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Article

Edge AI-enabled real-time process control in smart plywood production: IoT integration and intelligent automation framework

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ABSTRACT

In response to the technical requirements for real-time quality control in the hot pressing process of intelligent plywood production, this study proposes a real-time process control framework driven by edge AI. This framework employs a three-layer edge intelligence architecture. This work shows a practical and efficient boundary node model application scheme for defect detection with multi-level lightweight strategies. In particular, this work builds a decision level data fusion approach for visual detection data and process parameters based on rules for defect-process parameter association mapping. Experimental results have shown that this designed scheme can efficiently detect defects in an edge computing environment. Additionally, with more multi-source fusion being considered in the site environment, the overall detection efficiency might be improved while maintaining a stable closed-loop control system. After that, quality enhancement for products and efficiency improvement for detection were realized. The results provide a feasible method for utilizing engineering processes for enhanced online quality detection for the plywood hot-pressing process based on practical experiences for intelligence upgrades in wood processing.

1. Introduction

As the world moves ahead with Digital Transformation in manufacturing globally, the increasing emphasis on advanced concepts of Industry 4.0 redefines conventional manufacturing concepts with Intelligent Manufacturing being a leading catalyst for intensified industrial competitiveness [1]. Concepts such as Internet of Things integration, Artificial Intelligence integration, and Cyber-physical Systems integration facilitate real-time observation and optimal adjustment of manufacturing processes [2]. As industrial Internet of Things technology continues to mature and advance, more and more conventional manufacturing structures continue to witness a transformation towards data-enabled Intelligent Production Systems. This is most visible in other discrete manufacturing sectors such as wood processing today [3]. The introduction of the Industry 5.0 concept further emphasizes the importance of human-machine collaboration and sustainable manufacturing, prompting researchers to explore human-centered intelligent manufacturing architectures [4]. Intelligent manufacturing system design with balanced efficiency and collaborative requirements continues to attract broad focus as a leading research concern within academia and more with industrial interests today [5]. Cyber-physical Systems with advanced networking concepts for enhanced sensor networking and embedded computation capabilities continue to provide a strong technical basis with diverse practical applications for Intelligent Manufacturing today and for equipment observation and optimal adjustment for diverse industrial processes [6]. Plywood manufacturing is an excellent case study for validation of edge intelligence since it involves very high real-time control requirements, some coupling characteristics of multi-parameters, and a typical continuous process. The hot-pressing process, which has a direct impact on the bonding strength and surface quality of the final product, is fundamental to various applications in the areas of construction, interior design, and furniture. Minor variation in hot pressing temperature, pressure, or holding time is sufficient to cause defects. In reality, quality checking of plywood is carried out in most plywood factories by a human eye; that is, it is a manual checking process. It is not only inefficient but also fails to provide information in real time.

The implementation of cyber-physical systems in industry is also facing some challenges in terms of complexity of integration and cost of maintenance [7]. Currently, the Industry 4.0 architecture struggles to strike a balance between real-time performance and reliability, with data silos being a common issue [8].

TinyML is a type of machine learning that has recently gained a great deal of traction as a result of the growing demand for smart computing in embedded systems. At its core, it focuses on accelerating deep learning models to efficient operation on milliwatt-level devices. This is done through model compression and quantization [9]. Further, with the maturity of knowledge distillation and sparse training, it has found application in complex tasks like industrial anomaly detection and equipment monitoring [10]. Inference on ultra-low-power IoT devices has been verified. The deployment scheme based on microcontrollers can control the inference delay within milliseconds [11]. The machine learning technology in edge computing has achieved rich results in lightweight network architectures and edge-cloud collaboration mechanisms [12]. Technologies such as hardware accelerators and compiler optimizations in embedded systems provide support for model deployment in resource-constrained environments [13]. Edge federated learning can prevent the invasion of industrial data privacy through training models in a distributed manner in the industrial Internet of Things (IIoT) scenario [14]. The combined development of sensor networks and data platforms at the application level of industrial IoT is accelerating the construction of intelligent factories. The role of IoT technology in the manufacturing industry has expanded to all links of the value chain, such as production scheduling and quality traceability [15]. The next-gen IoT technology features the enhancement of edge intelligence and semantic interoperability [16]. The intelligent factory architecture driven by software-defined networks achieves flexible configuration but the applicability in real-time demanding closed-loop control scenarios still needs verification [17]. The wood defect detection technology has evolved from traditional image processing to deep learning methods, and convolutional neural networks demonstrate significant advantages in detection accuracy [18]. Through the combination of data augmentation and transfer learning, regional convolutional neural networks are capable of addressing the problem brought by insufficient training samples. However, these studies mainly focus on offline detection and less concerned with edge deployment and real-time control [19]. Data-driven process monitoring technology is a powerful way to intelligently operate manufacturing systems [20]. Multi-sensor data fusion can construct a more comprehensive representation of production status [21]. The predictive maintenance research in the context of Industry 4.0 has formed a complete system covering data collection, model construction, and decision optimization [22].

Despite the significant improvements made by the above studies in their respective fields, the assessment of smart plywood production's practical needs reveals serious limitations in existing work. Primarily, Edge AI research has emphasized general-purpose use cases with a noticeable lack of custom solutions for the wood processing industry. The penetration of industrial IOT architecture into continuous production processes such as hot pressing has also been little researched. It has been observed that deep learning defect detection methods do not pay adequate attention to real-time assurance and closed-loop control capabilities under edge deployment constraints. The desired fully closed-loop system, covering everything from defect detection results to process parameter changes, has not yet been reached. Considering the discussion above, the current study attempts to develop an edge AI real-time process control framework for smart plywood manufacture. Using IoT and smart automation technologies, the framework closes the loop in sub-100 milliseconds for defect detection process and adjustment of the processes. The research provides a three-layered edge intelligence architecture for the hot-pressing process of plywood. Further, lightweight detection modeling is designed which is of great significance in respect to the characteristics of plywood defects. The proposed framework incorporates multi-source IoT perception and edge fusion mechanisms. In addition, association mapping mechanisms between defect type and hot-pressing parameters is also put forward. The results of this study can facilitate the intelligent transformation of the wood processing industry and improve the quality stability of plywood through their theoretical and practical significance.

2. Methods

2.1 Edge intelligence system architecture

Plywood manufacturing is an example of a multi-process, collaborative manufacturing system which is marked by complex interdependencies among various parameters related to product quality. It can be seen that the mapping between the processes that control the generation of product quality, in relation to the parameters relating to the hot pressing process, in the case of plywood manufacturing, is rather complex. In a manufacturing plant, the veneer layers that are coated with adhesive are placed inside a hot-pressing machine during the manufacturing process. When the process is initiated, the machine supplies both heat and press action, thereby enabling heat transfer and pressure application, which induces cross-linking/curing of the adhesive, thereby adhesively bonding the veneer layers into a panel that possesses required mechanical specifications. Hot pressing takes place at a temperature of 120-150°C, a unit pressure of 1.0-1.5 MPa, and a holding time of 5-10 minutes, consistent with established plywood manufacturing specifications [23].

The parameters are strongly coupled, meaning that any deviation of any of the parameters can result in quality defects such as bubbles, delamination or adhesive failure. The typical cloud computing systems will normally show an end-to-end response time range of 300–500 ms for time-critical control loop processes, which is due to the wide area network communication time for data transmission as well as the processing time at the server. However, in the hot press process, there is a need for adjusting parameters to be effective within 100 ms for the next production cycle. To address the technical bottleneck mentioned above, this work is inspired by IoT-smart manufacturing monitoring platforms design principles [24]. A three-level architecture for controlling edge intelligence is proposed to provide computing powers on the shop floor. The cloud-based operations of defect detection and control decision-making for hot-pressing processes are moved to the edge through installation of edge computing nodes close to the equipment.

This architecture is divided into three functional layers which include: device perception layer, edge computing layer, and cloud management layer. The several layers make sure that data can be exchanged and functions can work together through a common interface. The device perception layer collects varied data from multiple sources in real time. The main components of the system are industrial vision inspection units installed at the infeed and outfeed stations of the hot press machine, with a resolution of 1920×1080 at a sampling frequency of 30 fps. Moreover, an array of sensors for process parameters is spread out over a number of locations on the hot press plate so that these can exactly read the process parameters (sampling frequency 100Hz).

Sensor accuracy in factory environments is subject to thermal drift affecting temperature readings near the hot press surface and electromagnetic interference from motor drives influencing pressure transducer signals, which are mitigated through periodic calibration cycles and shielded cabling installations. The edge computing layer is installed on shop-floor industrial edge servers to perform light pre-processing and inference, multi-source fusion, and control decision generation which are all computationally intensive tasks. The cloud management component mainly manages version control and remote updates to edge models. The historical data is archived for long-term storage, along with providing remote monitoring facilities to process engineers. Differently, instead of adopting a conventional edge-cloud manufacturing paradigm where data preprocessing is conducted by edge nodes, with inference computed by cloud servers, this work proposes an integrated architecture for lightweight deep learning inference and decision-level multi-source fusion at the edge level. In this design, a unified perception-control loop is completed within sub-100 ms response time without relying on cloud services. The topology and data flow relationships of this three-tier architecture are illustrated in Figure 1. As illustrated in Figure 1, the functional module division across each layer and the data interaction paths between layers are demonstrated. The device perception layer and edge computing layer utilize the MQTT lightweight message transmission protocol for data uplink. Operating on a publish/subscribe model, this protocol features a header overhead of only 2 bytes, effectively adapting to the practical constraints of bandwidth limitations and network jitter in industrial environments [25]. MQTT was preferred over OPC UA because of its lower overhead in resource-limited nodes, while IEEE 1588 PTP was preferred over NTP to provide sub-millisecond synchronization accuracy to allow a 5 ms tolerance for data alignment.

Temporal consistency in multi-source data is realized through IEEE 1588 Precision Time Protocol for network synchronization, where every acquisition node stamps the data frame to facilitate alignment between different modes in a 5-millisecond tolerance. This synchronization time remains below the minimum timescale of defect formations to ensure that combined data is obtained under the same manufactured state conditions, while clock drift compensation for robustness is realized through ongoing PTP communication messages checked at the fusion level.

2.2 A lightweight edge defect detection model

Defects that occur during the hot pressing of plywood affect its physical and mechanical properties and the grade of appearance quality. Closed-loop control can only be achieved by firstly correctly identifying what type of defects exist. Secondly, the defective areas must also be properly localized. The current study focuses on the detection of four common defects developed during the hot-pressing process. Bubble defects manifest as localized circular protrusions with diameters of 3-18 mm, caused by rapid moisture vaporization under excessive veneer moisture content or heating rate. Delamination defects appear as linear or curved dark bands along the grain direction at internal interfaces between veneer layers, resulting from insufficient or uneven adhesive coverage. Debonding defects, distinguished from delamination by their location, present as irregular gaps concentrated at panel peripheries due to inadequate edge adhesion strength. Glue penetration defects appear as irregular dark stains on panel surfaces caused by excessive adhesive migrating through veneer pores during pressing. Wide-scale variation, strong morphological variability, and similarity to natural wood grain patterns present common visual difficulties of these defects. Candidate models considered for the detection network architectures for selection to suit the problem of defect detection based on the metrics of accuracy, efficiency, and viability for real-time edge deployment included YOLOv5 variants, MobileNet-SSD, EfficientDet, and Faster R-CNN.

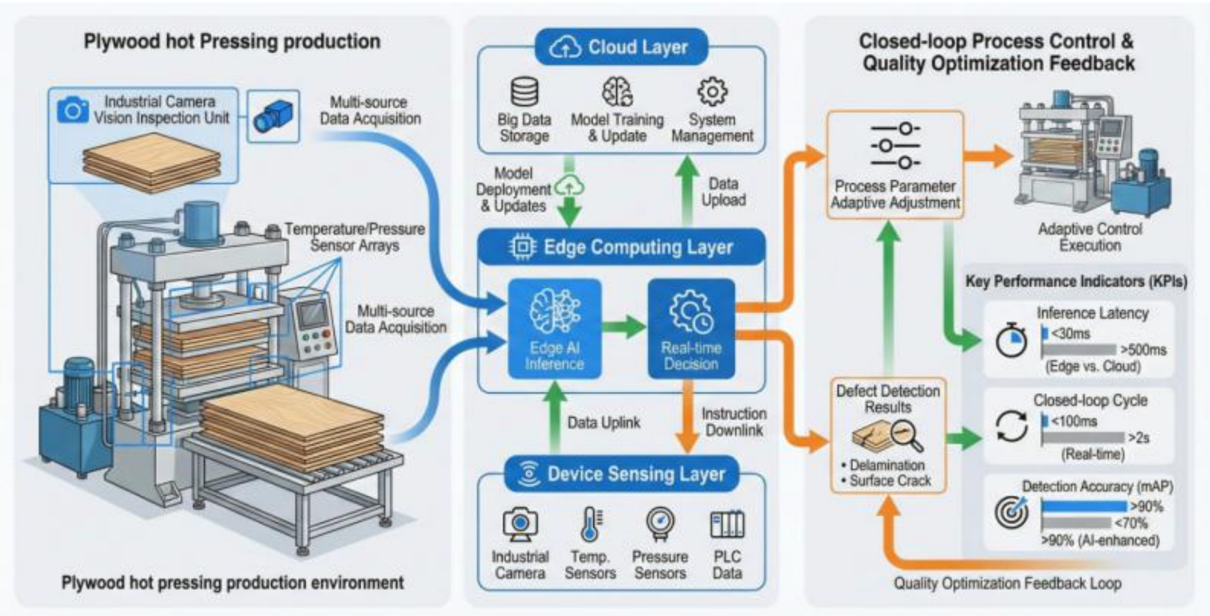

Figure 1. The edge intelligent control architecture of the hot-pressing process of plywood

The selection was based on the superiority of adaptability offered by YOLOv8n to diverse defect shapes with variable aspect ratios and the single-stage approach that provides significantly lower latency compared to two-stage detectors like Faster R-CNN [26]. The work proposes a light-weight optimization framework for edges in a multi-layered architecture that involves structural transformations, precision reduction, and optimization of the inference engine. At a structural level, depth-wise separable convolutions were used as substitutes for conventional convolutions, while structured channel pruning was applied to eliminate 30% of the channels in the features based on L1-norm importance. Post-training static weight quantization was applied to change the precision from FP32 to INT8, which used 500 training images to calibrate all layers for optimal scaling based on entropy minimization. A TensorRT optimizer is used for fusion and kernel auto-tuning based on the edge device. This lightweighting strategy is inspired by the design principles of online learning on edge devices and semantic model management [27], while also incorporating deployment experience from deep learning systems in resource-constrained industrial settings [28].

The evaluation of model performance is a crucial aspect in the field of object detection, where the standard metric of mAP@0.5 is employed to measure the efficacy of detection algorithms. The assessment of detection capability for evaluation purposes is primarily carried out using two main parameters: precision (P) and recall (R). They are calculated using equations P = TP / (TP + FP) and R = TP / (TP + FN), where TP, FP, and FN represent true positives, false positives, and false negatives, respectively. The mean Average Precision (mAP) for multi-class detection is computed as:

$$mAP@\tau = \frac{1}{C}\sum_{C=1}^{C} AP_C = \frac{1}{C}\sum_{C=1}^{C}\int_0^1 P_c\,(R)dR \quad (1)$$

where C denotes the number of defect categories (C = 4 in this study), AP_C represents the Average Precision for the c-th category calculated as the area under its precision-recall curve, and $P_C R$ is the precision at recall level R with Intersection-over-Union threshold $\tau = 0.5$.

2.3 IoT and Real-Time Process Control

The effective integration of visual inspection results with process parameters constitutes the foundation of data for achieving precise closed-loop control. The present study implements decision-level multi-source data fusion at the edge computing layer, integrating defect identification outputs with hot-pressing status monitoring information through spatio-temporal correlation. Decision-level fusion employs a weighted evidence combination strategy to integrate visual inspection and parameter monitoring results:

$$P(D_k|E) = \frac{P(D_k|E_v)^{\alpha}\cdot P(D_k|E_p)^{1-\alpha}}{\sum_{j=1}^{N} P(D_j|E_v)^{\alpha}\cdot P(D_j|E_p)^{1-\alpha}} \quad (2)$$

where D_k denotes the k-th defect category ($k = 1,2,\ldots, N = 5$ including four defect types and one normal category), E_v and E_p represent visual evidence from detection model outputs and process parameter evidence from sensor readings respectively, and the final classification follows $\widehat{D} = argmax_k P(D_k|E)$. The fusion weight $\alpha = 0.7$ was determined through empirical tuning on the validation dataset with values ranging from 0.5 to 0.9, achieving optimal balance between visual detection reliability and process parameter complementarity based on the higher discriminative capacity of image-based defect recognition.

The methodology for multi-sensor data quality assessment and fusion in intelligent manufacturing environments provided the fundamental framework for the present study [29]. Building upon this foundation, targeted optimizations were implemented to meet the real-time requirements of the plywood hot-pressing process. The integrated workflow for multi-source data fusion and closed-loop control is illustrated in Figure 2. As demonstrated in Figure 2, the complete information processing process commences with the collection of raw data and culminates in the execution of the control command. The chain comprises four stages: data processing, temporal alignment, decision fusion and action implementation. In the preprocessing stage, visual data is subjected to adaptive histogram equalization and Gaussian filtering, while process parameter data undergoes outlier elimination and a sliding window smoothing process.

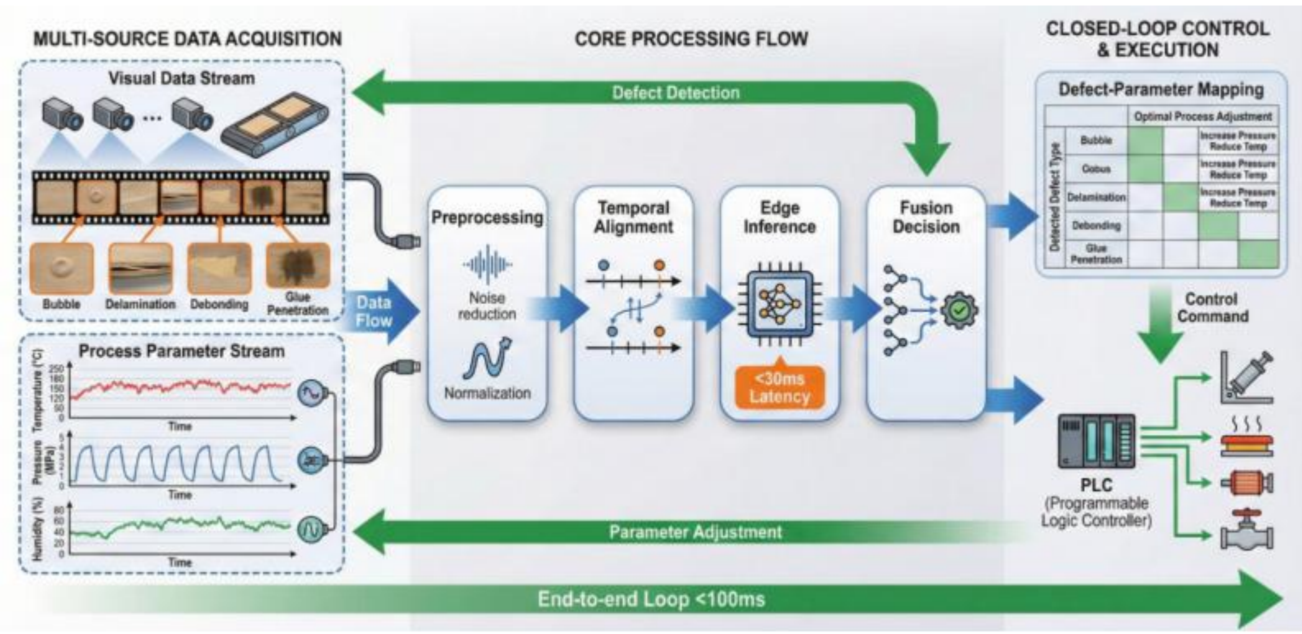

Figure 2. Multi-source data fusion and real-time closed-loop control process

During the process of time alignment, data streams characterized by varying sampling rates are synchronized to a shared reference time. This is achieved through the implementation of linear interpolation techniques, with the synchronization process being guided by high-precision, time-stamped data. The control cycle of the system is an essential component of the end-to-end process. The closed-loop control system is restricted to a response time of 100 ms, which is imposed on all stages of delay, ensuring the real-time response of the hot pressing process.

$$T_{loop} = T_{acq} + T_{det} + T_{fus} + T_{com} + T_{exe} < 100ms \quad (3)$$

where T_{acq} denotes image acquisition latency including exposure and frame transfer; T_{det} represents detection model inference time; T_{fus} indicates multi-source data fusion computation time; T_{com} represents PLC communication latency via Modbus TCP, and T_{exe} denotes actuator execution time for physical parameter adjustment.

The process of associating defect detection outcomes with process control directives constitutes a pivotal phase in the realization of intelligent automation control. The present study establishes correlation rules between defect types and process parameter deviations based on the thermal pressing mechanism of plywood. The defect parameter mapping process has a methodological grounding rooted in concepts of deep reinforcement learning and the digital twin paradigm, although employing a rule-based approach that is suitable and appropriate for the deterministic control of industrial processes. The application of deep reinforcement learning concepts can be identified with the treatment of the control of the industrial process as a sequential decision problem, where defect identification is the observation of the state and the regulation of parameters is the action [30]. Digital twin methodology informed the specification of adjustment magnitudes in Table 1 through offline process simulation that evaluated defect formation probability under various parameter perturbations [31]. The defect-parameter correlation mapping and control strategy are presented in Table 1.

Table 1. Defect type - process parameter association mapping and control strategy

Defect Type	Typical Morphology	Primary Cause	Recommended Adjustment
Bubble	Circular protrusion, 3-18mm	Excessive temperature or rapid heating	Reduce Temperature 3-8°C
Delamination	Linear/curved dark bands	Insufficient or uneven pressure	Increase pressure 0.08-0.15MPa
Debonding	Irregular peripheral gaps	Inadequate holding time	Extend holding 20-45s
Glue Penetration	Irregular dark stains	Over-application of adhesive	Reduce glue spread 5-15%

The objective of Table 1 is to establish a correlation mapping mechanism between four typical categories of defect and process parameters. This research looks to build a basis for decision-making in adaptive control. Bubble defects occur as circular formations whose diameters vary between 3mm and 18mm. Bubble defects occur because of two leading effects: using very high temperatures during hot pressing and fast heating. The adjustment process involves decreasing temperatures by 3 to 8°C. Delamination defects occur as linear to curved dark zones. As pointed out above, these problems occur because of low and ununiform pressure application. A possible remedy would be to increase pressure by 0.08 to 0.15 MPa. Insufficient time has also been indicated to be a source of debonding defects where irregular gaps are observed along edges; therefore, this time needs to be prolonged by 20 to 45 seconds. The presence of dark spots indicates penetration of adhesives to the surface. This often occurs where much adhesive has been used. Consequently, a possible adjustment would involve decreasing adhesives quantity by 5 to 15%.

The translation from defect detection outputs to PLC control commands operates through a deterministic pipeline at the edge computing layer. Upon fusion decision completion, the edge controller retrieves the corresponding parameter adjustment from Table 1 based on the identified defect category, with the adjustment magnitude scaled by defect confidence score and affected area ratio. The computed parameter modification is encoded into Modbus TCP frames and transmitted to the PLC via industrial Ethernet within 5 ms. The PLC executes parameter adjustments through analog output modules interfacing with hot press actuators for temperature regulation via heating element power modulation, pressure control via hydraulic valve positioning, and holding time modification via cycle timer adjustment.

3. Results

3.1 Experimental configuration and lightweight optimization

To verify the efficiency of the developed framework, a systematic experimental validation was performed for this research work. The experiments were conducted using a hardware environment equipped with the NVIDIA Jetson Xavier NX edge computing board along with TensorRT 8.4 and CUDA 11.4. In order to ensure the fairness of the experiments, all comparative experiments were conducted on identical hardware and software configurations. The hardware and network specifications of the edge computing platform are summarized in Table 2 to facilitate experimental reproducibility.

Table 2 summarizes the edge computing platform configuration, where the 15W power mode balances computational performance with factory thermal constraints, and MQTT QoS level 1 ensures reliable data delivery with acceptable protocol overhead. Data sources for model training and validation encompass public industrial defect datasets and a self-built plywood defect dataset. The public datasets selected for inclusion in this study are MVTec AD (https://www.mvtec.com/company/research/datasets/mvtec-ad) and Kolektor SDD (https://www.vicos.si/resources/kolektorsdd/).
The former contains a wide array of samples of surface defects across multiple industrial products, while the latter focuses specifically on surface crack and scratch detection. Both datasets are widely used for comparison with industrial vision inspection algorithms. To bridge domain gaps between general industrial defects and plywood-specific categories, the model was pre-trained on public datasets to learn generic defect features and subsequently fine-tuned on a self-built plywood dataset, with texture-aware data augmentation to enhance cross-domain generalizability while preserving wood-specific pattern recognition capability. The self-built dataset was collected from an operational hot press line over a four-week period, comprising four defect categories with 4,826 annotated samples partitioned into training (3,378), validation (724), and test (724) subsets through stratified random sampling. Image acquisition employed industrial

cameras with 1920×1080 resolution mounted perpendicular to the panel surface at the hot press outfeed station, with diffuse LED illumination to minimize specular reflections from adhesive residues. All samples were annotated by professionals with over five years of quality inspection experience. A two-stage validation protocol was implemented to ensure annotation reliability, wherein each image was independently labeled by two inspectors with a third adjudicating disagreements, followed by cross-validation on a random 10% subset to verify inter-annotator consistency.

Table 2. Hardware and network specifications of edge computing platform

Category	Parameter	Specification
Edge Platform	Model	NVIDIA Jetson Xavier NX
	GPU	384-core Volta, 48 Tensor Cores
	CPU	6-core Carmel ARM v8.2
	Memory	8 GB LPDDR4x
	Power Mode	15W
Runtime Resource	Model Memory Footprint	2.8 MB (INT8)
	Inference Latency	19.6 ms
Network	Industrial Ethernet	100 Mbps
	MQTT Version	3.1.1
	MQTT QoS Level	1
Time Sync	Protocol	IEEE 1588v2 PTP
	Alignment Tolerance	< 5 ms
PLC Interface	Protocol	Modbus TCP
	Communication Latency	< 5 ms

The evaluation criteria for this analysis are precision, recall, and average precision with a precision level of 0.5 (mAP@0.5). Precision and average precision with a precision level of 0.5 are standard parameters used for object detection. The average precision at an IoU threshold of 0.5 calculates average precision for each class with IoU=0.5. The comparison of values for critical parameters before and after lightweight optimization are shown in Table 3. As shown in Table 3, with multi-level lightweight optimization, the number of model parameters was pruned from 3.2 million to 2.3 million, computational complexity reduced from 8.7 GFLOPs to 5.4 GFLOPs, and model storage was compressed from 6.3 MB to 2.8 MB. In terms of inference performance with the NVIDIA Xavier NX board, while the single-frame inference time was reduced from 35.8 ms to 19.6 ms, the detection accuracy of mAP@0.5 decreased from 91.7% to 90.2%, which marked a drop of about 1.5%. The 1.5 percentage point accuracy reduction remains above the 85% threshold typically required for automated industrial visual inspection systems, while the 45.3% latency improvement is essential for satisfying the 100 ms closed-loop constraint by preserving sufficient time margin for subsequent fusion and communication stages.

Table 3. Comparison of key performance metrics before and after model lightweight optimization

Performance Metric	Original Model (YOLOv8n)	Lightweight Model	Change Rate
Parameters (M)	3.2	2.3	↓28.1%
FLOPs (G)	8.7	5.4	↓37.9%
Model Size (MB)	6.3	2.8	↓55.6%
Inference Latency (ms)	35.8	19.6	↓45.3%
mAP@0.5 (%)	91.7	90.2	↓1.6%

3.2 An evaluation of the performance of defect detection models

The capability of lightweight models to function as expected for real-world detection tasks marks a very important measure for model engineering applicability assessment. In order to verify the capability of the model to detect and accurately locate four types of surface defects in the plywood, this research selects several samples for visualization purposes. In order to demonstrate the generalisation capability of the model, two samples from each defect category were selected, with these categories being distinguished by different dimensional, shape or contrast characteristics. The results of the detection process are illustrated in Figure 3.

As demonstrated in Figure 3, the results for the detection efficiencies of the four defect categories are presented. The first and second rows (a)(b) bubbles are identified as circular bright spots with a high degree of certainty; (c)(d) delamination is characterised as horizontal linear dark bands; (e)(f) debonding is described as an irregular distribution with a lower degree of certainty due to the complexity of the specimen; (g)(h) glue penetration is noted as diffuse circular dark spots. The model under consideration has been demonstrated to possess the capability to accurately localise a wide range of defects. As demonstrated in the figure, the lightweight model is capable of accurately identifying and locating the four defect categories. Glue penetration and bubble defects have confidence levels typically above 90%, while those with complex morphologies for debonding defects give confidence levels between 75% to 84%. The model has shown its ability to perform effectively even when a defect has a maximum dimension of 5mm.

Differences in morphological features and defect mechanisms lead to inherently diverse difficulties when processing defect types. A quantitative evaluation is therefore essential to characterize detection capability boundaries for each defect category, enabling comprehensive performance assessment and informing deployment strategies. The goal of this research work is to undertake a more systematic assessment of model capability concerning its precision performance based on varying levels of recall. This facilitates a more systematic and detailed assessment of precision performance across recall levels. Precision-recall curves are employed to quantify the Average Precision (AP) for each defect category, representing the area under the curve that integrates precision across recall levels. The category-specific results are presented in Figure 4.

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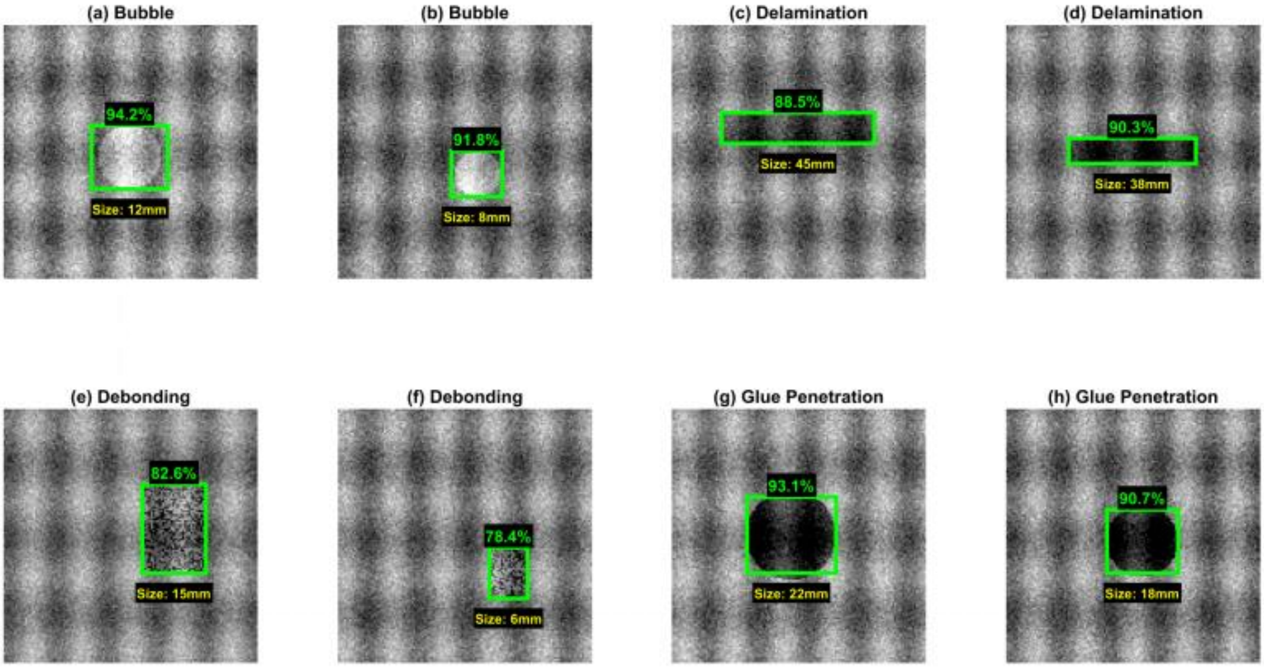

Figure 3. Representative defect detection results with confidence scores

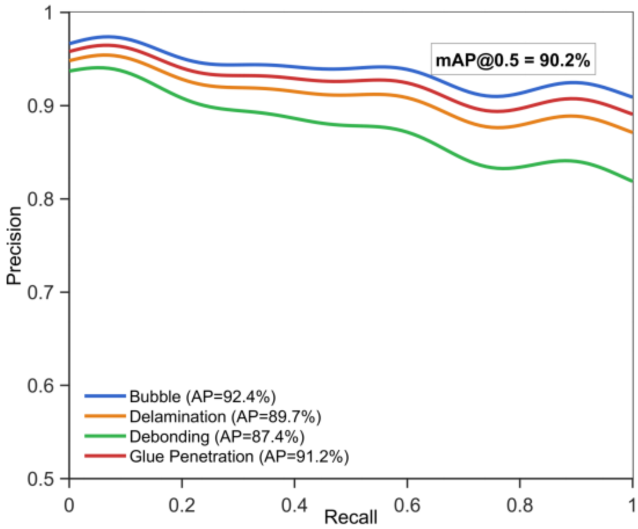

Figure 4. Precision-recall curves for four defect categories

As demonstrated in Figure 4 above, the bubble defect demonstrates the highest AP value of 92.4%. The next most prevalent defect is glue penetration defect, with an AP value of 91.2%. Delamination defects have been observed to bear a resemblance to the natural pattern of wood grain, and have been found to have an AP value of 89.7%. Conversely, the lowest AP was observed for debonding defects with complex morphology (87.4%). These results are in accordance with industrial inspection accuracy criteria. In order to demonstrate the efficacy of the proposed model, a comparison with existing models must be made. The present study employs a comparative approach to analyse the overall competitiveness of a lightweight model against its mainstream counterparts. To this end, five representative algorithms YOLOv5n, YOLOv5s, YOLOv8n, MobileNetV3-SSD and EfficientDet-D0 have been selected for objective comparison. The most common lightweight architectures used for object detection on edges are categorized by the above approaches. A comparison study was conducted using the same division of datasets, data augmentation techniques, and training parameters for each model. The comparison assessment used TensorRT INT8 mode with a Jetson Xavier NX board. As shown in Table 4 below, the performance of models based on parameters, FLOPs, inference time, and model sizes are included. As shown in Table 4, the precision of the model stands at 90.2%, with 2.3 million parameters and a 19.6 ms inference time. Following INT8 quantization, YOLOv8n loses 0.4 percent points in precision. This might be because the prediction and ground truth values vary marginally. However, there is a large drop in inference time of 16.2%. Additionally, model sizes are reduced by 12.5%. Compared with YOLOv5s with 91.6 percent precision as a benchmark, similar precision with a 68 percent reduction in parameters and 39.5 percent improvement in inference time can be achieved with this model. Compared with YOLOv5n, which achieves 86.8% precision, our model demonstrates 3.4 percentage points higher accuracy despite 3.4ms longer inference time (19.6ms vs 16.2ms). This model clearly outperforms all other models in terms of precision and efficiency. Note that Table 3 results represent INT8 models. This is because model sizes were reduced due to INT8 quantization. The original YOLOv8n model size of 6.3 MB was reduced to 3.2 MB after INT8 quantization.

3.3 Edge deployment and real-time verification

The industrial usefulness of a defect detection model relies not only on its ability to accurately pick out defects but also on efficiency and real-time execution capability for resource-limited edge environments. This section addresses validation for efficiency and effectiveness of strategy execution on a resource-limited environment.

Table 4. Comparison with state-of-the-art detection methods

Method	mAP@0.5 (%)	Params (M)	FLOPs (G)	Latency (ms)	Size (MB)
YOLOv5n	86.8	1.9	4.5	16.2	1.8
YOLOv5s	91.6	7.2	16.5	32.4	7.3
YOLOv8n	91.3	3.2	8.7	23.4	3.2
MobileNet V3-SSD	84.7	2.5	5.8	18.3	2.6
Efficient Det-D0	86.2	3.9	10.2	34.8	4.3
Ours	90.2	2.3	5.4	19.6	2.8

In order to measure the individual role and interactions of the three lightweight methods: depthwise separable convolution replacement, channel pruning, and INT8 quantization, a progressive ablation approach was used. The model used for comparison was YOLOv8n. Additionally, experiments were run using a Jetson Xavier NX board with a validation data set consisting of 724 images. In order to reduce possible variations in results for average inference time measurements, a total of 1,000 evaluations were used. Simultaneously, model sizes were included based on their actual memory usage levels following each stage. The performance measurements for each configuration are shown in Table 5.

As shown in Table 5, the ablation study quantifies the individual contribution of each lightweight optimization step. Depthwise separable convolution reduces latency by 20.7% (35.8→28.4 ms) with negligible accuracy loss of 0.2 percentage points. Channel pruning contributes an additional 14.8% latency reduction (28.4→24.2 ms) and 23.5% size compression (5.1→3.9 MB) at a cost of 0.7 percentage points in accuracy. INT8 quantization combined with TensorRT engine optimization yields the final 19.0% latency improvement (24.2→19.6 ms) and 28.2% size reduction (3.9→2.8 MB) with 0.6 percentage points accuracy decrease, demonstrating that each optimization module provides measurable benefits with acceptable precision trade-offs.

Table 5. Ablation study on lightweight optimization strategies

Configuration	mAP@0.5 (%)	Latency (ms)	Model Size (MB)
Baseline (YOLOv8n FP32)	91.7	35.8	6.3
+ Depthwise Separable Conv	91.5	28.4	5.1
+ Channel Pruning (30%)	90.8	24.2	3.9
+ INT8 Quantization	90.2	19.6	2.8

The underlying hypothesis for the architecture of edge computing considers the removal of data transmission delay to provide true real-time response. To validate this supposed benefit, a comparison between this solution and existing cloud-based deployment methods needs to be considered. To compare and measure end-to-end response time for identical detection tasks based on both methods of cloud and edge computing for systematic analysis of this study, a comparison test was performed. The edge approach used a Jetson Xavier NX for inference processing infrastructure, while a data center server with a GPU RTX 3080 was used. Connected via the corporate campus network, the round-trip network latency measured during the experiment ranged from 8 to 15 milliseconds. However, in actual operation, end-to-end latency exhibited significant variability due to concurrent requests from multiple production lines, server task queuing, and network traffic fluctuations. It was observed that both solutions processed the same 1000-frame continuous test image sequence. The complete end-to-end latency from image acquisition completion to detection result output was recorded during the experiment. The statistical characteristics of the latency distribution are illustrated in Figure 5.

The delay distribution of the two deployment schemes is shown in Figure 5. The edge scheme (Figure 5a) shows an average delay of 20.7 ms, and 94.2% of the samples are less than 30 ms. In contrast, the cloud solution (Figure 5b) shows an average long-tail distribution of 373.1 ms, verifying the significant advantages of edge deployment in real-time industrial control.

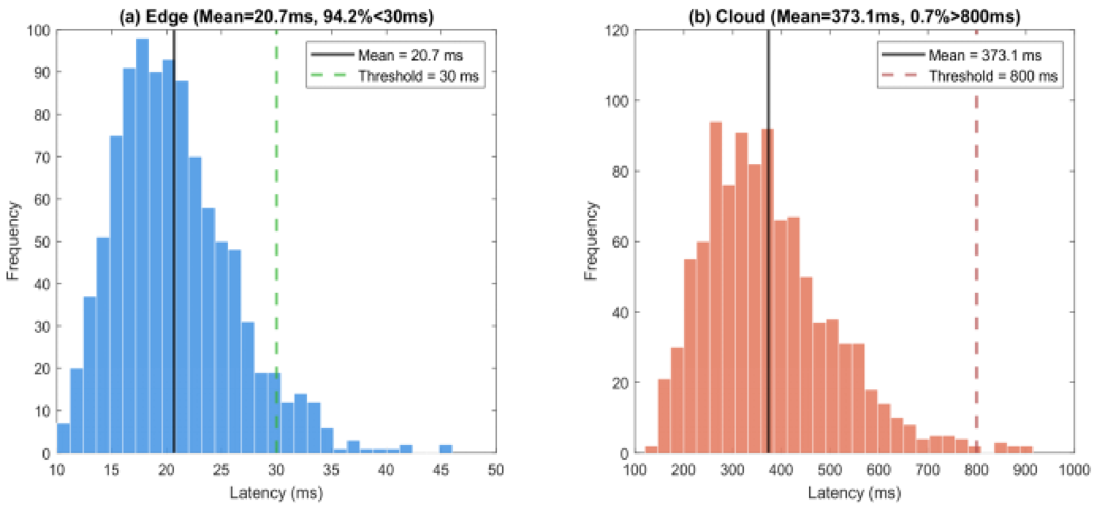

Figure 5. Latency comparison between edge and cloud deployment

3.4 Multi-source data fusion and closed-loop control validation

The edge deployment of detection models establishes the basis for real-time process control, while the efficacy of multi-source data fusion strategies and closed-loop control mechanisms directly determines the overall application value of intelligent manufacturing systems. This section undertakes verification from two dimensions: data fusion effectiveness and control stability. Quality inspection in industrial Internet of Things (IoT) environments has the capacity to acquire two types of perceptual data simultaneously: visual images and process parameters. The proposed approach demonstrates a decision level fusion scheme that aims to capitalize on multi-source information for better inspection results. A comparison experiment has been conducted to determine whether any performance benefits were achieved with the fusion scheme over single-source methods. The visual scheme only utilized imaging data from industrial cameras. The parameter scheme only made use of process information from temperature, pressure, and humidity sensors. The fusion scheme fused the two data sources using decision level fusion. Each scheme was tested using a common set of 200 production samples. The inspection results were measured using detection rate, false alarm rate, and false negative rate. The results are illustrated in Table 6. As shown in Table 6, the decision-level fusion strategy achieves 92.1% detection rate, representing a 3.7 percentage point improvement over visual-only inspection and 28.9 percentage points over parameter-only monitoring. The fusion approach simultaneously reduces the false alarm rate from 7.8% to 5.6% and the miss rate from 11.6% to 7.9%, demonstrating that process parameter provides effective complementary discrimination for ambiguous visual cases while visual inspection compensates for the limited defect-specific sensitivity of indirect parameter anomaly detection.

Table 6. Overall production quality improvement

Data Source	Detection Rate (%)	False Alarm Rate (%)	Miss Rate (%)
Visual Only	88.4	7.8	11.6
Process Parameters Only	63.2	14.1	36.8
Fusion (Ours)	92.1	5.6	7.9

The stability and reliability of a real-time closed-loop control system during extended continuous operation will determine its industrial applicability. In order to assess the true performance of the control architecture presented in this paper, a 72-hour stability test on a production line was conducted. The system continued to function during the testing period. In instances where defects were identified or process parameters exceeded warning limits, the closed-loop control process was initiated. The complete timeline for defect detection to effecting the process parameter adjustment command by the PLC was recorded systematically. From a total of 2,847 valid control cycle samples collected, 1,000 samples were extracted in accordance with the uniform sample extraction protocol. The response times that occur over specific periods are illustrated in the accompanying Figure 6.

The closed-loop control response is shown in Figure 6. The time series (Figure 6a) shows an average response of 81.2 ms, and 89.5% of the samples are below the 100 ms threshold. The histogram (Figure 6b) shows that the standard deviation is 14.6 ms, and the response is concentrated between 60 and 95 ms, confirming the stable real-time control performance. The use of intelligent control systems is anticipated to be one of the factors that would majorly aid in improving quality as well as increasing efficiency levels with regard to production. In a bid to validate any engineering benefits emanating from the use of such systems within a particular environment, data regarding productions was obtained for a period of three months prior to and subsequent to system installation. The data used in this particular study includes statistical measures such as defect rate, first-pass yield rate, average time for inspection for boards, and false rejection rate. The defect rate stands determined via re-inspection done manually for inspection of defect levels for completion. The "first-pass yield rate" refers to a total number of produced goods that would go undetected within a single inspection. False rejection refers to a total percentage of undetected goods that would end up being rejected. This data is laid out in Table 7. As shown in Table 7, system deployment reduced defect rate from 5.2% to 2.8% (46.2% improvement) and inspection time from 11.8 to 4.6 seconds per board (61.0% efficiency gain), while first-pass yield increased from 90.6% to 94.3% and false rejection rate declined from 3.7% to 2.1%, validating the practical engineering value of the proposed framework.

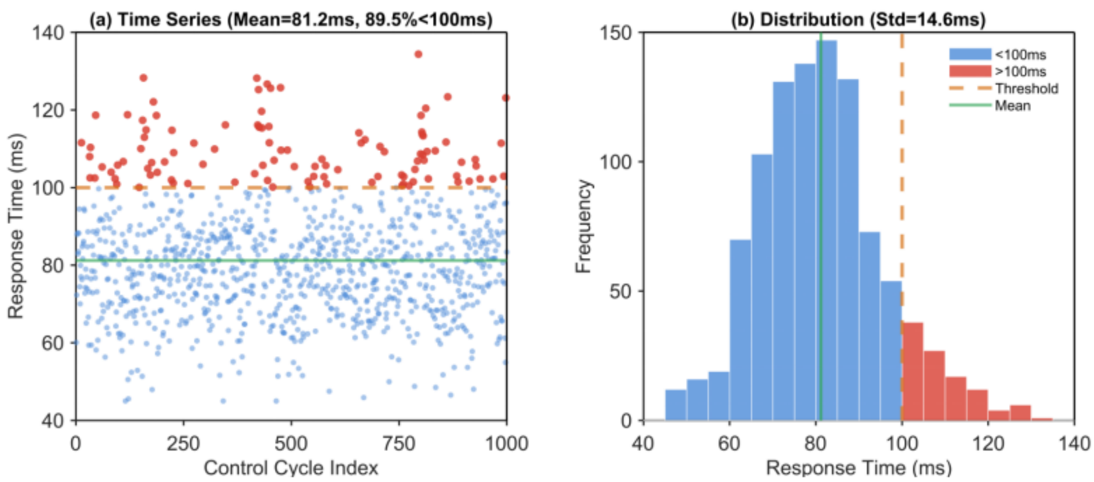

Figure 6. End-to-end control loop response under continuous operation

Table 7. Example of the table with caption

Metric	Before Deployment	After Deployment	Improvement
Defect Rate (%)	5.2	2.8	↓ 46.2%
First-pass Yield (%)	90.6	94.3	↑ 3.7pp
Average Inspection Time (s/board)	11.8	4.6	↓ 61.0%
False Rejection Rate (%)	3.7	2.1	↓ 43.2%

4. Discussion

A lightweight model for defect detection introduced in this paper shows a total detection accuracy of 90.2%, with a total inference time of 19.6 ms in an edge environment. Compared with state-of-the-art results in current edge vision detection studies, this results in a marked improvement. In industrial defect detection tasks, compact network methods with attention mechanisms introduced in this field have evolved to efficiently decrease computational cost without affecting detection quality [32]. In intelligent plywood processing tasks, a combination of integrated deep separable convolution and structure pruning approaches showcases a similar compression effect and therefore proves practical feasibility for appropriate engineers for a tailored lightweight design in the wood processing industry. The 45% decrease in inference time , associated with a 1.5 percentage point decrease in accuracy, is considered a good trade-off for the industry, particularly when the real-time system that was achieved resulted in a 46.2% decrease in defect rate and a 61.0% improvement in efficiency of inspection. Recent studies on real-time object detection for edge devices indicate that maintaining inference delays below 30 ms is a critical operational requirement for most current industrial vision tasks [33]. This system performs 19.6 ms for inference time requirements and thus retains sufficient time for stage-wise fusion processing and subsequent control decisions. A number of industrial experiments have shown suitability for outstanding techniques employed for complex texture-based small object detection tasks [34]. With the average precision rate of 87.4% on debonding defects, being 5.0 percentage points lower than the best bubble category, there is still a challenge here as far as morphological complexity is concerned. Geometric patterns in debonding defects are irregular with high intra-class variances compared to the circular shapes of bubbles. Additionally, these defects border areas where the wood grains are likely to be exposed in end due to edge irregularities.

Edge solution deployment proves distinct benefits concerning response time compared with cloud architecture designs. This observation finds a scientific basis in previous studies. A literature review of response time in Edge Computing for IIoT reveals that uncertainty involved in network transmission remains a major barrier for real-time cloud solution execution [35]. The findings of this study demonstrate that cloud-based solutions exhibit an average latency of 373.1ms, characterized by a long-tail distribution. This observation substantiates the conclusions drawn. Edge intelligence can be applied practically for time-sensitive industrial applications. The efficacy of moving inference computations close to data sources in mitigating network jitter effects on control stability has been demonstrated [36]. An 89.5% closed-loop control compliance rate validates the applicability of the edge architecture in intelligent plywood hot-pressing processes. A 3.7 percentage point increase in the detection rate (from 88.4% to 92.1%) was achieved through the implementation of multi-source data fusion strategies, thereby substantiating the complementary value of visual information and process parameters. Research on process parameter optimization based on digital twins has demonstrated that collaborative analysis of multidimensional data can capture quality fluctuation patterns that are difficult to characterize using single data sources [37]. In the contemporary business environment, there is an increasing trend of automation in industrial machinery. Concurrently, there has been a notable advancement in the field of predictive maintenance, which employs the analysis of runtime data streams to identify patterns in historical data. The aim of using this approach is to optimize the precision of anomaly detection [38].

The integration of this approach has been considered a vital part of building innovative predictive maintenance solutions. Experimental work in industrial automation has indicated that end-to-end delays in detection and execution time are taken into account for closed-loop control [39]. The design architecture has proven capable of supporting a mean closed loop cycle time of 81.2 ms. Thus, this design has demonstrated its viability in supporting closed loop requirements for dynamic adjustment in the hot-pressing operation. The modular structure facilitates horizontal scaling through replication of the edge nodes in edge computing. Every production line provides a respective edge node running independently for local inference and control, with network connectivity to the cloud layer for model updates and cloud storage of data. Resource utilization metrics reveal sufficient margin for increased density of sensors per line. Further, the network bandwidth increases linearly with the number of lines for cloud data upload and does not hamper edge-local closed-loop control. This can be ensured through the use of environmental protection enclosures that are air-purged to counter the effects of dust, the use of global shutter sensors with short exposure times to improve resistance to vibrations and closed-loop LED lighting systems that make use of Adaptive Histogram Equalization to ensure that lighting is stable.

At the application level in wood processing, the design of the intelligent plywood production control system appears to be a viable contribution to existing literature. In previous studies associated with intelligent wood processing monitoring, researchers have only focused on offline analysis [40]. Conversely, the integration of edge AI with real-time closed-loop control serves to bridge the technological divide in online process adjustments. Recent research into the integrated framework of intelligent manufacturing systems suggests that the close integration of perception, decision, and execution is essential for autonomous manufacturing [41]. The proposed edge intelligence configuration consists of a three-layer system that manages edge-level operations through the edge computing layer. The findings indicate that the defect rate has been reduced by 46.2%, and the detection efficiency of the proposed detection system has been enhanced by 61.0%. This outcome demonstrates the practical engineering value of the framework in intelligent plywood. Nevertheless, several limitations of the current implementation warrant acknowledgment. The self-built dataset of 4,826 samples from a single production facility may limit model generalization to environments with different wood species or adhesive formulations, and the four-category defect taxonomy does not encompass all possible defect manifestations. The 72-hour closed-loop validation demonstrates short-term stability but does not establish long-term reliability under seasonal variations or equipment aging. The rule-based defect-parameter mapping ensures deterministic control behavior but lacks adaptive capability to accommodate process drift. Future research directions include transfer learning approaches for rapid adaptation to new production environments, online learning mechanisms for refining mapping rules based on operational feedback, and incorporation of additional sensing modalities such as infrared thermography for subsurface defect detection.

5. Conclusion

The present study puts forward a proposal for an artificial intelligence (AI)-driven framework with the objective of real-time process control in production, with a view to meeting the technical requirements for real-time quality control in intelligent plywood production. The framework employs a three-layer architecture of edge intelligence for the purposes of defect detection and control decision-making. The system can be deployed in the production environment. The model uses a multi-layer light-weight approach that incorporates deep separable convolutions, channel pruning concepts, and INT8 quantization techniques for efficient deployment of edge models. Furthermore, the model uses a data fusion strategy for multi-source data. The experimental results reveal that a smaller model achieves a 90.2 % level of detection with a 19.6 milliseconds average inference time for model execution using a Jetson Xavier NX environment. Compared to typical cloud model execution environments, response time for completion of tasks using edges has minimized response time from 373.1 milliseconds to 20.7 milliseconds. Also, data fusion for multi-source data has amplified the level of detection from 88.4 percent to 92.1 %. Additionally, in 89.5 % of cases tested, a closed loop control system ensured a cycle time of 100 milliseconds. As a consequence of such techniques being employed, a 46.2 % reduction in the number of defects in end products was observed. Also, efficiency for defect detection techniques increased by 61.0 percent. The results confirm that implementing edge AI technology may help reformat and sharpen intelligence in the wood processing industry. The proposed framework has the potential to facilitate online quality inspection of plywood hot-pressing processes. Consequently, it could serve as a valuable reference point for the enhancement of conventional manufacturing processes to a more intelligent, data-driven paradigm.

Ethical issue

The authors are aware of and comply with best practices in publication ethics, specifically regarding authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with research ethics policies. The authors adhere to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the authors.

Conflict of interest

The authors declare no potential conflict of interest.

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