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Deep Learning for Smart Manufacturing: Methods and Applications

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Abstract- Smart manufacturing leverages advanced data analytics alongside physical science to enhance system performance and decision-making processes. With the proliferation of sensors and the Internet of Things (IoT), there is a growing necessity to manage vast amounts of manufacturing data characterized by high volume, velocity, and variety. Deep learning techniques offer sophisticated analytics tools for processing and analyzing such big manufacturing data. This paper presents a comprehensive survey of commonly utilized deep learning algorithms and discusses their applications in making manufacturing processes "smart." It begins by discussing the evolution of deep learning technologies and their advantages over traditional machine learning approaches. The paper then delves into computational methods based on deep learning specifically designed to enhance system performance in manufacturing. Various representative deep learning models are comparatively discussed. Finally, the paper highlights emerging research topics in deep learning and summarizes future trends and challenges associated with utilizing deep learning for smart manufacturing.

Keywords–*smart manufacturing, Deep learning technologies, proliferation of sensors, Internet of things,*

1. Introduction

The manufacturing sector has undergone substantial changes in the last century, progressing from the assembly line at Ford to contemporary ideas like cloud manufacturing. Multiple nations have formulated comprehensive plans to harness the potential of emerging technologies like the internet of things (iot) and data science. Smart manufacturing, which involves interconnected machines and advanced computational intelligence, strives to improve product quality and sustainability while minimizing expenses.

Recent developments in internet of things (iot), cloud computing, and cyber physical systems (cps) have played a crucial role in supporting modern manufacturing. Advanced analytics, powered by data-driven intelligence, enables the conversion of extensive data into actionable insights without necessitating a profound comprehension of physical actions.

Extensive research has been dedicated to studying data mining techniques and machine learning algorithms for making informed decisions in the manufacturing industry. Nevertheless, conventional machine learning encounters difficulties in managing vast amounts of data in smart manufacturing because of the increasing volume of multimodal data and its high dimensionality. Deep learning, a significant advancement in artificial intelligence, enables automatic feature learning and high-volume modeling, making it a powerful analytics tool for smart manufacturing in the era of big data. This paper seeks to present an up-to-date analysis of advanced deep learning techniques and their utilization in the field of smart manufacturing. It presents a cutting-edge framework that utilizes deep learning for advanced analytics in manufacturing, delves into common deep learning models, and explores their practical applications in the industry. The paper also discusses obstacles and upcoming developments in deep learning for smart manufacturing The paper is structured as follows: Section 2 reviews data- driven artificial intelligence techniques with a focus on the superiority of deep learning. Section 3 discusses the challenges and opportunistic need for deep learning in smart manufacturing and introduces typical deep learning models. Section 4 summarizes the latest applications of deeplearning techniques in smart manufacturing. Finally, thechallenges and future trends of deep learning in smart manufacturing are discussed.

2. Overview of data driven intelligence

2.1. The evolution of data-driven artificial intelligence

Artificial intelligence (ai) has experienced various stages of development, ultimately being identified as the leading technology trend by gartner's top 10 strategic technology trends in 2017. The historical development and key models of AI are presented in table 1. The origin of artificial neural network (ann) can be traced back to the 1940s, when the mp model and hebb rule were introduced to comprehend the functioning of neurons in the human brain. The initial workshops at Dartmouth College established the groundwork for artificial intelligence (ai) capabilities, suchas chess playing and logical problem-

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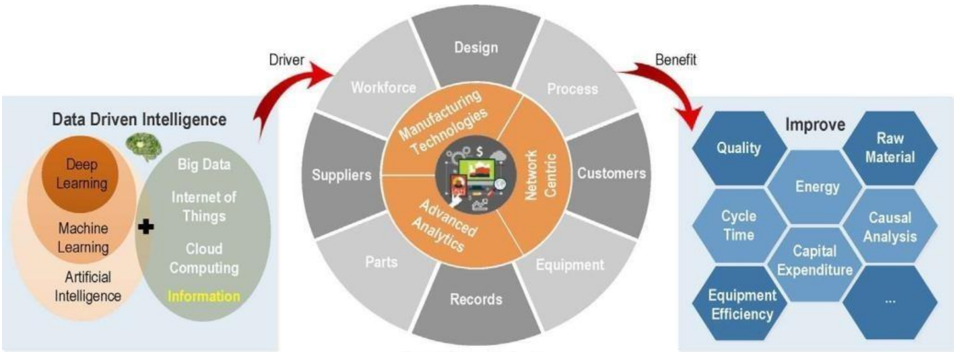
solving. In 1956, the perceptron model was introduced, mimicking human learning through linear optimization. Subsequently, the adaptive linear unit was created for practical purposes such as communication and weather forecasting. Unfortunately, the constraints of linear optimization posed challenges for AI in solving nonlinear problems, such as xor classification.



The progression to the second wave of artificial intelligence (ai) in the 1980s was accompanied by the creation of the hopfield network circuit and the back propagation (bp) algorithm to tackle nonlinear challenges. The boltzmann machine (bm) incorporated randomness into neural networks, whereas the support vector machine (svm) utilized kernel functions for classification and regression purposes. Traditional machine learning methods relied on human intervention for feature extraction, which restricted their effectiveness to pre-designed features.

The advent of deep learning brought about a major transformation in ai's abilities, as it harnessed the power of data representation learning rather than relying on manual feature engineering. The restricted boltzmann machine (rbm) and auto encoder (ae) were used to develop layer- wise learning algorithms for extracting features. The recurrent neural network (rnn) and long short-term memory (lstm) models were created to analyze sequential data. The convolutional neural network (cnn) transformed image processing tasks by combining convolutional and pooling layers in a stacked manner.

As the complexity of deep learning models grew with deeper hierarchical structures, difficulties arose in training and optimizing them. Significant advancements such as the deep belief network (dbn), deep auto encoder, sparse auto encoder (sae), and deep boltzmann machine enhanced the efficiency of model training and feature extraction. The deep convolutional neural network (dcnn) performed exceptionally well in recognizing images, whereas the generative adversarial network (gan) introduced adversarial training to generate realistic data samples.

Recent advancements include attention-based lstm models, along with ongoing developments of new ai models at a rapid pace.

2.2. Comparison between deep learning and traditional machine learning

Recent advancements include attention-based lstm models, along with ongoing developments of new artificial intelligence (ai) technologies.

Models were moving quickly. Both deep learning and traditional machine learning are artificial intelligence techniques that rely on data to model intricate connections between input and output, as illustrated in fig. 2. Nevertheless, deep learning exhibits unique characteristics that differentiate it from conventional machine learning, including the way it learns features, constructs models, and trains itself.

Deep learning combines the process of feature learning and model construction within a single model, typically through end-to-end optimization, and may involve the use of different kernels or parameter tuning. The deep neural network's architecture, consisting of multiple hidden layers, allows for complex non-linear operations at various levels, enabling the extraction of intricate underlying structures from input representations. For example, in image processing, features such as edges, corners, contours, and object parts are abstracted layer-by-layer. These abstracted features are then utilized in the classifier layer for the purpose of classification and regression. Deep learning functions as a self-learning framework, requiring minimal human intervention, and simultaneously trains model parameters.

In contrast, conventional machine learning follows a sequential approach, where feature extraction and model construction are performed independently, typically in a step-by-step manner. The initial step in extracting handcrafted features involves transforming raw data into various domains, such as statistical, frequency, and time-frequency domains, to capture essential information. This process necessitates the expertise of domain specialists. Subsequently, the process of feature selection is performed to improve relevance and minimize redundancy before incorporating features into the machine learning model. Traditional machine learning techniques usually have shallow structures with only a few layers, depending on optimization algorithms like bp neural network, support vector machine, logistic regression, and handcrafted features. This process of extracting and selecting features is time-consuming and heavily dependent on domain knowledge.

As a result, deep learning showcases unique distinctions from conventional machine learning methods, as outlined in table 2. The abstract representation at a high level.

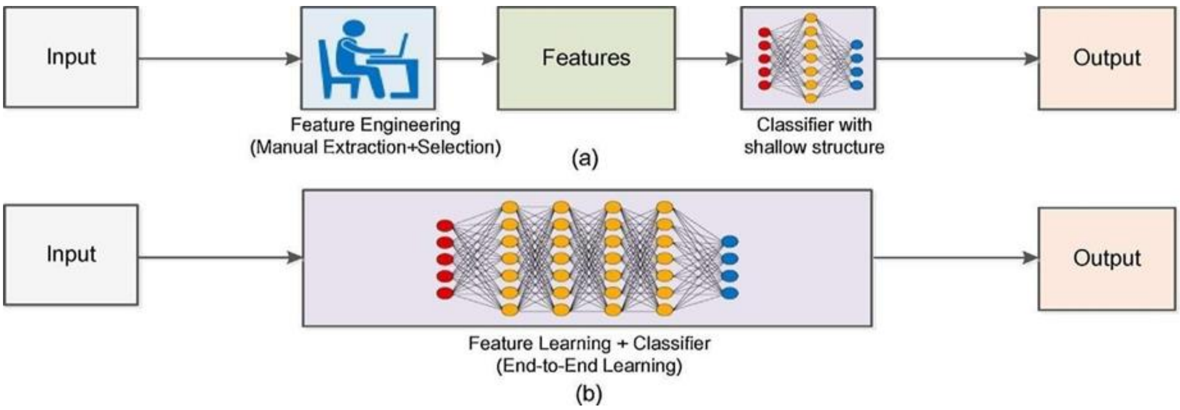
Learning enhances the flexibility and adaptability of deep learning, enabling it to handle diverse data types and sources effectively. Moreover, the complex hierarchical structure in deep learning enables the modeling of intricate relationships that are not easily captured by simpler structures in traditional machine learning. The mathematical proof of this advantage has been established. In the context of big data in smart manufacturing, the ability to bypass feature engineering is considered highly advantageous because of the difficulties involved in this process.

3. Deep learning for smart manufacturing

In order to identify the relevant articles in our selected field, we explored six popular academic research databases, namely (1) ieee explore, (2 as smart manufacturing integrates new technologies like iot and big data, the focus shifts towards harnessing manufacturing intelligence to benefit the entire organization. The manufacturing industry is currently experiencing a significant increase in the amount of sensory data being generated, which comes in various formats, has different meanings, and is organized in different ways. This information is obtained from different areas within the manufacturing company, such as the different products they make, the equipment they use, the processes they follow, the work done by employees, and the conditions in the environment. Proper data modeling and analysis are essential in smart manufacturing to handle the large volume of data and enable real-time data processing.

Deep learning becomes a significant milestone in computational intelligence, especially in extracting knowledge from large sets of data. Deep learning techniques are essential in enabling autonomous learning from data, identifying patterns, and supporting decision-making, as illustrated in fig. 3. These methods allow for various levels of data analysis, from descriptive analytics to prescriptive analytics. Descriptive analytics summarizes events by capturing product conditions, environmental factors, and operational parameters. Diagnostic analytics delves into the underlying Performance or equipment failure. Predictive analytics employs statistical models to anticipate future production potential or equipment deterioration by analyzing historical data. Prescriptive analytics takes it a step further by suggesting specific actions to improve production resultsor address problems, offering valuable insights into the potential outcomes of each decision.

By utilizing advanced analytics powered by deep learning, manufacturing facilities can be transformed into highly efficient and intelligent smart facilities.



The advantages include cost savings, the ability to quickly adapt to changes in consumer demand, increased productivity, reduced downtime, better visibility, and improved extraction of value from operations to remain competitive on a global scale.

In the field of manufacturing intelligence, numerous advanced deep learning architectures have been created, and research in this domain is growing at a fast pace. This paper explores common deep learning architectures, including convolutional neural networks, restricted Boltzmann machines, auto encoders, and recurrent neural networks, and their different variations. The focus is on the ability of these architectures to learn and extract features, as well as their role in building complex and advanced deep learning models.

3.1. Convolutional neural network

The convolutional neural network (cnn) is a type of artificial neural network that was initially developed for processing images in two dimensions. Recent studies have also investigated its effectiveness in analyzing sequential data, such as natural language processing and speech recognition. In CNNs, feature learning is achieved by alternating and stacking convolutional layers and pooling operations.

Convolutional layers apply multiple local kernel filters to raw input data, extracting invariant local features. Subsequent layers in the network extract important features by performing pooling operations such as max pooling (choosing the highest value within a region) or average pooling (calculating the average value of a region). Although max pooling is effective for extracting sparse features, global pooling across all samples may not be the most efficient approach.

After implementing multi-layer feature learning, fully-connected layers transform the two-dimensional feature map into a one-dimensional vector, which is subsequently used in the construction of the model through a softmax function. The standard CNN architecture typically consists of stacking convolutional, pooling, and fully-connected layers.

CNNs are trained using gradient-based backpropagation to minimize the mean squared error or cross-entropy loss function. CNs provide benefits such as limited interactions with nearby objects, shared parameters to reduce complexity, and a representation that remains unchanged regardless of object positions.

This paper provides a detailed examination of cnns, emphasizing their wide range of applications in diverse data analysis tasks, their architectural components, training methods, and advantageous properties in effectively managing intricate data structures.

3.2. Restricted Boltzmann machine and its variant

The restricted boltzmann machine (rbm) is a neural network consisting of two layers: one for visible inputs and another for hidden states. There is a symmetric relationship between visible and hidden units, but no connections exist within the same layer. Rbm functions as an energy-based model, with the visible layer serving as the input for data and the hidden layer extracting relevant features. Hidden nodes are assumed to be conditionally independent, and the weights and offsets of both layers are adjusted iterativelyto come as close as possible to the original input within the visible layer. The concealed layers are perceived as separate representations of the visible layer.

The parameters in the hidden layers act as features that help describe input data, making it easier to code and reduce the dimensionality of the data. Techniques like logistic regression, naïve bayes, bp neural network, and support vector machine can be used to classify and predict data after being trained with supervised learning methods. Rbm's capability to automatically identify and extract essential features from training datasets, thereby bypassing local minimum values, has garnered growing interest. Different versions of the model have been created usingrbm as the basic learning component. A deep belief network (dbn) is built by stacking multiple recurrent neural networks (rbms), with the output of one layer's hidden units becoming the input for the next layer's visible units.

Dbn training usually starts with a fast greedy algorithm for initialization, and then fine-tunes using a contractive wake- sleep algorithm. Bayesian belief network is used for tasks that are closely related to the visible layers, while rbms are used for tasks that are further away from the visible layers. Dbn has a combination of directed and undirected layers, with the top two layers being undirected.

The deep boltzmann machine (dbm) can be seen as a deep structured recurrent neural network, where hidden units are arranged in a layered structure. There are direct links between neighboring layers, but no connections are permitted within a layer or between layers that are not adjacent. By combining multiple rbms, dbm can acquire intricate knowledge and produce detailed representations of input data. In contrast to dbn, dbm is an undirected network that requires more computational resources for joint training, whereas dbn can be trained layer-wise for improved efficiency.

3.3. Auto encoder and its variants

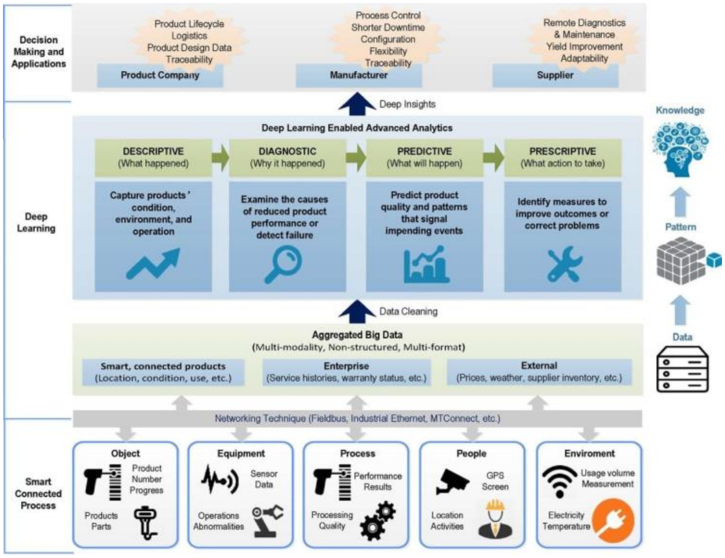
Joint training, unlike dbn, can be trained layer-wise to improve efficiency. The auto encoder (ae) is a machine learning algorithm that learns to extract features from data without needing labeled information. It consists of two primary components: the encoder and decoder, as illustrated in fig. 6. The encoder reduces data, particularly for complex inputs, by mapping them to a hidden layer. Conversely, the decoder reconstructs a rough approximation of the input. When employing a linear activation function and having fewer hidden layers than the number of input data dimensions, the linear auto encoder bears resemblance to principle component analysis (pca). Nevertheless, when dealing with complex and nonlinear input data, a deep auto encoder with additional hidden layers is required. The parameters of the auto-encoder are usually determined using stochastic gradient descent (sgd) to minimize the objective loss function, such as least square loss or cross-entropy loss.

Different variations of the ae have been created:.

The denoising auto encoder (dae) is an extension of the basic auto encoder, which trains it to reconstruct input data that has been corrupted with noise. This is accomplished by introducing isotropic Gaussian noise to the input andmotivating the hidden layer to uncover more resilient features.

Sparse auto encoder (sae): sae encourages sparsity by promoting the majority of hidden unit activations to be close to zero. This is advantageous even when there are numerous hidden units.

Contractive auto encoder (cae): cae emphasizes the development of robust representations by minimizing the impact of small perturbations, resulting in more stable features.



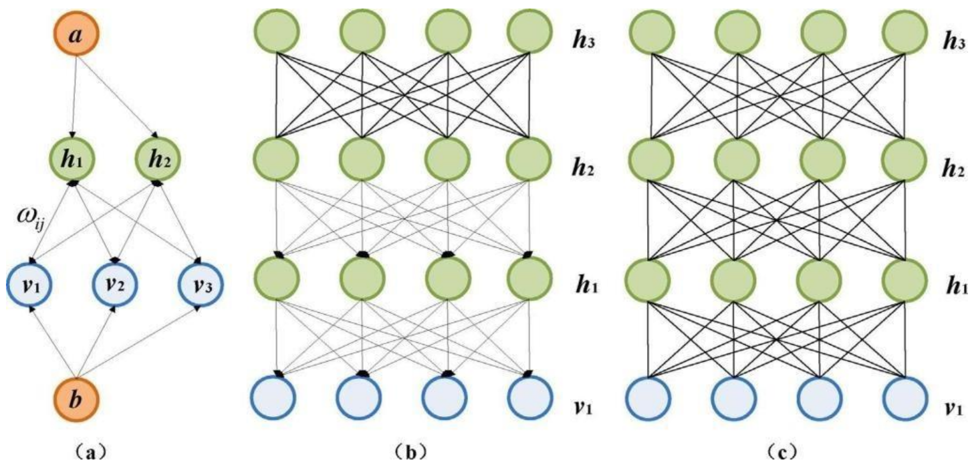
These variants enhance the capabilities of Auto Encoders and cater to specific data characteristics, making them versatile tools for feature extraction and representation learning in unsupervised settings.

3.4. Recurrent neural network and its variants

When comparing recurrent neural networks (rnns) with traditional neural networks, a distinctive characteristic of rnns is their topology connections between neurons, forming directed cycles specifically suited for sequence data, as depicted in fig. 7. This architectural design allows rnns to excel in feature learning from sequences by enabling information to be stored in hidden layers and capturing previous states from multiple time steps in the past. A new rule is introduced in rnns to calculate hidden states at various time intervals. Considering sequential input as a vector, the current hidden state is calculated in two parts using the same activation function (e.G., sigmoid or tanh function): one part is computed with the input, while the second part is derived from the hidden state at the preceding time step. Subsequently, the desired result is established.

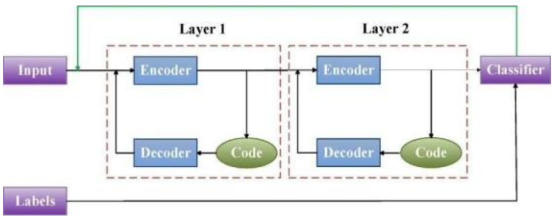
After analyzing the entire sequence, the hidden state becomes the learned representation of the input data, with a conventional multilayer perceptron (mlp) added on top to map this representation to the desired targets.

Unlike traditional neural networks, model training in RNNs is executed through Backpropagation Through Time (BPTT). Initially, RNNs are time-unrolled, considering each unrolled time step as an additional layer, followed by the application of the backpropagation algorithm to compute gradients. However, the vanishing/exploding gradient issue encountered during BPTT-based model training poses challenges for RNNs in capturing long-term dependencies within sequence data. To address these challenges, various enhancements have been proposed, with long short-term memory (LSTM) being extensively studied for its efficacy. The core concept of LSTM lies in its cell state, facilitating linear information flow. Unlike the single recurrent structure in RNNs, LSTMs incorporate gates such as the forget gate layer, input gate layer, and output gate layer to regulate the cell state. This allows each recurrent unit to dynamically capture long-term dependencies across varying time scales, overcoming RNN's limitations in handling long-term sequence data.



3.5. Model comparison

The mentioned deep learning architectures, such as CNN and RNN, offer sophisticated composition mechanisms for learning representations and constructing models. RBM and AE play crucial roles in layer-by-layer pretraining of deep neural networks, enabling the characterization of input data. In these models, the top layers usually represent the targets, with SoftMax layers applied for classification tasks involving discrete values and linear regression layers for predictions with continuous targets. The use of labelled data determines whether DBN, AE, and their variants fall under unsupervised learning or semi-supervised learning, while



CNN, RNN, and their variants are categorized as supervised learning. Table 3 provides an overview of the pros and cons of these typical deep learning models.

Furthermore, a variety of typical deep learning packages, including both open-source and commercial software, are readily available to the public. These packages, as outlined in Table 4, greatly facilitate the exploration and implementation of deep learning techniques in diverse manufacturing scenarios.

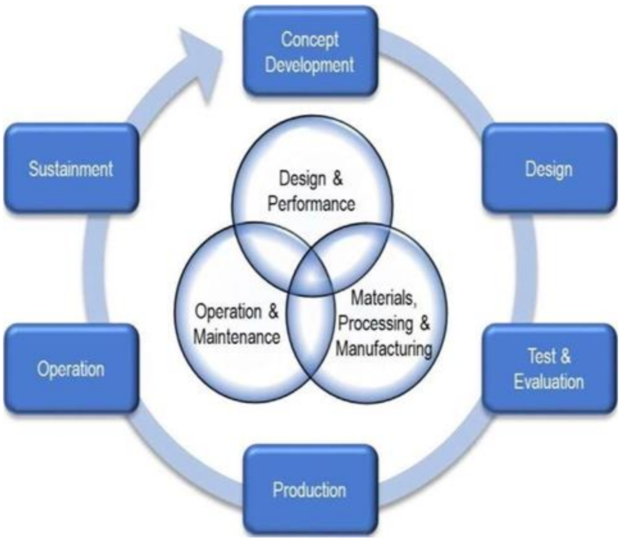
This reframed content focuses on the key concepts and categorization of deep learning models, emphasizing their applications in manufacturing scenarios and the availability of relevant software tools.

5.Applications to smart manufacturing

Computational intelligence plays a vital role in smart manufacturing, providing accurate insights that enable informed decision-making. Machine learning techniques have been extensively studied and applied across different stages of the manufacturing process, from the initial concept to production, operation, and even sustainability. A thorough examination of data mining applications in manufacturing engineering encompasses various facets, including production processes, operations, fault detection, maintenance, decision support, and improvement of product quality.

Conversations about the development and future direction of manufacturing highlight the importance of data modeling and analysis in promoting manufacturing intelligence. The article discusses various applications of machine learning in the manufacturing industry, showcasing notable examples. Additionally, smart manufacturing necessitates the implementation of prognostics and health management (phm) to tackle current and future needs for effective and flexible production.

In recent years, deep learning has gained significant prominence in the manufacturing industry. This research paper offers a comprehensive overview of the latest deep learning methodologies and their applications in manufacturing, with a specific emphasis on areas like product quality inspection, fault diagnosis, and defect prediction.



4. Descriptive analytics for product quality inspection

Surface integration inspection is typically conducted using machine vision and image processing techniques to identify surface defects and enhance product quality in manufacturing. Traditional machine learning methods have shown progress and reliability in this domain, requiring various pre-processing techniques such as structural-based, statistical-based, filter-based, and model-based approaches to extract relevant features with expert knowledge. However, the dynamic nature of modern manufacturing systems often necessitates a redesign of feature representation for each new product, especially considering intricate texture patterns, intensity variations, and arbitrary sizes, orientations, and shapes of surface defects.

To address these challenges, deep learning techniques have emerged as effective solutions due to their ability to learn high-level generic features applicable across various textures and difficult-to-detect defect cases. Convolutional Neural Networks (CNNs), originally designed for image analysis, have become particularly suitable for automated defect identification in surface integration inspection tasks. For instance, researchers have designed Deep CNN architectures optimized using backpropagation and stochastic gradient descent algorithms, showcasing improved error rates compared to traditional methods.

CNNs have also been employed for feature extraction directly from pixel representations of defect images, demonstrating effectiveness across different defect types and textured surfaces. Additionally, generic CNN-based approaches have been proposed for patch feature extraction and defect area prediction, resulting in enhanced accuracy even with limited datasets for automated surface inspection systems.

4.1. Diagnostic analytics for fault assessment.

Manufacturing systems are susceptible to various failures caused by degradation or abnormal operating conditions, resulting in issues like excessive load, defection, fracture, overheating, corrosion, and wear. These failures can lead to higher operating costs, decreased productivity, increased waste of disqualified parts, and unexpected downtime. To implement smart manufacturing effectively, it's crucial for smart factories to monitor machinery conditions, detect incipient defects, diagnose failure root causes, and integrate this information into manufacturing production and control processes.

With the availability of aggregated data from smart sensory and automation systems, deep learning techniques have become widely explored for machinery fault diagnosis and classification. Convolutional Neural Networks (CNNs) have been particularly impactful, integrating feature learning and defect diagnosis within a single model. CNNs have found applications in various domains such as bearing, gearbox, wind generator, and rotor fault diagnosis. To adapt CNNs for time series data analysis, different approaches have been developed, including transforming time series data into matrices, using frequency spectra, and leveraging time-frequency spectra obtained through wavelet transforms.

Deep Belief Networks (DBNs) have also gained attention due to their fast inference and ability to encode high-order network structures by stacking Restricted Boltzmann Machines (RBMs). DBNs have been applied in fault diagnosis scenarios for aircraft engines, chemical processes, compressors, bearings, high-speed trains, and wind turbines. DBN models typically utilize preprocessed features from techniques like Teager-Kaiser energy operators or wavelet transforms instead of raw data.

Auto Encoders (AEs) are another focus area for unsupervised feature learning, with learned features then used in traditional machine learning models for training and classification. Different AE variants, such as sparse Auto Encoders, stacked denoising Auto Encoders, and

Contractive Auto Encoders, have been explored for various fault diagnosis tasks. These AE models enhance feature robustness and improve diagnostic analytics in fault diagnosis systems.

Overall, deep learning models demonstrate superiority over traditional machine learning techniques, such as support vector machines and BP Neural Networks, especially in terms of classification accuracy, making them highly valuable for smart manufacturing applications.

4.2. Predictive analytics for defect prognosis

To improve manufacturing efficiency and reduce maintenance costs, implementing an intelligent maintenance strategy is essential. This strategy helps manufacturers assess in-service system conditions and predict optimal maintenance schedules. The historical temporal data plays a critical role in predictive maintenance, making deep recurrent neural networks (RNNs) highly valuable due to their ability to model temporal patterns effectively. Specifically, Long Short-Term Memory (LSTM) networks have emerged as a key tool for predicting defect propagation and estimating the Remaining Useful Life (RUL) of mechanical systems or components.

Researchers have explored various RNN architectures for different predictive maintenance tasks. One study introduced a competitive learning-based RNN for long-term health status prognosis of rolling bearings. Another proposed a local feature-based Gated Recurrent Unit (GRU) network for sequence representation learning in machine health monitoring. Additionally, an integrated approach combining Convolutional Neural Networks (CNN) and bi- directional LSTM was developed for machining tool wear prediction.

Vanilla LSTM models have shown promise in estimating RUL under complex conditions, while stacked LSTM networks have been effective for anomaly prediction in aerospace systems. Deep Belief Networks (DBNs) have also been investigated for their feature learning capabilities, particularly in modeling complex relationships in semiconductor manufacturing processes and predicting resource demands in cloud computing environments.

Overall, these deep learning techniques offer significant potential for enhancing predictive maintenance strategies and predictive analytics in manufacturing and related industries, contributing to improved operational efficiency and cost savings.

5. Discussions and outlook

The advancement of smart manufacturing has led to the integration of smart sensors and the Internet of Things (IoT) into various machineries. However, many companies face challenges in effectively utilizing the data generated by these systems. They lack the necessary software and models to interpret and analyze the data for practical insights. Simultaneously, academic research often focuses on developing cutting-edge artificial intelligence (AI) models without considering their real-world applications inmanufacturing processes.

As manufacturing processes become more intricate, there are significant challenges in clarifying the data and formulating the right problems to address. Five key gaps have been identified in smart manufacturing innovation, including strategies for data collection and utilization, predictive model design, and connectivity within factories and control processes.

To meet the demand for advanced analytics in smart manufacturing, deep learning has emerged as a promising approach due to its feature learning capabilities and deep network structures. However, implementing deep learningin the manufacturing industry poses challenges, especially in handling large volumes of diverse and high-velocity data. Overcoming these challenges requires addressing issues related to data management, model selection, visualization, developing generic models, and adopting incremental learning strategies.

The future development trends in deep learning for smart manufacturing revolve around optimizing data handling processes, selecting appropriate models, enhancing model visualization techniques, creating generic models applicable across various domains, and implementing incremental learning approaches for continuous improvement and adaptation. These trends aim to streamline the adoption and deployment of deep learning technologies in real-world manufacturing applications.

5.1. Data matter

Applications A common assumption in machine learning is that algorithms can achieve better performance with larger and higher-quality datasets. Consequently, the effectiveness of deep learning models heavily relies on the scale and quality of the data they are trained on. Deep learning has shown remarkable efficacy in handling specific types of data, such as images, speech, vibrations, and other well- defined tasks. However, challenges arise when dealing with high-dimensional, multi-modal, and unstructured data, which is prevalent in real-world scenarios throughout a product's lifecycle.

The complexity of multi-sensory data collection across all stages of a product's life can pose difficulties for deep learning algorithms. They may struggle to directly process such diverse data, leading to challenges like the curse of dimensionality. Strategies such as extracting relevant features to reduce dimensionality and incorporating task-specific regularization terms can enhance deep learning model performance in these scenarios.

Overall, navigating the complexities of multi-dimensional, multi-modal data and overcoming class imbalance challenges are critical areas for enhancing the application of deep learning models in real-world scenarios. Various strategies and techniques can be employed to improve the robustness and effectiveness of deep learning algorithms in handling diverse and imbalanced datasets.

5.2. Model selection

Deep learning models offer specialized solutions for various problems encountered in manufacturing processes.However, selecting the appropriate model can be challenging due to the complexity involved. Several criteria can guide the selection of deep learning algorithms. Firstly, the choice between supervised and unsupervised algorithms depends on the availability of labeled data. Supervised algorithms are suitable for data-rich but knowledge-sparse problems where labeled data is accessible, while unsupervised algorithms may be more suitable when expert knowledge is limited. Secondly, considering the strengths and weaknesses of each algorithm is essential for general applicability.

5.3. Model visualization

Model visualization plays a crucial role in ensuring that the insights and decisions generated by deep learning models are understood and accepted by manufacturing engineers. Deep neural networks are often viewed as black-box models due to their complexity, making it challenging to explain internal computations or interpret abstract feature representations. Visualization techniques such as t-SNE for data visualization and activation visualization for deep neural network layers can offer insights into model construction and configuration.

5.4. Generic model

Deep learning models can serve as generic solutions for manufacturing intelligence problems, as they are not limited to specific machines. However, building high hierarchical models with multiple layers for complex problems remains challenging. Architecture design, hyper-parameter optimization, and parallel implementation using GPU and Hadoop technologies are crucial for enhancing model performance and scalability.

5.5. Incremental learning

Incremental learning capabilities are essential for deep learning algorithms to adapt to new problem setups and data velocities. Transfer learning, which leverages pre-trained models from related tasks for initialization and fine-tuning, can enable knowledge reuse and updating. Techniques like maximum mean discrepancy (MMD) measure can evaluate domain discrepancies and facilitate knowledge transfer for smart manufacturing applications.

6. Conclusion

Deep learning has emerged as a powerful tool with substantial potential for revolutionizing advanced analytics within the realm of smart manufacturing. Its capability to provide decision-makers with actionable insights and real- time performance measures is significant. However, despite the promising results witnessed so far, there are several key limitations and challenges that need to be addressed to fully unlock its potential and facilitate further advancements inthe field.

One of the critical challenges is model selection. With a myriad of deep learning models available, choosing the right one for a specific manufacturing problem can be daunting. Factors such as the availability of labeled data, the complexity of the problem, and the general applicability of the selected algorithm must be carefully considered to ensure optimal performance.

Visualization also plays a crucial role in enhancing understanding and acceptance of deep learning models among manufacturing engineers. These models are often perceived as black boxes due to their complexity, making it challenging to interpret their internal computations and abstract feature representations. Techniques such as t-SNE for data visualization and activation visualization for deep neural network layers can provide valuable insights and improve model construction and configuration.

Developing generic models that can address a wide range of manufacturing intelligence problems is another area of focus. While deep learning models offer versatility, building high hierarchical models with multiple layers for complex problems remains a challenge. Architectural design, hyper- parameter optimization, and parallel implementation using advanced computing resources like GPUs and cloud computing are critical for enhancing model performance and scalability.

Additionally, incremental learning capabilities are essential for adapting deep learning algorithms to new problem setups and data velocities. Transfer learning, which leverages pre-trained models from related tasks for initialization and fine-tuning, can enable knowledge reuse and updating, facilitating faster adaptation to changing manufacturing scenarios.

Looking ahead, the evolution of computing resources, particularly in cloud and fog computing, holds immense potential for further enhancing the capabilities of deep learning in smart manufacturing. These advancements can lead to more convenient and on-demand computing services, ultimately driving innovation and efficiency in the manufacturing industry.

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