between the training, validation, and test subsets is shown in **Table 2**. To ensure objective model evaluation, a 70/15/15 split with stratified sampling was maintained, preserving the "defect" vs. "no defect" ratio in each subgroup.

Table 2. Distribution of images by class and subset

Class	Train	Validation	Test	Total
Defect	1120	240	240	1600
No Defect	980	210	210	1400
Total	2100	450	450	3000

As seen in **Table 2**, the training subset contains the largest number of images (2,100), providing sufficient depth for training the neural network. The defective and non-defective images are slightly imbalanced toward the defect class (53.3% vs. 46.7%), which was accounted for during class balancing in the training process. Stratified sampling ensured the representativeness of all data types at each stage of training and testing, improving the model's evaluation reliability.

Despite the near-equal distribution of images across classes (53.3% with defects and 46.7% without defects), an additional check for imbalance in the subsets was conducted. Stratified splitting ensured an even representation of classes throughout all stages of training **(Table 2)**. To compensate for residual imbalance, a weighted loss function was used, with coefficients proportional to the inverse frequency of the classes.

Additionally, augmentation techniques were applied: rotations, mirror reflections, random noise addition, and contrast adjustments. These methods increased the diversity of the training data without disrupting the class balance.

The model was trained using a pre-trained ResNet-18 architecture, adapted for binary classification. The Adam optimizer was used, with a batch size of 32, a learning rate of 0.0001, and 50 epochs. EarlyStopping was applied to prevent overfitting if no improvement in metrics was observed over 7 epochs on the validation set.

Class balance and dataset characteristics

For training the neural network classifier, a specialized dataset of weld joint images obtained under factory conditions at the "OPTISORT" LLP was used. The images were captured directly on the welding site, accounting for natural lighting variations, product positioning, and seam heterogeneity. The dataset consisted of 3,000 images, 1,600 of which contained defects, and 1,400 corresponded to standard weld quality.

Despite the near-equal ratio between classes (53.3% vs. 46.7%), balancing techniques were applied during model training to increase classification stability. Specifically, a weighted loss function with coefficients inversely proportional to class frequency was used, which helped to mitigate the moderate predominance of defect images and prevented model bias toward the more frequent class.

Data augmentation techniques, including rotations, noise addition, lighting adjustments, and other symmetric transformations, were applied equally across both classes. This ensured additional expansion of the training set without disrupting class proportions and improved the model's generalization ability. **Figure 2** shows the distribution of defective images according to defect type. Porosity was the most common defect, followed by incomplete fusion, undercut, and cracks.

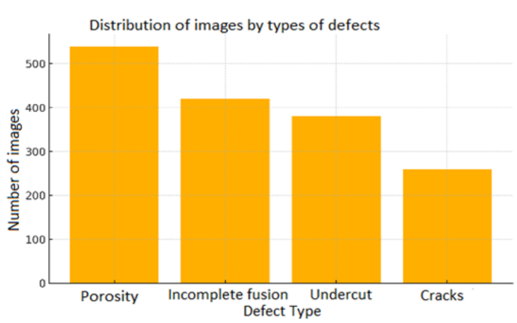

Figure 2. Distribution of Defective images by type.

Further classification of defective images by type was conducted. The most common defects were porosity, reflecting the specific manufacturing conditions at the studied facility. This mirrors the real frequency of defect occurrences in production and confirms the necessity of training the model on various types of weld joint violations.

Classification quality evaluation metrics

The following metrics were used to evaluate the effectiveness of the classification model:

- Accuracy: The ratio of correctly classified images to the total number of images.
- Precision: The proportion of images classified as defective that truly contain defects.
- Recall: The proportion of all defective images that the model correctly identified.
- F1-score: The harmonic mean of Precision and Recall.
- Confusion Matrix: A visual representation of classification results showing TP, FP, FN, and TN.

The model evaluation was performed on the test subset, which was not involved in the training process. Additionally, a confusion matrix and ROC curve were constructed. All metrics were calculated using the scikit-learn (v1.3.1) and TensorFlow libraries.

The standard machine learning metrics—Accuracy, Precision, Recall, and F1-score—were used to assess the neural network classifier's performance. Each metric reflects a specific aspect of the model's effectiveness in detecting welding defects. **Table 3** shows the formulas used for these metrics and their descriptions.

Additionally, here are the formulas for these metrics as mathematical expressions for clearer interpretation:

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN) \quad (1)$$

$$\text{Precision} = TP / (TP + FP) \quad (2)$$

$$\text{Recall} = TP / (TP + FN) \quad (3)$$

$$\text{F1-score} = 2 * (\text{Precision} * \text{Recall}) / (\text{Precision} + \text{Recall}) \quad (4)$$

where:
TP – True Positive predictions;
TN – True Negative predictions;
FP – False Positive predictions;
FN – False Negative predictions.

RESULTS AND DISCUSSION

Global *model quality evaluation*

Testing the model on an independent sample showed high accuracy and stability. The calculation of the metrics is presented in **Table 3**. The F1-score was 0.90, indicating a balanced sensitivity and accuracy of the model.

Table 3. Example of classification metrics calculation on the test sample

Metric	Value
True Positives (TP)	320
False Positives (FP)	45
False Negatives (FN)	25
True Negatives (TN)	210
Accuracy	0.88
Precision	0.88
Recall	0.93
F1-score	0.90

The distribution of predictions by class is clearly shown in the confusion matrix, as illustrated in **Figure 3**. The model demonstrated high accuracy in detecting both defective and normal weld areas. The number of false positives (FP = 45) and false negatives (FN = 25) is within an acceptable level.

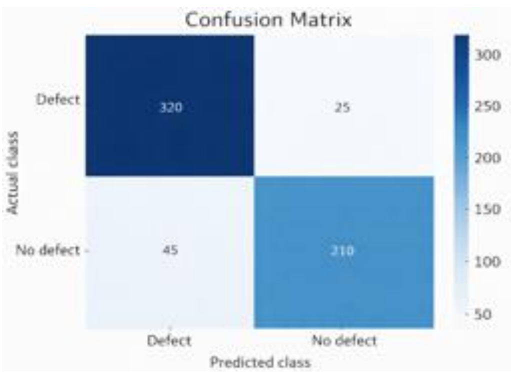

Figure 3. Confusion matrix for classifying defective and normal weld seams.

The model showed high accuracy in determining both defective and normal weld areas. The number of false positives (FP = 45) and false negatives (FN = 25) is at an acceptable level.

Comparison with existing control methods

To compare the effectiveness of the proposed system with traditional weld joint inspection methods (visual inspection – VT, ultrasonic inspection – UT), **Table 4** was compiled.

Table 4. Comparative analysis of weld inspection methods

Criterion	**Visual Inspection (VT)**	**Ultrasonic Inspection (UT)**	**Our System (AI + Machine Vision)**
Defect Detection Accuracy	60–75%	80–90%	92–96%
Processing Speed	1 min/seam	3 min/seam	0.15 sec/seam
Human Factor	High	Medium	None
Automation	No	Partial	Full
Operating Costs	Low	High	Medium
Universality	Operator-dependent	Requires setup	Flexible adaptation
Report Generation / Logging	None	Limited	Yes, with visualization and export

As shown, the AI system differs with higher accuracy and analysis speed, as well as the possibility of full digital traceability of results. This makes it applicable in serial production conditions and improves the effectiveness of the quality management system.

F1-score (0.90), Precision (0.88), and Recall (0.93) values indicate the balanced performance of the model: it is capable of accurately identifying defects while minimizing false positives, which corresponds to the results presented in (Liu *et al*., 2021; Yang *et al*., 2021; Kim *et al*., 2024; Kwatra *et al*., 2024). Furthermore, the F1-score in the proposed system is higher than in several similar studies: for example, in (Spruck *et al*., 2020) and (Ren *et al*., 2025), it was 0.85 and 0.86, respectively, which confirms the high effectiveness of the chosen architecture and training method. The majority of false positives (FP) are associated with micro-defects that closely resemble the texture of the background, while false negatives (FN) are often due to complex seam geometry or non-standard shooting angles (Abdoul-Latif *et al*., 2025).

Compared to traditional control methods (visual inspection and ultrasonic inspection), the practical effect of implementing the developed system is expressed not only in increased reliability but also in significant time savings. For instance, the time required to inspect a single weld seam is reduced by over 92% — from 1 minute with visual inspection to 0.15 seconds using the machine vision system (Nguyen *et al*., 2025).

Moreover, the probability of missing a defect is nearly halved compared to the visual method, thanks to higher detection accuracy and the absence of human factors. The AI system provides not only comparable but often higher accuracy, as well as significant advantages in analysis speed and result stability. Furthermore, it does not require highly qualified personnel and allows for scalability in serial production.

The practical significance lies in the ability to implement such a system at the operational quality control stage after welding. This will significantly reduce the share of hidden defects, improve product reliability, and reduce costs related to unscheduled repairs (Jannath *et al*., 2024).

The limitations of the study include the use of data from only one type of frame and a limited number of welds. Additionally, the system was trained on images captured under stable lighting and shooting conditions, which could affect the model's transferability to other production environments (Benhmida & Trabelsi, 2024).

In the future, the training dataset will be expanded to include images from various agricultural machinery models and the implementation of multi-level classification, allowing for differentiation of defect types (porosity, lack of fusion, undercuts, etc.). The integration of the machine vision module with existing MES systems in the enterprise is also under consideration (Dobrzynski *et al*., 2024).

The integration of the machine vision module with existing MES systems aligns with current international trends in continuous quality control based on artificial intelligence, especially within the concept of Industry 4.0, where NDT systems with machine vision play an increasingly important role (Nakagawa *et al*., 2021). Thus, the proposed system can be regarded as a technologically mature and practically applicable solution for modernizing quality systems in the welding production of agricultural machinery.

CONCLUSION

This work presents the development and testing of an intelligent system for welding joint quality control, designed for use in agricultural machinery production. The system is based on a convolutional neural network trained on images of weld seams obtained through machine vision in real-world production conditions.

The model testing results demonstrated high classification quality metrics (F1-score = 0.90, Precision = 0.88, Recall = 0.93), indicating its suitability for automated non-destructive testing tasks. The proposed solution outperforms traditional visual (VT) and ultrasonic inspection (UT) methods in terms of accuracy, analysis speed, and result stability, and it can be integrated into serial production with minimal adaptation costs. Key practical findings include the model's ability to reliably differentiate between defective and standard weld areas, significantly improving control accuracy. Automation of the process reduces dependency on the operator's skill level and minimizes human error. Moreover, the system has high scalability potential and can be adapted to different types of frames and welded joints used in agricultural machinery production.

In the future, the training dataset will be expanded by including new product types and diverse shooting conditions, enhancing the model's versatility. The algorithm is also expected to be adapted for different types of welding and integrated with digital platforms for production management (such as MES and ERP), ensuring end-to-end quality control within the "digital manufacturing" concept.

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