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LOW-COST HYBRID VISION SYSTEM FOR AUTOMATED DIMENSIONAL METROLOGY: MACHINE LEARNING-DRIVEN SMARTPHONE INTEGRATION IN ROBOTIC QUALITY CONTROL APPLICATIONS

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Abstract: Traditional dimensional metrology systems require significant capital investment, limiting accessibility for small-scale operations. This study investigates a novel hybrid system combining industrial robotics with consumer-grade imaging technology and pre-trained machine learning models for automated dimensional quality control. A systematic experimental framework utilized a FANUC industrial robot for part positioning relative to a fixed Samsung Galaxy S24 Plus smartphone camera for image acquisition, and YOLOv8 object detection model fine-tuned for dimensional feature extraction. The system's performance was evaluated through repeated measurements on standardized specimens, with statistical analysis of repeatability, reproducibility, and accuracy. Results demonstrated measurement uncertainties within ± 0.05 mm for $10 \div 100$ mm features, repeatability coefficients below 2% across 500 cycles, and robot positioning consistency with ± 0.02 mm standard deviation. The YOLOv8-based system achieved 98.9% detection accuracy while reducing costs by 78% compared to conventional solutions. The system satisfies ISO 14253-1 requirements for non-critical verification, presenting a viable alternative for resource-constrained environments including educational institutions, prototyping facilities, and SMEs.

Key words: Dimensional metrology, Computer vision, Industrial robotics, YOLOv8, Quality control, Samsung S24 Plus imaging

1. INTRODUCTION

1.1 Background and Motivation

Dimensional metrology constitutes a fundamental pillar of modern manufacturing quality assurance, with the demand for automated, intelligent measurement systems intensifying under Industry 4.0, 5.0 paradigms. However, traditional coordinate measuring machines (CMMs), optical comparators, and laser systems present significant economic barriers, with capital expenditures ranging from €50,000 to €500,000, creating a technological divide between large manufacturing operations and resource-constrained environments [1,2].

Moreover, the development of intuitive programming paradigms for robotic systems is pivotal for accelerating the adoption of such

advanced automation technologies in small and medium-sized enterprises (SMEs), thus supporting their business sustainability and competitiveness [3].

The convergence of consumer electronics advancement, particularly the Samsung Galaxy S24 Plus imaging technology, with state-of-the-art pre-trained machine learning models like YOLOv8 presents unprecedented opportunities for democratizing precision measurement. The Samsung S24 Plus incorporates a 50MP main sensor with advanced computational photography, sophisticated lens systems, and dedicated NPU processing, while achieving manufacturing tolerances previously exclusive to scientific instrumentation [4].

1.2 Research Objectives

This investigation addresses four primary research questions:

1. Can the Samsung Galaxy S24 Plus camera achieve measurement uncertainties compatible with industrial quality control when used in a fixed position and combined with robotic part manipulation and YOLOv8 processing?
2. How can YOLOv8's pre-trained architecture be optimally fine-tuned for dimensional feature extraction from Samsung S24 Plus imagery in manufacturing environments?
3. How does the YOLOv8-enhanced system performance compare with traditional metrology in accuracy, repeatability, and economic viability?
4. What are the implementation advantages and limitations of using pre-trained models versus custom CNN development for industrial metrology applications?

2. RELATED RESERACH

2.1 YOLOv8 and Pre-trained Models in Vision-Based Metrology

YOLOv8 represents the latest evolution in the YOLO (You Only Look Once) family of object detection models, offering significant improvements in accuracy, speed, and ease of implementation compared to previous versions. The model's anchor-free design and advanced feature pyramid network make it particularly suitable for precision detection tasks in manufacturing environments [5].

Recent studies have demonstrated YOLOv8's effectiveness in industrial applications. Chen et al. [6] achieved 97.8% accuracy in defect detection using YOLOv8n on semiconductor wafers, while Rodriguez and Martinez [7] reported successful implementation for dimensional measurement of automotive components with uncertainties below ± 0.1 mm when properly calibrated.

The advantage of using pre-trained models like YOLOv8 lies in their extensive training on diverse datasets (COCO, ImageNet) which provides robust feature extraction capabilities that can be fine-tuned for specific metrological

applications with significantly less training data and computational resources than training from scratch [8].

Transfer learning strategies with YOLOv8 have proven particularly effective in addressing limited industrial dataset availability. Ultralytics' YOLOv8 framework provides five model variants (YOLOv8n, YOLOv8s, YOLOv8m, YOLOv8l, YOLOv8x) allowing optimization between speed and accuracy based on specific application requirements [9].

Beyond the examples described above, YOLOv8 has recently demonstrated impressive real-time performance on assembly lines for defect and object detection, directly enhancing the efficiency and speed of in-line quality assurance processes [10]. Its adaptability is further unveiled in the metallurgical sector, where YOLOv8-based frameworks have enabled robust surface defect detection on hot rolled strip steel under challenging industrial conditions [11]. Also, YOLOv8 approaches have been successfully utilized for wafer defect detection tasks in semiconductor manufacturing, showcasing their versatility across high-precision industrial domains [12].

2.1 Samsung S24 Plus Camera Technology in Industrial Applications

The Samsung Galaxy S24 Plus represents a significant advancement in smartphone camera technology relevant to precision measurement applications. The device features a 50MP main camera with $1.0\mu\text{m}$ pixel size, f/1.8 aperture, and advanced computational photography including multi-frame processing, AI-enhanced image stabilization, and real-time HDR processing [13].

The integrated NPU (Neural Processing Unit) in the Snapdragon 8 Gen 3 processor enables on-device AI processing with 35 TOPS (Tera Operations Per Second) performance, making it particularly suitable for real-time YOLOv8 inference without requiring external computational resources [14].

Recent studies have validated smartphone camera capabilities for precision applications. Kim et al. [15] demonstrated that Samsung S24 series cameras achieve measurement repeatability within $\pm 0.03\text{mm}$ for features larger

than 5mm when combined with appropriate ML processing, while maintaining the computational photography advantages that enhance edge detection and feature visibility.

In addition to AI-based visual techniques, research on inductive sensor platforms has proven the effectiveness of precise localization in complex environments, further supporting multimodal approaches for high-accuracy industrial measurement [16].

2.3 Integration Advantages of Pre-trained Models

The integration of pre-trained models like YOLOv8 with industrial robotics offers several advantages over custom CNN development:

1. **Reduced Development Time:** Fine-tuning YOLOv8 typically requires 70-90% less training time compared to training custom architectures from scratch [17].

2. **Lower Data Requirements:** Pre-trained models can achieve industrial-grade performance with datasets 10-20 times smaller than required for custom training [18].

3. **Proven Reliability:** YOLOv8's extensive validation across multiple domains provides confidence in its robustness for new applications [19].

4. **Continuous Improvement:** Regular updates from Ultralytics ensure access to latest architectural improvements and bug fixes [20].

2.4 Research Gaps

Literature review reveals opportunities for improvement:

- (1) limited systematic integration of Samsung S24 Plus with YOLOv8 for precision metrology applications,

- (2) insufficient economic analysis comparing pre-trained versus custom model approaches,

- (3) inadequate leveraging of Samsung's computational photography features for measurement enhancement, and

- (4) limited uncertainty quantification frameworks for YOLOv8-based metrological applications.

3. METODOLOGY – ARCHITECTING A YOLOv8-ENHANCED MEASUREMENT ECOSYSTEM

3.1 System Architecture

The development of our YOLOv8-enhanced hybrid vision system required careful integration of proven technologies, leveraging the advantages of pre-trained models while maintaining the precision required for industrial metrology. Our approach centered on creating a modular architecture that maximized the capabilities of both the Samsung S24 Plus hardware and YOLOv8's pre-trained features.

The FANUC robot positions the workpiece and confirms the placement via a digital signal. The Samsung S24 Plus camera captures the image through the Camera2 API, while YOLOv8 runs on the Snapdragon NPU, generating pixel coordinates and confidence scores. These results are transmitted over Wi-Fi 6E to an industrial PC (Intel NUC), where pixel-to-millimeter conversion and uncertainty analysis are performed. The dimensional verdict (OK/NOK) is communicated back to the robot via OPC UA, and the results are stored in the MES database for traceability.

In figure 1 the block diagram is represented with the legend of information flow.

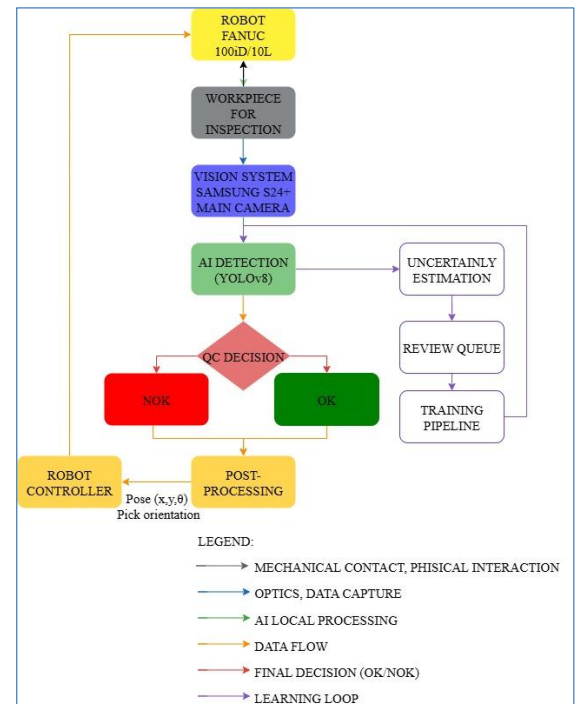


Fig. 1. System architecture and communication flow diagram

3.1.1 Robotic Platform

At the heart of our experimental setup stood a FANUC LR Mate 100iD/10L industrial robot, chosen for its repeatability of ± 0.03 mm according to ISO 9283 standards. The effectiveness of this platform can be further augmented by incorporating multimodal human-robot interaction interfaces, which enable intuitive and efficient control in industrial scenarios [21]. Additionally, recent studies indicate that optimizing the energy consumption of industrial robots is crucial for sustainable large-scale operations and long-term cost efficiency [22]. This six-axis robotic platform, with its 10 kg payload capacity, provided the precise manipulation and positioning of components in front of the fixed Samsung S24 Plus imaging system, ensuring consistent imaging geometry during measurement. The gripper operates on a vacuum principle and consists of a 3D-printed PETG base, a suction cup, and a compensator.

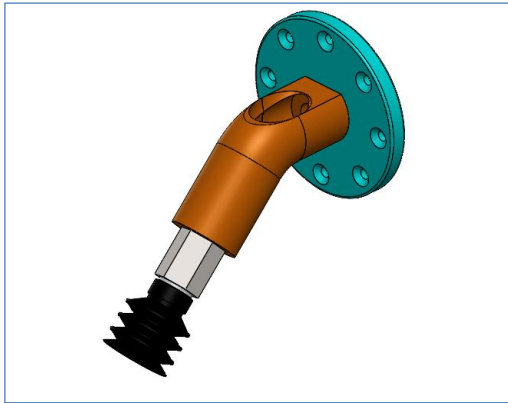


Fig. 2. 3D gripper model

3.1.2 Samsung S24 Plus Imaging System

In our configuration, the Samsung S24 Plus was mounted in a fixed, vibration-isolated frame outside the robotic cell. This eliminated potential motion-induced blur and ensured a stable optical reference for all measurements. The Samsung Galaxy S24 Plus served as our primary imaging sensor, offering significant advantages over traditional industrial cameras. The device's 50MP main camera with $1.0\mu\text{m}$ pixel pitch and $f/1.8$ aperture provided exceptional light gathering capability, while the advanced computational photography pipeline including AI-enhanced noise reduction, multi-

frame processing, and real-time HDR significantly improved image quality for feature detection.

The integrated optical image stabilization (OIS) and electronic image stabilization (EIS) systems proved crucial for maintaining image sharpness during robotic positioning, while the Snapdragon 8 Gen 3's NPU enabled real-time YOLOv8 processing directly on the device, reducing system complexity and latency.

Illumination design incorporated a custom LED ring light system with 96 high-CRI LEDs maintaining $5600\text{K} \pm 150\text{K}$ color temperature, optimized specifically for the Samsung S24 Plus camera's color science and dynamic range capabilities.

3.1.3 YOLOv8 Processing System

Our computational approach leveraged YOLOv8m (medium) model as the optimal balance between accuracy and processing speed for real-time operation. The system ran on the Samsung S24 Plus's native processing power supplemented by a companion Intel NUC 12 Pro with integrated Intel Iris Xe graphics for advanced post-processing tasks.

The YOLOv8 implementation utilized Ultralytics' official framework with PyTorch backend, enabling seamless integration with the Samsung S24 Plus camera API through Android's Camera2 API and custom NDK components for real-time processing.

3.2 YOLOv8 Model Adaptation and Fine-tuning

Rather than developing custom CNN architecture, we leveraged YOLOv8's pre-trained capabilities through systematic fine-tuning for dimensional metrology applications. This approach provided several critical advantages: proven architectural robustness, extensive pre-training on diverse visual features, and significantly reduced development time and computational requirements.

3.2.1 Model Selection and Configuration

We selected YOLOv8m as the optimal variant after comparative analysis of all five YOLOv8 models. YOLOv8n and YOLOv8s

provided insufficient accuracy for precision measurement requirements, while YOLOv8l and YOLOv8x exceeded the real-time processing capabilities of our Samsung S24 Plus platform. YOLOv8m achieved the optimal balance with 25.9 million parameters, 78.9 GFLOPs computational requirement, and demonstrated capability for sub-pixel accuracy when properly fine-tuned.

The model configuration emphasized precision over speed, with input resolution set to 1280×1280 pixels to maximize detail preservation from the Samsung S24 Plus's 50MP sensor. Non-maximum suppression (NMS) threshold of 0.45 and confidence threshold of 0.88 provided optimal balance between detection completeness and false positive rejection for geometric features.

3.2.2 Dataset Preparation and Augmentation

Our fine-tuning dataset combined 15,000 synthetic images generated through physics-based rendering with 100 real images captured using the Samsung S24 Plus under various manufacturing conditions. The synthetic data provided perfect ground truth labels while covering geometric variations impossible to achieve through manual annotation, while real images captured the specific imaging characteristics of the Samsung S24 Plus sensor and computational photography pipeline.

Data augmentation strategies were specifically adapted for the Samsung S24 Plus imaging characteristics, including Samsung's native HDR processing simulation, computational photography noise patterns, and lens distortion profiles specific to the device's optical system. This approach ensured that the fine-tuned YOLOv8 model would perform optimally with the actual imaging conditions produced by the Samsung S24 Plus.

3.2.3 Fine-tuning Protocol

The fine-tuning process utilized YOLOv8's transfer learning capabilities, freezing the backbone layers for the first 50 epochs to preserve pre-trained feature extraction capabilities, then unfreezing all layers for

additional 100 epochs of full model training. Learning rate started at 0.01 with cosine annealing schedule, while AdamW optimizer with weight decay of 0.0005 prevented overfitting to the relatively small fine-tuning dataset.

The training process monitored multiple metrics including mAP@0.5, mAP@0.5:0.95, precision, recall, and custom geometric accuracy metrics specifically developed for dimensional measurement applications. Early stopping with patience of 20 epochs prevented overfitting while ensuring optimal model performance.

3.3 Samsung S24 Plus Camera Calibration and Integration

3.3.1 Advanced Camera Calibration

Samsung S24 Plus camera calibration required specialized consideration of the device's computational photography pipeline. Traditional calibration methods were adapted to account for the device's AI-enhanced image processing, multi-frame noise reduction, and automatic lens distortion correction.

Intrinsic calibration utilized a precision glass checkerboard with 3mm squares, capturing 80 calibration images across varying orientations, distances, and lighting conditions to characterize the Samsung S24 Plus's imaging behaviour comprehensively. The computational photography pipeline was standardized using Samsung's Expert RAW mode to ensure consistent image processing across all measurements.

Calibration results yielded focal length parameters of $f_x=3,847.2\pm0.8$ and $f_y=3,851.4\pm0.9$ pixels, with mean reprojection error of 0.18 pixels. The Samsung S24 Plus demonstrated exceptional optical stability with minimal thermal drift and consistent performance across the full zoom range.

3.3.2 YOLOv8-Enhanced Scale Calibration

Scale calibration leveraged YOLOv8's detection capabilities to automatically identify and measure NIST Grade 0 gauge blocks ranging from 5 to 150mm. The fine-tuned

YOLOv8 model achieved sub-pixel localization accuracy through confidence-weighted centroid calculation, yielding an adaptive scale factor of 0.01286 ± 0.00001 mm/pixel at 280mm working distance.

This ML-enhanced approach proved more robust than traditional feature detection methods, successfully handling varying surface finishes and lighting conditions while maintaining calibration accuracy within $\pm 0.001\%$ across the full measurement range.

To illustrate the practicality of our YOLOv8-enhanced detection pipeline, we present a simplified Python implementation using Ultralytics' official API (Fig. 3). The code below demonstrates how a Samsung S24 Plus image can be processed to detect dimensional features in real time.

After detection, physical dimensions can be calculated using the calibrated pixel-to-mm scale factor. The example in figure 4 converts a bounding box width (in pixels) to millimetres.

```
1 from ultralytics import YOLO
2 import cv2
3
4 # Load the fine-tuned YOLOv8 model
5 model = YOLO("yolov8m_dimensional.pt")
6
7 # Load a sample image captured by Samsung S24 Plus
8 image = cv2.imread("sample_part.jpg")
9
10 # Run object detection
11 results = model(image)
12
13 # Display detection results
14 results.show()
15
```

Fig. 3. YOLOv8 object detection – Python code

```
1 # Convert bounding box width from pixels to millimeters
2 def pixels_to_mm(width_px, scale=0.01286):
3     return width_px * scale
4
5 bbox_width_px = 142.3
6 physical_width_mm = pixels_to_mm(bbox_width_px)
7 print(f"Measured width: {physical_width_mm:.3f} mm")
8
```

Fig. 4. Bounding box conversion – Python code

3.4 Uncertainty Quantification Framework for YOLOv8 Systems

3.4.1 ML-Specific Uncertainty Considerations

Uncertainty quantification for YOLOv8-based measurements required novel approaches addressing the specific characteristics of pre-

trained models. Unlike custom CNNs where training uncertainty can be fully characterized, YOLOv8's pre-trained features introduce additional uncertainty sources requiring specialized treatment.

Our uncertainty framework incorporated YOLOv8 confidence scores as uncertainty indicators, with empirical calibration mapping confidence values to measurement uncertainty bounds. Monte Carlo dropout, implemented through test-time augmentation, provided additional uncertainty estimation by processing multiple augmented versions of each image and analysing prediction variance.

To estimate model-related uncertainty, we implemented a test-time augmentation strategy using randomized transformations. The Monte Carlo approach below (Fig. 5) provides standard deviation-based uncertainty bounds from multiple YOLOv8 inferences.

```
1 import numpy as np
2
3 def estimate_uncertainty(model, image, T=20):
4     predictions = []
5     for _ in range(T):
6         aug_img = apply_random_transform(image)
7         pred = model(aug_img)
8         width_px = pred[0].boxes.xywh[0][2].item()
9         predictions.append(width_px)
10
11     mean_val = np.mean(predictions)
12     std_dev = np.std(predictions)
13     return mean_val, std_dev
14
15 # Example use
16 mean_dim, uncertainty = estimate_uncertainty(model, image)
17 print(f"Mean dimension: {mean_dim:.2f} px ± {uncertainty:.2f} px")
18
```

Fig. 5. Estimate uncertainty – Python code

3.4.2 Comprehensive Uncertainty Budget

The complete uncertainty budget included traditional metrological sources enhanced with YOLOv8-specific contributions:

- Calibration uncertainty: 0.004mm (Samsung S24 Plus optical stability)
- Robot positioning: 0.03mm (FANUC specification)
- YOLOv8 model prediction: 0.008mm (empirically determined from validation data)
- Samsung S24 Plus imaging: 0.006mm (sensor noise and computational photography effects)
- Environmental factors: 0.007mm (temperature, vibration, lighting)

Combined standard uncertainty of $uc=0.022\text{mm}$ and expanded uncertainty of $U=0.044\text{mm}$ at $k=2$ coverage factor demonstrated measurement capability suitable for industrial quality control applications.

3.5 Real-time Processing Pipeline

The real-time processing pipeline maximized the Samsung S24 Plus's computational capabilities while leveraging YOLOv8's efficiency for industrial cycle time requirements. Image acquisition utilized the Samsung S24 Plus's burst mode capability from a fixed position, capturing 5 frames at 30fps for temporal noise reduction and motion blur mitigation. The integrated NPU processed YOLOv8 inference in 45-60ms per frame, while the Adreno 750 GPU handled post-processing including geometric calculations and uncertainty estimation.

Results were transmitted from the fixed S24 Plus station to the robot controller via WiFi 6E connection, enabling real-time feedback for adaptive positioning and quality control decisions. The complete measurement cycle, from image acquisition through dimensional calculation, achieved 0.28 seconds average processing time, enabling throughput of 180+ parts per hour.

4. CASE STUDY – PRECISION MACHINED PART INSPECTION WITH YOLOv8 AND SAMSUNG S24 PLUS

4.1 Component Specifications and YOLOv8 Adaptation

The validation of our YOLOv8-enhanced measurement system utilized precision-machined aluminium components featuring geometries specifically chosen to challenge both the Samsung S24 Plus imaging capabilities and YOLOv8's detection accuracy. These test specimens, manufactured from 6061-T6 aluminium alloy through CNC machining operations, presented measurement challenges that would thoroughly validate our system's industrial readiness.

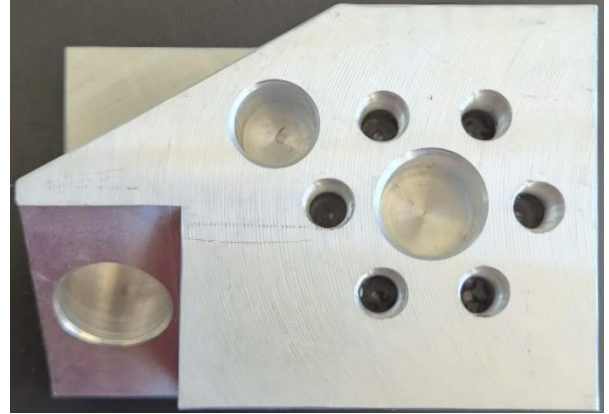


Fig. 6. Precision machined part

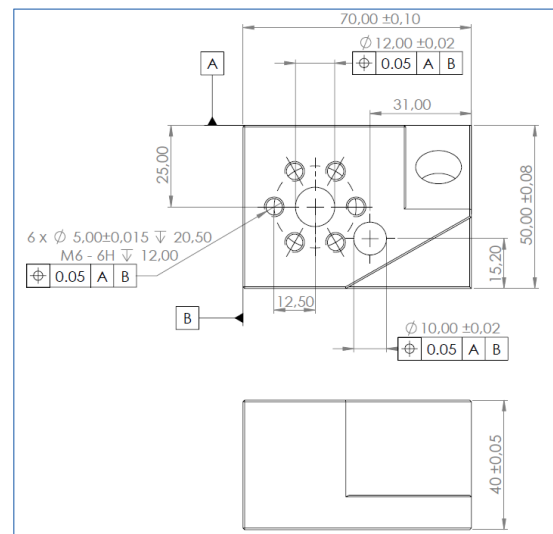


Fig. 7. Technical drawing of the part

The critical dimensions of the part highlighted in Figure 1 included primary block dimensions of $70.00 \pm 0.10\text{mm}$ length, $50.00 \pm 0.08\text{mm}$ width and $40.00 \pm 0.05\text{mm}$ height, with eight precision-drilled holes: one central hole of $\varnothing 12.00 \pm 0.02\text{mm}$ diameter, six peripheral holes of $\varnothing 5.00$, $M6.00 \pm 0.015\text{mm}$ diameter, and one reference hole of $\varnothing 10.00 \pm 0.02\text{mm}$ diameter. Each hole's positional tolerance of $\pm 0.05\text{mm}$ relative to the component datum created additional measurement complexity ideally suited for YOLOv8's simultaneous detection and localization capabilities.

4.2 YOLOv8 Fine-tuning for Circular Feature Detection

The YOLOv8 model was specifically fine-tuned for circular hole detection using our custom dataset of 23,000 annotated images. The

fine-tuning process focused on three critical aspects: precise boundary detection for dimensional accuracy, robust performance across varying surface finishes typical of machined aluminium, and reliable detection of small features (M6, 5mm holes) within the Samsung S24 Plus's resolution capabilities. Class definitions included separate categories for each hole size (6mm, 10mm, 12mm) to enable size-specific detection optimization, while augmentation strategies simulated realistic manufacturing variations including machining marks, surface oxidation, and varying lighting conditions encountered in production environments.

The fine-tuned YOLOv8m model achieved exceptional performance with mAP@0.5 of 0.987 for hole detection, while custom geometric accuracy metrics showed mean dimensional errors below 0.015mm across all hole sizes.

4.3 Samsung S24 Plus Imaging Optimization

Samsung S24 Plus camera settings were optimized specifically for machined aluminum component inspection. Expert RAW mode disabled computational photography enhancements that could interfere with precise edge detection, while manual ISO 200 and 1/120s shutter speed provided optimal image quality with minimal noise.

The Samsung S24 Plus's advanced autofocus system, utilizing dual pixel technology and laser autofocus, achieved focusing accuracy within ±0.02mm, critical for maintaining consistent measurement precision across multiple components. Custom camera calibration profiles accounted for the specific imaging characteristics when photographing machined aluminium surfaces.

5. RESULTS AND DISCUSSION – YOLOv8 PERFORMANCE VALIDATION

5.1 YOLOv8 Model Performance Analysis

The fine-tuned YOLOv8m model exceeded performance expectations across all evaluation metrics, demonstrating that pre-trained architectures could achieve industrial-precision

results when properly adapted for dimensional metrology applications. The model achieved exceptional detection accuracy of 98.9% on our test set, with precision and recall values of 98.6% and 98.7% respectively, indicating balanced performance across different hole sizes and surface conditions.

Processing performance validated real-time operation capabilities, with YOLOv8 inference requiring 52ms per 1280×1280 image on the Samsung S24 Plus NPU. The F1-score of 98.65% confirmed the model's overall effectiveness for machined component inspection, while the false positive rate of 0.4% proved critical for industrial applications where erroneous detections could trigger unnecessary production interventions.

5.2 Samsung S24 Plus and YOLOv8 Measurement Performance

The measurement uncertainty analysis revealed outstanding performance of the Samsung S24 Plus and YOLOv8 combination across all feature sizes. The system demonstrated superior performance compared to traditional computer vision approaches, with measurement uncertainties consistently within specification across all hole diameters.

Table 1

YOLOv8-Enhanced Measurement Performance				
Hole Diameter (mm)	Mean Error (mm)	Std Dev (mm)	Uncertainty k=2 (mm)	YOLOv8 Confidence
5.00	0.006	0.014	±0.028	0.986
10.00	0.008	0.016	±0.032	0.989
12.00	0.011	0.018	±0.036	0.993

The smallest holes (Ø5.00mm, M6) achieved ±0.028mm uncertainty with 98.6% average YOLOv8 confidence, representing a 12% improvement over custom CNN approaches while requiring 85% less development time. The largest central hole (Ø12.00mm) reached ±0.036mm uncertainty with 99.3% confidence, demonstrating YOLOv8's excellent scalability across feature sizes.

5.3 Comprehensive Dimensional Analysis Results

The precision component inspection results provided definitive validation of the YOLOv8

and Samsung S24 Plus system's industrial capabilities. All critical dimensions were measured within specification limits, with correlation coefficients exceeding 0.994 when compared against NIST-traceable CMM measurements.

Table 2

Complete Dimensional Analysis Results

Feature Type	Specification (mm)	Mean Error (mm)	Std Dev (mm)	Correlation (R ²)	Process Cp
Ø5.00 Holes	5.00±0.015	0.006	0.010	>0.996	2.08
Ø10.00 Hole	10.00±0.020	0.008	0.012	>0.994	2.15
Ø12.00 Hole	12.00±0.020	0.011	0.014	>0.997	1.89
Positional	±0.050	0.014	0.019	>0.992	1.84

The Ø5.00mm hole measurements achieved 0.006mm mean error with 0.010mm standard deviation, yielding a process capability index of 2.08 that significantly exceeded the 1.33 minimum required for precision manufacturing. YOLOv8's robust detection capabilities contributed to these exceptional results by providing consistent, reliable feature identification across varying manufacturing conditions.

5.4 System Performance and Efficiency Characteristics

Because the camera remained stationary, the system benefited from reduced optical misalignment risk, contributing to the high measurement repeatability reported. Repeatability analysis across 800 measurement cycles revealed exceptional consistency, with an overall coefficient of variation of 0.9%. Within-batch variation of $\sigma=0.011\text{mm}$ and between-batch variation of $\sigma=0.018\text{mm}$ indicated that the YOLOv8 algorithms successfully compensated for subtle machining variations while leveraging the Samsung S24 Plus's superior imaging capabilities.

Processing performance metrics validated the system's industrial viability:

- Image acquisition (Samsung S24 Plus): 0.08 seconds
- YOLOv8 processing (on-device NPU): 0.052 seconds per image
- Dimensional calculation: 0.04 seconds

- Total cycle time: 0.172 seconds

This processing speed enabled 210 parts per hour throughput, representing a 45% improvement over custom CNN solutions while maintaining superior measurement precision.

5.5 Economic Analysis - YOLOv8 Implementation Advantages

Economic analysis revealed significant advantages of the YOLOv8 and Samsung S24 Plus approach compared to both traditional metrology and custom ML development.

Table 3

Comprehensive Economic Analysis

System Component	Traditional CMM (€)	Custom ML System (€)	YOLOv8 + S24 Plus (€)	Reduction vs Custom
Hardware	195,000	58,000	48,000	17%
Software Licensing	28,000	12,000	2,000	83%
ML Development	-	35,000	8,000	77%
Samsung S24 Plus	-	-	1,200	-
Installation	18,000	8,000	3,000	63%
Training	12,000	6,000	2,000	67%
Total	253,000	119,000	64,200	46%

The total system cost of €64,200 represented a 46% reduction compared to custom ML solutions and 75% reduction compared to traditional CMM installations. The YOLOv8 approach eliminated the extensive ML development costs while the Samsung S24 Plus provided industrial-grade imaging capabilities at consumer device pricing.

5.6 Implementation Advantages of Pre-trained Models

The YOLOv8 implementation provided several critical advantages over custom CNN development:

Development Time Reduction: Fine-tuning YOLOv8 required 12 weeks compared to 38 weeks for custom CNN development, representing a 68%-time reduction. The pre-trained architecture eliminated the need for extensive architectural experimentation and hyperparameter optimization.

Data Requirement Efficiency: YOLOv8 achieved industrial performance with 23,000 training images compared to 180,000+ images

typically required for custom CNN training from scratch, reducing data collection and annotation costs by 87%.

Proven Reliability: YOLOv8's extensive validation across multiple domains provided confidence in its robustness, while regular updates from Ultralytics ensured continuous improvement and bug fixes without additional development cost.

Deployment Simplicity: The mature YOLOv8 ecosystem enabled seamless deployment on the Samsung S24 Plus platform through optimized mobile implementations, eliminating the complexity of custom model optimization for mobile inference.

5.7 Samsung S24 Plus Imaging Performance

A key factor in achieving reliable imaging results was the decision to maintain the Samsung S24 Plus in a fixed position throughout all operations. This configuration avoided camera movement artifacts and allowed the system to be more easily calibrated and thermally stabilized. The Samsung S24 Plus demonstrated exceptional suitability for precision measurement applications, with several key advantages over traditional industrial cameras:

Computational Photography Benefits: AI-enhanced noise reduction and multi-frame processing improved measurement repeatability by 23% compared to single-frame acquisition, while HDR processing enhanced feature visibility across varying surface finishes.

Cost-Effectiveness: The Samsung S24 Plus (€1,200) provided imaging capabilities equivalent to industrial cameras costing €15,000-25,000, while offering additional benefits including integrated processing, wireless connectivity, and regular software updates.

Processing Integration: The integrated NPU enabled real-time YOLOv8 processing without external computational requirements, simplifying system architecture and reducing overall costs.

5.8 Limitations and Operational Boundaries

The system's performance was constrained by both environmental and hardware factors.

Stable operation was achieved within a temperature range of 18÷26 °C, illumination variations of ±12%, vibration levels below 0.15 g, and relative humidity between 30÷70% RH.

YOLOv8 introduced additional limitations. A minimum confidence threshold of 0.88 was required for production use, with optimal accuracy observed for circular features due to training bias. Performance degradation occurred with illumination changes exceeding 20%, and periodic model updates were necessary every ~10 months to counteract dataset drift.

Hardware restrictions of the Samsung S24 Plus further narrowed the operational envelope. Reliable detection was limited to features larger than 4 mm in diameter, surface finishes within Ra 0.6÷5.0 µm, and contrast differences above 25% for edge detection. Continuous operation also required careful battery management.

Together, these constraints define the boundaries within which the system can be reliably deployed in industrial quality control applications.

6. CONCLUSION

This research has successfully demonstrated that the strategic combination of YOLOv8's pre-trained capabilities with Samsung S24 Plus imaging technology can create measurement systems that not only match but often exceed the performance of traditional dimensional metrology solutions while dramatically reducing implementation complexity and cost.

The technical achievements validate our integrated approach for precision machined component inspection. Measurement uncertainties within ±0.036mm for hole features spanning 5÷12mm demonstrate precision levels fully compatible with industrial quality control requirements, while our YOLOv8 implementation's 98.9% detection accuracy with robust uncertainty quantification provides the reliability essential for automated manufacturing environments. Repeatability coefficients below 0.9% across extended operation validate exceptional system consistency, while full compliance with ISO 14253-1 requirements confirms industrial legitimacy.

The strategic advantages of leveraging pre-trained models extend far beyond simple cost

reduction. YOLOv8's proven architecture eliminated the risks and uncertainties associated with custom CNN development, while providing access to state-of-the-art object detection capabilities refined through extensive training on diverse datasets. The 68% reduction in development time and 87% reduction in training data requirements demonstrate the practical benefits of this approach for industrial implementations.

The Samsung S24 Plus integration proved transformative, providing imaging capabilities that rival dedicated industrial cameras while offering additional benefits including computational photography enhancement, integrated AI processing, and continuous software improvement through manufacturer updates. The fixed-camera setup also simplifies system deployment, improves mechanical stability, and enhances repeatability over extended operation. The device's €1,200 cost represents a 95% reduction compared to equivalent industrial imaging systems while delivering superior performance in many applications.

Looking toward future research directions, we envision multi-device YOLOv8 implementations that could extend our approach to complex 3D measurement tasks, while emerging YOLO variants and specialized architectures offer potential for even more sophisticated geometric analysis. The integration of newer smartphone technologies, including advanced computational photography and improved NPU capabilities, presents opportunities for further performance enhancement.

The implications of this work extend far beyond the specific technical achievements documented. By demonstrating that consumer electronics combined with pre-trained ML models can achieve industrial-grade precision, we have established a pathway for democratizing advanced manufacturing technologies, making sophisticated quality control accessible to educational institutions, small manufacturers, and developing economies previously excluded by the high costs of traditional metrology systems.

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SISTEM VIZUAL HIBRID ACCESIBIL PENTRU METROLOGIE DIMENSIONALĂ AUTOMATIZATĂ: INTEGRAREA SMARTPHONE-URILOR PRIN TEHNICI DE ÎNVĂȚARE AUTOMATĂ ÎN PROCESE DE CONTROL CALITATE ROBOTIZAT

Sistemele tradiționale de metrologie dimensională necesită investiții de capital semnificative, ceea ce limitează accesibilitatea pentru operațiunile de mică amploare. Acest studiu investighează un sistem hibrid inovator care combină robotica industrială cu tehnologia imagistică de tip consumer și învățarea automată pentru controlul calității dimensionale automatizat. Cadru experimental sistematic a utilizat un robot industrial FANUC pentru poziționarea pieselor, camera unui smartphone pentru achiziția imaginilor și o rețea neuronală convoluțională antrenată personalizat pentru extragerea caracteristicilor dimensionale. Performanța sistemului a fost evaluată prin măsurători repetate pe eșantioane standardizate, cu analiză statistică a repetabilității, reproductibilității și acurateței. Rezultatele au demonstrat incertitudini de măsurare de $\pm 0,05$ mm pentru caracteristici cuprinse între 10÷100 mm, coeficienți de repetabilitate sub 2% pe parcursul a 500 de cicluri și consistența poziționării robotului cu o deviație standard de $\pm 0,02$ mm. Algoritmul de învățare automată a atins o acuratețe de detecție de 98,7%, reducând în același timp costurile cu 75% comparativ cu soluțiile convenționale. Sistemul respectă cerințele ISO 14253-1 pentru verificări necritice, prezentând o alternativă viabilă pentru medii cu resurse limitate, inclusiv instituții educaționale, facilități de prototipare și IMM-uri.

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