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The Applications of AI in Smart Technologies and Manufacturing

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Abstract

Smart manufacturing has been driven forward by intelligentization, a major industrial production trend over the last several decades, with the help of AI technology. The modernization of AI by various modern businesses has given birth to a novel concept known as Industrial Artificial Intelligence (IAI), which serves as the technological basis for smart manufacturing. Artificial intelligence (AI) driven manufacturing improves several parts of closed-loop production chains, from

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production processes to product delivery. Considerably, the field of production monitoring has profited from IAI's incorporation of domain expertise. Modern artificial intelligence techniques, including adversarial training, transfer learning, and deep neural networks, are widely used in manufacturing for diagnostic and predictive maintenance purposes. IAI is widely believed to be a crucial technology that will propel industrial production forward in the future. Artificial intelligence (AI) driven manufacturing and its monitoring applications are thoroughly reviewed in this study. More precisely, it summarizes the primary IAI technologies and discusses their everyday use cases concerning the three primary production monitoring facets of problem detection, residual useful life forecast, and quality inspection. The current issues and potential avenues for IAI research are also covered. By incorporating them into the overview, this study further presents the papers on Monitoring with AI in Smart Manufacturing in this targeted part.

Keywords: Artificial Intelligence, Deep Learning, Diagnosis of Faults, Machine Learning, Smart Manufacturing.

1. Introduction

Scientific and technological developments have advanced industrial manufacturing during the last 150 years via digitization, electrification, and automation. It is believed that industrial intelligence will be the subsequent development in manufacturing, which is the combination of data and AI technologies with advanced production processes to make it possible for intelligent perception, analysis, reasoning, control, and decision-making (Zhou, 2018). The foundation of industrial intelligence is smart production. In broad strokes, it is the natural merging of several cutting-edge technologies from various fields, including IT, communications, manufacturing, and the web. Furthermore, it constantly integrates cutting-edge technology like digital twins and the IoT (Lee, 2018).

Accordingly, the idea of innovative manufacturing develops in step with contemporary technology. These days, most people think that cloud computing, the IoT, AI algorithms, cyber-physical systems (CPS), and big data analytics represent the last frontier of smart industrial technologies. The industrial intelligence ecosystem comprises four technologies: cyber, cloud computing, data analytics, and big data (Gamer, 2020).

The modern theory holds that smart manufacturing emerged due to a convergence of many emerging technologies, such as artificial intelligence algorithms, cloud computing, big data analytics, the Internet of Things (IoT), and cyber-physical systems. Information technology, data analytics, cloud computing, and big data are the backbone of an intelligence ecosystem. Self-evolving production is how we characterize smart manufacturing equipped with the intelligence of humans capable of both learning and learning to learn, despite the particular technology that could be useful now or possibly in the future. Consequently, smart manufacturing might keep becoming better (Boem, 2019).

Modern business leaders consider smart manufacturing the gold standard for measuring a country's industrial prowess. Most industrialized nations have enacted laws and initiatives to encourage smart manufacturing and give homegrown manufacturers a leg up in the global marketplace. Such programs exist in several nations; for example, "Made in China 2025" in China, "Advanced Manufacturing Partnership" in the United States, "Industry 4.0" in Germany, "High-value Manufacturing Strategy" in the United Kingdom, and "New Robot Strategy" in Japan. Industrial artificial intelligence technologies are the primary source of support for intelligent manufacturing. Despite the relative youth of the relevant literature, IAI is seeing meteoric growth in both interest and funding, as well as remarkable advancements in both theory and practice (Yuan, 2019).

Industrial artificial intelligence technologies are the primary source of support for intelligent manufacturing. Modeling, diagnostics, prediction, optimization, decision-making, and deployment are the six main strategies that makeup IAI. From supply chain management to process quality control, they have permeated every facet of industrial manufacturing (Jin, J., Yuan, 2020). Regarding IAI technology, real-time monitoring is one area that has been dramatically improved. Diagnostics, forecasting, and inspection are all part of real-time monitoring in the manufacturing process. For instance, fault diagnosis (FD) has been the subject of extensive research and is crucial to the security of smart manufacturing. Many industrialized nations actively participated in the development of FD. It typically entails fault detection and state monitoring for equipment maintenance and management. The unavoidable trend in industrial manufacturing is intelligentization (Carvalho, 2019).

A comprehensive solution to improve product efficiency and quality, enhance service levels, and drastically reduce energy consumption is presented by integrating AI with advanced manufacturing technologies rigorously. The topic of manufacturing monitoring is the main emphasis of this survey, which also discusses IAI quality inspection, remaining helpful life forecasts, and fault detection technologies (Erkoyuncu, J, 2020).

The current state of these technologies' research is methodically outlined, and the issues that IAI faces are also covered, along with potential fixes. The most recent developments in artificial intelligence (AI) in manufacturing, health monitoring and management, fault diagnosis and prognosis, and practical application will be shared via an AI special section in the IEEE/ASME Transactions on Mechatronics. An effort has been made to disseminate information on recent developments in artificial intelligence for smart manufacturing (Schleich, 2017).

Production monitoring is a crucial link in the production cycle, along with quality inspection, remaining functional life forecasts, and fault diagnostics. Since the introduction of smart manufacturing, two key technological drivers have been approaches based on machine learning and deep learning, and IAI technologies have found extensive use in all three of these areas. While FD, RUL, and QI tailor standard AI-based techniques (such as GAN, CNN, attention mechanism, and GNN) to achieve specific goals, these methods continuously evolve. The future seems bright for IAI systems, which do pretty well in monitoring output.

Analyzability, interpretability, generalization, and robustness are the four main focuses of IAI's future development. The primary goal of the first two is to make IAI technology more applicable in real-world settings. The ability to endure unpredictability in the environment, data, and systems is crucial for IAI algorithms. They should also be adaptable to various tasks in multiple domains, including monitoring, diagnosis, and prediction. Industrial production, which places a premium on risk assessment, is one area where causality analysis is important for model reasoning and decision-making. An increasing focus in the smart manufacturing industry is directed towards developing interpretable IAI technology. Autonomous industrial plants can't be realized without interpretable and analyzable IAI, so there's a movement toward using it for decision support and feedback loops. All built-in stability and closed-loop signal behavior models must undergo rigorous testing before operation, following the same protocols as conventional control systems. With the help of analyzable IAI, we can shift our focus from only monitoring equipment and quality to running the whole facility.

2. A General Review of AI in Industry

Using artificial intelligence (AI) technology and domain knowledge of standard industrial processes, IAI creates smart systems that can autonomously perceive, compare, predict, optimize, and adapt to meet multiple objectives in an efficient, dependable, and cost-effective manner (Shaikh, 2024). Machine learning, deep learning, and classical analytics are all forms of artificial intelligence (AI) that have helped solve issues related to decision-making, computer vision, natural language processing, and speech engineering. Figure 1 lists the six leading IAI technologies: modeling, detection, optimization, decision-making, and prediction.

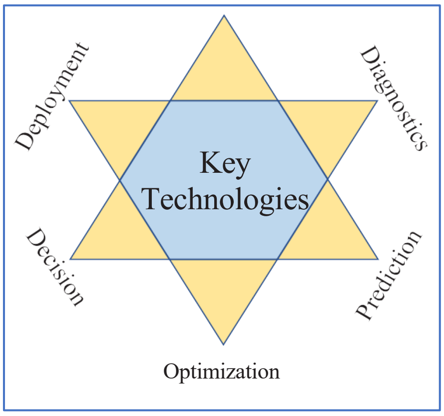

Fig. 1. Revolutionary AI Technologies for the Industrial Sector.

Whether design, manufacturing, process, assembly, warehousing, logistics, or sales, each industrial process has three main components: production, decision-making, and product service. Various pieces of machinery, such as sensors, assembly lines, workshops, and factories, fall within the equipment class. Environmental, energy, emissions, after-sales, operations, and maintenance comprise the supplemental category. (Ali, Syed Ibad, 2024) Among the many forms of artificial intelligence, industrial AI stands out.

2.1. *Making a Prediction*

Models play an essential role in production. Models built on industrial knowledge and mechanisms have uncovered numerous hidden laws, such as how to identify equipment or components, how process variables relate to product quality, and how the component process relates to the operational state of the production line. As a result, these models may show the ability of enterprises to produce and their level of competition while also reflecting the fundamental production process of manufacturing industries (Shaikh, Mohammad Shahnawaz, 2024). The manufacturing process as industrial CPS offered a novel way to uncover the evolution trend of CPS, uncover the switching logics between the subsystems, and find nonlinear coupled system dynamics.

The author (Mungale, 2024) notes that the method's intended usefulness in duplicating industrial processes like smart manufacturing, intelligent power grids, and robotics has led to its practical implementation in numerous situations. The authors (Ali, Syed Ibad, 2024) explained complex variational Bayesian inference on sparse network topologies for decoupling components in production.

2.2. *Diagnostics*

Because malfunctioning gear or processes in the manufacturing process may result in a dramatic decrease in product quality and even injuries or deaths, safety is a paramount concern in industrial production. Sensors often use photos, videos, and time series data to keep tabs on assembly lines, machines, and finished goods (Sheikh, M.S., 2024). Finding manufacturing process outliers and doing innovative online diagnostics are made possible using AI-based approaches to large data sets, such as deep learning, machine learning, and big data analysis. Supervised and unsupervised clustering and classification issues are typical approaches to these challenges. Using a deep learning architecture, noisy sensor inputs may have features like force, vibration, voltage, current, temperature, and sound automatically extracted (Preeti Chopkar, 2024).

It is possible to automatically extract features from various signals using a deep learning framework. These signals include vibration, voltage, current, temperature, sound, and force. The primary elements are structural strength and flexibility. A deep learning system was used from imperfect sensor data to automatically extract properties, including force, vibration, voltage, current, temperature, and sound. Bearings, gearboxes, cutters, and lithium batteries are industrial components that may benefit from the framework's high-precision diagnostic capabilities. With the help of a deep learning system, vibration, voltage, current, temperature, sound, and force may be automatically extracted from noisy sensor inputs (Himanshu Kitey, 2024).

2.3. *Prediction*

Improving industrial production relies heavily on precise forecasts. In predictive maintenance, demand prediction, and quality prognosis, data-driven forecasting approaches have become more popular due to the fast progress of big data, cloud services, and artificial intelligence technology. These techniques help lower costs, boost productivity, and enhance the safety and quality of industrial manufacturing. Predictive maintenance directs the development of efficient maintenance programs by estimating the remaining service life of industrial equipment based on monitoring data and empirical degradation information. By consulting a lexicon of mechanical operations, the producer foretells when risk management will be necessary. Coordinate the production chain and reduce waste based on the production line's previous monitoring data. Lastly, high-end manufacturing frequently uses quality prediction. Analyzing the manufacturing line's operation state and monitoring data allows for product quality prediction. After that, the production process is adjusted to prevent defective products from being manufactured. Notably, in recent years, the innovative idea of digital twin technology has increasingly influenced the field of quality inspection (Shaikh, M. S., 2016).

2.4. *Optimization*

Equipment-level optimization and system-level optimization are two key methods for increasing the effectiveness of industrial manufacturing. Industrial equipment parameters regulate the production process, which affects the final product's quality. Learning process parameters from monitoring data is standard due to the many unknown parameters. Unsupervised feature screening approaches such as principal component analysis, Laplacian score, and autoencoder accomplish the same goal as supervised feature screening methods like LDA, Lasso, and Fisher score.

Improving the quality and efficiency of industrial processes in real-time requires live parameter optimization based on AI. Consequently, many optimization methods have been developed (Ali, S. I., 2025). The many manufacturing operations that make up a production line sometimes need a wide range of industrial equipment. Collaboration in the production process is optimized according to the specified line-wide indices using data collected from manufacturing and equipment monitoring systems.

2.5. *Final Call*

The decisions must be finalized to complete the industrial production cycle linked to process optimization and equipment maintenance. During decision-making, various manufacturing-related aspects are considered to optimize and schedule operations and achieve corporate objectives. This category includes up-to-theminute market data, manufacturing status, operation indices, production directives, control directives, and operating circumstances. For example, to solve the scheduling issue of a parallel batch processor, Cao, Z. et al. (2024) used the reinforcement learning algorithm SARSA(Ż).

Depending on the decision-making process, industrial equipment maintenance may be predictive, preventative, or repaired. This group includes predictive maintenance, which many see as the "killer" app for the industrial Internet. It is possible to boost productivity, reduce equipment or process downtime, eliminate production downtime, and lower maintenance expenses via predictive maintenance. Prescriptive maintenance is an emerging trend that is rapidly expanding among healthcare professionals.

2.6. *Deployment*

By offering technical support platforms, deployment is essential to effectively implementing IAI. More precisely, the foundation for implementing AI models is hardware acceleration technology based on smart chips. Standard computing chips (such as CPUs) can no longer handle the need for processing in real-time during the online model reasoning stage due to the exponential expansion in data volume. Consequently, the creation of smart chips is essential for the use of IAI algorithms.

Hardware acceleration of the model interface is at the heart of intelligent chip technologies; this requires developing practical tools for software compilation and hardware designs. Smart chips are more efficient than traditional computer chips and use less electricity. Intelligent chip development has hastened the expansion of IAI applications.

Industrial AI seems to be growing in importance with the rapid expansion of industrial production. Numerous points in the manufacturing chain have been compromised. Examples of typical IAI use cases are shown in Figure 2. These include intelligent logistics and supply chain management, energy efficiency optimization and management, process quality control and inspection, and predictive equipment maintenance (Mohammad Shahnawaz Shaikh, 2016).

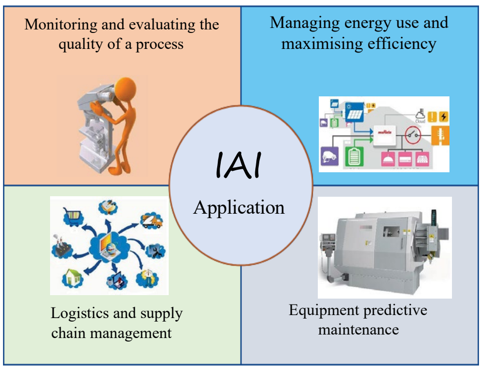

Fig. 2. Examples of Common Use Cases for Industrial AI.

An all-encompassing framework for presenting IAI is provided by intelligent monitoring programs such as quality inspection (QI), remaining functional life prediction (RULP), and fault diagnosis (FD). It allows for the successful communication of technological developments. The author outlines an intelligent monitoring architecture followed by sections covering AI-based algorithms for FD, RULP, and QI in that order (Mohammad Shahnawaz Shaikh, 2019). A summary of the conventional methods is in Figure 3.

3. Machine Learning for Defect Detection in Industrial Machinery

For industrial manufacturing, resilience and safety are essential. Using monitoring data, fault diagnostics seeks to avert potential mishaps and fatalities by identifying anomalous manufacturing processes and equipment operations. Highly efficient FD technologies are also required for minimum maintenance costs, outstanding performance, high flexibility, ideal platform independence, and acceptable interpretability.

When it comes to IAI fault diagnostics, machine learning is widespread. Methods that rely on machine learning are categorized as either deep machine learning or shallow machine learning according to the degree of granularity in the model structures. Concurrently, deep learning makes use of DNNs (e.g., Deep learning methods include things like Attention Mechanism (AM) and Transfer Learning (TL).

On the other hand, GRP, Hidden Markov Model, and Support Vector Machine are examples of shallow machine learning techniques that are more prevalent. Examples of these methods include CNNs, Graph Neural Networks (GNNs), and Long Short-Term Memory (LSTM).

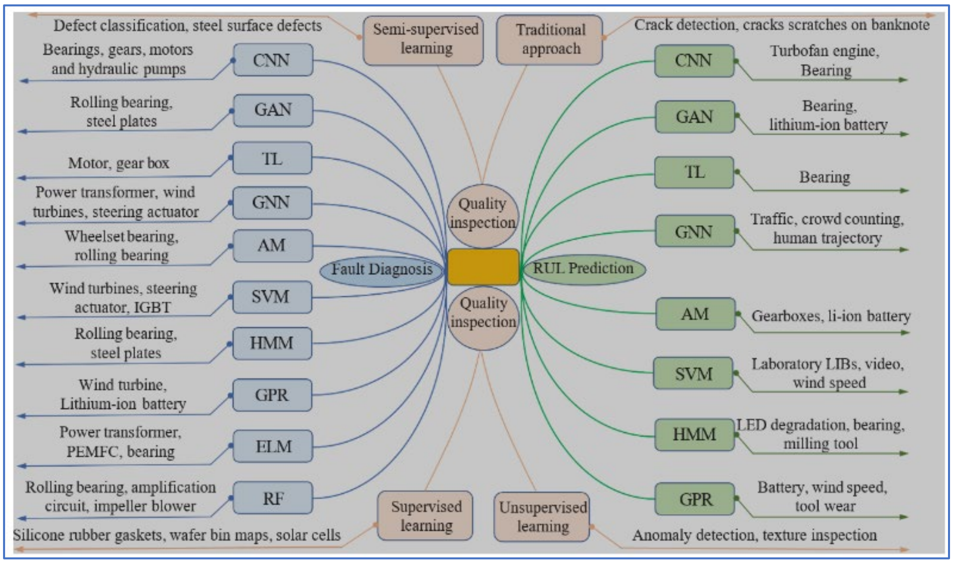

Fig. 3. Common AI Machine Learning Techniques and their Use in Industry.

More and more people are starting to pay attention to deep learning because of its success in defect identification. Intelligent fault diagnosis also includes investigating several approaches grounded on complex control theories.

3.1. *Standard Reference Datasets*

Methods and algorithm performance may be evaluated using standard reference datasets. Motor bearing vibration signals, bearing vibration signals, milling, and turbofan engine deterioration simulation databases are just a few online standard reference datasets accessible for problem detection.

3.2. *Machine Learning-Based Methods*

Machine learning-based diagnostic approaches typically include three steps: feature extraction, feature selection, and classification. Both automated and manual methods of feature extraction and selection are within reach. Expert knowledge aids AI feature extraction and selection in perceiving inherent properties, including system dynamics, beyond what automated feature learning using preset models can extract. Most diagnostic methods that rely on machine learning have three stages: feature extraction, feature selection, and classification. Both automated and manual methods exist for feature extraction and selection.

Unlike automated feature learning using preset models, which may extract abstract representations hidden in more complicated feature spaces, artificial expert knowledge helps with feature extraction and selection, allowing for better interpretation of inherent qualities like system dynamics. Interestingly, the deep learning framework frequently combines these two methods. Most methods for detecting machine failures use learned characteristics for categorization (Md. Shahnawaz Shaikh, 2016).

In their study, Chen S. et al. proposed a 1-D convolutional neural network (CNN) based approach for accurate fault type identification in rotating equipment with extra noise. This approach includes both known and undiscovered flaws. For 48 machine health states, two neural networks were trained to evaluate bearings and rotors separately. One-versus-all classifiers were created to discover undiscovered types of errors. The technique proved noise-resistant, resulting in consistent performance (Md. Shahnawaz Shaikh, Ankita Choudhry, 2016).

Using a Multi-manifold Deep Extreme Learning Machine (MDELM), Zhao introduced a new FD method for multi-channel motor-rotor systems. This method can handle data from numerous channels. The MDELM approach was enhanced by including both unsupervised and semi-supervised learning algorithms to provide semi-supervised fault classification. A BELM was used to explore discriminant feature information inside and across classes, and an ELM-MSF classifier with multi-manifold constraints was used to do unsupervised self-taught feature extraction. The recently developed MDELM shows exceptional learning efficiency using real-world data from motor-rotor systems.

Finding malfunctioning machinery is the job of a multi-node sensor network that uses support vector machines (SVMs) generated by mechanical vibrations. One system component was a V-TENG, a multilayer vibrational triboelectric nanogenerator used to harvest energy from operational machinery. The V-TENG's output was 3.33 mW/m3 due to the vibrational signal. A microcontroller-based SVSN (self-powered vibration sensor node) equipped with sensors and a wireless transmitter was built using the V-TENG. The three-SVSN network for defect diagnostics was built using support vector machines (SVMs) that analyzed acceleration and temperature data from the running system. The devised method accurately identified the machine's various operating situations.

3.3. *Other Approaches*

Under the end-to-end architecture, machine learning-based FD is a data-driven technique that doesn't take advantage of the target system's operational procedures or physical regulations. In addition to being cross-platform, these methods are very flexible. Using the same scenario for different circumstances may save much money on maintenance. However, machine learning-based techniques are often incomprehensible to human workers and susceptible to noise. Advanced control theories have been used to develop several methods that provide FD systems that are both robust and analyzable.

A fuzzy inference system (FIS)-based FD framework for electromechanical systems was presented by De Martini et al. Fuzzy INDices (F-IND) is a well-established framework for automatically constructing fuzzy rules. Each input variable uses the best and worst examples of the Membership Functions (MFs). Concurrently, according to Md, many fuzzy inference rules must be defined for Fuzzy Logic (FL) following input variables and MFs. Shahnawaz Shaikh and Kamlesh Gupta (2014), the method showed remarkable computation performance and detection accuracy when applied to electric motors.

An essential part of sensor Fault Tolerant Control (FTC) applications is estimating EHA states. The system is created with an EFIR estimator, UIOEFIR, using the Unknown Input Observer. According to the system, this hybrid estimator employing the UIO structure in the EFIR filter is used to estimate the unknown invoked-sensor-fault value. It does this without considering any process noise, previous knowledge of states, or measurements. The UIOEFIR estimator played a vital role in creating the fault diagnosis technique for a basic EHA sensor FTC architecture, which allows for discovering unknown sensor failure information. Despite uncertain environmental conditions, the suggested strategy maintained reliability and effectiveness (Md. Shahnawaz Shaikh, Kamlesh Gupta, 2014).

In their study, Zhang B. et al. suggested a method for reliably monitoring grinding wheel wear. This system could be used in many grinding scenarios, including those involving different kinds of wheels and workpiece materials. Using a unique normalization approach, the grinding process data were separated from other signals, such as accelerometers, power sensors, and sound emission sensors. The wheel type, workpiece material, and grinding settings may all be carefully considered. To predict how wheels would wear in reaction to adjustments to the grinding settings and to ascertain systemic wear, the model for tracking wheel wear used an interval type-2 Fuzzy Basis Function Network (FBFN) loaded with the provided characteristics. The results of the monitoring were consistent.

4. Extended Expected Life of Industrial Machinery

Data created to monitor vital production equipment has exploded due to the fast development of sensors, network transmission, data storage, and other new technologies. The primary goals of life prediction research are developing effective algorithms and extracting degradation information from monitoring data to provide accurate predictions of the remaining useful life.

Methods for data-driven RUL prediction mostly fall into two categories: statistical techniques and methods based on machine learning. The theory of statistics is the foundation of statistical methods. The usual procedure for processing data on equipment deterioration, making assessment indices, and determining the equipment's health state is principal component analysis or partial least square approaches. However, the quality of the data and stringent statistical theory prerequisites restrict the use of these techniques. On the other hand, machine learning-based approaches are more adaptable and valuable, and they have been widely used for RUL prediction with remarkable success in recent years. Consequently, this section mainly focuses on strategies that are based on machine learning (Syed Ibad Ali, 2024).

4.1. *Standard Reference Datasets*

As in FD, the proposed methods are evaluated using standard reference datasets. Turbofan engine data sets for milling corrosion modeling and the FEMTO and IMS bearings are the only well-known examples of such RULP datasets.

4.2. *Approaches Based on Machine Learning*

A GMSVM algorithm that incorporates stacking ensemble learning is used to assess health. Missing value processing and anomalous value elimination were done before determining a degrading system's health status: the Pearson correlation coefficient and statistical aspects.

A health evaluation technique was proposed using the Generalized Multiclass Support Vector Machine (GMSVM) algorithm with stacking ensemble learning. Missing value processing and anomalous value elimination were done before assessing a degrading system's health status. Features were determined to be efficient based on statistical characteristics and the Pearson correlation coefficient. With slight variation and volatility, the experimental findings show that the GMSVM approach achieves remarkable multiclass efficiency.

It is forecasted that the RUL for the cutting wheel degradation process will be used using a supervised attention mechanism utilizing deep neural network architecture and high-resolution picture datasets. The IMS-Foxconn dataset, created by the Intelligent Maintenance Systems lab in collaboration with the Foxconn Technology Group, provides a fresh take on image-based prognostics. The experimental findings demonstrated that the proposed method outperformed the standard DCNN, LSTM, and NoSupAtt methods.

Machine health monitoring uses a discriminative feature learned using a novel Generative Adversarial Networks (GAN) model. An Auto-Encoder (AE) was used as the generator in the suggested model to comprehend the distribution of standard samples in the latent representation space and signal spectra. Results from the experiments show that it is possible to monitor the degradation of machines and identify early signs of equipment problems with high sensitivity.

4.3. *Other Approaches*

Additionally, there are distinct benefits to methods based on degradation models and fusing model data. Despite extensive research into data-driven methodologies based on machine learning, they can extract valuable insights from equipment deterioration.

A multi-state prognostic model with flexible transition mechanisms for various operating conditions elucidated the process of accumulated damage that varies with age and environmental factors. The necessary health measures may be calculated using a matrix-based approximation technique with little computational overhead. Complete operational data collection was accomplished by developing an Equipment Electro-Cardiogram (EECG). A maintenance plan was created, and an APL-EECG optimization approach was implemented to make an intelligent assembly line more efficient.

5. Industrial Product Quality Control

The contemporary industrial sector cannot function without quality inspection (QI) of manufactured goods. Automated quality inspection offers high-quality and efficient monitoring procedures, unlike traditional methods that depend on human experience. The primary types of quality improvement strategies include more conventional methods and those based on machine learning, namely supervised, semi-supervised, and unsupervised learning.

5.1. *Standard Reference Datasets*

Here are some examples of online Standard Reference Datasets that QI can use to compare methods and validate inspection algorithms: road crack, PCB analysis, nanofibrous materials, non-woven fabric, X-ray, saliency flaw in magnetic tile, pictures of fissures in solar cells, and the surface of steel strips.

5.2. *Approaches Based on Machine Learning*

Modern advancements in artificial intelligence have evolved classical quality improvement into intelligent quality improvement in many vital areas, such as healthcare, transportation, and aerospace. Using sophisticated machine learning algorithms for quality inspection processes is the newest AI adoption trend, intending to achieve reliable process monitoring and quality control. Unsupervised learning, semi-supervised learning, and supervised learning are common machine learning approaches used by intelligent quality assurance and control systems. By reducing the rates of product rejection and defects, these algorithms help businesses become more productive and profitable.

A particular surface monitoring system is essential for fused deposition modeling techniques to achieve quick reaction times and exact defect identification within a cloud-based framework. The CNN-based model was created to efficiently and accurately classify defects and provide a heuristic technique based on component geometry to perform adaptive firing position planning.

Based on the distribution of burn-through points during fluctuation periods, Du S. et al. created an Elman neural network with an extra classification model to anticipate the mode of operation of iron ore sintering operations. Using fluctuation intervals to describe the time-series data acquired by the sensors was a crucial part of the endeavor. The time-series sensory data was first reduced in dimensionality using principal component analysis (PCA), and then the fluctuation interval was extracted using fuzzy information granulation.

The anticipated positions of the end-effectors were made for the Tri-Pyramid Robot, a three-degrees-of-freedom (DOF) over-constrained parallel robot. A mix of parametric and non-parametric calibration methods was used to arrive at the final positions. To be more specific, the end-effector's spatial location data was collected using a laser tracker on a test rig. The kinematic robot model's structural parameters were then determined using the least-squares technique.

For the non-parametric calibration and machine vision inspection, a trained neural network was used to foresee non-geometric faults such as backlash and link deformations. A lightweight CNN was then employed to identify and classify defective goods accurately. The pre-processing of the picture data included applying probabilistic Hough transform and Gaussian filtering to remove noise and irrelevant background contents, respectively. With the help of an online inspection method, the created system worked wonders with flawed and flawless bottle images.

5.3. *Other Approaches*

Although deep learning has become the de facto standard for surface inspection, many still rely on more conventional statistical and spectral approaches. A new field-based sensing approach is required to replicate the Eddy Current (EC) density field. This study calculated the inverse solutions to the EC model instead of previous studies that used forward EC models to replicate the unknown conductivity distribution. Achieved online machining error predictions on thin-wall workpieces using a knowledge-infused sparse Bayesian regression technique. A hidden association between cutting location, cutting parameters, online measured cutting forces, and machining defects was unearthed by training the recommended Bayesian model.

Using a no-subsampled sheared transform, the author broke down the original pictures into subbands of various sizes and directions. A novel column filtering method based on the envelope grey level gradient was used to eliminate the uneven background of the approximation subband. Noise and texture interferences were removed from the detail subbands using a shear-let coefficient variance discriminator. This discriminator compares the template's full Fourier spectrum to the inspection image, a global Fourier image reconstruction method for finding and localizing minor defects in images without periodic patterns. Similarly, the least squares approach was employed with the quaternion wavelet transform to identify scratches and cracks in banknote photos.

6. Existing Problems and Challenges

Industrial AI can find hidden patterns in the vast amounts of data produced by production processes, increasing production efficiency and lowering manufacturing process usage. Even though FD/RULP/QI has advanced significantly, as covered in the sections above, the IAI still confronts several obstacles at this point:

6.1. *Heterogeneous Data*

In arbitrary high-dimensional areas, industrial equipment such as ERP, production lines, and manufacturing execution systems (MES) provide diverse and intricate data. There are various formats for industrial data: (a) time series data on temperature, pressure, and vibration; (b) infrared nondestructive testing technology is used to obtain image data; (c) ultrasonic, acoustic emission, and ray testing, among other methods, are used to collect video and audio data; and (d) information about operations, management, logistics, and service is included in the documentation.

6.2. *Data Inequity*

Researchers and manufacturers often face imbalanced data issues caused by the extensive use of sensors in intelligent plants. The low percentage of operational data indicating machine failure is a hallmark of this issue. Furthermore, failure data points are not always consistent with one another. Conversely, much data comes from conventional operational samples with similar characteristics. Consequently, unskewed data presents significant challenges for traditional extraction of feature and selection methods.

If the satisfaction model is biased and created from an unbalanced training dataset, assessment measures like area under the curve and accuracy might potentially deceive consumers. Since the model first learns from samples in the majority or standard class, it cannot comprehend the characteristics of the unsuccessful data. When given imbalanced training datasets, most popular classifiers, including SVM and ANN, perform poorly on the test dataset but learn from balanced datasets.

6.3. *Complexity*

Complex learning algorithms and massive datasets are required to train advanced industrial production processes. The primary goal of machine learning algorithms is to achieve high model accuracy, regardless of the expense of training. There has been a dramatic increase in the number of training parameters and weights used in deep learning models in recent years, leading to increased computing costs and memory requirements.

As a result, most machine learning techniques have difficulty digesting input in real-time. All the equipment, people, objects, processes, raw materials, and working conditions that could affect an application need to be able to be handled by the proposed machine learning models.

6.4. *Uncertainty*

Uncertainty about the final product quality in CPS intelligent manufacturing processes can emerge at various stages. This category falls under uncertainty in inputs, modeling mistakes in manufacturing processes, network system resource and communication uncertainties, environmental uncertainties, and expert opinion. These risks increase throughout production, particularly for complicated components needing multi-stage manufacturing procedures. Machine learning algorithms' generalisability and resilience will take a nosedive if these sources of uncertainty are disregarded.

6.5. *Model-Black Box*

Most ML techniques train their models using domain information or existing expert knowledge. They build so-called "black box" models using production data to decipher the input-output correlations. The learning process is opaque, and a model's learned weights tell us nothing about the model's behavior—this is true irrespective of how good machine learning is. The industrial sector relies significantly on models for decision-making, and without model interpretability, the broad usage of AI platforms may be seen as untrustworthy.

Consequently, decisions about the upkeep of vital parts and accurate tools and machinery in the aerospace, military, and other essential industries have traditionally depended on past knowledge and specialists. To make the output of machine learning models of industrial systems easily understandable for human experts and engineers, these models must be visible, understandable, and explainable.

7. Research Prospective

To address the aforementioned smart manufacturing difficulties, we pinpoint the following elements that will assist producers in moving the IAI from lab environments to the production floor.

7.1. *Engineering Features*

Data augmentation, knowledge transfer across related categories via transfer learning, and domain adaptive learning are some techniques that may be used to compensate for non-balanced samples. Additionally, the diversity of training samples is increased through feature expansion. In particular, high-dimensional data can be embedded into low-dimensional spaces using supervised and unsupervised learning-based feature selection techniques, from which critical information and hidden features can be recovered.

7.2. *Strongness and Durability*

Recent evidence from real-world applications shows that measurement noise and data outliers may influence machine-learning models, leading to inaccurate classification. Reliable optimizers, parameter regularization, and robust loss functions can all help to increase the machine learning model's resilience. Potential solutions for creating efficient tools to assess suggested models thoroughly can be found by integrating uncertainty treatment strategies like probabilistic modeling into the neural network architecture.

7.3. *Generalization*

Methods based on stochastic optimization and distributed optimization for compressed learning have been introduced in response to the large amounts of data, strong evidence, and parameters linked with deep learning models utilized in industrial production. An array of complex optimization methods are used to optimize the model's structure and super-parameters. Algorithms for industrial AI must have good generalizability to carry out optimization, prediction, diagnostic, and monitoring tasks efficiently and on the go.

7.4. *Interpretability*

Alongside the current IAI techniques, an interactive mechanism between machine learning models and expert knowledge of industrial production should be built. Elements of interpretable IAI include features that can be explained, a machine learning architecture that can be presented, and a way to evaluate the outcomes that can be explained. Users can understand, trust, and operate smart manufacturing systems once the models' reasoning and decision-making processes are transparent. Defense Advanced Research Projects Agency (DARPA) of the United States launched an explainable AI initiative in 2016, emphasizing human-computer interaction in IAI. Applying game theory to tree-based models allows one to examine feature properties.

Domain specialists may see detected sub-sequences as traits that may be interpreted. The attention mechanism assesses the weights associated with the network layers to rank the characteristics across the whole image, video, and text for more accurate and interpretable predictions. It is a novel concept in machine learning.

8. Conclusion

The future of mass production is predicted to be smart manufacturing. IAI is the engine that propels AI-powered production. It combines AI technology with domain knowledge that is particular to an industry. In general, two main factors are propelling the inevitable upward trend of AI. One, cutting-edge innovations like cyber, the IoT, and cloud computing allow for very efficient data gathering, transit, storage, and administration, which speeds up the creation of large amounts of data. Hence, big data is the foundation upon which industrial intelligence is created. Artificial intelligence (AI) advancements have been substantial during the last several decades, particularly in machine learning, deep learning, and transfer learning. Two key aspects of these approaches substantially facilitate the evolution of smart manufacturing. Data is king for most AI systems since they use massive datasets. With the help of IAI technologies' end-to-end design, we can outperform today's complex production systems while requiring a fraction of the domain expertise. Consequently, IAI provides the framework for industrial intelligence in terms of technology. Emerging manufacturing processes driven by AI often include intelligent features such as self-reflection, self-analysis, self-planning, self-management, and self-development. As a result, production chains driven by artificial intelligence (AI) are very dependable and efficient, and they cover the whole gamut, from sourcing raw materials to distributing completed items.

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