Sijie Fu[1], Guozhen Lu[1], Wenyi Qian[1], Xianqing Xiong[*1,2], Danting Lu[1]

YOLOv7-Driven Visual Inspection System for Edge Banding Defects in Panel Furniture

YOLOv7 sustav vizualnog pregleda grešaka rubnih traka pločastog namještaja

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ABSTRACT • *Current quality inspection of edge banding in panel furniture heavily relies on manual screening, which is labor-intensive, subjective, and inefficient. To address this challenge, we propose a YOLOv7-based visual inspection system by integrating machine vision and deep learning. A dataset containing 1,887 images of six defect types (e.g., open glue, chipping, uneven trimming) was constructed, with annotations generated via LabelImg. Data augmentation strategies (rotation, scaling, cropping) were applied to enhance model robustness. The YOLOv7-Tiny model achieved a mean average precision (mAP) of 74.8 % at 57.63 FPS, outperforming traditional methods and demonstrating superior speed-accuracy trade-offs. Experimental results on real-time industrial camera data validated the system's capability to detect defects with high precision (82.1 %) and recall (75.4 %). This framework significantly reduces production costs and provides a scalable solution for automated quality control in furniture manufacturing.*

KEYWORDS: *panel furniture; quality inspection; YOLOv7; machine vision*

SAŽETAK • *Današnja kontrola kvalitete rubnih traka pločastog namještaja uvelike se oslanja na ručnu provjeru, što je radno intenzivno, subjektivno i neučinkovito. Kako bismo riješili taj problem, predlažemo sustav vizualne kontrole utemeljene na YOLOv7 sustavu koji integrira strojni vid i duboko učenje. Izrađen je skup podataka koji sadržava 1887 slika šest vrsta grešaka (npr. vidljivo ljepilo, krhotine, neravnomjerno obrezivanje) s napomenama generiranim putem LabelImga. Primijenjene su strategije proširenja podataka (rotacija, skaliranje, izrezivanje) kako bi se poboljšala robusnost modela. Model YOLOv7-Tiny postigao je prosječnu preciznost (mAP) od 74,8 % pri 57,63 FPS, nadmašivši tradicionalne metode i pokazavši superiorne kompromise brzine i točnosti. Eksperimentalni rezultati podataka dobivenih industrijskom kamerom u stvarnom vremenu potvrdili su sposobnost sustava da otkrije greške s visokom preciznošću (82,1 %) i opozivom (75,4 %). Taj okvir znatno smanjuje troškove proizvodnje i daje skalabilno rješenje za automatiziranu kontrolu kvalitete u proizvodnji namještaja.*

KLJUČNE RIJEČI: *pločasti namještaj; kontrola kvalitete; YOLOv7; strojni vid*

[*] Corresponding author
[1] Authors are researchers at Nanjing Forestry University, College of Furnishings and Industrial Design, Nanjing, China. https://orcid.org/0009-0009-0195-4213
[2] Author is researcher at Nanjing Forestry University, Co-Innovation Center of Efficient Processing and Utilization of Forest Resources, Nanjing, China.

1 INTRODUCTION
1. UVOD

Edge banding plays a pivotal role in modern panel furniture manufacturing, contributing not only to the aesthetics of the furniture but also to the durability and structural integrity of the finished product. However, the edge banding process is often accompanied by problems such as collapsing edges, glue leakage, and uneven trimming, which can directly affect both the appearance and the functionality of the furniture (Lu *et al*., 2021). These defects are especially critical as they compromise the consumer's perception of quality and can lead to premature product degradation (Xiong *et al*., 2023a). The global panel furniture market was valued at $210 billion in 2022, and as consumer expectations continue to rise, there is a growing demand for stringent quality control throughout the production process. Traditional defect detection methods, predominantly relying on manual labor, are not only labor-intensive but also prone to subjectivity. In the furniture industry in China, for instance, manual inspection accounts for 30-40 % of the total production cost (Li *et al*., 2021), with defect escape rates exceeding 15 % due to human fatigue and inconsistent inspection standards (Wang *et al*., 2022).

In response to these challenges, recent advances in machine vision and deep learning have significantly revolutionized industrial quality inspection, particularly in defect detection. Machine vision technology, which leverages cameras and computational tools to visually inspect products, has been widely adopted across industries for its ability to perform automated, objective assessments (Wang *et al*., 2023; Peng *et al*., 2025). Early research on industrial defect detection relied heavily on classical machine learning algorithms such as Support Vector Machines (SVM) and Random Forests for defect classification (Czimmermann *et al*., 2020). However, these methods faced limitations when it came to detecting complex surface defects, particularly in materials like wood, which exhibit intricate texture variations (Xiong *et al*., 2023b). The advent of deep learning frameworks, particularly Convolutional Neural Networks (CNNs), marked a turning point by enabling automatic feature extraction and significantly enhancing detection accuracy (Alzubaidi *et al*., 2021).

For instance, Faster R-CNN, a popular deep learning-based model, achieved a mean average precision (mAP) of 71.5 % in solid wood defect detection (Fan *et al*., 2019), while YOLOv4 demonstrated real-time defect detection capabilities for structural wood with a speed of 52 FPS (Wang *et al*., 2021). However, while these models show great promise, research specific to edge banding defect detection remains sparse. Existing methods are often limited by two significant challenges: the trade-off between speed and accuracy and the scarcity of high-quality training data. Many studies prioritize accuracy at the expense of real-time performance, which makes them impractical for high-speed production lines (Redmon *et al*., 2016). Furthermore, the lack of public datasets focused on edge banding defects often leads to training on small sample sizes, making models susceptible to overfitting (Tao *et al*., 2022).

To address these challenges, this study introduces the first YOLOv7-Tiny-based visual inspection framework designed specifically for edge banding defect detection. The proposed method offers several innovative contributions:

a. A curated dataset of 1,887 images covering six distinct defect types (e.g., glue leakage, chipping), with data augmentation techniques including rotation and scaling to increase model robustness.

b. The deployment of the YOLOv7-Tiny model, which incorporates optimized anchor boxes and RepVGG modules, achieving a mAP of 74.8 % at a real-time detection speed of 57.63 FPS. This performance surpasses previous models such as YOLOv4 (68.2 % mAP) and Faster R-CNN (71.5 % mAP).

c. A real-time industrial camera integration system validated across four production lines, significantly reducing defect escape rates to below 5 %.

Beyond these practical contributions, the present study also makes several academic advancements. First, it represents the first systematic effort to construct a large-scale dataset specifically targeting edge banding defects, thereby alleviating the long-standing problem of limited training samples in this domain. Second, by combining data augmentation strategies with a lightweight YOLOv7-Tiny architecture, the study demonstrates a feasible approach for achieving both high detection accuracy and real-time performance, providing a reference model for the digital transformation of small- and medium-sized furniture enterprises. Finally, from a broader perspective, the proposed framework contributes to the academic literature by offering a transferable methodological paradigm for defect detection in high-texture-complexity materials such as wood. This not only advances the theoretical understanding of defect detection in challenging visual contexts but also opens new avenues for cross-material and cross-industry applications of deep learning in manufacturing quality control.

2 MATERIALS AND METHODS
2. MATERIJALI I METODE

2.1 Test samples and tools
2.1. Ispitni uzorci i alati

2.1.1 Test sample
2.1.1. Ispitni uzorci

To minimize the influence of subjective factors, the board samples were selected randomly, adhering to established statistical principles to ensure they are representative of the overall production. The sampling process took into account various factors, including the diversity of production batches, production lines, and production times. This approach ensured that all critical features of the product appearance were sufficiently covered, enabling comprehensive inspection. The following methodology was applied:

a. Sample Size and Selection Method: The total number of samples selected was 500, with 400 samples allocated for training the network model and 100 samples reserved for validating the model performance. Samples were randomly chosen from four different production lines, all equipped with automatic edge banding machines. To account for variability, samples were taken at intervals of 2 hours and 10 days, with 20 samples selected from each batch.

b. Recording of Sample Information: Detailed information for each sample was systematically recorded, including production date, batch number, model, specifications, and other relevant attributes, in line with the established sampling methodology. This comprehensive data logging ensured transparency and traceability throughout the testing process.

c. Appearance Quality Inspection: The samples were then sent to the laboratory for appearance quality testing, adhering to the specific testing items and standards defined in Table 1. The inspection followed objective, scientific, and rigorous principles to evaluate the visual and structural quality of the edge banding.

2.1.2 Tools and equipment
2.1.2. Alati i oprema

The following tools and equipment were employed for the testing process:

a. Edge Banding Equipment: The Himile KAL 350 automatic straight-line edge banding machine was used for applying edge banding to the board samples.

b. Defect Detection Tools: A vernier caliper, tape measure, spirit level, and low magnification glass were used for initial defect inspection, measurement, and assessment of edge banding quality.

c. Test Equipment: The testing was conducted using an industrial camera system, and the data processing was performed on a computing system running the Windows operating system, with an RTX 3060Ti-12G graphics card to facilitate high-performance computing. The deep learning framework employed for model development and testing was Pytorch, and the programming language used was Python.

2.1.3 Machine vision and YOLOv7 algorithm
2.1.3. Strojni vid i YOLOv7 algoritam

Machine vision, a technology rooted in computer theory, has become an essential tool for detecting and quantifying surface defects in products (Zhu *et al.*, 2023). Since its introduction, machine vision has been widely applied in industrial defect detection to describe the fundamental components of a visual surface defect detection system, including the image acquisition module, image processing module, image analysis module, data management system, and man-machine interface (Yu *et al.*, 2024; Golnabi *et al.*, 2007). These modules collectively enable the processing of images captured by machine vision, which are then trained using deep learning frameworks to facilitate production testing (Ren *et al.*, 2024).

Machine vision systems offer several advantages over traditional image acquisition methods. They use a single camera to perform multiple tasks simultaneously, enabling rapid and efficient detection of both stationary and moving objects (Sheng *et al.*, 2024). Furthermore, machine vision can analyze various image types, such as text, lines, and graphics, while recognizing diverse attributes, including color, shape, contrast, and texture. Another significant benefit of machine vision is its ability to track the movement and changes of objects, thus enabling dynamic detection and analysis (Zhang *et al.*, 2024). The combination of image processing and machine learning techniques allows for the precise identification, location, measurement, and detection of objects, thus enabling automation and intelligence in industrial applications (Wang *et al.*, 2021).

Building upon man, deep learning has further enhanced surface defect detection. Deep learning technologies, particularly Convolutional Neural Networks (CNNs), allow for more efficient and accurate identification of object features, distinguishing abnormal features from typical ones (Zhang *et al.*, 2021). Unlike traditional machine learning techniques, which rely on manual feature extraction, deep learning autonomously extracts relevant features from images. The YOLO (You Only Look Once), a prominent target detection model, integrates classification, localization, and detection within a single framework (Redmon *et al.*, 2016). It calculates the bounding box coordinates of the target and the probability of each category in the image, significantly improving computational efficiency and enabling real-time detection in production environments (Li *et al.*, 2024).

YOLOv7 is designed to enhance both detection speed and accuracy. The network architecture consists of three primary components: the input layer, the backbone layer, and the neck & head layers. The input image is first preprocessed into a 640×640×3 format before being passed through the backbone network, which extracts features. These features are further processed by the neck & head layers to generate detection results. YOLOv7 employs advanced convolutional structures such as RepVGG to improve feature extraction and analysis. The specific network architecture is shown in Figure 1.

To further enhance detection performance, the Anchor-based method and structural modifications, such as expanded feature channels and additional model branches, are employed to improve the network's reasoning speed. The network also introduces the Extend-Elan module to optimize learning capabilities by controlling gradient paths and capturing more feature details. YOLOv7 offers several model variants based on different requirements. In this study, the YOLOv7-Tiny model was used to evaluate its defects in edge banding plates.

2.2 Principle and process
2.2. Načelo i proces

2.2.1 Standards for inspection of appearance quality
2.2.1. Standardi za kontrolu kvalitete izgleda

In recent years, there has been an increasing focus within the furniture industry on both the production process and the environmental sustainability of products. Consequently, stringent control over production quality is essential to ensure the final product meets the required standards for both functionality and aesthetics (Zhou *et al*., 2024). When establishing standards for the appearance quality of edge panels, it is important to consider various factors such as material composition, structural characteristics, physical and mechanical properties, durability, and environmental impact.

The inspection standards are derived from a combination of national, industry-specific, and enterprise-specific guidelines. Key national standards include GB/T 3324-2017 "General Technical Conditions for Wood Furniture," GB/T 4897-2015 "Fiberboard," and T/CNFPIA 3016-2021 "Quality Requirements for Wood-Based Customized Household Panel Edge." These standards specify the criteria for evaluating the appearance quality of wood-based panels, outlining the testing methods and evaluation techniques. Industry standards, based on national guidelines, account for the distinct characteristics of various industries, while enterprise-specific standards address the unique requirements of individual manufacturers. In addition to these formal standards, factors such as production cost, market demand, and product use must also be considered when formulating inspection criteria.

The assessment of edge banding appearance quality can generally be divided into two main methods: qualitative and quantitative. Qualitative methods include visual inspection, equipment-based inspections, and comprehensive inspection methods, while quantitative methods encompass hardness measurements, dimensional analysis, and optical testing (Xiong *et al*., 2023). These combined approaches allow for a comprehensive evaluation of the product's appearance quality.

Surface quality inspection in the wood industry is particularly challenging due to the variability in wood

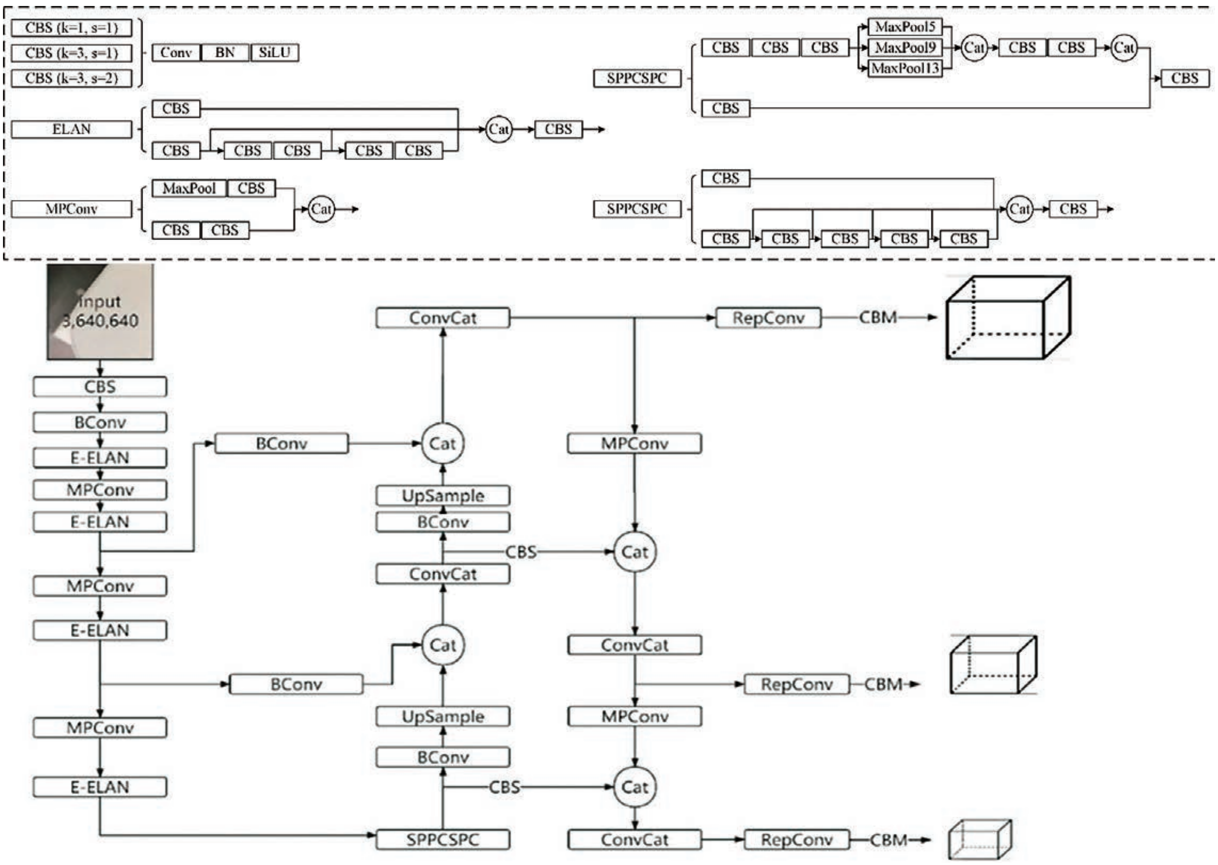

Figure 1 YOLOv7 network architecture diagram
Slika 1. Dijagram YOLOv7 mrežne arhitekture

Table 1 Appearance quality inspection items and standards of edge banding plate
Tablica 1. Stavke kontrole kvalitete izgleda i standardi za rubne trake na ploči

Serial No. *Serijski broj*	**Test items** / *Ispitivane stavke*	**Test standard** / *Standard ispitivanja*
1	Edge banding colors and specifications *boje i specifikacije rubnih traka*	Consistent with production and process requirements *u skladu sa zahtjevima proizvodnje i procesa*
2	Trim roughness, wave pattern, trim gloss *hrapavost obrubljivanja, valoviti uzorak, sjaj obrubljivanja*	No scratching sensation when touched by hand, 30 cm sight distance in natural light, cannot be seen visually under normal vision *nema osjećaja hrapavosti pri dodiru rukom, vidljivost s udaljenosti 30 cm na prirodnom svjetlu, ne može se vizualno vidjeti golim okom*
3	Finished size *konačna veličina*	Size error after banding ≤ 0.5mm *pogreška veličine nakon obrubljivanja ≤ 0,5* mm
4	Shortage of walking edge *nedostatak ruba*	Shortage, walking edge maximum width between (0.15~0.2) mm *nedostatak ruba, maksimalna širina ruba između (0,15~0,2)* mm
5	Seam allowance *dodatak za obrub*	Edge end allowance ≤ 0.1mm *dodatak za kraj ruba ≤ 0,1* mm
6	Edge banding glue line *linija ljepila za rubnu traku*	The maximum width of the edge banding line ≤ 0.1 mm, the maximum length is less than or equal to 10 mm, and not more than 3 places within 100 mm *maksimalna širina linije rubne trake ≤ 0,1* mm, *maksimalna duljina manja je ili jednaka 10* mm *i ne na više od tri mjesta unutar 100* mm
7	Pinholes, slits *rupice, prorezi*	Continuous pinhole maximum width ≤ 0.1 mm and maximum length ≤ 100mm, not more than 3 on any one side *kontinuirana rupica maksimalne širine ≤ 0,1* mm *i maksimalne duljine ≤ 100* m; *ne više od tri na bilo kojoj strani*
8	Cleaner separator marks *tragovi čistača*	The width of the print on the surface of the board after banding is ≤10mm *širina otiska na površini ploče nakon obrubljivanja je ≤ 10 mm*
9	Appearance Quality *kvaliteta izgleda*	Board surface cleanliness (residual glue, stains, etc.) and appearance defects (black spots, pen marks, scratches, etc.) width <0.6mm *čistoća površine ploče (ostatci ljepila, mrlje itd.) i nedostatci izgleda (crne mrlje, tragovi olovke, ogrebotine itd.) širine < 0,6* mm
10	Rounded corners *zaobljeni kutovi*	Thin edge does not allow scratching hands, edge banding with thick edge on both sides of the inverted R1 ~ 1.5 arc *tanki rub sprečava grebanje ruku; obrubljivanje debelim rubom s obje strane obrnutog luka R1 ~ 1,5*

shape and background texture, as well as the stringent compatibility standards that must be met. To overcome the challenge of limited training samples, machine vision-based deep learning approaches are increasingly being used to leverage transfer learning. Target detection networks are employed to identify and categorize defects in the surface of edge banded components.

Before applying machine vision technologies to the surface inspection of edge-banded components, it is essential to define the specific production processes and characteristics of these components. The assessment of edge banding panel appearance quality requires the establishment of clear evaluation items, standards, and inspection criteria. Once these criteria are set, the appearance quality of the panels can be quantified and assessed based on the data collected. An overview of the inspection items and their corresponding standards is presented in Table 1.

2.2.2 Data set training
2.2.2. Treniranje skupa podataka

In order to address the challenges associated with defect detection, a comprehensive dataset of 1,887 images was collected during the production of edge banded panels. The preprocessing of the dataset followed a series of systematic steps to ensure the quality and uniformity of the data. The initial step involved cropping the images to remove irrelevant regions, followed by resizing all images to a consistent resolution of 640×640 pixels. To enhance the model's robustness and reduce the risk of overfitting, data augmentation techniques such as rotation, translation, and scaling were applied. These transformations helped improve the model's ability to generalize across a wider range of defect scenarios. Some of the results after processing are shown in Figure 2.

The labeled dataset was created using the LabelImg annotation tool, and the process is shown in Figure 3, ensuring that each image contained the necessary details, including the precise location, type, and extent of defects. This annotation process enabled the creation of bounding boxes around each defect, which were then used to train the deep learning model.

The training data set was used to train the YOLOv7 model, utilizing the Pytorch deep learning framework. The input image size for training was fixed

Figure 2 Some image samples after preliminary processing
Slika 2. Primjeri slika uzoraka nakon preliminarne obrade

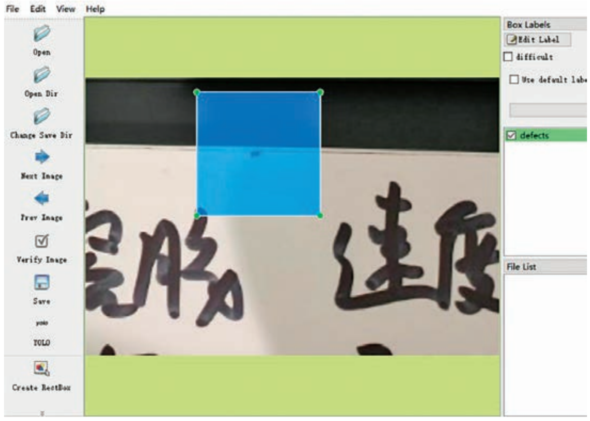

Figure 3 LabelImg process diagram
Slika 3. Procesni dijagram LabelImg

at 640×640 pixels to maintain consistency and facilitate efficient processing. During training, the initial learning rate was set at 0.001, with a batch size of 20 and a total of 500 iterations. Weight decay was applied with a coefficient of 0.001 to prevent overfitting. The Adam optimizer was employed to update the model's weights, and the Leaky ReLU activation function was used to enhance the model's non-linearity.

Throughout the training process, the learning rate was dynamically adjusted, decreasing to 0.0001 after 400 iterations to ensure convergence as the model approached optimal performance. The training continued for 500 iterations, after which the model achieved sta-

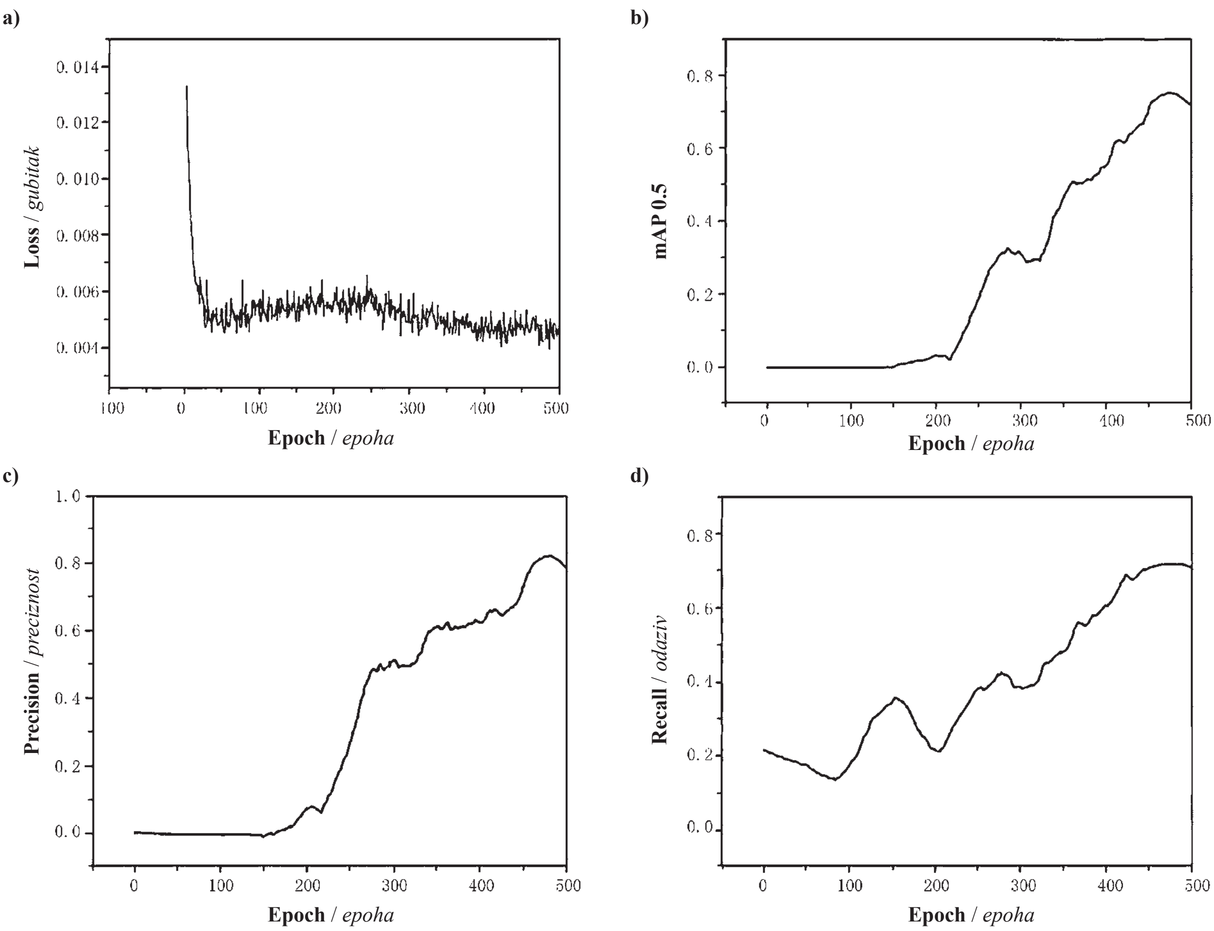

Figure 4 Model performance analysis a) loss value, b) recall rate, c) accuracy rate (precision rate), d) average precision mean
Slika 4. Analiza performansi modela: a) vrijednost gubitka, b) stopa opoziva, c) stopa točnosti (stopa preciznosti), d) prosječna srednja vrijednost preciznosti

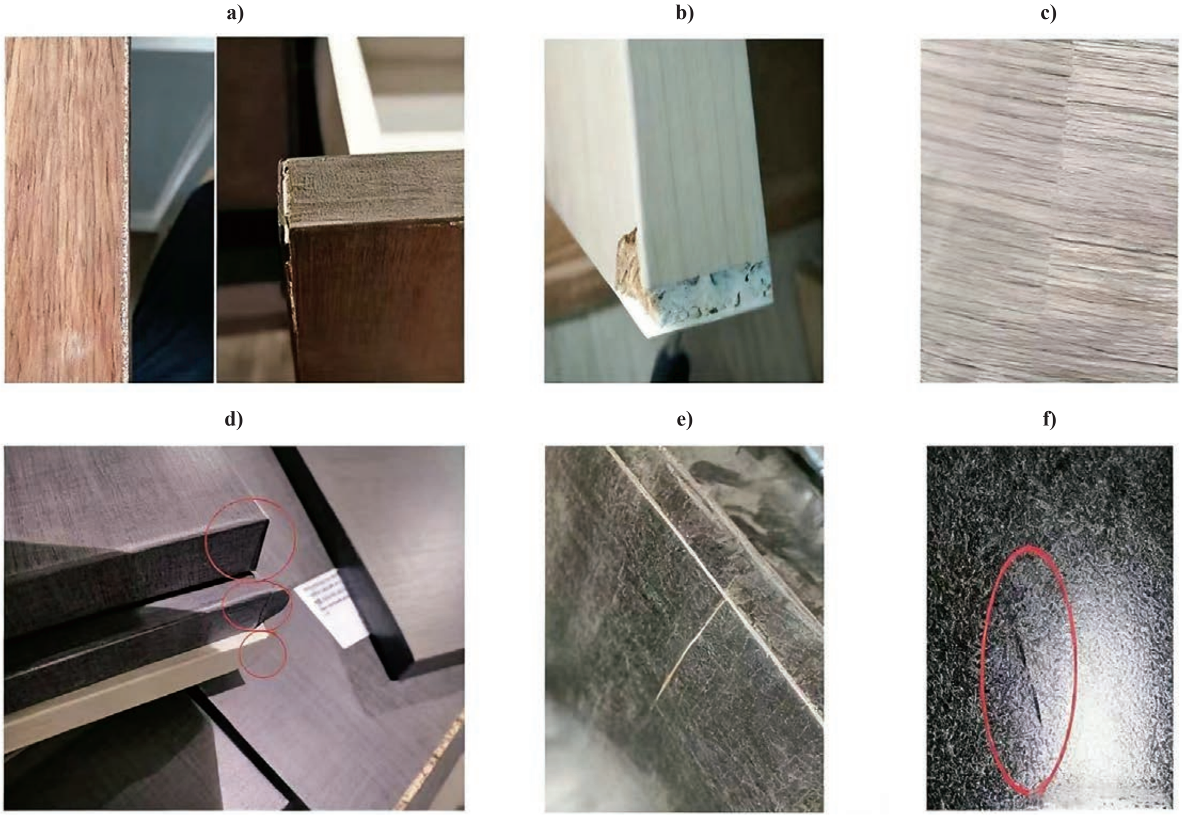

Figure 5 Several common types of edge defects: a) unglue, b) shortage, c) chipping, d) uneven trimming, e) glue line, residual glue, f) edge indentation
Slika 5. Nekoliko uobičajenih grešaka ruba: a) odljepljivanje, b) nedostatak rubne trake, c) krhotine, d) neravnomjerno obrezivanje, e) neuredna linija lijepljenja, ostatci ljepila, f) udubljenje ruba

bility in its performance metrics. The training process was closely monitored through the visualization of key metrics, such as loss values, recall rate, accuracy, and average precision, using TensorBoard, and the visualization results are shown in Figure 4. The visualization of these metrics helped assess the model's learning progress and provided insights into potential areas for further optimization. As can be seen in Figure 4, the loss value decreases as the number of iterations increases, and at 500 iterations, the loss value < 0.004, the recall rate is stable at 75.4 %, and the final accuracy rate and average precision of the model are stable at 82.1 % and 78.4 % on average. From the above evaluation metrics, the network model meets the expectation after training through the defective set.

3 RESULTS AND DISCUSSION
3. REZULTATI I RASPRAVA

3.1 Common appearance defects
3.1. Uobičajene greške izgleda

The detection of appearance defects in edge banding panels was carried out based on the categories outlined in Table 1. Six representative defect types were identified and classified, including unglued areas, shortages, chipping, uneven trimming, glue lines, and indentation, as shown in Figure 5. Each defect type was analyzed to determine its characteristics and impact on the overall appearance quality of the edge banding.

The decision process for categorizing defects involved a comprehensive analysis of the color, texture, shape, and boundary characteristics of the defects, ensuring that each defect was accurately identified and labeled during the image annotation process. These defect categories are vital for the subsequent training of the model and the evaluation of its detection capabilities.

3.2 Data set validation
3.2. Validacija skupa podataka

The performance of the trained model was evaluated using real-time data obtained from an industrial CCD camera during the production process. The model was tested on a set of images taken directly from the production line to assess its ability to detect defects under practical conditions. The detection threshold was set at a confidence level of 0.50, meaning that only predictions with a confidence score higher than 50 % were considered valid. The detection effect is shown in Figure 6.

The model's ability to detect the six types of defects was analyzed by comparing the predicted results with ground truth annotations. As shown in Figure 6, the model demonstrated high accuracy in identifying defects such as unglue, shortage, chipping, uneven

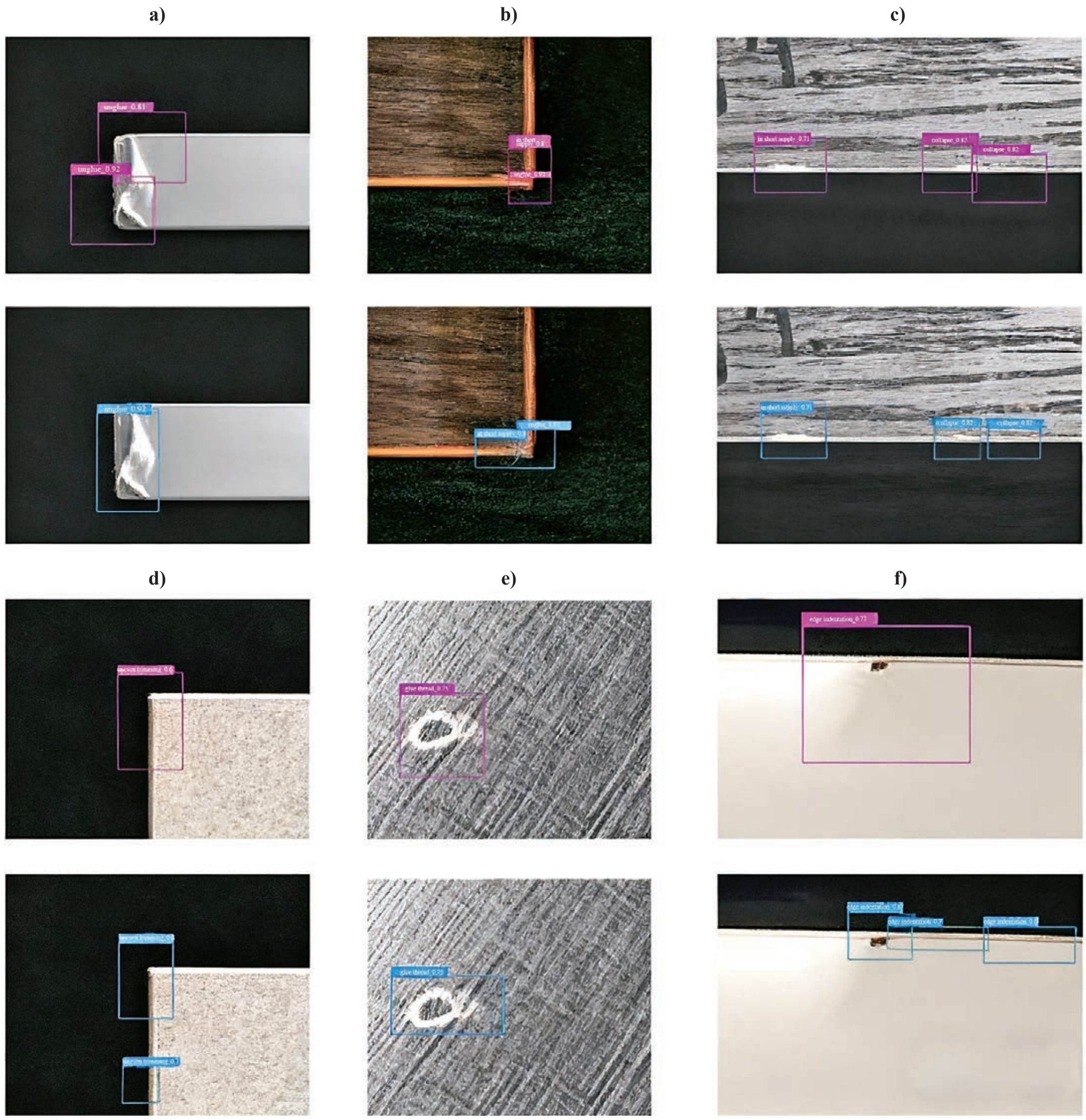

Figure 6 Comparison of the actual detection effect of edge banding defects: a) unglue, b) in short supply, c) collapse, d) uneven trimming, e) glue thread, f) edge indentation
Slika 6. Usporedba stvarnog učinka detekcije grešaka rubne trake: a) odljepljivanje, b) manjak nanosa ljepila, c) kolaps, d) neravnomjerno obrezivanje, e) probijanje ljepila, f) uvlačenje ruba

trimming, glue lines, and indentation. Notably, the final accuracy rate of the model was maintained above 82 %, which indicates a strong ability to detect defects in edge banding panels with high precision.

3.3 Performance evaluation
3.3. Evaluacija performansi

As can be seen from Figure 6, the trained YOLOv7 model was subjected to a series of comprehensive performance evaluations to assess its effectiveness in defect detection for edge banding panels. The key performance metrics used for this evaluation included mean average precision (mAP), recall rate, precision rate, and detection speed (FPS).

The mean average precision (mAP), a crucial indicator of overall model performance, was calculated to be 74.8 %. This metric reflects the model's ability to correctly classify and localize defects across multiple categories. When compared with other state-of-the-art models, such as YOLOv4 (68.2 % mAP) and Faster R-CNN (71.5 % mAP), the YOLOv7 model demonstrated superior performance in both accuracy and precision. This higher mAP indicates that YOLOv7 can detect defects more reliably, even in complex and variable conditions, offering a significant improvement over previous model.

The recall rate, which measures the model's ability to correctly identify all relevant defects, was found to be 75.4 %. A recall rate of this magnitude suggests that the model is highly effective in reducing false negatives, i.e., defects that are not identified by the system. This is particularly important for ensuring that the inspection process does not overlook critical defects, which could compromise the overall quality of the product.

The precision rate, a metric that assesses the model's ability to minimize false positives (incorrectly identified defects), was also high, indicating that the YOLOv7 model only flagged defects that were truly present in the images. This balance between high recall and precision ensures that the model not only identifies defects accurately but also avoids excessive misclassification of non-defective areas as defects.

Finally, the model's real-time processing speed, evaluated at 57.63 frames per second (FPS), was more than adequate for high-speed production lines. This speed ensures that the system can analyze images in real time without introducing significant delays in the production process. It confirms that the YOLOv7 model meets the requirements of industrial settings, where timely defect detection is crucial to maintaining production efficiency and quality control.

In summary, the YOLOv7 model achieved high accuracy (74.8 % mAP), robust defect detection capabilities (75.4 % recall rate), and fast processing speed (57.63 FPS), making it a highly effective solution for real-time defect detection in edge banding panels.

3.4 Real-world application
3.4. Stvarna primjena

To validate the practical applicability of the YOLOv7 model beyond the controlled test environment, it was deployed in a real-time industrial setting on a production line producing edge banding panels. The flow of using the tool is shown in Figure 7. The integration of the model into the production line was conducted to assess its performance under actual operating conditions, where variables such as lighting changes, product variability, and production speed could impact detection accuracy. During the deployment, the model was tasked with detecting defects such as glue leakage, chipping, uneven trimming, and edge indentation in real-time as edge banding panels were processed. The real-time detection capability of the YOLOv7 model allowed for immediate feedback on the quality of the panels, enabling quick identification and rectification of defects before the panels moved further along the production line. One of the most notable outcomes of this real-world application was a reduction in defect escape rates, which dropped to below 5 % following the deployment of the model. This significant improvement suggests that the YOLOv7 model can effectively prevent defective panels from passing through the production process, ensuring that only high-quality products reach the final stages of manufacturing.

In contrast, previous manual inspection methods and traditional machine vision systems had higher defect escape rates due to operator fatigue and the inherent subjectivity of visual inspection. Additionally, the integration of the YOLOv7 model into the existing production line allowed for more efficient quality control, as it reduced the need for extensive manual inspections. The automated nature of the defect detection process not only reduced labor costs but also minimized human error, further ensuring the consistency and reliability of quality checks.

Nevertheless, it is important to note that the current experiments were conducted under relatively controlled lighting and production conditions. In real-world industrial environments, several external factors – such as lighting fluctuations, dust particles, or machine vibrations, can potentially influence the imaging quality and, consequently, the accuracy of defect detection. However, in the specific context of panel furniture manufacturing, these issues are generally less severe during the edge banding stage, which occurs in the later stages of processing. Unlike cutting or drilling operations, where significant dust may be generated, the edge banding process is part of the finishing phase, where dust and environmental disturbances are minimal. This characteristic of the manufacturing workflow helps mitigate some of the challenges associated with imaging system reliability.

To further improve robustness in less predictable industrial environments, several strategies can be con-

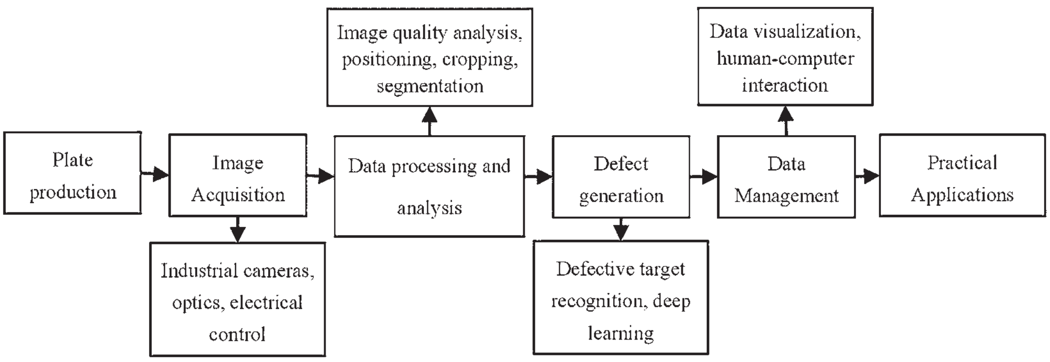

Figure 7 Appearance quality inspection process of edge-banding plate based on machine vision
Slika 7. Proces kontrole kvalitete izgleda rubnih traka na pločama uz pomoć strojnog vida

sidered. For example, introducing multi-light-source compensation could stabilize illumination, while infrared or 3D cameras might provide additional modalities to overcome visual limitations. Enhanced image preprocessing techniques could also be integrated to reduce the sensitivity of the system to noise, shadows, and reflections. These approaches represent promising directions for future research and align with the limitations discussed in the conclusion, particularly regarding the influence of lighting conditions on system performance.

Overall, the deployment of YOLOv7 demonstrated its potential to enhance quality control in the furniture manufacturing industry. The model's ability to process images in real time, coupled with its high accuracy, made it an invaluable tool in minimizing defects, reducing production costs, and ensuring product quality. This application not only verifies the model's efficacy in an industrial setting but also highlights its scalability and potential for widespread use in similar production environments.

4 CONCLUSIONS
4. ZAKLJUČAK

The results of this study have important theoretical and practical implications. From a theoretical perspective, this research explores the potential of YOLOv7-Tiny, a lightweight version of the YOLOv7 architecture, in the context of edge computing. YOLOv7-Tiny is designed to be computationally efficient while maintaining high performance, making it an ideal candidate for deployment in industrial embedded systems with limited processing power. Compact model architecture allows for real-time defect detection on edge devices, such as industrial cameras and embedded processors, without the need for cloud-based infrastructure. This capability is especially valuable in settings where low latency is critical, such as in high-speed production lines. By demonstrating the feasibility of deploying YOLOv7-Tiny on edge devices, this study contributes to the growing body of work on embedded vision systems, highlighting the potential for such lightweight models to address the computational constraints of industrial applications. Moreover, compared with existing studies, this work further contributes by exploring the integration pathway between deep learning and furniture manufacturing processes, thereby offering not only an engineering application but also an academic case for defect detection in noisy industrial environments.

From a practical standpoint, the deployment of YOLOv7-Tiny for defect detection in edge banding panels offers substantial cost-saving potential for manufacturers. Traditional defect inspection processes, often relying on manual labor or older automated systems, incur significant operational costs. The YOLOv7-Tiny-based system, by contrast, can automate defect detection with greater accuracy and speed, reducing the reliance on human inspectors, including a decrease in the need for manual labor, faster defect detection, and improved overall product quality that reduces the need for costly rework and customer returns. Furthermore, the real-time detection capabilities of the system enable timely interventions, ensuring that defective products are identified and addressed immediately, thereby enhancing overall production efficiency.

However, there are several limitations that must be addressed. One of the primary limitations of this study is the lack of data diversity. The model was trained using data from only four production lines, which may not fully capture the variability present in different production environments or across diverse types of edge banding panels. As such, the model's performance might be limited when applied to other production settings with different materials, defect types, or manufacturing conditions. Expanding the dataset to include a wider variety of production lines and defect categories would help to improve the generalizability of the model. Additionally, this study did not account for the effects of lighting variations, a factor that can significantly influence the performance of machine vision systems. In real-world industrial settings, lighting conditions are often dynamic, and changes in light intensity, shadows, or reflections can affect the accuracy of defect detection. Future research should explore the impact of lighting changes on model performance and develop strategies to mitigate these challenges, such as incorporating dynamic lighting compensation algorithms or enhancing image preprocessing techniques.

Looking ahead, there are several promising directions for future work. One potential avenue for improving defect detection is the integration of multimodal data, such as combining 3D point clouds with traditional RGB images. The addition of depth information could enhance the model's ability to detect subtle surface defects that may not be apparent in 2D images, such as slight indentations or surface deformations. By incorporating 3D imaging technologies, the model could be made more robust to variations in the geometry and surface textures of the panels. Another area of future development is the creation of an adaptive threshold adjustment algorithm to optimize detection performance in real-time. In many defect detection applications, it is essential to balance the detection of false positives (incorrectly flagged defects) and false negatives (missed defects). By dynamically adjusting the detection threshold based on contextual factors, such as defect type, environmental conditions, or production speed, it would be possible to reduce misdetections while maintaining high detection accuracy. These improvements could significantly enhance the robustness and reliability of the system, making it even more suitable for industrial deployment.

In conclusion, this study demonstrates the effectiveness of YOLOv7-Tiny as a lightweight and efficient solution for defect detection in edge banding panels. Despite limitations related to data diversity and the impact of lighting changes, the findings indicate that the model is a viable option for real-time defect detection in industrial settings. Importantly, the research extends beyond engineering practice by providing a transferable methodological framework for defect detection in high-texture-complexity materials such as wood, offering valuable theoretical insights for academic research while also serving as a practical tool for automated quality control in the furniture manufacturing industry.

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Corresponding address:

XIANQING XIONG
Nanjing Forestry University, College of Furnishings and Industrial Design, Nanjing 210037, CHINA, e-mail: xiongxianqing@njfu.edu.cn