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Evolving Landscape: Tracking Developments in the AI Industry

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ABSTRACT

The rapid development of the artificial intelligence (AI) industry is a prominent feature of the contemporary technology landscape. In recent years, the field of artificial intelligence (AI) has seen unprecedented growth and transformation, reshaping industries and societies around the world. This article emphasizes the importance of active monitoring of this dynamic sector, highlighting key aspects that require careful observation. Continuous monitoring of major technology companies, start-ups and research institutes at the forefront of AI innovation. We conclude with implications for developing research strategies and suggestions for future research directions.

INTRODUCTION:

The artificial intelligence (AI) landscape reflects the continued progress of technological advancement in our times.

As AI continues to develop at an unprecedented pace, its impact will ripple across industries, from healthcare and finance to transportation and entertainment.

Over the past few decades, AI has evolved from a conceptual framework into a transformative force shaping every aspect of modern life,you have to actively participate in its dynamics. Its implications go beyond algorithms and data: they touch ethics, fairness, policy and the very fabric of human existence.From keeping up with the latest advances in machine learning to navigating the complex web of AI governance and ethics, we'll take a deeper dive into the essential components that make up an effective AI oversight strategy.Raise awareness of the evolving AI regulations, ethical guidelines, and government policies that are shaping the AI ecosystem.

The field of AI is characterized by constant innovation and rapid growth, affecting industries, economies and societies on a global scale.First, in an age of breakneck technological progress, keeping a close eye on the AI industry is not just a matter of choice; it's a must for anyone investing in the present and future of technology.

Yet beneath the surface of AI's remarkable achievements lies a complex web of challenges and opportunities.

This vision is at the heart of the AI industry.It is a combination of computer science, mathematics, data analysis and advanced algorithms to create intelligent systems capable of performing tasks, making predictions and solving problems. Complex topic without explicit programming.Artificial intelligence techniques and methods are also being applied in a broader and growing range of fields, such as speech recognition, computer vision, robotics, and operations management.

The remainder of this article is organized as follows.

Part II provides an overview of the main concepts of “Development Landscape:

Track developments in the AI industry » This article introduces the articles in this section that focus on AI-based monitoring in smart manufacturing by integrating them into the big picture and showing how they contribute and Expanding the content of documents in this field.

These articles are specifically highlighted in the survey by bolding their references.

Overview of "Development Landscape:

TRACK DEVELOPMENT IN THE AI INDUSTRY :

The ever-changing terrain of the AI industry presents a fascinating journey through technological evolution.

These sectors, each with distinct dominance, reflect the potential capabilities that AI brings.

Finance, healthcare, transportation, and natural language processing, among many others, all find their place in this complex network.At the same time, the chart illustrates the growth of research and development, the continuous development of which reflects the industry's enthusiasm for exploration and discovery.

These key points tell the story of AI's transformation from a concept to a powerful driver of innovation across industries.Above the timeline, a graceful curve emerges, charting the path of technology adoption.

INTELLIGENCE*:*

The journey of the AI industry is marked by continuous growth and change, from its origins to its current state and beyond to a promising future. A timeline decorated with important milestones tells the story of AI's evolution from an idea to a powerful force for innovation in a variety of fields.The research and development chart illustrates the exponential growth of the knowledge that underpins advances in AI, driven by human ingenuity and curiosity.

KNOWLEDGE*:* It highlights the historical journey of the AI industry, traces its development from its inception to its current state, and hints at its future trajectory.

To achieve high-quality, efficient, reliable and low-cost multi-objective industrial operations, IAI combines AI technology and standard industrial process domain knowledge to create intelligent system, capable of self-awareness, self-comparison, and self-comparison,Prediction, self-optimization and self-adaptation.

AI technologies, including traditional analytics, machine learning, and deep learning techniques, have been applied to solve problems in computer vision, speech engineering, natural language processing, and decision.

Standard industrial processes include product manufacturing, decision making and services (e.g.Design, manufacturing, processes, assembly, warehousing and logistics, sales), equipment portfolio (e.g. Sensors, production equipment, production lines, workshops, factories) and additional categories (e.g. operations and maintenance, aftermarket, markets, emissions, energy consumption , environment).

IAI, as a member of the AI family, was developed in an industrial context.

IAI's key technology.

MODELING:

Modelling is of great importance in industrial production.

Models built from mechanisms and industrial knowledge reveal underlying regularities such as the failure process of equipment or components, the relationship between process parameters and product quality, the relationship between the operating status of the production line and the components process.

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Therefore, these models are able to reflect the basic production process of manufacturing industries and indicate the production capacity and competitiveness of enterprises.

Describing the manufacturing process as an industrial CPS, Yuan et al.

proposed a new method to determine the dynamics of nonlinear coupled systems using a dictionary of mechanical functions, exploring the transition logic between subsystems and revealing the development trend of CPS.

Due to the desired performance in industrial process modelling, the developed method has been successfully applied in many contexts such as robotics, smart manufacturing, and smart grids.

Jin et al.applied vibrational Bayesian inference to model complex networks with sparse network topology, which can be used to decouple production components.

DIAGNOSIS:

Safety is a basic requirement in industrial production, because abnormal operation of equipment or production processes can lead to significant deterioration in product quality, even accidents and injuries. Therefore, sensors are widely used to collect monitoring data in the form of images, videos and time series from production equipment, production lines and final products.

With massive data, big data analysis, machine learning, deep learning and other AI-based methods are used to realize intelligent online detection and diagnosis of abnormalities in the production process industry and to perform causality analysis.

These tasks are often solved as supervised or unsupervised classification and clustering problems.

For example, a deep learning framework was proposed in to automatically extract features from noisy sensor signals, including vibration, voltage, current, temperature, sound, and force.

This framework is rugged, flexible and achieves high-precision diagnostics for a variety of manufacturing parts containing bearings, milling cutters, gearboxes and lithium batteries.

PREDICTION:

Forecasting plays an important role in promoting industrial production.

With the rapid development of big data technology, cloud services and AI, data-driven forecasting methods have been widely used in maintenance prediction, demand forecasting and quality prediction.

, contributing to reducing costs, increasing efficiency and improving the quality and safety of industrial facilities. make.

In predictive maintenance, monitoring data and empirical knowledge of deterioration are used to predict the remaining useful life of industrial equipment, thereby guiding the development of strategies effective maintenance.

Based on historical monitoring data of the production line, manufacturers forecast the need to coordinate production lines, manage risks and reduce production waste.Finally, quality prediction is often applied in high-end manufacturing.Product quality is predicted by analyzing monitoring data and the operating status of the production line.The manufacturing process is then optimized to avoid defective products.

Notably, digital twin technology, as a new concept, has shown an increasing impact on the QA field in recent years.

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OPTIMIZATIN:

Optimization is a key technique to improve industrial production efficiency, divided into equipment-level optimization and system-level optimization.

The parameters of industrial equipment control the production process, which in turn affects the quality of the final product.Since many process parameters are not known a priori, they are often learned from data supervision using supervised feature screening [e.g., linear discriminant analysis (LDA), Fisher score, Lasso] or unsupervised feature screening [e.g., Principal Component Analysis (PCA), Laplacian Score, Auto Encoder (AE)].

Online optimization of process parameters using AI algorithms is crucial to improve the quality and efficiency of industrial processes in real time. Therefore, many optimization algorithms have been developed.Typically, a manufacturing process includes a series of industrial equipment, and a production line includes several manufacturing processes. Based on equipment and production process monitoring data, the cooperation between production processes is optimized in terms of the desired index for the entire production line.

DECISION:

Decision making is the key to closing the loop on industrial production, associated with the optimization of industrial processes and equipment maintenance.Decision making takes into account various factors related to production (e.g.real-time market information, production conditions, operating indicators, production instructions, control instructions and production conditions) to achieve business goals by performing optimization and planning.

RephraseFor example, Cao et al.Solved the scheduling of a parallel batch processor using the SARSA (λ) reinforcement learning algorithm.For industrial equipment maintenance, decision making comes down to restorative maintenance, preventive maintenance and predictive maintenance, of which predictive maintenance is considered one of the “killer” applications of the Industrial Internet.

Predictive maintenance can effectively reduce maintenance costs, eliminate production downtime, reduce equipment or process downtime, and improve productivity.Recently, prescriptive maintenance is a new trend that is growing rapidly.These methods not only predict likely errors but also prescribe what can be done to avoid errors altogether.

DEPLOYMENT:

Deployment is key to effective IAI implementation by providing a technical support platform.

Specifically, smart chip-based hardware acceleration technology is at the heart of deploying AI models.

With the rapid growth of data volumes, standard computer chips (e.g., processors) can no longer meet the demands of real-time processing at the online model inference stage.Therefore, inventing smart chips to implement IAI algorithms is a must.The essence of smart chip technology lies in hardware acceleration of communication models, including the design of hardware architecture and efficient software compilation tools.

Compared with traditional computer chips, smart chips are superior in computing power and lower power consumption.The development of smart chips has accelerated the popularization of IAI applications.

IAI appears to be playing an increasingly important role in the rapid development of industrial manufacturing.

It has penetrated many links in the production chain.

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Typical application scenarios of IAI include quality improvement and process quality control, energy management and energy efficiency optimization, smart supply chain and logistics, as well as security Maintain prediction equipment.

TYPICAL IAI APPLICATION SCENARIOS.

To further present the detailed technologies, IAI is specifically discussed in the context of smart surveillance including FD, RULP, and QI. Following the general framework of smart surveillance, the following sections will discuss AI-based algorithms for FD/RULP/QI in the sequence and typical methods summarized.
Typical IAI machine learning methods and its applications.

FD of manufacturing equipment with machine learning

Safety and durability are essential for industrial production. FD aims to prevent accidents and possible casualties by identifying abnormal operations of production processes and equipment from monitoring data. Additionally, highly efficient FD technologies are needed to achieve the goals with low maintenance costs, high flexibility, strong performance, desired platform independence, and good interpretability.

Machine learning is a popular IAI technique for FD. Considering the depth of model structure, machine learning based methods are classified into two types, namely shallow machine learning methods and deep learning methods.
Shallow machine learning methods mainly contain extreme learning machines (ELM), Gaussian regression processes (GRP), support vector machines (SVM), and hidden Markov processes (HMM), while Deep Learning involves using deep neural networks [e.g.Rephrase, convolutional neurons (CNN), fully connected neural networks, long short-term memory (LSTM), generative adversarial networks (GANs), and neural networks graph meridians (GNN)] as well as advanced learning strategies [e.g., transfer learning (TL) and attention mechanisms (SUIS)].In recent years, deep learning has dominated FD and has received increasing attention. In addition, other approaches based on advanced control theory are also studied in the context of smart FD.

REFERENCE DATASET:

Benchmark datasets are often used to test the performance of algorithms and compare different methods.
Many benchmark datasets are available online for FD, including motor bearing datasets with vibration signals , bearing datasets with vibration signals, current, gear fault vibration dataset, milling dataset, and turbofan engine degradation simulation datasets.
Machine learning-based methods
Machine learning-based diagnostic methods typically include three steps:

1) Feature extraction; 2) feature selection; and 3) classification.
Feature extraction and selection can be performed artificially or automatically.Artificial feature extraction and selection benefit from expert experience and thus better interpretation of inherent properties, e.g.system dynamics, while machine learning of features Through the designed models it is possible to extract summary representations

embedded in more complex feature spaces.Notably, these two approaches are often combined in the context of deep learning. Machine error detection is often formulated as a classification problem and approached using learned features.

Proposed a 1-D CNN-based approach for diagnosing known and unknown camera defects under additional noise, which reliably identifies the nature of mixed defects.Two neural networks were developed to evaluate rotors and bearings corresponding to 48 machine health conditions.The one-versus-all classifier is designed to identify previously unseen error types.It turns out that this method has good anti-interference ability, thus providing stable performance.

Proposed a new FD method for multi-channel motor-rotor system via multi-channel deep learning machine (MDELM) for multi-channel data processing.The MDELM algorithm is designed combining unsupervised and semi-supervised learning schemes, where unsupervised self-learning feature extraction is performed using modified ELM-based sparse filtering and a manifold ELM classifier with manifold constraints is applied to explore the discriminative feature within the class and between the information classes to achieve semi-supervised defect classification.

The designed MDELM shows outstanding learning performance for industrial data from motor-rotor systems.
Developed a multi-node sensor network for machine fault detection using SVM based on mechanical vibration energy.This method uses a multilayer vibrating turboelectric Nano generator (V-TENG) to extract energy from operating machinery.V-TENG produces power with a power density of 3.33 mW/m3 when activated by vibration motion.The self-powered vibration sensor node (SVSN) is built on a microcontroller integrated with wireless sensors and transmitters, powered by V-TENG.SVM is used to construct a three-SVSN network for FD by analysing the acceleration and temperature data of the operating machine.The developed method makes it possible to accurately identify different working conditions of the machine.

Other approaches

Machine learning-based FD are data-driven methods in an end-to-end framework that does not exploit the physical rules or operating mechanisms of the target system.These methods are flexible and applicable to many platforms. Scenarios developed for one scenario can be transferred to other scenarios, thus leading to low maintenance costs. However, machine learning-based methods are sensitive to noise and in most cases cannot be understood by humans.To provide robust and analysable FD systems, various techniques have been invented using advanced control theories.

De Martini and proposed a FD framework for electromechanical systems based on a fuzzy inference system.
While fuzzy logic requires specification of a large number of fuzzy inference rules in terms of input variables and member functions (MF), the developed fuzzy indexing framework automatically generates fuzzy rules from the specification. Describe the worst and best cases in terms of the quality of MFs.of each input variable.
This method has been applied to electric motors, giving high computational efficiency and detection accuracy.

Developed an unknown input (UIO) integrated extended finite impulse response (UIOEFIR) estimator to estimate the state of electrohydraulic actuators (EHA) in applications sensor fault tolerance control (FTC).
This hybrid estimator exploits the UIO structure in the EFIR filter and estimates the system state as well as the unknown value of the invoked sensor error without prior knowledge of the state and voice process or measurement noise.The UIOEFIR estimator contributed to the FD algorithm in EHA's simple sensor FTC architecture to detect unknown sensor error information. The developed method shows outstanding and reliable performance under chaotic environmental conditions. Proposed a robust grinding wheel wear monitoring system applicable to different grinding conditions (e.g. different grinding wheel types and work piece materials).A new normalization scheme has been applied to extract features from signals collected during the grinding process through power sensors, accelerometers, and acoustic sensors in order to separate these features from other factors.
Factors related to grinding wheel type, work piece material and grinding parameters.With the selected features, a type 2 interval fuzzy basis function network was used as a grinding wheel wear monitoring model to predict grinding wheel wear under different grinding conditions and estimate the variance based on the selected features. on the fluctuation of characteristics, leading to robust monitoring performance.

RULP for production equipment

With the rapid development of sensors, data storage, network transmission and other new technologies, a lot of data is generated to monitor critical manufacturing equipment.
Most research on lifespan prediction focuses on extracting deterioration information from monitoring data and developing effective algorithms to accurately predict remaining useful life.

Data-driven RUL prediction techniques are generally divided into two groups, which are statistical methods and machine learning-based methods. Statistical methods are based on statistical theory.Principal components analysis or partial least squares methods are commonly used to process data down to the device level, establish ranking metrics, and evaluate device condition. However, the application of these methods is limited by data quality and the strict prerequisites of statistical theory. In contrast, machine learning-based methods are more flexible and practical, becoming commonly used techniques for RUL prediction in recent years with great success.Therefore, this section mainly deals with machine learning based methods. Machine learning-based RUL prediction techniques include feature extraction, condition indexing, feature selection, and RULP. These steps are performed in very different ways for shallow learning and deep learning frameworks.

REFERENCE DATASET

Similar to FD, a benchmark dataset is applied to test the proposed methods. Some well-known benchmark datasets for RULP include the Turbojet Engine Degradation Simulation Dataset , FEMTO Bearings Dataset , IMS Bearings Dataset , and milling.

MACHINE LEARNING-BASED METHODS

RUL prediction based on machine learning is attracting more and more attention. Similar to FD, representative RULP methods include support vector regression , HMM, GRP, CNN , deep belief networks, and recurrent neural networks.Proposed a health assessment method consisting of stacked ensemble learning and generalized multilayer support vector machine (GMSVM) algorithm.Before assessing the condition of the degraded system, removal of outliers and handling of missing values were performed.Statistical features and Pearson correlation coefficients were applied to the selected performance characteristics.Experimental results show that the GMSVM algorithm achieves high multi-class efficiency with low variance and bias.Used supervised AM using a deep neural network framework to predict RUL for realistic cutting wheel degradation with a high-resolution image dataset.The IMS-Foxconn dataset from the Intelligent Maintenance Systems Laboratory and Foxconn Technology Corporation was introduced, providing a new perspective on image-based prognostics.Experimental results have confirmed the effectiveness and superiority of the proposed method compared to traditional DCNN, LSTM and NoSupAtt.

Developed a new GAN model to learn the discriminant function for machine condition monitoring.The proposed model used AE as a generation tool to learn the data distribution of regular samples embedded in the signal spectral space and latent representation space. Experiments have demonstrated that high sensitivity to incipient machine anomalies and the ability to characterize machine degradation progression can be achieved.

OTHER APPROACHES

Although data-driven methods based on machine learning have been widely studied, degraded model-based methods and unified model data methods also have their own advantages in that they can exploiting insights into device degradation processes.Duan and Deng used a prognostic model to describe the cumulative aging and environmental damage process, which includes a large number of states and dynamic transition mechanisms under different operating conditions.different actions.A matrix approximation method has been developed to calculate key health metrics to achieve low computational load.

Proposed an equipment electrocardiogram (EECG) mechanism to collect all operational data.APL-EECG optimization strategy was applied to improve the efficiency of the smart production line, and a preventive maintenance strategy was designed.

QA of industrial products plays an important role in modern industries. Compared to traditional methods that rely on expert experience, automated QA provides high-quality, highly efficient monitoring processes.QA methods can be classified into two categories, including machine learning-based approaches (i.e.supervised, semi-supervised, and unsupervised learning) and other traditional methods.

REFERENCE DATASET

Many benchmark datasets are available online for QI to verify developed inspection algorithms and compare different methods, including the road crack dataset , the dataset for printed circuit board (PCB) volume , nanofiber material data set, steel strip surface data set , X-ray data set , defects of magnetic tiles , images of cracks on solar cells and nonwoven fabrics.

MACHINE LEARNING-BASED METHODS

Recent advances in AI technology development have shifted traditional QA to intelligent QA in several key industries such as aerospace, automotive, and healthcare.The new paradigm of AI adoption is to apply advanced machine learning algorithms to QI processes to achieve highly reliable quality control and process monitoring.

Supervised, semi-supervised, and unsupervised learning are leading machine learning algorithms for intelligent quality improvement and quality control, helping to increase business productivity and profitability by reducing defect rates,product rejection and defects.

Propose a novel surface monitoring system for unified deposit modelling processes to achieve high defect detection accuracy with high response speed in a cloud-based framework.A heuristic algorithm was proposed to achieve adaptive planning of shot placement based on part geometry, and a CNN-based model was designed to achieve effective defect classification with high accuracy.Designed an Elman neural network with a different classification model to predict the operating mode of iron ore sintering, based on the distribution of burning point data in fluctuation ranges.The fluctuation range is the main feature of this study and is used to describe the time series signals acquired by the sensor.In terms of feature extraction, PCA and fuzzy information granulation methods were used to reduce high-dimensional time series sensory data and extract the corresponding fluctuation range.

Predict the position of the end effectors of a 3 DOF over constrained parallel robot (so-called tripyramid robot). The final positions are calculated using a combination of parametric and non-parametric calibration methods. More specifically, the spatial position data of the end-effector is collected on the test bench using a laser tracker. Then, the structural parameters of the robot kinematic model are determined using the least squares method.
For non-parametric calibration, non-geometric errors such as backlash and bond distortion are predicted using a trained neural network.Vuong et al applied lightweight CNN for machine vision inspection to identify and classify defective products without sacrificing accuracy.To preprocess the image data, Gaussian filtering and probabilistic Hough transform methods were used to avoid the influence of noise and remove irrelevant background content.
The developed method, as an online inspection method, demonstrated superior performance on both defective and error-free bottle images.

Compare to Another approach

Besides deep learning dominating the surface inspection field, traditional statistical and spectroscopic methods are also widely used.

Propose a novel field-based detection method that reconstructs an eddy current (EC) density field that allows full machine perception to identify and quantify features or defects (such as stress residue, corrosion and microstructural anomalies).
This work addressed the inverse solutions of the EC model, different from the forward EC models used in previous studies, to reconstruct the unknown conductivity distribution.

Used a knowledge-integrated sparse Bayesian regression method to obtain online machining error predictions on thin-walled parts.

The proposed Bayesian model was trained to learn the hidden pattern between machining errors and cutting parameters, cutting positions, and cutting forces measured online.

Applied the non-subsampling shear let transform to decompose the original images into multiple sub-bands in different directions and scales.

A new column filter based on the contour grey level gradient was used to remove irregular background in the approximate sub band, and a shear let coefficient variance discriminator was used to remove noise and texture noise in detailed sub-bands.

Tsai and Huang proposed a comprehensive Fourier image reconstruction method to detect and identify small defects in irregular sample images by comparing the entire Fourier spectrum of the sample with the control image. Similarly, Gai used quaternion wavelet transform and least squares method to detect cracks and scratches on banknote images.

CURRENT ISSUES AND CHALLENGES

Industrial AI can use large volumes of data generated by manufacturing processes to identify hidden patterns, helping to improve production efficiency and reduce production process consumption. Although significant progress has been made within the FD/RULP/QI framework as outlined in the sections above, the current phase of IAI still faces a number of challenges.

DATA IS HETEROGENEOUS

The data sets generated by industrial equipment, production lines, manufacturing execution systems, and enterprise resource planning systems are complex and heterogeneous across arbitrarily large spaces.

Industrial data comes in different formats such as:

Vibration, pressure and temperature data are time series.

Image data is obtained using infrared non-destructive testing technology.

Video and audio data are collected by ultrasonic testing, acoustic emission testing, beam testing and other means.

Documented data includes logistics, management, operations and services.

DATA IMBALANCE

While sensors have been widely deployed in smart factories, one of the typical challenges that manufacturers and researchers face is the problem of data imbalance. This problem is characterized by the fact that only part of the operating data constitutes a machine error.Additionally, the error data points are often different.

In contrast, data samples that behave normally represent the majority of the data and share common characteristics. Therefore, conventional feature extraction and selection methods are not suitable for imbalanced data.

Additionally, evaluation metrics (e.g., accuracy and area under the curve) can mislead users due to biased content models generated from unbalanced training data sets.

The model does not learn the characteristics of error data because it focuses on the instances of the majority class, i.e., normal data.Most traditional classifiers such as SVM and artificial neural networks (ANN) learn from balanced data sets, but show poor generalization on the test data set due to the training data set unbalanced.

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COMPLEXITY

Learning advanced industrial manufacturing processes requires huge datasets and complex learning algorithms. Machine learning algorithms focus on achieving high model accuracy without concern for training costs.
For deep learning, models have been trained increasingly intensively in recent years without the limitations of large numbers of parameters and training weights, leading to high computational costs and set requirements.Therefore, real-time data processing is a challenge for most machine learning methods.More importantly, the proposed machine learning models should adapt themselves to different application cases and be able to take into account various impact factors such as device, operator, target audience, technique, etc.production techniques, raw materials and working conditions.

UNCERTAINTY

In the CPS smart manufacturing process, sources of uncertainty in final product quality can arise from multiple steps, including embedded sensor measurement uncertainty, input uncertainty, and model error.
production process configuration, network system resources and communication, environmental uncertainty, and subjective uncertainty of experience.
Experts.
Additionally, these uncertainties accumulate over time during the manufacturing process, especially for complex parts that require multi-step manufacturing processes.Without considering the influence of these sources of uncertainty, the robustness and generalizability of machine learning techniques will be significantly reduced.

BLACK BOX MODEL

Most machine learning methods train models without domain knowledge or professional experience.
They build so-called “black box” models to describe input-output relationships using data obtained during the production process.However, despite the remarkable performance of machine learning, the learning process is not transparent and the model's learned weights reflect little information about the model's behavior.
In the industrial sector, where trust in the model is essential for decision makers, deploying AI platforms at scale can be considered unreliable without interpretability of the model.
For this reason, maintenance decisions for precision instruments/equipment and critical components in the military, aerospace and other key industrial sectors are always based on previous experience and experts in the field.
This therefore requires understandable, interpretable and transparent machine learning models of industrial systems, allowing clear explanation of the results of system models to experts/engineers.
human.

Research prospects

To address the above challenges in smart manufacturing, we identify the following aspects that will help manufacturers move IAI from the lab to the factory.

Feature engineering

To handle unbalanced positive and negative samples, methods including data augmentation, knowledge transfer between similar categories using TL, and domain adaptive learning can be used to compensate . Additionally, feature expansion is used to improve the diversity of training samples.In particular, feature selection methods based on unsupervised learning and supervised learning can be combined to integrate high-dimensional data into low-dimensional space, thereby extracting hidden features and main information.

RELIABILITY

In practical applications, machine learning models have recently been shown to be susceptible to uncertainties (i.e.
data outliers and measurement noise) in the input data, which can leading to misclassification.The robustness of machine learning models can be improved through robust loss functions, parameter regularization, and reliable optimizers.Integrating uncertainty handling techniques such as probabilistic models into neural network structures offers potential solutions in establishing effective tools for rigorous analysis of proposed models.

GENERALIZATION

Accelerated learning algorithms based on stochastic optimization and distributed optimization have been proposed to handle large amounts of data, high personalization, and many parameters of deep learning models in industrial production.

Hyper parameters and model structure are automatically optimized using intelligent optimization algorithms.

Ultimately, IAI algorithms are expected to be highly generalizable to meet various industrial needs such as monitoring, prediction, diagnosis, and optimization in a fast and portable manner.

INTERPRETATION ABILITY

The interaction mechanism between expert industrial production experience and machine learning models needs to be established along with existing IAI methods.

Explainable IAI includes aspects of explainable feature extraction, explainable machine learning architecture, and evaluation of explainable results. Essentially, the models' inference and decision-making processes become transparent, and users can understand, trust, and manage smart manufacturing systems effectively.

In 2016, the US Defines Advanced Research Projects Agency proposed an explainable AI program to emphasize human-machine interaction in IAI.

Lundberg et al. proposed tree models with a certain degree of interpretability based on game theory for object attributes.In terms of time series data collected by sensors (e.g., acceleration, voltage, current, and temperature), the shape method proposed by explored a dark discriminant series multilayer of a time series data layer.The identified subsequence's can be considered as features that can be interpreted by domain experts.When it comes to image, video, and text data, a recent new machine learning concept called AM evaluates specific weights associated with network layers to determine the relative importance of features in image/video/text sets, thus ensuring prediction results with superior reliability and interpretability.

CONCLUSION

Smart manufacturing is expected to be the next generation of industrial production.

IAI integrates AI technology and industry domain knowledge as the main force supporting AI-based manufacturing.

In general, industrial intellectualization is an inevitable development trend, driven by two main factors.

First, advanced technologies, including IoT, cloud computing and networking technologies, enable highly efficient data collection, transmission, storage and management, thereby accelerating data creation big.

As a result, big data forms the foundation of industrial intelligence.Second, AI technologies such as machine learning, deep learning, and TL have seen significant development in recent decades.These methods are characterized by two main attributes that strongly support the development of smart manufacturing.

First of all, most AI algorithms are data-driven, allowing them to make the best use of the availability of Big Data. Additionally, IAI technologies are based on an end-to-end framework, delivering satisfactory performance with low knowledge demands in a field where it is increasingly difficult to learn from highly complex manufacturing systems.

in modern industries. Therefore, IAI can realize industrial intelligence by providing a technology platform.

Overall, IAI technologies bring new production methods with intelligent characteristics such as self-awareness, self-comparison, self-prediction, self-adaptation and self-optimization.Therefore, AI-based manufacturing is equipped with highly efficient and reliable production lines, from the production process to the logistics of the final product.

Production monitoring is one of the important links in the complete production chain, including FD, RULP and QI.

With the development of smart manufacturing, IAI technology has been widely applied in these three fields, in which methods based on machine learning or deep learning are the two main technological drivers.In general, FD, RUL, and QI apply popular AI-based methods (e.g., CNN, GAN, AM, GNN) to accomplish various tasks, while these methods are customized based on specific applications.Overall, IAI technology demonstrates outstanding performance in production monitoring and shows great potential for the future.

It is believed that the future development of IAI will focus on four aspects, namely robustness, generalizability, interpretability, and analysis ability.The first two aim to further improve the applicability of IAI technology in real-world applications.Specifically, IAI algorithms must be robust against uncertainties arising from the system, data, and environment.Furthermore, they should be applied in different domains for different tasks such as monitoring, forecasting, and diagnosis.As a field that emphasizes risk assessment, industrial manufacturing especially requires causal analysis to inform model reasoning and decision making.

The development of explainable IAI technologies is increasingly attracting attention in the field of smart manufacturing.There is also a trend to use IAI not only for decision support but also as part of a feedback loop with the ultimate goal of creating self-sustaining industrial plants, which requires also interpretable IAI and analysable.

The developed models need to be analyzed like traditional control systems taking into account closed-loop signal behavior and stability before commissioning.IAI can analytics drive the shift from a primary focus on quality monitoring and equipment maintenance to real-world whole plant operations.

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