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Sistem Inspeksi Visual Berbasis Kecerdasan Buatan untuk Kualitas Manufaktur: Tinjauan Literatur

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Abstrak

Inspeksi visual merupakan proses kontrol kualitas yang kritis dalam industri manufaktur modern. Metode inspeksi manual tradisional menghadapi keterbatasan signifikan dalam hal akurasi, konsistensi, dan throughput. Perkembangan pesat dalam bidang kecerdasan buatan (AI), khususnya computer vision dan deep learning, telah membuka peluang baru untuk otomasi sistem inspeksi visual dengan tingkat akurasi yang superior. Penelitian ini menyajikan tinjauan literatur sistematis yang menganalisis 52 studi peer-reviewed yang dipublikasikan antara Januari 2019 hingga Oktober 2024. Metodologi penelitian mengikuti pedoman PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) dengan pencarian sistematis melalui database IEEE Xplore, ScienceDirect, Springer, ACM Digital Library, dan Google Scholar. Kriteria inklusi mencakup studi empiris yang mengimplementasikan teknik AI/ML untuk inspeksi visual dalam konteks manufaktur dengan hasil kuantitatif. Hasil analisis menunjukkan dominasi metode deep learning (87% dari total studi) dengan arsitektur Convolutional Neural Networks (CNN) sebagai pendekatan paling populer (64%), diikuti oleh YOLO series (27%) dan R-CNN variants (21%). Transfer learning dari model pre-trained digunakan dalam 71% studi untuk mengatasi keterbatasan dataset. Tingkat akurasi yang dilaporkan berkisar dari 92,3% hingga 99,8% dengan median 96,7%. Aplikasi terdistribusi di berbagai sektor: elektronik (31%), otomotif (25%), food processing (17%), farmasi (13%), dan manufaktur umum (14%). Tantangan utama yang teridentifikasi meliputi keterbatasan dataset berlabel (67% studi), kebutuhan komputasi tinggi (54% studi), generalisasi lintas kondisi produksi (51% studi), dan class imbalance (46% studi). Penelitian ini memberikan kontribusi berupa framework komprehensif untuk pemilihan teknik AI yang tepat, identifikasi best practices dalam implementasi, dan roadmap penelitian masa depan termasuk pengembangan few-shot learning, explainable AI, dan integrasi edge computing.

Kata Kunci – Kecerdasan Buatan, Computer Vision, Deep Learning, Convolutional Neural Networks, Manufaktur, Kontrol Kualitas, Inspeksi Visual, Deteksi Cacat, Industry 4.0

Artificial Intelligence-Based Visual Inspection Systems for Manufacturing Quality Control: A Systematic Literature Review

Abstract

Visual inspection is a critical quality control process in modern manufacturing industries. Traditional manual inspection methods face significant limitations in terms of accuracy, consistency, and throughput. Recent rapid developments in artificial intelligence (AI), *particularly in computer vision and deep learning, have opened new opportunities for automated visual inspection systems with superior accuracy levels. This research presents a systematic literature review analyzing 52 peer-reviewed studies published between January 2019 and October 2024. The research methodology follows PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines with systematic searches through IEEE Xplore, ScienceDirect, Springer, ACM Digital Library, and Google Scholar databases. Inclusion criteria encompass empirical studies implementing AI/ML techniques for visual inspection in manufacturing contexts with quantitative results. Analysis results demonstrate the dominance of deep learning methods (87% of total studies) with Convolutional Neural Networks (CNN) architecture as the most popular approach (64%), followed by YOLO series (27%) and R-CNN variants (21%). Transfer learning from pre-trained models was utilized in 71% of studies to address dataset limitations. Reported accuracy rates range from 92.3% to 99.8% with a median of 96.7%. Applications are distributed across various sectors: electronics (31%), automotive (25%), food processing (17%), pharmaceutical (13%), and general manufacturing (14%). Main challenges identified include limited labeled dataset availability (67% of studies), high computational requirements (54% of studies), generalization across production conditions (51% of studies), and class imbalance (46% of studies). This research contributes a comprehensive framework for appropriate AI technique selection, identification of implementation best practices, and a future research roadmap including few-shot learning development, explainable AI, and edge computing integration.*

Keywords – Artificial Intelligence, Computer Vision, Deep Learning, Convolutional Neural Networks, Manufacturing, Quality Control, Visual Inspection, Defect Detection, Industry 4.0

PENDAHULUAN

Latar Belakang

Kontrol kualitas merupakan elemen fundamental dalam mencapai keunggulan kompetitif di era Industri 4.0. Inspeksi visual tetap menjadi salah satu metode quality assurance yang paling prevalensi digunakan, mencakup lebih dari 50% aktivitas kontrol kualitas di berbagai sektor manufaktur [1]. Namun, inspeksi manual tradisional menghadapi sejumlah keterbatasan inherent: fatigue-induced error rates mencapai 20-30% setelah 2 jam inspeksi kontinyu [2], variabilitas antar-operator hingga 15% [3], keterbatasan throughput untuk high-speed production lines, dan biaya tenaga kerja yang terus meningkat.

Transformasi digital yang dipicu oleh paradigma Industri 4.0 telah mengakselerasi adopsi teknologi intelligent automation dalam manufaktur. Menurut laporan Markets and Markets [4], pasar global untuk automated visual inspection systems diproyeksikan tumbuh dari USD 1.2 miliar pada tahun 2023 menjadi USD 2.3 miliar pada tahun 2028, dengan CAGR sebesar 13.8%. Pertumbuhan ini didorong oleh kemajuan signifikan dalam computational power, ketersediaan large-scale datasets, dan breakthrough dalam algoritma deep learning.

Kecerdasan buatan, khususnya computer vision dan deep learning, menawarkan solusi transformatif untuk mengatasi limitasi inspeksi manual. Teknologi ini memungkinkan deteksi defect dengan akurasi tinggi (>95%), konsistensi judgment yang superior, processing speed hingga 100+ inspections per second, dan kemampuan untuk mengidentifikasi subtle defects yang mungkin terlewatkan oleh human inspectors [5]. Penelitian oleh Lin et al. [6] menunjukkan bahwa sistem AI-based inspection dapat mengurangi false rejection rate hingga 60% dan meningkatkan overall equipment effectiveness (OEE) sebesar 15-25%.

Gap Penelitian

Meskipun volume penelitian tentang AI-based visual inspection terus meningkat, terdapat beberapa gap signifikan dalam literatur eksisting. Review yang dipublikasikan sebelumnya [7], [8] fokus pada *specific domains* atau *techniques* tertentu, namun belum ada *comprehensive analysis* yang mengintegrasikan perkembangan terkini *across multiple sectors* dan *techniques*. Gap spesifik yang teridentifikasi meliputi:

1. Ketiadaan *systematic synthesis* tentang *comparative performance* berbagai AI *architectures* dalam *manufacturing contexts*.
2. *Limited understanding* tentang praktis *implementation challenges* dan *mitigation strategies*.
3. Kurangnya *framework* untuk pemilihan *appropriate AI techniques* berdasarkan *manufacturing requirements*.
4. *Insufficient exploration* tentang *generalization capabilities across different production conditions*.

Tujuan Penelitian

Penelitian systematic review ini bertujuan untuk:

1. Mengidentifikasi dan mengklasifikasikan teknik AI yang digunakan untuk visual inspection dalam manufaktur.
2. Mengevaluasi secara komparatif *performance metrics (accuracy, precision, recall, processing speed)* dari berbagai *approaches*.
3. Menganalisis *implementation challenges* dan *mitigation strategies* yang *reported* dalam *literature.*
4. Mengidentifikasi *research gaps* dan *future directions* untuk *advancing the field.*
5. Menyediakan *practical guidelines* untuk *practitioners* dalam memilih dan implementing *AI-based inspection systems.*

Hasil penelitian ini diharapkan dapat menjadi reference comprehensive bagi akademisi dan praktisi dalam memahami *state-of-the-art AI-based visual inspection systems* dan *facilitating informed decision-making* dalam adopsi dan implementasi.

METODOLOGI PENELITIAN

a. Desain Penelitian

Penelitian ini mengadopsi metodologi systematic literature review berdasarkan pedoman PRISMA (Preferred Reporting Items for Systematic

Reviews and Meta-Analyses) yang dikembangkan oleh Moher et al. [9]. Pendekatan sistematis ini dipilih untuk memastikan transparency, reproducibility, dan comprehensiveness dalam proses review. Keseluruhan proses review dilakukan antara Mei-Oktober 2024 oleh satu reviewer dengan validasi independen untuk 20% sample papers.

b. Strategi Pencarian Literature

Pencarian literatur dilakukan secara sistematis melalui lima database akademik utama: IEEE Xplore, ScienceDirect (Elsevier), Springer Link, ACM Digital Library, dan Google Scholar. Periode pencarian mencakup publikasi dari 1 Januari 2019 hingga 31 Oktober 2024, dengan fokus pada capturing recent advances dalam AI technology. Pemilihan timeframe ini didasarkan pada significant breakthroughs dalam deep learning architectures yang terjadi post-2018, termasuk publikasi YOLO v3 [10], EfficientNet [11], dan transformer-based vision models.

Search string dikonstruksi menggunakan Boolean operators untuk capturing relevant publications:

("artificial intelligence" OR "machine learning" OR "deep learning" OR "computer vision" OR "convolutional neural network" OR "CNN" OR "YOLO" OR "R-CNN" OR "neural network")

AND

("visual inspection" OR "quality control" OR "quality assurance" OR "defect detection" OR "anomaly detection" OR "surface inspection" OR "product inspection")

AND

("manufacturing" OR "production" OR "industrial" OR "factory" OR "assembly line")

c. Kriteria Seleksi

Kriteria Inklusi:

- Artikel *peer-reviewed* (*journal articles* dan *conference proceedings*) yang dipublikasikan dalam venue bereputasi.
- Studi empiris yang mengimplementasikan AI/ML *techniques* untuk visual *inspection*.
- Aplikasi dalam konteks *manufacturing* atau *industrial production*.
- Menyajikan *quantitative performance metrics* (*accuracy, precision, recall, F1-score*, atau *processing time*).
- Publikasi dalam bahasa Inggris dengan *full-text accessible*.
- Menggunakan *real manufacturing data* atau *realistic synthetic data* untuk validation.

Kriteria Eksklusi:

- *Review papers, survey papers*, dan *meta-analyses* (untuk menghindari *double-counting*).
- Studi tanpa *manufacturing application context* (misalnya *medical imaging, surveillance*).
- *Theoretical papers* atau *conceptual frameworks* tanpa *empirical validation*.
- Publikasi *duplicate* (*same study published in multiple venues*).
- *Short papers (<4 pages)* dengan *insufficient methodological details*.
- *Workshop papers* dan *technical reports* yang belum melalui *rigorous peer-review.*

d. Proses Seleksi dan Screening

Proses seleksi dilakukan dalam empat tahap sesuai PRISMA guidelines [9]:

- Tahap 1: Identification - Initial database searches menghasilkan 412 publications. Setelah removing duplicates menggunakan Mendeley reference manager, tersisa 334 unique publications.
- Tahap 2: Screening - Title dan abstract dari 334 papers di-screen terhadap kriteria inklusi/eksklusi. Screening dilakukan secara independen dengan dokumentasi reasons for exclusion. Sebanyak 217 papers dieksklusi pada tahap ini (103 papers non-manufacturing context, 68 review/survey papers, 31 insufficient technical details, 15 tidak dalam bahasa Inggris).
- Tahap 3: Eligibility - Full-text dari 117 remaining papers diakses dan dievaluasi secara detail. Papers dinilai berdasarkan quality criteria including methodological rigor, clarity of reporting, adequacy of validation, dan contribution significance. Sebanyak 65 papers dieksklusi (28 papers insufficient quantitative results, 19 papers low quality methodology, 12 papers inadequate dataset description, 6 papers inaccessible full-text).
- Tahap 4: Inclusion - Total 52 papers memenuhi semua kriteria dan diinclude dalam final analysis. Untuk memastikan comprehensiveness, backward snowballing dilakukan dengan screening references dari included papers, namun tidak menghasilkan additional relevant papers yang memenuhi kriteria.

e. Ekstraksi Data dan *Quality Assessment*

Data extraction dilakukan menggunakan standardized data extraction form yang mencakup: (1) bibliographic information (authors, year, publication venue), (2) manufacturing domain dan application specifics, (3) AI/ML techniques employed (architectures, training strategies), (4) dataset characteristics (size, type, labeling approach), (5) performance metrics reported (accuracy, precision, recall, F1-score, processing time), (6) implementation details (hardware specifications, frameworks used), (7) challenges dan limitations identified, dan (8) future work suggestions.

Quality assessment menggunakan adapted CASP (Critical Appraisal Skills Programme) checklist dengan scoring rubric 0-10 points evaluating: research objective clarity (0-2 points), methodology appropriateness (0-2 points), dataset quality (0-2 points), validation rigor (0-2 points), dan reporting completeness (0-2 points). Papers dengan score <6 dikategorikan sebagai low quality dan dieksklusi. Mean quality score dari included papers adalah 7.8±0.9.

HASIL DAN PEMBAHASAN

Data Hasil

1. Karakteristik Studi yang Dianalisis

   Total 52 studi yang dianalisis menunjukkan distribusi temporal yang mencerminkan increasing research interest: 2019 (n=6, 11.5%), 2020 (n=8, 15.4%), 2021 (n=11, 21.2%), 2022 (n=13, 25.0%), 2023 (n=10, 19.2%), dan 2024 (n=4, 7.7%). Penurunan jumlah pada 2024 disebabkan oleh cutoff date di Oktober 2024. Publikasi terdistribusi di 28 different venues dengan IEEE Transactions dan Conferences mendominasi (35%), diikuti oleh Elsevier journals (27%), Springer publications (23%), dan lainnya (15%).

   Distribusi berdasarkan manufacturing sectors menunjukkan dominasi electronics manufacturing (n=16, 31%) dengan aplikasi utama PCB inspection, semiconductor defect detection, dan component placement verification. Automotive sector menempati posisi kedua (n=13, 25%) dengan fokus pada surface defect detection, weld inspection, dan assembly verification. Food processing applications (n=9, 17%) mencakup contamination detection, packaging inspection, dan product sorting. Pharmaceutical manufacturing (n=7, 13%) fokus pada tablet inspection dan packaging verification, sementara general manufacturing (n=7, 14%) mencakup diverse applications dari textile inspection hingga metal component verification.

2. Teknik AI dan Arsitektur yang Digunakan

   Distribusi Metode AI

   Deep learning methods secara signifikan mendominasi literature dengan 45 dari 52 studi (87%) mengimplementasikan neural network-based approaches. Traditional machine learning methods (n=7, 13%) terbatas pada applications dengan constrained computational resources atau well-defined feature spaces, utilizing techniques seperti Support Vector Machines (SVM), Random Forest, dan classical computer vision approaches dengan hand-crafted features [12].

   Arsitektur Deep Learning

   Convolutional Neural Networks (CNN) dan variannya merupakan arsitektur paling prevalent, digunakan dalam 33 dari 52 studi (64%). Specific architectures yang teridentifikasi meliputi:

- VGG series (VGG16, VGG19): 12 studi - dipilih untuk feature extraction richness meskipun computational cost tinggi [13]
- ResNet series (ResNet50, ResNet101): 15 studi - favorable karena skip connections yang memfasilitasi deeper networks tanpa vanishing gradient problems [14]
- MobileNet series: 6 studi - selected untuk edge computing applications dengan resource constraints [15]
- EfficientNet series: 8 studi - emerging choice untuk balancing accuracy dan efficiency [11]
- Custom CNN architectures: 11 studi - designed khusus untuk specific inspection requirements

YOLO (You Only Look Once) series diimplementasikan dalam 14 studi (27%), dengan distribusi: YOLO v3 (4 studi), YOLO v4 (5 studi), YOLO v5 (3 studi), dan YOLO v7 (2 studi). YOLO architectures primarily dipilih untuk real-time detection requirements di high-speed production lines, achieving processing speeds 50-100+ FPS dengan acceptable accuracy trade-offs [10], [16].

R-CNN variants (Region-based CNN) digunakan dalam 11 studi (21%), meliputi Faster R-CNN (7 studi) dan Mask R-CNN (4 studi) [17]. These architectures favored untuk applications requiring precise defect localization dan instance segmentation, particularly dalam complex visual environments dengan multiple defect types.

Hybrid approaches combining multiple architectures atau integrating deep learning dengan traditional computer vision techniques identified dalam 6 studi (12%). Examples include CNN untuk feature extraction combined dengan SVM untuk classification, atau dual-branch networks processing different image aspects simultaneously [18].

Transfer Learning and Training Strategies

Transfer learning dari pre-trained models merupakan strategi dominan, diimplementasikan dalam 37 dari 52 studi (71%). ImageNet pre-trained weights utilized dalam 29 studi (78% dari transfer learning studies), sementara 8 studi menggunakan COCO dataset pre-trained models [19]. Fine-tuning strategies bervariasi: full network fine-tuning (18 studi), partial layer fine-tuning dengan frozen early layers (15 studi), dan feature extractor usage dengan trained classifier (4 studi).

Data augmentation techniques extensively employed dalam 41 studi (79%) untuk addressing limited dataset sizes. Common augmentation methods include: geometric transformations (rotation, flipping, scaling - 39 studi), color space manipulations (brightness, contrast, saturation adjustments - 32 studi), noise injection (Gaussian, salt-and-pepper - 18 studi), dan advanced techniques seperti Mixup (3 studi) dan CutMix (2 studi). Generative approaches menggunakan GANs (Generative Adversarial Networks) untuk synthetic defect generation reported dalam 5 studi [20].

3. Performance Metrics dan Hasil

Tabel 1 menyajikan summary statistics dari performance metrics yang reported across studies:

Tabel 1. Summary Statistics Performance Metrics

Metrik	Range	Mean ± SD	Median	n
Accuracy (%)	92.3 - 99.8	96.7 ± 1.9	97.1	52
Precision (%)	90.5 - 99.6	95.8 ± 2.3	96.2	43
Recall (%)	89.2 - 99.4	94.9 ± 2.7	95.3	40
F1-Score (%)	90.8 - 99.5	95.3 ± 2.2	95.8	36
Processing Time (ms/image)	8 - 450	67 ± 89	32	31

Analisis menunjukkan bahwa accuracy rates consistently tinggi across studies, dengan 89% studies reporting accuracy >95%. Highest accuracies (98-99.8%) achieved dalam controlled industrial environments dengan consistent lighting, standardized product specifications, dan well-defined defect types [21]. Lower accuracy ranges (92-94%) associated dengan challenging scenarios: highly variable production conditions, complex multi-class defect taxonomies, atau small training datasets (<500 images per class).

Processing time menunjukkan significant variation, dengan YOLO-based approaches achieving fastest inference (8-25 ms/image, equivalent to 40-125 FPS), suitable untuk high-speed production lines [16]. CNN-based classification approaches demonstrated moderate speeds (25-80 ms/image), adequate untuk most manufacturing applications. Heavier architectures seperti Mask R-CNN requiring detailed instance segmentation showed slower performance (150-450 ms/image) but provided richer output information essential untuk certain applications [17].

4. Tantangan dan Limitasi Implementasi

Analisis challenges reported dalam literature mengidentifikasi empat kategori utama:

Keterbatasan Dataset

Limited availability labeled defect datasets merupakan challenge paling prevalent, reported dalam 35 dari 52 studi (67%). Manufacturers reluctant sharing proprietary defect data due to competitive sensitivity dan intellectual property concerns [22]. Typical dataset sizes berkisar 500-5000 images total, dengan severe class imbalance: defect samples often <5% of total dataset. Manual labeling cost prohibitive, dengan expert annotation time averaging 2-5 minutes per image untuk complex defects. Solutions attempted include synthetic defect generation menggunakan GANs [20], semi-supervised learning approaches [23], dan active learning untuk intelligent sample selection [24].

Computational Requirements

High computational demands untuk training dan inference reported dalam 28 studi (54%). Training deep networks requires significant GPU resources: typical training times 6-48 hours pada NVIDIA GTX 1080/2080 GPUs, dengan memory requirements 8-16 GB [25]. Deployment challenges particularly acute untuk edge computing scenarios di factory floor environments dengan limited hardware. Mitigation strategies include model compression techniques (pruning, quantization - 7 studi), knowledge distillation [26], dan neural architecture search untuk efficient architectures [27]. Cloud-based inference explored dalam 4 studi but faces latency concerns untuk real-time applications.

Generalization Challenges

Limited generalization across different production conditions identified dalam 27 studi (51%). Models trained pada specific datasets show performance degradation ketika deployed dalam different lighting conditions (day vs. night shifts), camera viewing angles, atau product variations (different batches, suppliers) [28]. Domain shift particularly problematic: model trained pada one production line often performs poorly pada another line producing similar products. Approaches untuk improving generalization include domain adaptation techniques [29], meta-learning frameworks [30], dan ensemble methods combining models trained pada diverse conditions. Continuous learning systems enabling online adaptation explored dalam 3 studi [31].

Class Imbalance

Severe class imbalance between defective dan non-defective samples reported dalam 24 studi (46%). Well-controlled manufacturing processes naturally produce very low defect rates (typically 0.5-3%), resulting dalam datasets dengan <5% positive samples [32]. This imbalance causes models biased toward majority class, dengan high accuracy but poor recall pada defect detection. Mitigation techniques employed include: weighted loss functions (18 studi), oversampling minority class dengan data augmentation (15 studi), undersampling majority class (8 studi), focal loss untuk hard example mining [33], dan synthetic minority oversampling techniques like SMOTE (4 studi).

Pembahasan

Hasil systematic review ini mengkonfirmasi mature state AI-based visual inspection technology untuk manufacturing applications. High accuracy rates (median 96.7%) across diverse domains demonstrate practical viability untuk industrial deployment. Dominasi deep learning approaches reflects superior feature learning capabilities dibanding traditional hand-crafted features, particularly untuk complex visual patterns dan subtle defect characteristics [2], [5].

Transfer learning emerged sebagai critical success factor, enabling effective model training despite limited manufacturing datasets [19]. Pre-trained models pada large-scale general image datasets (ImageNet) provide robust feature representations transferable ke manufacturing domains. Namun, domain gap antara natural images dan manufacturing contexts suggests opportunities untuk developing manufacturing-specific pre-training datasets atau self-supervised learning approaches trained directly pada unlabeled manufacturing images [34].

Architecture selection involves fundamental trade-offs between accuracy, speed, dan complexity. YOLO architectures provide optimal balance untuk real-time requirements, achieving acceptable accuracy (typically 94-97%) dengan superior inference speeds [10], [16]. CNN-based approaches offer higher accuracy (97-99%) suitable untuk offline inspection atau quality auditing [13], [14]. R-CNN variants provide detailed localization necessary untuk repair/rework guidance [17]. Practitioners should align architecture selection dengan specific manufacturing requirements: throughput rates, defect criticality, computational budget, dan downstream process integration needs.

Generalization remains significant challenge requiring sustained research attention. Current approaches typically require retraining atau fine-tuning when production conditions change significantly [28]. Industrial manufacturing demands robust systems maintaining performance across production batches, environmental variations, dan equipment changes. Few-shot learning [35], meta-learning [30], dan continual learning [31] approaches offer promising directions for developing adaptive systems. Domain-specific architectural innovations dan multi-domain training strategies warrant further exploration.

Dataset limitations present practical barrier to adoption, particularly untuk small-medium enterprises lacking resources untuk extensive data collection dan labeling [22]. Synthetic data generation using GANs shows promise but requires careful validation untuk ensuring realism [20]. Semi-supervised dan weakly-supervised learning approaches could significantly reduce labeling requirements [23], [36]. Industry collaboration untuk creating shared, anonymized benchmark datasets would accelerate research progress dan facilitate comparative evaluations.

Explainability dan interpretability largely underexplored dalam current research (only 6 studies addressed this). Industrial acceptance requires understanding why specific classifications made, particularly untuk critical applications dan regulatory compliance [37]. Integration dengan existing manufacturing systems (MES, ERP, quality management systems) rarely discussed but crucial untuk practical deployment. Cost-benefit analyses dan ROI evaluations would provide valuable guidance untuk industrial decision-makers.

Future research directions include: (1) developing manufacturing-specific foundation models trained pada diverse industrial imagery, (2) advancing few-shot dan zero-shot learning untuk rare defect types [35], (3) creating explainable AI frameworks untuk industrial contexts [37], (4) investigating edge computing optimizations untuk factory floor deployment [15], [27], (5) establishing standardized benchmark datasets facilitating reproducible research, (6) exploring hybrid approaches combining AI dengan physics-based models atau traditional inspection methods, dan (7) developing continuous learning systems adapting to evolving production conditions [31].

KESIMPULAN

Systematic review terhadap 52 studi peer-reviewed period 2019-2024 demonstrates bahwa AI-based visual inspection systems telah mencapai maturity level suitable untuk widespread industrial deployment. Deep learning approaches, particularly CNN architectures dan YOLO variants, consistently achieve accuracy >95% across diverse manufacturing domains including electronics, automotive, food processing, dan pharmaceutical manufacturing. Transfer learning dan data augmentation emerged sebagai essential strategies untuk addressing limited dataset availability, utilized dalam >70% studies.

Key findings meliputi: (1) Deep learning methods outperform traditional machine learning approaches dengan significant margins, (2) Architecture selection should balance accuracy requirements dengan processing speed constraints based on production line specifications, (3) Transfer learning enables effective deployment even dengan limited manufacturing datasets (>500 images), (4) Real-time performance (>30 FPS) achievable dengan YOLO architectures suitable untuk high-speed inspection, dan (5) Highest accuracies (98-99%) achieved dalam controlled environments dengan standardized products dan consistent imaging conditions.

Critical challenges requiring continued research attention include: limited availability labeled defect datasets (67% studies), computational resource requirements untuk training dan deployment (54% studies), generalization across production conditions (51% studies), dan severe class imbalance (46% studies). Addressing these challenges through synthetic data generation, model compression, domain adaptation, dan advanced sampling techniques will further enhance system reliability dan broaden applicability.

Practical recommendations untuk practitioners implementing AI-based inspection systems include:

1. Conduct thorough requirement analysis balancing accuracy needs, throughput requirements, computational budgets, dan integration constraints
2. Invest dalam quality dataset creation dengan representative defect samples dan expert labeling
3. Leverage transfer learning from pre-trained models untuk accelerating development
4. Implement comprehensive validation protocols testing performance across diverse production conditions
5. Establish continuous monitoring dan model updating procedures untuk maintaining performance over time
6. Consider hybrid approaches combining AI dengan traditional inspection methods untuk critical quality control
7. Plan untuk computational infrastructure supporting both training (GPU-equipped servers) dan inference (edge devices or cloud) requirements

SARAN

1. Research community should prioritize developing: manufacturing-specific foundation models, few-shot learning frameworks untuk rare defects, explainable AI methods, standardized benchmark datasets, dan integration frameworks dengan existing industrial systems. Industry-academia collaboration essential untuk accelerating practical deployment dan realizing full potential Industry 4.0 smart manufacturing.
2. Seiring continued advances dalam AI technology, edge computing capabilities, dan sensor technologies, AI-based visual inspection akan increasingly become standard practice dalam manufacturing quality control, contributing toward zero-defect manufacturing goals dan sustainable production systems. Systematic review ini provides comprehensive foundation supporting informed decision-making untuk researchers, practitioners, dan policymakers dalam advancing dan implementing these transformative technologies.

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