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AI-Powered Data Engineering Frameworks for Smart Manufacturing Quality Control

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ABSTRACT: AI-Powered Data Engineering Frameworks for Smart Manufacturing Quality Control presents an evidence-based, formal analysis of AI methods, data pipelines, and governance to improve defect detection and process reliability in smart manufacturing quality control. The contributions cover data engineering prerequisites—including data sources, quality requirements, acquisition approaches, ingestion methods, latency considerations, and integration—together with key decision-supporting AI techniques, a comprehensive system architecture for end-to-end quality control, and high-level data governance requirements.

Exploiting artificial intelligence (AI) to enhance manufacturer-automated quality control processes enables self-driving factories with reduced defect rates. AI methods are implemented for defect detection, correlation, and root-cause forecasting, closing the gaps between Machine Learning, Big Data, and IoT. Data quality proves decisive for these operations, raising specialized Data Engineering requirements across the entire analytical pipeline and including Quality Control Data Engineering-as-a-Service. By framing the analysis within the broader context of smart factory data engineering, a comprehensive set of Quality Control data quality requirements emerges and combinations of supervised, unsupervised, and time series methods are explored to tackle both defect detection and repair procedure prediction.

KEYWORDS: AI-Powered Quality Control, Smart Manufacturing Systems, Industrial AI Architectures, Manufacturing Data Engineering Frameworks, Defect Detection Algorithms, Root-Cause Analysis Modeling, Process Reliability Optimization, Machine Learning in Production, Industrial IoT (IIoT) Data Pipelines, End-to-End Quality Control Architecture, Data Governance in Manufacturing, Quality Control Data Engineering-as-a-Service, Real-Time Manufacturing Analytics, Supervised and Unsupervised Learning Integration, Time Series Forecasting for Maintenance, Data Quality Requirements in Smart Factories, Automated Inspection Systems, Big Data in Industrial Environments, Self-Driving Factory Paradigm, Intelligent Production Process Optimization.

I. INTRODUCTION

Artificial Intelligence (AI) can aid quality assurance (QA) with identifying defective products, determining their root cause, predicting future occurrences, and subsequently proposing corrective actions. The proposed integration framework offers an overview of the data requirements for AI methods and presents various AI techniques to improve QA in manufacturing. The focus is on supervised and unsupervised learning methods that require little to no expert knowledge for defining a model. Additionally, it outlines the data pipelines required to ingest the necessary data flow for AI-based QA activities and discusses essential data governance concepts.

Every revolution since the First Industrial Revolution (Industry 1.0) has benefited from improvements and optimizations in the manufacturing process. The current trend of merging the physical world with the digital world is known as Cyber-Physical System (CPS). A CPS uses technology such as IoT, Cloud, Big Data, and AI to improve manufacturing processes. Industry 4.0 adopts smart and autonomous systems that enable machines to monitor the manufacturing processes and make decisions based on real-time data, such as detecting system failure, predicting future incidents, and adapting or optimizing production schedules. However, the success of AI techniques requires considerable amounts of relevant data of high quality, which is often challenging to provide.

1.1. Overview of AI in Quality Control

Smart manufacturing envisions an intelligent factory that unites personnel and AI algorithms as partners in production. Integrating AI into business processes promises unparalleled advantages but entails novel decision-making hazards. Consequently, devising strategies and rules to blueprint, supervise, orchestrate, and govern AI-aligned data pipelines

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emerges as essential.

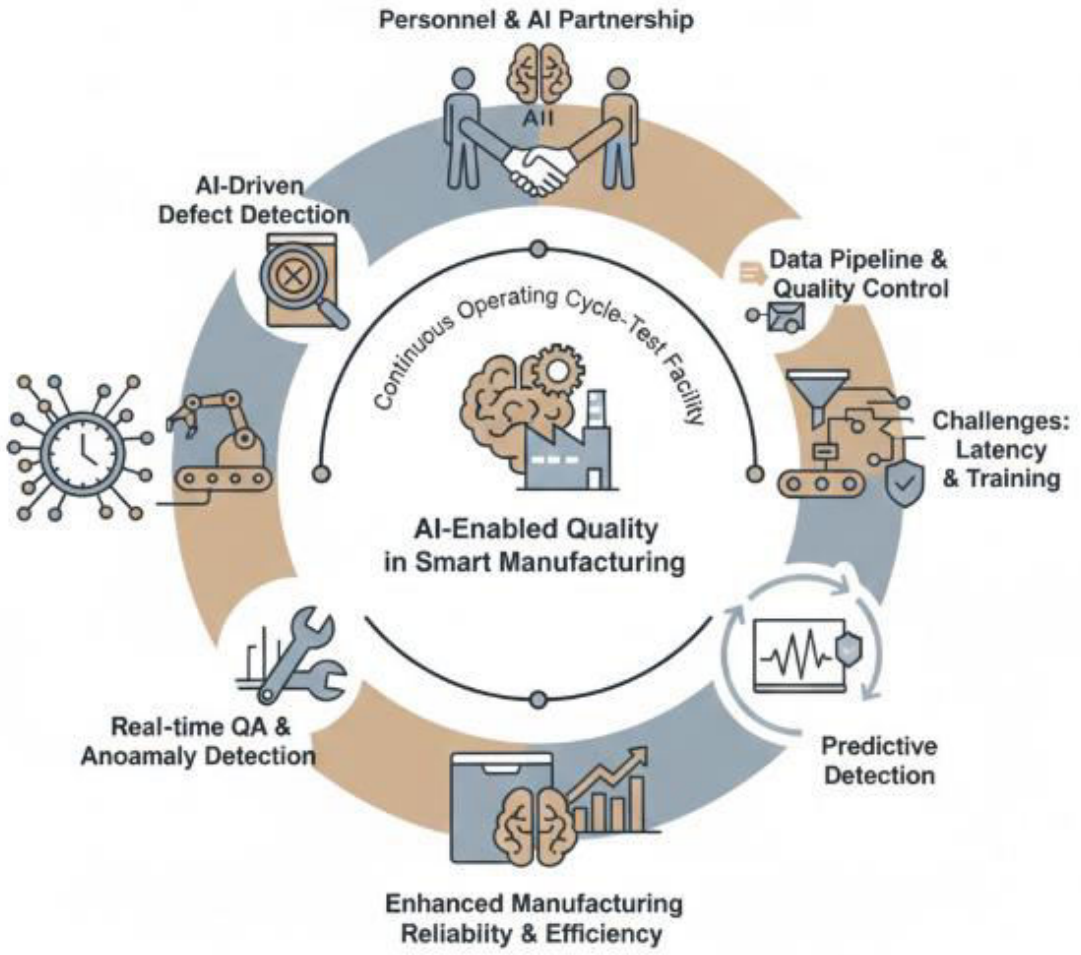

Fig 1: Synergizing Human-AI Collaboration in Industry 4.0: A Framework for Integrated Quality Assurance and Real-Time Data Pipeline Governance in Smart Factories

One pivotal deployment area is intelligent Quality Control (QC), where the AI mission is to detect-defect-label-localize-repair with utmost automation accuracy and reliability. AI-driven defect-detection technology shrinks and minimizes mistakes in the complex process, yet Quality Assurance (QA) is an unexplored dimension in intelligent factories beyond sustainable-hazard-free emissions. Integrating QA within the AI-Data pipeline raises timing-synchronization-latency challenges, for extensive resources are devoted to training-defect-detection models.

AI empowers modern Industry 4.0 applications across the entire process-decision supply chain-operations, availing anomaly-based predictive maintenance systems in traditional sectors of telecommunication, manufacturing, automotive transportation, and power. Specific reference to the quality-control branch of applications, Pesic et al. develop a set of supervised defect-detection solutions commonly used in plants, delineate label-quality requirements, and scrutinize data-quality requirements throughout the data pipeline process-creation-execution in open-source mode. With smart manufacturing's data-flooded factories serving as backgrounds, the integration of deployment of QA processes-systems is viewed through the steered lens of a continuously operating-cycle-test facility, targeting mainly defect-detection systems and the quality of data fed and real-time-streamed to trained model solutions.

II. THEORETICAL FOUNDATIONS OF AI-DRIVEN QUALITY CONTROL

Quality control in smart manufacturing systems depends on efficient QA defect detection to minimize interruptions and strengthen reliability. The relationship between AI methods, data engineering, data governance, and decision-making in defect detection is explored to deepen understanding of dependencies and guidelines for applying AI techniques in QA. The analysis clarifies concepts for AI methods supporting the manufacturing quality-control task and identifies issues

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in data pipelines that affect defect-detection quality. Precise terminology improves communication between domain experts and data engineers and motivates smart factories to develop and maintain high-quality data pipelines.

Four theorems address quality-control methods, defect detection, data governance, and data pipelines to yield the assumptions and limitations. Experiments with quality-control data in visual domain support the work. A detailed discussion of AI methods and techniques used for defect detection is consistent with supervised machine- and deep-learning techniques and additional methods such as clustering. The problem, advantages, and challenges of applying AI methods for manufacturing quality control and product QA are comprehensible to practitioners, promote guided research, and inform data engineers responsible for establishing data pipelines capable of supporting defect detection in QA.

Equation 1) Supervised defect detection as a classification problem

Step 1: Define the data

- For each product/sample i: features x_i (image/video/3D point cloud) and label y_i.
- Binary case (OK vs Defect): $y_i \in \{0,1\}$.
- Multi-class case: $y_i \in \{1, \dots, K\}$ (multiple defect types).

Step 2: Model outputs

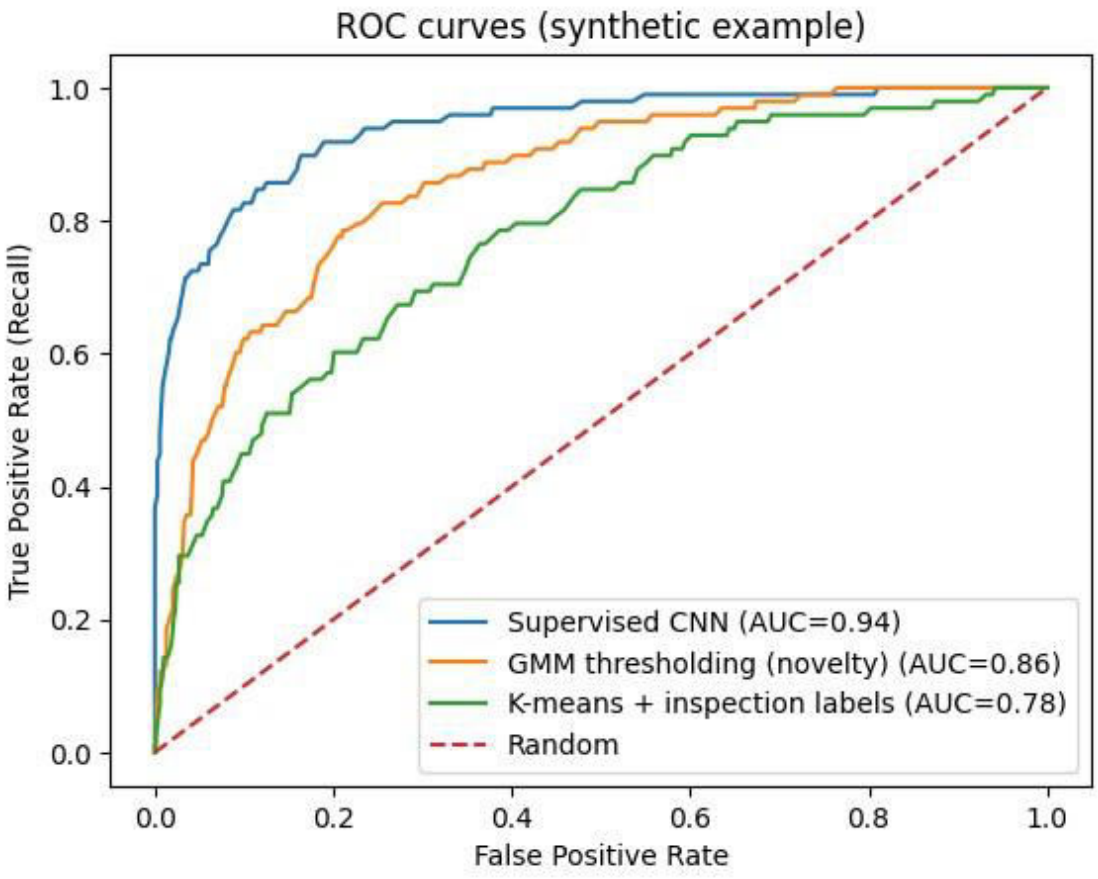
- Binary: model outputs probability $\hat{p}_i = P(y_i = 1 \mid x_i)$.
- Multi-class: model outputs class probabilities via softmax:

$$z_{ik} = f_k(x_i; \theta), \quad \hat{p}_{ik} = \frac{e^{z_{ik}}}{\sum_{j=1}^{K} e^{z_{ij}}}$$

Step 3: Decision rule (thresholding)

For binary classification:

$$\hat{y}_i = \begin{cases} 1 & \text{if } \hat{p}_i \geq \tau \\ 0 & \text{if } \hat{p}_i < \tau \end{cases}$$



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2.1. Key Concepts in AI-Enhanced Quality Assurance

Artificial intelligence (AI) technology is revolutionizing software engineering at every phase of the software lifecycle. Though abundant empirical evidence of its efficacy remains scarce, adoption is escalating rapidly—and therefore also the desire to understand AI's implications for the quality assurance (QA) of intelligent systems. A theory of decision-making by data-centric AI-foundation model-driven software agents suggests that, in the domain of QA, AI technology enhances not only the detection of product faults in addition to process biases, but also the costs and hazards of testing, shaping, and maintaining test data accordingly. Data supply accuracy and reliability are in fact value drivers for cloud-based testing services, and AI detection methods are not a complete substitute for traditional QA.

Testing and assessing the correct performance of software is fundamental to software engineering, and yet, because of its complexity and non-determinism, ground-truth-based testing—even for classification systems—remains challenging. The development of appropriate input samples is key, and new categories of systems relying on data-centric AI foundation models give rise to new QA propositions: it is no longer just the system being tested but also the "data generator" that must be tested and assessed. In the context of autonomous or self-driving cars, testing must go beyond traditional test-data sampling methods such as random or edge-case sampling, since it cannot be guaranteed that the data generated by the data-centric AI systems are of good enough quality for the intelligent systems built on top of them, implying that introducing QA stages is paramount.

Model	Accuracy	Precision	Recall
Supervised CNN	0.56	0.215	0.98
GMM thresholding (novelty)	0.568	0.213	0.939
K-means + inspection labels	0.519	0.185	0.857

III. DATA ENGINEERING ESSENTIALS FOR SMART MANUFACTURING

Smart factories harness abundant data from various sources, including production processes, operational equipment, and personnel, to enhance decision-making. Unlike traditional enterprise data warehouses, smart manufacturing information requires not only reliability and compliance but also lower price and faster update speed. Moreover, data must meet the specific requirements of different AI methods—labelled samples for supervised learning, entire space for unsupervised learning, and historical defect locations for quality monitoring.

Data sources encompass physical sensors such as cameras, environmental sensors, and in-line inspection equipment, as well as electronic systems like a manufacturing execution system (MES). Because additional sensors are costly, condition monitoring wearables are valuable sparing resources. Construction errors and equipment limitations hinder data quality. Intelligent sensors assist sampling, synthetic aperture imaging improves resolution, and streaming data management minimizes gross errors. The realtime data transfer capability of the equipment is crucial. Smart factories support synchronic ordering of multiple cameras and synchronisation of different systems, so that video streams can be correctly combined during labelled sample preparation, labelled sample generation for supervised methods can use automated machines to evaluate improved quality with low cost, and batch and online classification can be implemented in parallel.

Equation 2) Confusion matrix and performance metrics (QC-critical)

Step 1: Confusion matrix counts

For binary classification:

- TP: predicted defect & actually defect
- FP: predicted defect but actually OK (false alarm / false reject)
- TN: predicted OK & actually OK
- FN: predicted OK but actually defect (missed defect; often most costly)

Step 2: Derived metrics

Accuracy $= \frac{TP+TN}{TP+TN+FP+FN}$ Precision $= \frac{TP}{TP+FP}$ ("When we flag defect, how often correct?") Recall (TPR) $= \frac{TP}{TP+FN}$ ("How many real defects do we catch?") $F_1 = \frac{2 \cdot \text{Precision} \cdot \text{Recall}}{\text{Precision}+\text{Recall}}$

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Step 3: ROC curve

- Define:

$\text{TPR}(\tau) = \frac{TP(\tau)}{TP(\tau)+FN(\tau)}$ $\text{FPR}(\tau) = \frac{FP(\tau)}{FP(\tau)+TN(\tau)}$

- Sweep $\tau \in [0,1]$ to plot TPR vs FPR.
- **AUC** is the integral (numerically trapezoidal):

$$\text{AUC} = \int_0^1 T\,PR(FPR)\,d(FPR)$$

Step 4: Precision–Recall curve

Because defect detection is often imbalanced, PR curves are commonly more informative than ROC.

- Sweep τ, plot $Precision(\tau)$ vs $Recall(\tau)$.
- PR-AUC:

$$\text{PR-AUC} = \int_0^1 P\,recision(Recall)\,d(Recall)$$

3.1. Data Acquisition and Ingestion

Smart manufacturing relies heavily on digital twins, data-driven applications, and integrated infrastructures to make the best use of artificial intelligence. Data acquisition and ingestion — the phase of data engineering that captures and transfers data into event capture and processing systems — face a wide spectrum of requirements during operations. The degree of data quality and the choice of architecture for data ingestion predict whether the intended application uses the data for performing at its best.

Data can be acquired from a variety of sources: process sensors, equipment logs, human operators, service logs, artificial sensors, the surrounding environment, and more. Depending on the nature of the information being collected, a digital twin may need information from within the process — such as spatial scans — or from external sources, including those related to market trends, competitors, and stored knowledge. Some values need to be sourced with a high temporal resolution; for instance, temperature must often be recorded every few milliseconds, while market prices are typically uploaded every few seconds or minutes. Latency — the time delay introduced when analysing data — affects business, and a certain tolerance or limits must be defined. Time-sensitive information can be missed or delayed depending on tolerance — the acceptable lag before usefulness diminishes or disappears entirely — and, ideally, the digital twin is aware of every event that occurs at the detection speed of the fastest sensor, even if some events remain invisible or are temporally out of sync. The design of the ingestion layer must therefore take into account the scarceness of the different data sources, the risks of re-triggering previously ingested data, the acceptable latency of data acquisition, and the detection tolerances.

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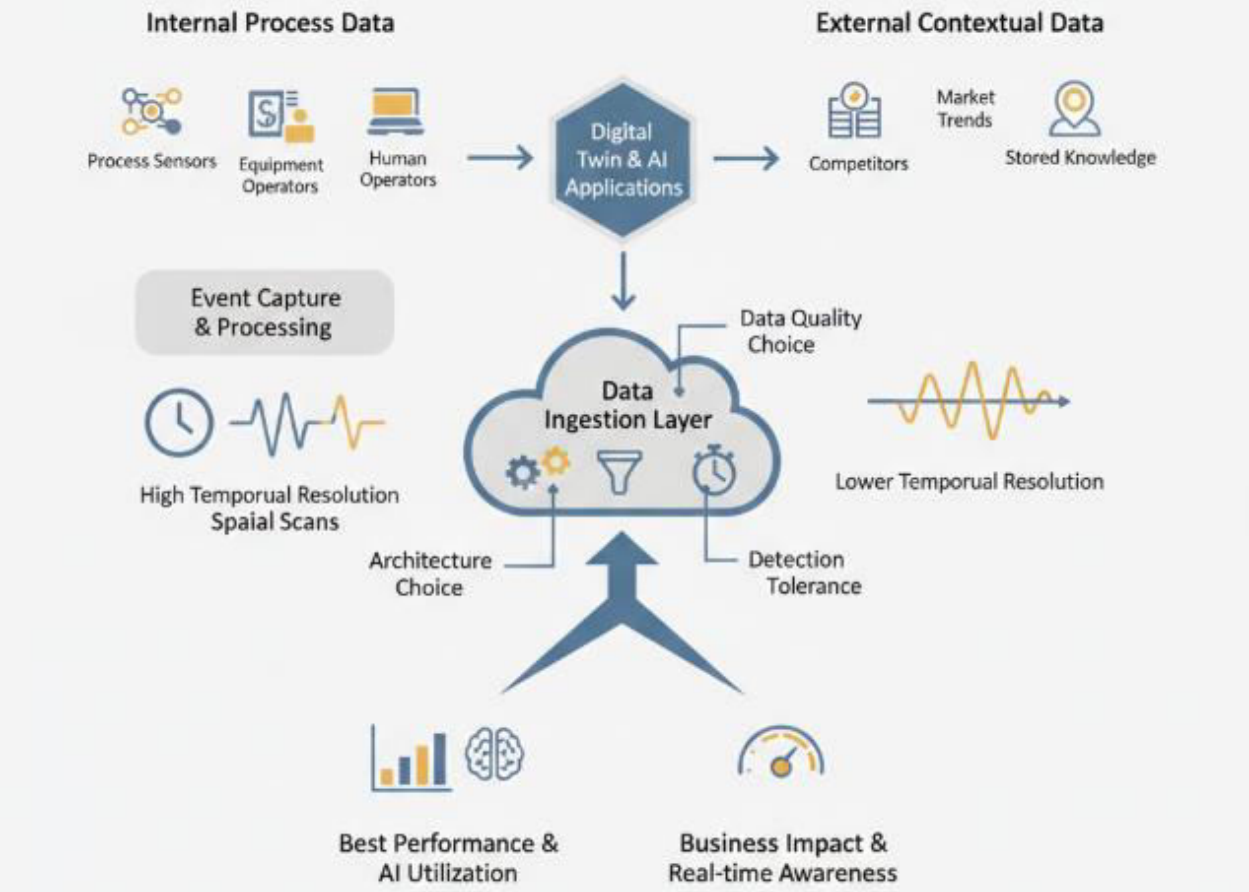

Fig 2: Optimizing Data Ingestion for Digital Twins: A Framework for Temporal Resolution, Latency, and Detection Tolerance in Smart Manufacturing

3.2. Data Transformation and Feature Engineering

Additional features supporting the classification task may emerge through data engineering practices such as feature extraction and selection. Feature extraction generates new features from the available data, either through transformation, aggregation, or fusion. Examples include score calculations based on raw imaging data or threshold-based defect detection. The most relevant features may also be automatically or manually identified and extracted from the original data. Data fusion creates new features based on the combination of already existing information. One prominent example in the literature is the transformation of distinct camera images of a workpiece into a new representation comprising a concatenation of the different channel values, which serves as input for RGB image-based classification methods.

A related process is feature selection, which attempts to find the optimal subset of available features for the classification task. Assumptions about label availability and quality determine its suitability as preparation for supervised machine learning methods. Such label information can derive from domain knowledge, operational conditions, or preceding or concurrent tasks. In unsupervised or anomaly detection, these constraints are not present, opening up numerous possibilities for various statistical and non-statistical techniques, used individually or in tandem. Clustering approaches such as k-means or DBSCAN group similar observations, while novelty detection approaches are able to detect new, previously unseen class types. A more advanced method is thresholding, which uses an additional supervised model to detect outliers based on a normal operating range defined by a clean dataset. Proper choice of the underlying clustering technique and attendant parameters influences the system performance, requiring experimentation and testing to determine the best solution for a particular quality use case.

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IV. AI METHODS FOR QUALITY CONTROL

Understanding the requirements for, details of, and practical implementation concerns around data engineering lays the foundation for evidence-based selection and deployment of AI methods for quality control. Detection of defects can be treated as a supervised learning problem, where algorithms are trained to predict visual labels indicating the presence or absence of defects across multiple classes. Candidate methods, covering image, video, and 3D point-cloud data modalities, are enumerated, as are strategies for generating the required labeled training data. Metrics for gauging model performance and mitigating real-world consequences of misclassifications are discussed, along with processes for evaluating classification accuracy across deployment scenarios.

When labeled samples are scarce or unavailable, unsupervised learning provides alternative approaches. These explore underlying data distributions to build models of operating conditions that are then applied for novelty detection, such as marking images as anomalous without explicitly labeling defect categories. Other techniques cluster the training samples, labelling clusters via inspection and using these labels for later classification. In these scenarios, particular attention should be paid to the clustering process, with thorough analysis of the detected groups. A third approach, unsupervised thresholding, appraises test samples by determining threshold values for metrics computed for a given sample and compared against thresholds determined via separate validation sets. For these methods, classifiers can easily be added or swapped out, depending on hardware, latency, or accuracy requirements.

Equation 3) Unsupervised learning: clustering (k-means objective)
k-means derivation
Step 1: Choose K cluster centers $\mu_1, \dots, \mu_K$.
Step 2: Define assignment variables
Let $c(i) \in \{1, \dots, K\}$ be the cluster index assigned to sample x_i.
Step 3: Define the objective (within-cluster sum of squares)

$$J = \sum_{i=1}^{n} \|x_i - \mu_{c(i)}\|^2$$

Step 4: Alternating minimization

- **Assignment step** (fix μ, minimize wrt $c(i)$):

$$c(i) = \underset{k}{\operatorname{argmin}} \parallel x_i - \mu_k \parallel^2$$

- **Update step** (fix assignments, minimize wrt μ_k):

Take derivative:

$$\frac{\partial}{\partial \mu_k} \sum_{i:c(i)=k} \parallel x_i - \mu_k \parallel^2 = 0 \Rightarrow \mu_k = \frac{1}{N_k} \sum_{i:c(i)=k} x_i$$

where N_k is the number of points in cluster k.

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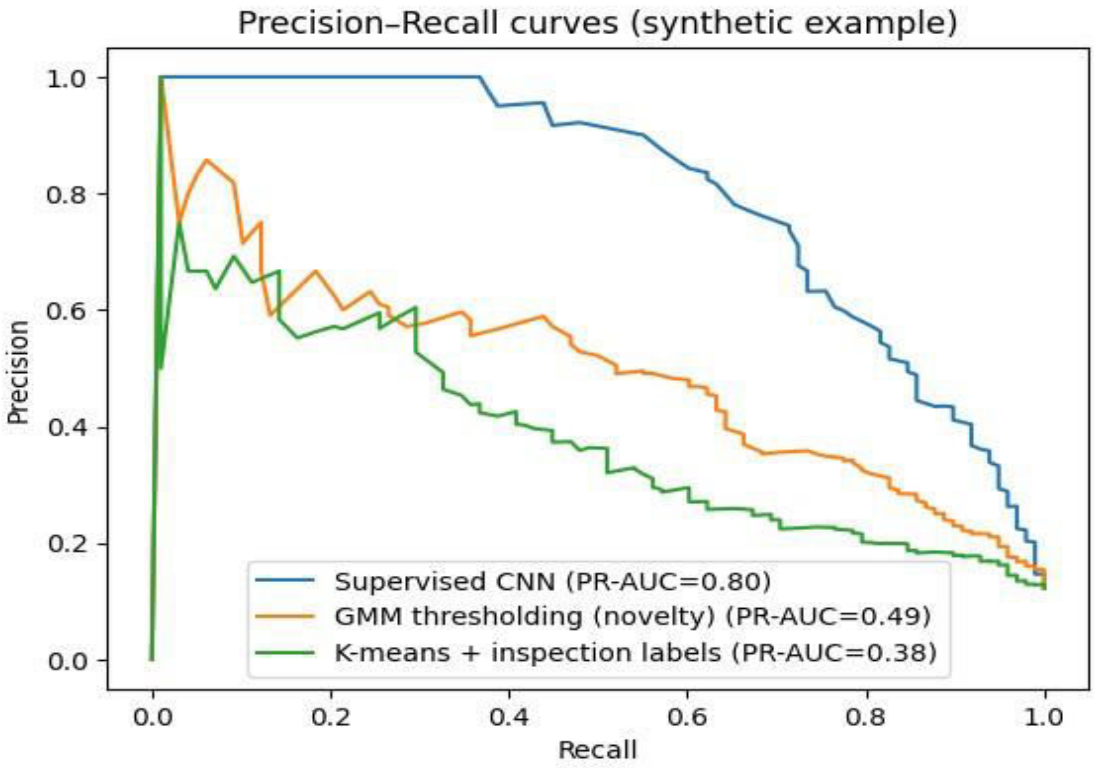

4.1. Supervised Learning for Defect Detection

Quality control defect detection is often a supervised classification problem, where labeled defect examples are available to train the model. Regardless of the industrial sector, obtaining comprehensive sample coverage for every defect mutant is cumbersome and expensive. Attention and resources are primarily directed towards the frequent and costly defects. When the number of label occurrences for a specific defect is limited, methods with a compromise between performance and the sufficient sample size are employed. When test data achieves reasonable balance among the defect coverage, especially the rare defect offenders, performance metrics elucidate the quality of the model training. However, the novelty defect classes are not necessarily present for labeling.

Recent works attempt to infer surrogate labels for the defect patterns or to optimize the labeling purpose by leveraging other industry sensors. Moreover, quality estimation techniques are discussed that elaborate the defect types through hard misclassified examples from the classifier. Other approaches employ XAI methods to investigate characteristics of training sets and support the labeling operations. Great attention has been devoted to model oversight and auditability through various sensitive metrics, example-wise model prediction confidence calibration, and cross-domain verification. To mitigate the labor-intensive annotation effort, active learning adopts the underlying distribution and model behavior to focus on the most critical samples for manual labeling. Given the limited number of hit-and-run defect samples, drop-out based augmentation methods generate additional noise redundancy in the images to complement tranining.

Quality control fatique detection represents another classical supervised learning classification model in manufacturing. Human stress recognition comes from aggregated knowledge in the surrounding atmosphere using a multitude of context sources, including images, videos, audios, thermometer, and other sensors. Support Vector Machine, Decision Tree, Taylor Expansion and Neural Network are the trend models in the information fusion of Quality Attitude Analysis.

4.2. Unsupervised and Anomaly Detection Techniques

Unsupervised learning methods are also essential for defect detection and quality control. In some cases, collecting sufficient labeled samples is difficult or impossible due to temporal or spatial constraints (e.g., for rare types of defects); hence, supervision is not feasible. Unsupervised learning may allow these samples to be synthesized with limited resources, avoiding the reliance on highly skilled domain experts. In addition, evolving quality-control tasks

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may benefit from online training without incurring the labeling cost each time a new anomaly appears or a previously trained model becomes stale. Nevertheless, distinguishing quality- from non-quality defects requires some degree of domain knowledge, especially thresholding acts.

Unsupervised methods can be categorized into clustering and novelty detection (or outlier detection). The first type clusters observations in the feature space without prior knowledge about class labels. Each cluster represents a coherent group of data instances possessing similar features. Samples whose features deviate significantly from these groups may point to manufacturing defects. The second approach learns the distribution of the training observations and applies the fitted distribution for novelty detection during inference. Quality defects can be detected by flagging observations that fall outside the learned distribution. Methods can also be combined. For example, anomalies identified by novelty detection could be clustered to decide whether specific corrective actions make sense, or the clustering outcome can be further inspected with novelty detection techniques to identify potential erroneous samples affecting the model.

	Pred OK (0)	Pred Defect (1)
Actual OK (0)	352	350
Actual Defect (1)	2	96

V. SYSTEM ARCHITECTURE FOR END-TO-END QUALITY CONTROL

End-to-end quality control constitutes a comprehensive deployment of the discussed AI methods to fully anticipate quality issues before they arise during actual production. System architecture encapsulates the orchestration of data pipelines, the modular nature of individual components, the need for concurrent operation in multiple instances, and requirements for system scalability and fault tolerance.

A data pipeline for end-to-end quality control can be orchestrated as shown in Figure 1, combining several elements that can be processed independently but share the same goal of integrating intelligence into the manufacturing process for quality assurance. These components address important aspects of AI–QA integration. The defect detection module encompasses labelled quality data along with the latest defect detection model, while anomaly detection utilises different heterogeneous data streams not usually exploited for QA, such as that from remote data collection systems. The combination of both solutions forms a comprehensive quality assurance framework by enabling defects to be detected as early as possible within the production pipeline.

The feedback loop from the model monitoring module allows these data streams to be leveraged concurrently for improved overall manufacturing robustness during production, paralleling the stream of model predictions. Individual components may also be scaled independently in event-driven mode, allocating generate–aggregate resources according to the current workflow manage-ment. Any event-driven component may also trigger alerts for those users assigned the corresponding roles in the data governance model.

Equation 4) Unsupervised novelty detection via Gaussian Mixture Model (GMM) + thresholding
Step 1: Model the normal data distribution
Assume features $x \in \mathbb{R}^d$ arise from a mixture of K Gaussians:

$$p(x) = \sum_{k=1}^{K} \pi_k \ \mathcal{N}(x \mid \mu_k, \Sigma_k)$$

where $\pi_k \geq 0, \sum_k \pi_k = 1$.
Step 2: Gaussian density

$$\mathcal{N}(x \mid \mu, \Sigma) = \frac{1}{(2\pi)^{d/2}|\Sigma|^{1/2}} \exp\left(-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu)\right)$$

Step 3: Compute a novelty score
Common score = **negative log likelihood**:

$$s(x) = -\log p(x)$$

- If $p(x)$ is small (unlikely under normal), $s(x)$ is large → anomalous.

Step 4: Threshold selection using validation

$$\tau = Q_{1-\alpha}(s_1, \ldots, s_m)$$

so that only α fraction of clean data exceed it (target false alarm rate).

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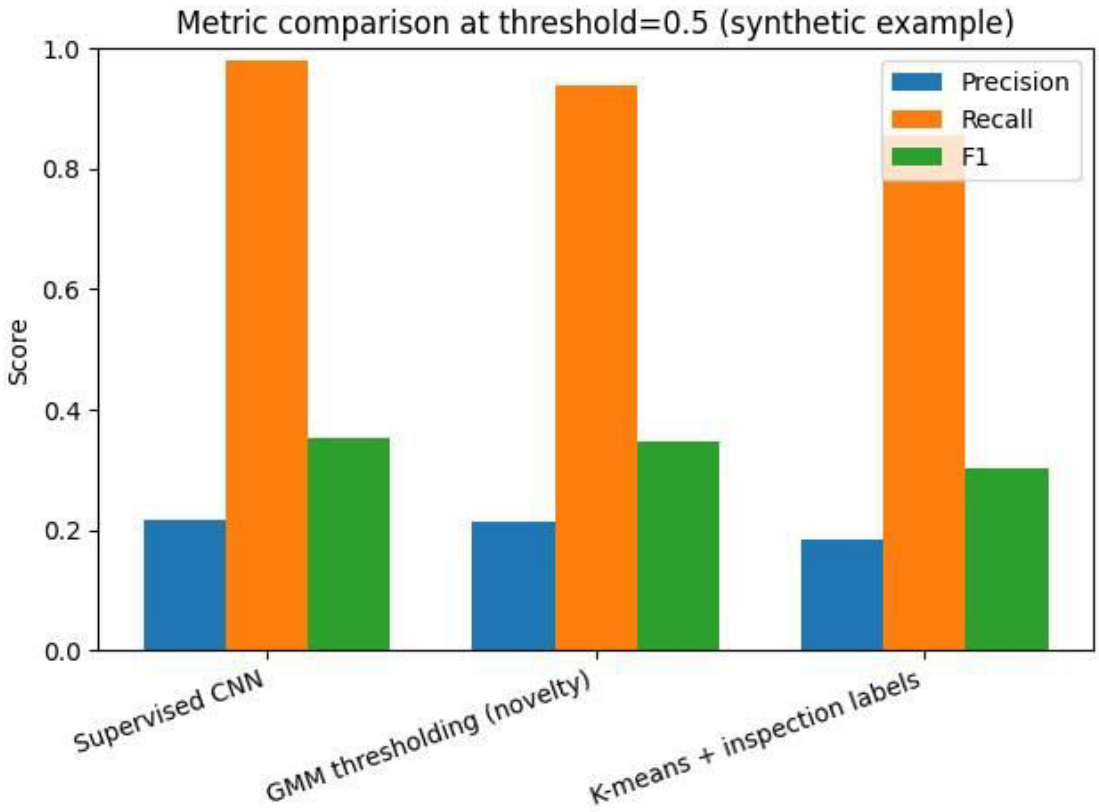
Step 5: Detection rule

$$\hat{y} = \begin{cases} 1 \text{ (anomaly/defect)} & \text{if } s(x) > \tau \\ 0 \text{ (normal)} & \text{otherwise} \end{cases}$$



5.1. Data Pipeline Orchestration

Data pipelines for real-time quality control applications must be carefully orchestrated to allow for seamless dataflow through the various processing and analysis stages. To accommodate different development, resource, and fulfilment requirements, different approaches may be adopted. Rather than deploying every component as an independent service possibly replicated across multiple nodes, it is often feasible to organize the pipeline as a directed acyclic graph (DAG) to allow for in-process calls between modules thus avoiding the overhead of networked communications. Nevertheless, pipelines must remain modular enough to allow independent scaling and upgrading; a design pattern employing modular stages that manage their own scaling and build-time dependencies allows for flexible and potentially efficient pipelines.

A sample pipeline implementing a Gaussian mixture thresholding approach for novelty detection in an image dataset is also illustrated.MSIGraph is used to provide a testbed for early-stage development of pipelines, which can subsequently be translated into production-grade execution engines such as Apache Airflow, Python-based co-processors in Azure Data Factory, or Talend. MSIGraph supports modular orchestration along DAGs, allowing both live synchronisation with camera streams and real-time FPS monitoring.

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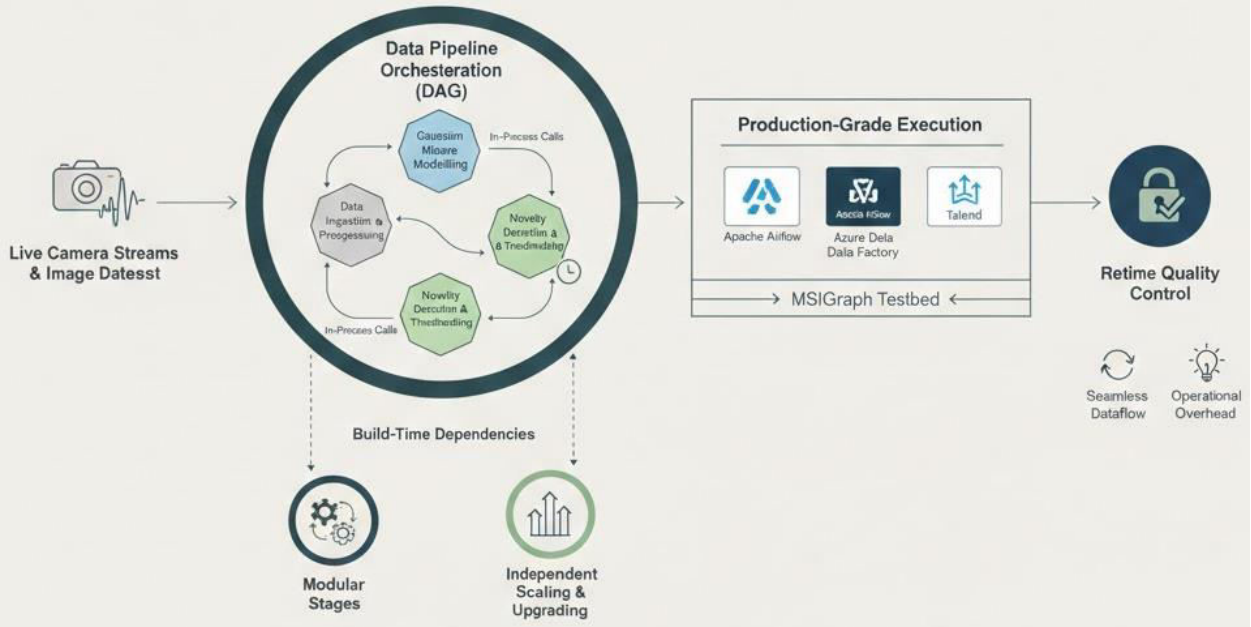

Fig 3: Optimizing Real-Time Quality Control via Modular DAG Orchestration: A Hybrid Framework for Low-Latency In-Process Execution and Scalable Production Deployment

5.2. Model Training, Evaluation, and Deployment

Nesting multiple models in a hierarchical pipeline allows deploying the whole structure in one go, which helps reduce deployment and monitoring efforts. Regarding model deployment, issues such as security and privacy become relevant when the model encompasses the whole pipeline of an input-annotated system. The monitoring should start with the data collector and sink nodes. In most production systems, monitoring the model includes quality checks in batches at a defined frequency using a test set. Models should not stagnate, and a lifecycle plan covering training, evaluation, and deployment needs to be defined.

To manage model drift effectively, retraining on an annotated dataset should occur at intervals shorter than drift detection, so deployment can ensure the same data source that is aligned with deployment strategy. An alert for model drift or quality degradation should initiate retraining, and evaluation of such pull requests on service quality is vital. The business-logic modules monitoring the business, such as profit and loss, will eventually report insufficient-quality results. Monitoring should trigger a retraining request as a noise alarm. Monitoring is essentially informing the stakeholder of potential problems and degradation that require resolution.

VI. DATA GOVERNANCE, SECURITY, AND COMPLIANCE

Data quality can deteriorate over time due to software bugs, hardware malfunctions, or changes in environmental conditions, thereby creating the risk of structural breaks and affecting the reliability of models deployed in production. Hence, similar to space mission planning, production AI solutions require a full-stack effort that includes not only the models themselves but also the infrastructure for their continuous training, validation, deployment, monitoring, and lifecycle management, as well as data pipelines that are orchestrated end to end. These additional aspects are especially important in safety-critical applications. Fig. 7 illustrates a possibly multi-cloud infrastructure that supports these operations and can therefore be exploited to address the entire production AI lifecycle.

As such, the entire data pipeline is also critical for the reliability of the application. To guarantee data quality, data provenance and lineage need to be tracked, auditability needs to be guaranteed, and the necessary roles, policies, and access controls must be defined. Due to the potentially sensitive nature of the application, deploying the appropriate security measures is also required: data masking, data encryption, and policy-based data governance enable complying with legislation, thus helping to minimize the risk of incurring fines.

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Equation 5) End-to-end latency and "tolerance" in ingestion (pipeline math)

Step 1: Define timestamps

- Event occurs at time t_{event}.
- AI decision becomes available at time $t_{decision}$.

Step 2: Define end-to-end latency

$$L = t_{decision} - t_{event}$$

Step 3: Decompose pipeline latency (sum of components)

For a modular DAG pipeline :

$$L = L_{acq} + L_{ingest} + L_{prep} + L_{infer} + L_{post} + L_{deliver}$$

If cloud adds network:

$$L_{cloud} = L_{acq} + L_{net} + L_{ingest} + \cdots$$

Step 4: Tolerance constraint

Let tolerance be T_{tol} (maximum useful lag).

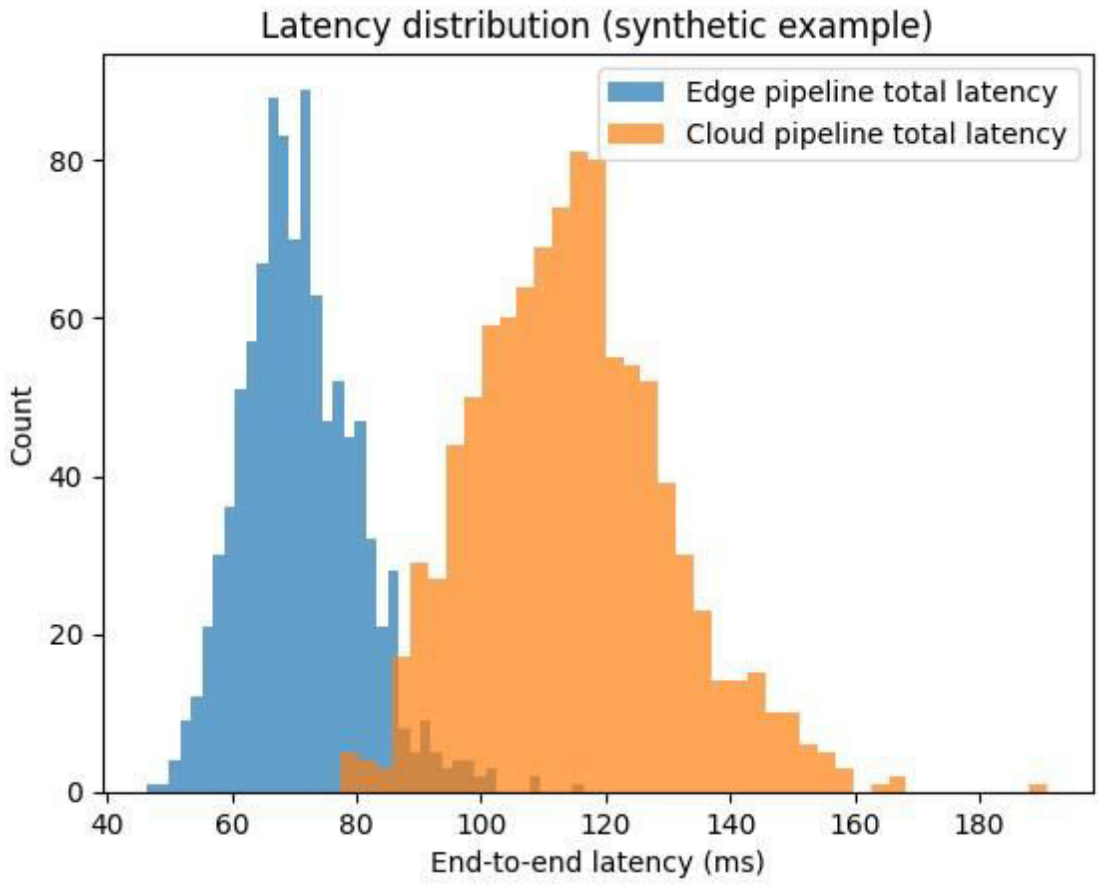
A decision is "timely" if:

$$L \leq T_{tol}$$

Step 5: Timeliness as a measurable KPI

Over N events:

$$\text{Timeliness} = \frac{1}{N}\sum_{i=1}^{N} \mathbf{1}\,[L_i \leq T_{tol}]$$



6.1. Data Provenance and Lineage

Provenance and lineage describe the origin and history of data, enabling auditing, compliance verification, and impact assessment of data quality problems. Provenance encompasses metadata about the origin of data and any modifications made to its structure, while lineage focuses on the sources and resultant products of data.

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The ability to track data provenance is essential for users to trust data. Provenance requirements vary across different domains and groups. For instance, regulatory compliance mandates precise documentation of provenance. In AI applications, provenance information is vital for identifying compliance violations, security breaches, and data quality issues that may lead to compromised intelligence, such as model bias. Organizations are increasingly mandated to maintain data provenance for auditing purposes.

A well-defined data lineage not only aids in auditability but also supports data quality management by identifying the source of defects for corrective actions. By specifying when, how, and from where data is produced, lineage information enables organizations to pinpoint the responsible parties and determine whether a defect originated during acquisition or during data transformation. Furthermore, these details inform data quality assessments and provide insights into data reliability.

6.2. Privacy and Access Control

Data privacy and security are paramount in manufacturing, not least for ensuring regulatory compliance (Johnson et al., 2019; Peisert et al., 2019). Privacy protection techniques increase development and operational costs by breaking linkages between users and their data; they thereby hamper data sharing for model training (Yang et al., 2021). Data masking substitutes or alters sensitive data in well-defined ways that allow for analytics but do not expose sensitive information (Shen et al., 2019). In less highly protected environments, data encryption transforms data into lossy formats indistinguishable to unauthorized users. Searchable encryption—involving modification of indexed datasets—enables data sharing without full decryption (Song et al., 2010). Policy-aware data-sharing solutions automate the management of owner-lender trust relations (Wang et al., 2019).

Privacy protection, authentication, and access-control techniques must be commensurate with data sensitivity, threat landscape, and usage intention (Ani et al., 2021). More generally, security controls must address all assets and threats holistically, spanning data, models, and underlying services (Muster et al., 2021). New data-policy concepts shift security focus from data protection to governance, relying in part on sensitive-data usage profiles and policy enforcers that prohibit usage contrary to users' preferences, regardless of data location or origin. Identity access management ensures secure, on-demand access to manufacturing resources, with security groups tailored to specific roles.

VII. CONCLUSION

Key insights confirm that quality-control defect detection in complex products lends itself readily to AI leveraging supervised or unsupervised learning; pipeline construction requires Data Engineering skill; and governance is needed to address AI model life-cycle maintenance, privacy, security, and compliance. First, the challenge of providing model predictions in near real time can be handled with a low-latency Data Engineering framework that ushers and pre-processes test data into the models in a streaming fashion. Importantly, the framework can be based on either graphical programming environments for lowcoding of minimal pipelines in the cloud and at the edge or open-source data-integration code patterns with full programmability in dedicated mode. Such end-to-end construction of the AI capability nanoservice can also tackle issues of high-volume execution and fault tolerance, scaling automatically across replicated, load-balanced components.

Second, although the skill domain of Data Engineering has thus far remained fairly distinct from AI model training and application, exemplar A data pipeline brings these elements together; such frameworks make Data Engineering accessible both to nonexperts and to experts who like to stay in touch with the technology's rapid evolution. Third, future-proven Data Engineering learning paths seamlessly integrate the required multi-purpose knowledge domains. Finally, although Content Engineering cannot be demonstrated yet, it is key to managing the model life cycle, privacy, security, and compliance of AI in production systems. Specifically, Data Engineering Frameworks—as applied here to near-real-time quality-control defect detection and grouped into readiness areas—are consequential support for practitioners, enabling credible experimentation that addresses this critical domain of Industry 4.0.

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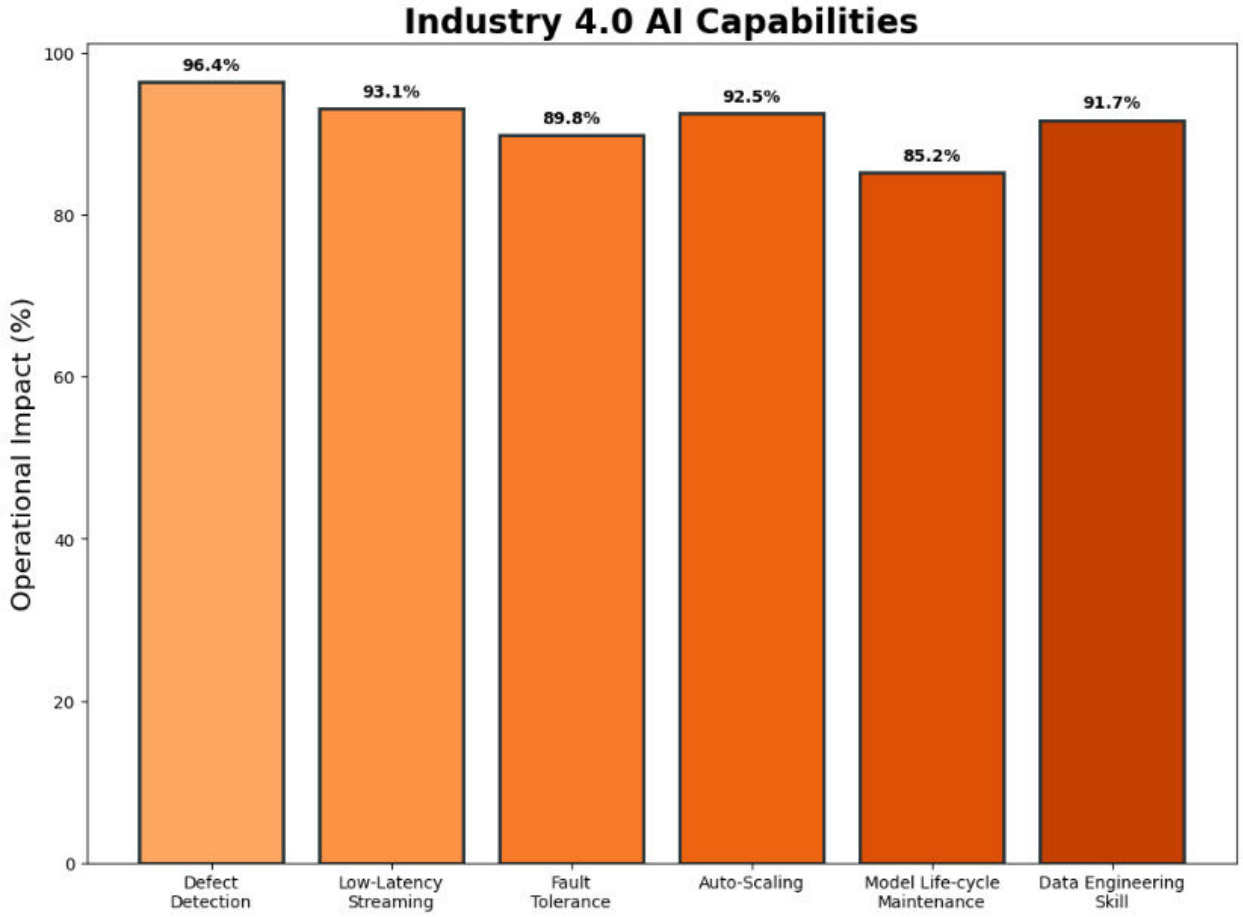

Fig 4: Industry 4.0 AI Capabilities

7.1. Final Thoughts and Future Directions

The rapid advancement of Artificial Intelligence has opened up a new era in the field of Quality Control Automation and supported by Data Engineering Pipelines for Manufacturing Quality Control. The need to ensure that AI-Based Data Engineering Pipeline can truly provide the right Business Value, mainly associated with quality and reliability defect detection in industrial applications, has become a fundamental need.In the present work, the necessity of choosing the right AI algorithm to be incorporated in a Data Engineering Pipeline for Quality Control Automation has been performed, giving an overview of the steps needed to cover to successfully implement the system, from Definition of the Business and Quality Requirements, from a Data Quality Analysis, to Algorithm Choice and Imperative, while no effort has been put on the Implementation since, due to the specifics of the real production environment where the system is being deployed, the implementation is being carried out on the ground.

Three important open points have emerged that still For AI to truly be integrated in Data Engineering Pipelines for Manufacturing Quality Control and Quality Control Automation, further research is needed in the next months: 1. Define how to provide evaluation metrics for all Quality Control QA Function, where not all use case related to Product Quality Detection fall into the traditionalTraining - Test - Validation paradigm in the AI community. Models can be used as shadow models or as novel detection models. In these cases, AI community proposes to use additional test-sets with plenty of false tests, others propose to define test setsNavon Model, where only new classes are tested. None of these proposals cover cases of importance of the main product with not negligible ratio of new classes. 2. Create definition of Quality Control Automation scope in QMS terms.Basically QA Function associate responsibilities where Quality Control Automation Systems are Safety System-Automatic Inspection acceptance - and so on. 3. Define the role of Data Quality within the Data Engineering Pipeline in Manufacturing Quality Control The rapid advancement of Artificial Intelligence has opened up a new era in the field of Quality Control Automation. The need for AI applications to provide Non-Functional Processes related to Data.

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REFERENCES

[1] Lee, J., Bagheri, B., & Kao, H. A. (2015). A cyber-physical systems architecture for Industry 4.0-based manufacturing systems. Manufacturing Letters, 3, 18–23.
[2] Kalisetty, S. (2024). Deep learning frameworks for multi-modal data fusion in retail supply chains: enhancing forecast accuracy and agility.
[3] Lasi, H., Fettke, P., Kemper, H. G., et al. (2014). Industry 4.0. Business & Information Systems Engineering, 6(4), 239–242.
[4] Nagabhyru, K. C. (2024). Data Engineering in the Age of Large Language Models: Transforming Data Access, Curation, and Enterprise Interpretation. Computer Fraud and Security.
[5] Qi, Q., & Tao, F. (2018). Digital twin and big data towards smart manufacturing. Enterprise Information Systems, 12(9–10), 1105–1121.
[6] Aitha, A. R. (2024). Generative AI-Powered Fraud Detection in Workers' Compensation: A DevOps-Based Multi-Cloud Architecture Leveraging, Deep Learning, and Explainable AI. Deep Learning, and Explainable AI (July 26, 2024).
19. Spackman, K. A., Campbell, K. E., & Côté, R. A. (1997). SNOMED RT. JAMIA, 4(6), 640–649.
[7] Wan, J., Tang, S., Li, D., et al. (2018). A manufacturing big data solution for active preventive maintenance. IEEE Transactions on Industrial Informatics, 13(4), 2039–2047.
[8] Varri, D. B. S. (2022). A Framework for Cloud-Integrated Database Hardening in Hybrid AWS-Azure Environments: Security Posture Automation Through Wiz-Driven Insights. International Journal of Scientific Research and Modern Technology, 1(12), 216-226.
[9] Wang, S., Wan, J., Zhang, D., et al. (2016). Towards smart factory for Industry 4.0. International Journal of Distributed Sensor Networks, 12(1), 1–12.
[10] Garapati, R. S. (2023). Optimizing Energy Consumption in Smart Build-ings Through Web-Integrated AI and Cloud-Driven Control Systems.
[11] Lu, Y. (2017). Industry 4.0: A survey on technologies and applications. Journal of Industrial Information Integration, 6, 1–10.
[12] Nagubandi, A. R. (2023). Advanced Multi-Agent AI Systems for Autonomous Reconciliation Across Enterprise Multi-Counterparty Derivatives, Collateral, and Accounting Platforms. International Journal of Finance (IJFIN)-ABDC Journal Quality List, 36(6), 653-674.
[13] Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep learning. MIT Press.
[14] Vardhan Kumar Bandi, V. D. (2024). Automated Feature Engineering Systems in Large-Scale Healthcare Data Environments. Journal of Neonatal Surgery, 13(1), 2127–2141. Retrieved from https://www.jneonatalsurg.com/index.php/jns/article/view/10004.
[15] Krizhevsky, A., Sutskever, I., & Hinton, G. (2012). ImageNet classification with deep convolutional neural networks. Advances in Neural Information Processing Systems, 25, 1097–1105.
[16] Gottimukkala, V. R. R. (2023). Privacy-Preserving Machine Learning Models for Transaction Monitoring in Global Banking Networks. International Journal of Finance (IJFIN)-ABDC Journal Quality List, 36(6), 633-652.
[17] Chollet, F. (2017). Xception: Deep learning with depthwise separable convolutions. CVPR Proceedings, 1251–1258.
[18] Davuluri, P. N. Integrating Artificial Intelligence into Event-Driven Financial Crime Compliance Platforms.
[19] Bergmann, P., Fauser, M., Sattlegger, D., & Steger, C. (2019). MVTec AD—A comprehensive real-world dataset for unsupervised anomaly detection. CVPR Proceedings, 9592–9600.
[20] Kushvanth Chowdary Nagabhyru. (2023). Accelerating Digital Transformation with AI Driven Data Engineering: Industry Case Studies from Cloud and IoT Domains. Educational Administration: Theory and Practice, 29(4), 5898–5910. https://doi.org/10.53555/kuey.v29i4.10932
[21] Ruff, L., Vandermeulen, R. A., Görnitz, N., et al. (2018). Deep one-class classification. ICML Proceedings, 4393–4402.
[22] Meda, R. (2023). Intelligent Infrastructure for Real-Time Inventory and Logistics in Retail Supply Chains. Educational Administration: Theory and Practice.
[23] Schlegl, T., Seeböck, P., Waldstein, S. M., et al. (2017). Unsupervised anomaly detection with GANs. Information Processing in Medical Imaging, 146–157.
[24] Amistapuram, K. (2024). Generative AI in Insurance: Automating Claims Documentation and Customer Communication. Turkish Journal of Computer and Mathematics Education (TURCOMAT), 15(3), 461–475. https://doi.org/10.61841/turcomat.v15i3.15474
[25] Breunig, M. M., Kriegel, H. P., Ng, R. T., & Sander, J. (2000). LOF: Identifying density-based local outliers. ACM SIGMOD, 93–104.

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| Volume 6, Issue 6, November - December 2024 |

DOI:10.15662/IJEETR.2024.0606020

[26] Rongali, S. K., & Kumar Kakarala, M. R. (2024). Existing challenges in ethical AI: Addressing algorithmic bias, transparency, accountability and regulatory compliance.
[27] Agentic AI in Data Pipelines: Self Optimizing Systems for Continuous Data Quality, Performance and Governance. (2024). American Data Science Journal for Advanced Computations (ADSJAC) ISSN: 3067-4166, 2(1).
[28] Bishop, C. M. (2006). Pattern recognition and machine learning. Springer.
[29] Pandugula, C., Kalisetty, S., & Polineni, T. N. S. (2024). Omni-channel Retail: Leveraging Machine Learning for Personalized Customer Experiences and Transaction Optimization. Utilitas Mathematica, 121, 389-401.
[30] Batini, C., & Scannapieco, M. (2016). Data and information quality. Springer.
[31] Kalisetty, S. (2023). The Role of Circular Supply Chains in Achieving Sustainability Goals: A 2023 Perspective on Recycling, Reuse, and Resource Optimization. Reuse, and Resource Optimization (June 15, 2023).
[32] Sculley, D., Holt, G., Golovin, D., et al. (2015). Hidden technical debt in machine learning systems. Advances in Neural Information Processing Systems, 28, 2503–2511.
[33] Segireddy, A. R. (2024). Machine Learning-Driven Anomaly Detection in CI/CD Pipelines for Financial Applications. Journal of Computational Analysis and Applications, 33(8).
[34] Amershi, S., Begel, A., Bird, C., et al. (2019). Software engineering for machine learning. IEEE Software, 36(5), 56–67.
[35] Varri, D. B. S. (2024). Adaptive and Autonomous Security Frameworks Using Generative AI for Cloud Ecosystems. Available at SSRN 5774785.
[36] Breck, E., Cai, S., Nielsen, E., et al. (2017). The ML test score. IEEE Big Data Proceedings, 1123–1132.
[37] Keerthi Amistapuram. (2024). Federated Learning for Cross-Carrier Insurance Fraud Detection: Secure Multi-Institutional Collaboration. Journal of Computational Analysis and Applications (JoCAAA), 33(08), 6727–6738. Retrieved from https://www.eudoxuspress.com/index.php/pub/article/view/3934
[38] Zaharia, M., Das, T., Li, H., et al. (2012). Discretized streams: Fault-tolerant streaming computation. USENIX NSDI, 423–438.
[39] Kreps, J., Narkhede, N., & Rao, J. (2011). Kafka: A distributed messaging system. NetDB Workshop.
[40] Inala, R. Revolutionizing Customer Master Data in Insurance Technology Platforms: An AI and MDM Architecture Perspective.
[41] Carbone, P., Katsifodimos, A., Ewen, S., et al. (2015). Apache Flink: Stream and batch processing. IEEE Data Engineering Bulletin, 38(4), 28–38.
[42] Singireddy, J. (2024). AI-Enhanced Tax Preparation and Filing: Automating Complex Regulatory Compliance. European Data Science Journal (EDSJ) p-ISSN 3050-9572 en e-ISSN 3050-9580, 2(1).
[43] van der Aalst, W. M. P. (2016). Process mining: Data science in action (2nd ed.). Springer.
[44] Varri, D. B. S. (2023). Advanced Threat Intelligence Modeling for Proactive Cyber Defense Systems. Available at SSRN 5774926.
[45] Tao, F., Qi, Q., Liu, A., & Kusiak, A. (2018). Data-driven smart manufacturing. Journal of Manufacturing Systems, 48, 157–169.
[46] Paleti, S. (2024). Transforming Financial Risk Management with AI and Data Engineering in the Modern Banking Sector. American Journal of Analytics and Artificial Intelligence (ajaai) with ISSN 3067-283X, 2(1).
[47] Wan, J., Cai, H., & Zhou, K. (2015). Industrie 4.0: Enabling technologies. IEEE Access, 3, 1567–1579.
[48] Kalisetty, S., & Singireddy, J. (2023). Optimizing Tax Preparation and Filing Services: A Comparative Study of Traditional Methods and AI Augmented Tax Compliance Frameworks. Available at SSRN 5206185.
[49] Zhang, C., Yang, J., & Chen, Y. (2023). AI-enabled defect detection in smart factories using hybrid deep learning models. IEEE Access, 11, 94532–94545.
[50] Sheelam, G. K., & Koppolu, H. K. R. (2024). From Transistors to Intelligence: Semiconductor Architectures Empowering Agentic AI in 5G and Beyond. Journal of Computational Analy- sis and Applications(JoCAAA), 33(08), 4518-4537.
[51] Li, X., Sun, Q., & Wang, H. (2024). Real-time industrial anomaly detection with edge-cloud collaborative learning. IEEE Transactions on Industrial Informatics, 20(2), 1324–1336.
[52] Aitha, A. R. (2023). CloudBased Micro services Architecture for Seamless Insurance Policy Administration. International Journal of Finance (IJFIN)-ABDC Journal Quality List, 36(6), 607-632.
[53] Li, X., Sun, Q., & Wang, H. (2024). Real-time industrial anomaly detection with edge–cloud collaborative learning. IEEE Transactions on Industrial Informatics, 20(2), 1324–1336.
[54] Kolla, S. H. (2024). RETRIEVAL-AUGMENTED GENERATION WITH SMALL LLMS FOR KNOWLEDGE-DRIVEN DECISION AUTOMATION IN ENTERPRISE SERVICE PLATFORMS. Turkish Journal of Computer and Mathematics Education (TURCOMAT), 15(3), 476–486. https://doi.org/10.61841/turcomat.v15i3.15497.
[55] Zhang, C., Yang, J., & Chen, Y. (2023). AI-enabled defect detection in smart factories using hybrid deep learning models. IEEE Access, 11, 94532–94545.

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| Volume 6, Issue 6, November - December 2024 |

DOI:10.15662/IJEETR.2024.0606020

[56] Guntupalli, R. (2024). Enhancing Cloud Security with AI: A Deep Learning Approach to Identify and Prevent Cyberattacks in Multi-Tenant Environments. Available at SSRN 5329132.
[57] Tao, F., Qi, Q., Liu, A., & Kusiak, A. (2018). Data-driven smart manufacturing. Journal of Manufacturing Systems, 48, 157–169.
[58] Kolla, S. K. (2021). Designing Scalable Healthcare Data Pipelines for Multi-Hospital Networks. World Journal of Clinical Medicine Research, 1(1), 1–14. Retrieved from https://www.scipublications.com/journal/index.php/wjcmr/article/view/1376
[59] Lee, J., Bagheri, B., & Kao, H. A. (2015). A cyber-physical systems architecture for Industry 4.0-based manufacturing systems. Manufacturing Letters, 3, 18–23.
[60] Yandamuri, U. S. AI-Driven Decision Support Systems for Operational Optimization in Hospitality Technology.
[61] Lu, Y. (2017). Industry 4.0: A survey on technologies, applications and open research issues. Journal of Industrial Information Integration, 6, 1–10.
[62] Koppolu, H. K. R., & Sheelam, G. K. (2024). Machine Learning-Driven Optimization in 6G Telecommunications: The Role of Intelligent Wireless and Semiconductor Innovation. Global Research Development (GRD) ISSN: 2455-5703, 9(12).
[63] Wan, J., Tang, S., Li, D., et al. (2018). A manufacturing big data solution for active preventive maintenance. IEEE Transactions on Industrial Informatics, 13(4), 2039–2047.
[64] Lahari Pandiri, "AI-Powered Fraud Detection Systems in Professional and Contractors Insurance Claims," International Journal of Innovative Research in Electrical, Electronics, Instrumentation and Control Engineering (IJIREEICE), DOI 10.17148/IJIREEICE.2024.121206.
[65] Wang, S., Wan, J., Zhang, D., Li, D., & Zhang, C. (2016). Towards smart factory for Industry 4.0: A self-organized multi-agent system with big data-based feedback and coordination. International Journal of Distributed Sensor Networks, 12(1), 1–12.
[66] Rongali, S. K. (2023). Explainable Artificial Intelligence (XAI) Framework for Transparent Clinical Decision Support Systems. International Journal of Medical Toxicology and Legal Medicine, 26(3), 22-31.
[67] Bergmann, P., Fauser, M., Sattlegger, D., & Steger, C. (2019). MVTec AD—A comprehensive real-world dataset for unsupervised anomaly detection. Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, 9592–9600.
[68] Inala, R. AI-Powered Investment Decision Support Systems: Building Smart Data Products with Embedded Governance Controls.
[69] Ruff, L., Vandermeulen, R. A., Görnitz, N., et al. (2018). Deep one-class classification. Proceedings of the 35th International Conference on Machine Learning, 4393–4402.
[70] Kolla, S. K. (2021). Architectural Frameworks for Large-Scale Electronic Health Record Data Platforms. Current Research in Public Health, 1(1), 1–19. Retrieved from https://www.scipublications.com/journal/index.php/crph/article/view/1372.
[71] Schlegl, T., Seeböck, P., Waldstein, S. M., Schmidt-Erfurth, U., & Langs, G. (2017). Unsupervised anomaly detection with generative adversarial networks. Information Processing in Medical Imaging, 146–157.
[72] Guntupalli, R. (2024). AI-Powered Infrastructure Management in Cloud Computing: Automating Security Compliance and Performance Monitoring. Available at SSRN 5329147.
[73] Breunig, M. M., Kriegel, H. P., Ng, R. T., & Sander, J. (2000). LOF: Identifying density-based local outliers. Proceedings of the ACM SIGMOD International Conference on Management of Data, 93–104.
[74] Uday Surendra Yandamuri. (2023). An Intelligent Analytics Framework Combining Big Data and Machine Learning for Business Forecasting. International Journal Of Finance, 36(6), 682-706. https://doi.org/10.5281/zenodo.18095256
[75] Sculley, D., Holt, G., Golovin, D., et al. (2015). Hidden technical debt in machine learning systems. Advances in Neural Information Processing Systems, 28, 2503–2511.
[76] Meda, R. (2024). Agentic AI in Multi-Tiered Paint Supply Chains: A Case Study on Efficiency and Responsiveness. Journal of Compu-tational Analysis and Applications (JoCAAA), 33(08), 3994-4015.
[77] Amershi, S., Begel, A., Bird, C., et al. (2019). Software engineering for machine learning: A case study. IEEE Software, 36(5), 56–67.
[78] Rongali, S. K. (2024). Federated and Generative AI Models for Secure, Cross-Institutional Healthcare Data Interoperability. Journal of Neonatal Surgery, 13(1), 1683-1694.
[79] Breck, E., Cai, S., Nielsen, E., Salib, M., & Sculley, D. (2017). The ML test score: A rubric for ML production readiness and technical debt reduction. Proceedings of IEEE Big Data, 1123–1132.
[80] Meda, R. (2024). Agentic AI in Multi-Tiered Paint Supply Chains: A Case Study on Efficiency and Responsiveness. Journal of Compu-tational Analysis and Applications (JoCAAA), 33(08), 3994-4015.

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DOI:10.15662/IJEETR.2024.0606020

[81] Zaharia, M., Das, T., Li, H., et al. (2012). Discretized streams: Fault-tolerant streaming computation at scale. Proceedings of the USENIX Symposium on Networked Systems Design and Implementation, 423–438.
[82] Velangani Divya Vardhan Kumar Bandi. (2024). Intelligent Data Platforms For Personalized Retail Analytics At Scale. Metallurgical and Materials Engineering, 30(4), 1011–1027. Retrieved from https://metall-mater-eng.com/index.php/home/article/view/1011-1027
[83] Carbone, P., Katsifodimos, A., Ewen, S., et al. (2015). Apache Flink: Stream and batch processing in a single engine. IEEE Data Engineering Bulletin, 38(4), 28–38.
[84] Keerthi Amistapuram. (2023). Privacy-Preserving Machine Learning Models for Sensitive Customer Data in Insurance Systems. Educational Administration: Theory and Practice, 29(4), 5950–5958. https://doi.org/10.53555/kuey.v29i4.10965
[85] van der Aalst, W. M. P. (2016). Process mining: Data science in action (2nd ed.). Springer.
[86] Chava, K. (2024). The Role of Cloud Computing in Accelerating AI-Driven Innovations in Healthcare Systems. European Advanced Journal for Emerging Technologies (EAJET)-p-ISSN 3050-9734 en e-ISSN 3050-9742, 2(1).
[87] Batini, C., & Scannapieco, M. (2016). Data and information quality: Dimensions, principles and techniques. Springer.
[88] Siva Hemanth Kolla. (2023). Deep Learning–Driven Retrieval-Augmented Generation for Enterprise ITSM Automation: A Governance-Aligned Large Language Model Architecture. Journal of Computational Analysis and Applications (JoCAAA), 31(4), 2489–2502. Retrieved from https://www.eudoxuspress.com/index.php/pub/article/view/4774
[89] Li, Z., Wang, Y., & Zhang, H. (2024). AI-driven visual inspection and quality prediction in Industry 4.0 manufacturing systems. Journal of Manufacturing Systems, 72, 210–224.
[90] Davuluri, P. S. L. N. (2024). AI-Driven Data Governance Frameworks for Automated Regulatory Reporting and Audit Readiness. Metallurgical and Materials Engineering, 30(4), 996–1010. Retrieved from https://metall-mater-eng.com/index.php/home/article/view/1936
[91] Jiang, G., Solbrig, H. R., Chute, C. G. (2014). HL7 FHIR. JAMIA, 21(3), 391–400.
[92] Sasi Kumar Kolla. (2023). Big Data–Driven Machine Learning Frameworks for Clinical Risk Prediction. International Journal of Medical Toxicology and Legal Medicine, 26(3 and 4), 44–59. Retrieved from https://ijmtlm.org/index.php/journal/article/view/1456.
[93] Weber, G. M., Murphy, S. N., McMurry, A. J., et al. (2009). The Shared Health Research Information Network. JAMIA, 16(4), 458–466.
[94] Bandi, V. D. V. K. (2023). Production-Grade Machine Learning Pipelines For Healthcare Predictive Analytics. South Eastern European Journal of Public Health, 189–205. Retrieved from https://www.seejph.com/index.php/seejph/article/view/7057