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Robotic Inspection Systems in Data-Driven Manufacturing: Architectures, Applications, and Implementation Insights from Romanian Industry

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Abstract: This paper presents an analysis of contemporary robotic automation systems deployed in industrial quality control processes, with specific applications in Romanian manufacturing sectors. The research examines the integration of advanced sensing technologies, machine learning algorithms, and adaptive robotic systems to enhance measurement accuracy, consistency, and throughput in manufacturing environments. Through four case studies involving cast parts, electrical wires, wood components, and mold parts from manufacturing industries within Romania, we demonstrate up to a 99% improvement in defect detection and up to a 68% reduction in inspection times compared to traditional methods. The implementation framework proposed addresses common challenges in system calibration, environmental variability, and cross-platform data integration within the context of Romania's transition toward Industry 4.0 standards. Our findings suggest that the convergence of robotics with Industrial Internet of Things (IIoT) platforms represents a critical advancement in quality assurance for Romania's evolving manufacturing ecosystems.

Key words: Robotic automation, quality control, machine vision, artificial intelligence, industrial metrology, Industry 4.0, Romanian manufacturing.

1. INTRODUCTION

Romania's manufacturing evolution toward data-driven operations has transformed quality control methodologies, with traditional manual inspection proving insufficient for modern production complexity [1], [2]. Robotic automation offers compelling solutions combining flexibility, precision, and adaptability, particularly critical as Romania transitions toward higher-value production for European market competitiveness [3], [4]. This research examines robotic quality control implementation frameworks within Romanian manufacturing contexts, investigating how advances in sensing technologies, artificial intelligence, and robotics create new measurement possibilities. The study analyses economic impacts across Romanian sectors, focusing on ROI, operational benefits, and workforce considerations. Implementation experiences from cast parts, electrical wires,

wood components, and mould manufacturing industries provide insights into adaptation strategies for varying automation infrastructure levels.

2. LITERATURE REVIEW

2.1 Evolution of Quality Control in Manufacturing

The progression of quality control methodologies has seen significant transformation from statistical process control techniques to current cyber-physical inspection systems [1], [5], [6]. We review this historical development within the Romanian industrial context, where quality control practices have evolved rapidly following EU accession in 2007 [7], [8]. Romania's manufacturing sector has undergone accelerated modernization as multinational corporations established production facilities, bringing international quality standards and advanced measurement technologies [9], [10].

2.2 Robotic Technologies in Inspection Processes

Recent developments in collaborative robots, autonomous mobile inspection platforms, and specialized end-effectors have expanded the application scope of robotics in quality control [11], [12]. Romanian implementations have benefited from technology transfer through multinational industrial partnerships. The study highlights advancements such as adaptive robot path planning algorithms, high-precision force-controlled measurement techniques, multi-modal sensing integration methodologies, and collaborative safety frameworks for human-robot inspection teams - each applied within diverse manufacturing environments [13], [14]. Romanian manufacturers have demonstrated aptitude in developing custom integration solutions that accommodate legacy equipment while implementing modern robotic inspection capabilities [15].

2.3 Artificial Intelligence in Defect Detection

Machine learning and deep learning algorithms have revolutionized visual and tactile inspection capabilities [4]. The study investigates the application of classical machine vision and machine learning techniques for automated defect detection across various component types: traditional image processing methods are applied to wood components and electrical wires, while machine learning algorithms are employed for identifying anomalies in mold parts and optimizing inspection sequences for cast components.

2.4 Research Gaps and Opportunities

Despite significant advances, substantial challenges remain in the seamless integration of robotic quality control systems with broader manufacturing ecosystems in Romania. This section identifies critical research gaps that this paper addresses, particularly concerning system interoperability, calibration persistence, and data traceability.

Romania's manufacturing sector presents unique implementation challenges, including [15], [16], [17], [18], [19], [20]:

- Varying levels infrastructure across different industrial regions

- Skills availability disparities between urban technology centres and traditional manufacturing areas
- Integration with existing ERP systems commonly used in Romanian industry
- Cost-effective implementation approaches suitable for Romania's diverse manufacturing base, from multinational corporations to local SMEs.

The opportunities identified focus particularly on leveraging Romania's strong IT sector capabilities to develop innovative software solutions that can enhance robotic quality control systems while maintaining cost-effectiveness.

3. METHODOLOGY

3.1 System Architecture

We propose a modular system architecture for robotic quality control that emphasizes interoperability and scalability across diverse Romanian manufacturing environments. The architecture comprises five key layers adapted to accommodate the varying technological maturity levels found across Romania's industrial landscape:

I. Sensing Layer: Data acquisition is achieved through classical machine vision systems and conventional measurement tools such as 2D cameras, lighting systems, and contact/non-contact dimensional sensors. Romanian applications frequently combine commercially available vision sensors with locally developed fixtures and calibration setups, especially when inspecting wood components and electrical wires [9], [21], [22].

II. Processing Layer: Image pre-processing and feature extraction are carried out using edge computing units or PC-based systems, depending on the scale of deployment. Common techniques include thresholding, edge detection, and pattern matching for simpler tasks, and feature vector generation as input for lightweight machine learning models [1], [23], [24].

III. Decision Layer: This layer relies on supervised machine learning models (e.g., decision trees, support vector machines, or k-nearest neighbours) trained on labelled defect data to classify surface or structural anomalies in mould parts and cast components. Confidence

scoring mechanisms support manual review in critical applications [3], [25], [26].

IV. Execution Layer: Depending on the complexity of the production environment, feedback from the decision layer is used to trigger sorting, marking, or rejection mechanisms via PLCs or integrated robotic cells. Adaptive inspection sequences, especially for cast components, are configured through parameter-based rule systems rather than autonomous planning algorithms [27].

V. Integration Layer: The system interfaces with existing quality management and manufacturing execution platforms through standardized protocols. Romanian manufacturers typically integrate these systems with SAP, Microsoft Dynamics, or locally developed MES platforms, enabling traceability and centralized quality reporting even in semi-automated setups [2], [24], [28].

3.1.1 Case Study Selection Criteria

Selection criteria ensured comprehensive evaluation across Romania's manufacturing landscape: (1) sector diversity for system adaptability validation, (2) varying automation levels from manual to semi-automated operations, (3) different inspection complexity requirements, (4) historical quality data availability for baseline establishment, and (5) management commitment to extended evaluation periods. Selected implementations represent four manufacturing categories: precision casting (automotive), electrical assembly (wire harness), woodworking (furniture), and precision moulding, ensuring findings address broad quality control challenges across Romanian manufacturing sectors.

3.1.2 Performance Evaluation Framework

A standardized four-phase framework ensured consistent assessment: (1) Baseline establishment (4 weeks) documenting existing methods and performance metrics, (2) Implementation phase (2÷4 weeks) including installation and training, (3) Transition phase (2-3 weeks) with parallel operation, (4) Evaluation phase (6 months) providing comprehensive performance data. Data collection protocols

included automated result logging, manual verification procedures, structured operator interviews, and regular management assessments.

3.2 Experimental Setup

To validate our proposed architecture, experimental implementations were conducted across four distinct Romanian manufacturing environments:

- Cast Metal Parts Vision Inspection Cell
- Wood Assembly Vision Inspection System
- Wire Assembly Vision Inspection System
- Component Presence Vision Inspection in Moulds

Each implementation utilized standardized testing protocols to evaluate performance metrics including defect detection accuracy, inspection cycle time, system adaptability to product variations, and integration complexity. Implementations were designed to accommodate Romanian industrial conditions, including power supply stability considerations and facility layout constraints typical of retrofitted industrial buildings common in some regions.

3.3 Evaluation Methodology and Data Collection

3.3.1 Baseline Performance Establishment

Baseline metrics were established through 4-week systematic data collection, analysing 12-month historical records for seasonal variations. Time-motion studies documented existing processes, while defect detection capabilities were assessed through structured sampling with independent verification. Cost analysis encompassed inspection labour, equipment utilization, scrap rates, and quality-related delays.

3.3.2 Performance Metrics Definition

Primary metrics included detection accuracy (percentage of actual defects correctly identified), cycle time (complete inspection sequence duration), throughput capacity (parts processed per unit time), and system availability (operational time percentage). Secondary metrics addressed operator workload reduction,

training requirements, maintenance demands, and system adaptability.

3.3.3 Data Collection Protocols

Automated systems recorded all inspection results including part identification, parameters, and cycle times. Manual verification involved 10% random sampling for accuracy calibration. Operator feedback was collected through monthly structured interviews, with quarterly management assessments evaluating operational impacts and economic benefits.

4 CASE STUDIES

4.1 Cast Metal Parts Vision Inspection Cell

Company Profile and Challenge Romanian precision foundry producing 250,000+ automotive components annually across 15 geometries, serving domestic and European OEM customers with ISO/TS 16949 compliance. Manual inspection created inconsistent defect detection and significant labour requirements, with primary challenges in surface defect detection (porosity, inclusions, machining marks) on complex geometries.

System Configuration Robotic cell comprised two FANUC R-2000iC/125L robots with custom PSC Automation end-effectors, dual Keyence CV-X400 vision systems with LumiTrax lighting, and rotary indexing table with three stations. Keyence PLC-based control with integrated HMI enabled adaptive inspection sequences.

Implementation Process Four-phase, 12-week implementation: baseline data collection and design validation (weeks 1-2), mechanical installation and integration (weeks 3-6), calibration and programming (weeks 7-9), training and validation (weeks 10-12). Critical challenges included legacy system integration and environmental calibration.

Performance Results After six months: surface defect detection improved from 65% to 91-95%, subtle defect detection from 60% to 80%. Cycle time reduced from 5 to 3.3 seconds (34% improvement), with 98% system availability. Benefits included eliminated fatigue effects and comprehensive quality traceability.

Economic Analysis Total cost €180,000, annual savings €95,000 (labour €45,000, scrap €30,000,

efficiency €20,000). 22-month payback period, five-year NPV €285,000 at 8% discount rate.

4.2 Wood Assembly Vision Inspection System

Company Profile and Challenge Romanian furniture manufacturer producing 180,000 engineered wood units annually for residential/commercial applications. Quality challenges included crack detection, joint integrity verification, and surface finish assessment, with manual inspection creating inconsistencies across shifts and inspectors.

System Configuration Keyence CV-X490F vision system with wood-optimized lighting, dual-belt conveyors, pneumatic fixation systems, and custom PSC Automation software incorporating wood-specific image processing algorithms.

Implementation Status Advanced implementation with completed mechanical installation and ongoing software optimization. Preliminary testing validated detection capabilities, with final commissioning scheduled within 4-6 weeks.

Preliminary Results: Initial testing shows 85-90% crack detection rates (>0.5mm width), repeatability reached to 90% (28% improvement), >92% system reliability during testing phases.

Economic Projections: Investment €125,000 projected annual savings €75,000. Expected 18-month payback, five-year NPV €220,000 at 8% discount rate.

4.3 Wire Assembly Vision Inspection System

Company Profile and Quality Control Challenge Romanian automotive wire harness manufacturer specializing in electrical component manufacturing for domestic and export markets. Production involves complex wire insertion and assembly processes requiring precise quality verification to meet automotive industry standards. Traditional manual inspection methods created bottlenecks and inconsistent detection of incorrectly inserted wires, affecting production throughput and assembly reliability.

System Configuration and Technical Specifications Comprehensive vision inspection system incorporating three Keyence cameras for complete inspection coverage: two

Keyence IV3 cameras for wire integrity identification and one camera for final assembly quality verification. Pneumatic gripper and cylinder systems provide reliable wire fixation during assembly operations. Warning light tower indicates process status (alarm/OK/NOK), while HMI interface enables operator alerts and system parameterization.

System identifies operator-introduced wires in fixation systems for assembly operations, performing integrity verification and final quality assessment through coordinated multi-camera inspection sequences.

Implementation Process and Timeline

Implementation followed structured approach with baseline establishment, mechanical installation, vision system calibration, and operator training phases. Critical challenges included coordinating multiple camera systems for synchronized inspection and integrating pneumatic handling systems with existing production line controls.

Performance Results and Analysis After six months operation: wire insertion accuracy achieved 99% improvement in detecting incorrectly inserted wires, eliminating major quality defects. Cycle time reduction of 50% eliminated significant production bottlenecks, substantially improving manufacturing throughput. Wire verification repeatability reached 90% for inserted wire verification, ensuring consistent quality standards.

Operational benefits included significant operator workload reduction and improved wire insertion process efficiency, contributing to enhanced workplace ergonomics and reduced manual handling requirements.

Economic Analysis and ROI Investment recovery achieved within 8 months, exceeding initial projections due to substantial cycle time improvements and reduced quality-related delays. Annual operational savings resulted from decreased inspection labour, eliminated rework costs, and improved production efficiency.

4.4 Component Presence Vision Inspection in Moulds

Company Profile and Quality Control Challenge Precision assembly manufacturer

specializing in mould-based assembly processes for complex component systems. Manufacturing operations require comprehensive component presence verification to ensure assembly integrity and prevent missing components in final products. Traditional inspection methods relied on operator verification, creating potential for human error and intentional or unintentional component exclusion.

System Configuration and Technical Specifications

Vision-based verification system comprises single Keyence IV3 camera for component identification, specialized mould-based cable/component fixation systems, and warning light tower for process status indication (alarm/OK/NOK). HMI interface provides operator alerts and enables system parameterization for different component variants.

System performs automated component identification in assembly processes, ensuring correct assembly completion and appropriate removal of assembled elements from devices, preventing component exclusion errors.

Implementation Process and Current Status

Implementation addressed critical quality assurance requirements through systematic integration of vision inspection with mould-based assembly operations. System configuration focused on reliable component detection across varying assembly configurations and environmental conditions.

Performance Results and Analysis After six months operation: component detection accuracy achieved 99% improvement in detecting components introduced in assembly processes, virtually eliminating missing component defects. Quality control efficiency improved through 75% cycle time reduction, eliminating production bottlenecks. Verification repeatability reached 99% for inserted component verification, ensuring consistent assembly quality.

Assembly integrity improvements significantly enhanced component presence verification reliability, reducing customer quality complaints and warranty issues.

Economic Analysis and ROI Investment recovery period of 13 months validated economic viability, with ongoing operational

savings from reduced inspection labor, eliminated rework costs, and improved customer satisfaction. Long-term benefits include enhanced product reliability and reduced warranty-related expenses.

5. RESULTS AND DISCUSSION

5.1 Technical Performance Evaluation

Robotic quality control systems implemented across Romanian manufacturing facilities demonstrated significant improvements across multiple performance dimensions (Table 1): Traditional image processing methods were applied to wood components and electrical wires, while machine learning algorithms were employed for identifying anomalies in mould parts and optimizing inspection sequences for cast components.

Detection accuracy improved by **17÷53%** compared to manual inspection, particularly in scenarios involving complex geometries in mould and cast parts, where traditional visual checks were previously unreliable.

Inspection cycle times were reduced by **28÷69%**, depending on the complexity and variability of the components, with wood components and electrical wires showing the most rapid improvements due to simpler visual patterns.

Measurement repeatability saw significant enhancement-up to **an order of magnitude**-in dimensional checks for mould and cast components, where consistent evaluation had been difficult to achieve manually.

Table 1: Performance Metrics Comparison			
Metric / Case Study	Traditional Method (Value ± Standard Error)	Robotic System (Value ± Standard Error)	Improvement (%) (95% Confidence Interval)
Case study: Cast Metal Components			
Detection Accuracy (%)	65% ± 3% (Manual Inspection)	93% ± 2%	43% (40-47%)
Inspection Time (s)	5s ± 1s	3.3s ± 1s	34% (28-43%)
Repeatability (mm)	±0.08mm ± 0.01mm	±0.02mm ± 0.005mm	75% (70-80%)
Case study: Wood Assemblies			
Detection Accuracy (%)	80% ± 4% (Visual Inspection)	96% ± 2%	20% (17-24%)
Inspection Time (s)	N/A	N/A	N/A
Repeatability (mm)	70% ± 2%	90% ± 1%	28% (26-31%)
Case study: Wire Harness Assemblies			
Detection Accuracy (%)	70% ± 5% (Manual Inspection)	99% ± 1%	42% (33-50%)
Inspection Time (s)	60s ± 5s	30s ± 1s	50% (47-52%)
Repeatability (%)	80% ± 5%	90% ± 2%	12.5% (8-15%)
Case study: Component Presence in Molds			
Detection Accuracy (%)	68% ± 4% (Visual Inspection)	99% ± 1%	46% (39-53%)
Inspection Time (s)	6s ± 2s	2s ± 0.5s	67% (63-69%)
Repeatability (%)	90% ± 3%	99% ± 1%	10% (8-12%)

The **system's adaptability** allows for the inspection of several different types of product

variants without the need to modify the vision system hardware, proving particularly beneficial in environments where both wood-based and moulded components are handled, with frequent product changes.

Romanian implementations demonstrated high robustness even in older industrial facilities characterized by inconsistent lighting conditions and temperature fluctuations. The combination of traditional vision systems and lightweight machine learning models provided reliable performance across all four component categories while remaining cost-effective and flexible.

5.2 Implementation Challenges and Solutions

Common obstacles encountered during implementation in Romanian manufacturing environments included:

- Environmental variability affecting sensor performance, particularly in facilities with limited climate control
- Integration complexities with legacy quality management systems common in Romanian manufacturing
- Calibration drift in prolonged operation, exacerbated by vibration conditions in older factory buildings
- Workforce adaptation and skill development requirements within Romania's evolving labour market

Solutions developed specifically for the Romanian context included:

- Hardened sensing enclosures with independent environmental control
- Custom middleware development by Romanian software firms specializing in legacy system integration
- Enhanced calibration protocols with more frequent verification intervals
- Targeted training programs developed in collaboration with Romanian technical universities and vocational schools

A particularly successful approach was the creation of mixed implementation teams combining international robotics expertise with local technical knowledge, bridging potential communication gaps while ensuring systems addressed specific Romanian manufacturing conditions.

5.3 Economic Impact Analysis

Cost-benefit analysis across Romanian implementation sites revealed (Table 2):

- Initial investment recovery periods ranging from 8 to 22 months, with faster recovery in multinational operations than in domestically owned facilities
- Labor cost reductions of 25÷45% in quality assurance departments, an important consideration in Romania's evolving labour market where skilled worker availability has become increasingly constrained
- Scrap rate decreases of 15÷28% attributable to earlier defect detection, delivering substantial material savings particularly in higher-value manufacturing operations
- Indirect benefits including improved product traceability and enhanced data availability for process improvement initiatives, supporting broader digital transformation efforts

Table 2: Economic Impact Analysis per Case Study

Case Study	Initial Cost (estimated)	ROI (months)	Labor Cost Reduction (%)	Scrap Rate Decrease (%)	Key Indirect Benefits
Cast Metal Components	150,000 EUR	22	35	20	Product conformity, process data
Wood Assemblies	35,000 EUR	(In implement.)	(Estimate) 25	(Estimate) 10	Improved quality
Wire Harness Assemblies	20,000 EUR	8	45	28	Bottleneck elimination, operator efficiency
Component Presence in Moulds	20,000 EUR	13	40	15	Assembly integrity, error prevention

6. LIMITATIONS AND CONSIDERATIONS

Research Limitations: Case selection based on opportunity rather than randomized sampling may introduce bias toward technologically ready organizations. Six-month evaluation may not capture long-term reliability or seasonal variations. Comparison primarily against manual methods limits insights into alternative automated solutions. Economic assumptions may not reflect long-term market fluctuations.

Technical Limitations: Vision performance affected by environmental factors (lighting, dust, dirt on the parts, parts precision (tolerance)/position adjustment, elasticity (for cables)). Machine learning algorithms require periodic retraining. Integration complexity increases with diverse legacy systems. Calibration drift requires systematic maintenance protocols.

Economic Considerations: ROI calculations assume consistent production volumes. Implementation success depends on operator acceptance and training effectiveness. Benefits may not transfer across different cost structures or production scales. Ongoing support requirements may affect long-term costs.

7. CONCLUSION AND FUTURE WORK

Research Findings Study demonstrates robotic quality control viability across Romanian manufacturing, with 90÷99% defect detection improvements and 28÷69% cycle time reductions. System reliability >90% confirms operational stability. Romanian facilities show strong adoption capabilities with local integrator expertise.

Manufacturing Implications Romanian manufacturers achieve competitive advantages through robotic inspection, with 8÷22-month investment returns across diverse contexts. Local technical capabilities enable cost-effective, tailored implementations while building domestic expertise in advanced manufacturing.

Scientific Contribution Research contributes systematic evaluation frameworks for emerging manufacturing economies, extending literature on technology adoption in Central/Eastern European industrial contexts. Documented implementation approaches address common emerging market challenges.

Future Research Extended 2÷3-year longitudinal studies needed for long-term validation. Comparative analysis with alternative technologies would inform optimal selection criteria. Standardized evaluation frameworks would facilitate broader adoption. AI applications and Industry 4.0 integration represent promising research directions.

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Sisteme Robotizate de Inspecție în Producția Bazată pe Date: Arhitecturi, Aplicații și Perspective de Implementare din Industria Românească

Articolul analizează implementarea sistemelor robotizate de inspecție în controlul calității din industria prelucrătoare românească, evidențiind integrarea senzorilor avansați, a algoritmilor de învățare automată și a roboticii adaptive. Patru studii de caz din sectoare industriale locale (piese turnate, fire electrice, produse din lemn și prezența pieselor în matriță) indică îmbunătățiri de până la 99% în detecția defectelor și o reducere de până la 68% a duratei inspecției. Se propune un cadru de implementare care abordează provocări legate de calibrare, variabilitatea mediului și integrarea datelor, în contextul adoptării standardelor Industrie 4.0. Convergența roboticii cu platformele IIoT este evidențiată drept un factor cheie în modernizarea asigurării calității în România.

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