Status Quo, Advances and Futures of Machine Learning in Fault Detection and Diagnosis for Energy: A Review

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Abstract. Fault Detection and Diagnosis (FDD) plays a crucial role in maintaining the integrity and efficient operation of modern industrial systems, from manufacturing sectors to process industries. FDD involves identifying and classifying abnormal conditions that could lead to equipment failure, production inefficiencies, or safety hazards. However, traditional FDD techniques face challenges in handling vast data and complex system dynamics and ensuring timely and accurate fault detection in dynamic environments. Manual inspections and heuristic approaches are inadequate, and statistical process control methods have limitations in capturing complex relationships and adapting to evolving process conditions. To overcome these challenges, advanced techniques such as deep learning-based approaches have emerged, leveraging the capabilities of neural networks for fault detection and diagnosis. These approaches have shown promising results in handling high-dimensional, nonlinear, and time-varying process data. This paper reviews the advancements, challenges, and prospects of deep learning in FDD in industrial systems. Firstly, it discusses the emergence and development of deep learning methods applied to FDD and their applications in relevant fields. Secondly, a new development path that combines deep learning with big data is proposed to address the increasing production data in modern industrial settings. Finally, the opportunities and limitations of deep learning in FDD are clarified, providing insights for future research and development in this area.

Keywords: Energy · Process fault detection and diagnosis · Machine learning · Deep learning · Big data

1 Introduction

The industrial applications of Fault Detection and Diagnosis (FDD) are diverse and critical in modern industrial systems. From manufacturing sectors like automotive and electronics to process industries such as chemicals and metallurgy, efficient operation and

H. Gaber (Ed.): CEES 2024, LNEE 1222, pp. 170–183, 2024.
https://doi.org/10.1007/978-981-97-5775-6_12

quality assurance are paramount [1]. FDD is critical for maintaining the integrity of these systems [2]. It involves identifying and classifying abnormal conditions that could lead to equipment failure, production inefficiencies, or safety hazards. The goal of FDD is not just to detect faults early but also to accurately diagnose the type, severity, and location of these faults for timely rectification. For instance, in power plants, FDD systems detect anomalies in turbines and boilers and prevent catastrophic failures [3]. FDD is essential for optimising performance and reducing maintenance costs in renewable energy, such as wind and solar. In the oil and gas industry, FDD can help detect leaks, corrosion, erosion, blockages, and equipment failures in pipelines, wells, refineries, and offshore platforms. In the chemical and pharmaceutical industries, FDD is essential in monitoring and controlling product quality and purity and ensuring process safety and compliance [4].

However, applying FDD systems faces several challenges, including handling the vast amount of generated data, dealing with complex and non-linear system dynamics, and ensuring timely and accurate fault detection in dynamic environments. Traditional FDD techniques, such as data-driven, model-based, rule-based, or hybrid approaches, may be unable to cope with these challenges, especially when the system is subject to uncertainties, disturbances, noise, and changes [5]. During the past few years, the rapid development of artificial intelligence and extensive data analysis have brought new avenues for improving the performance and robustness of FDD techniques.

Historically, FDD in industrial settings relied heavily on manual inspections and heuristic approaches based on operator experience [6]. As the complexity and scale of industrial processes increased, these methods became inadequate. Introducing statistical process control methods like Multivariate Statistical Process Control (MSPC) [7] marked a significant advancement. Techniques like Principal Component Analysis (PCA) and Independent Component Analysis (ICA) became popular due to their ability to handle multiple process variables simultaneously [8–10]. However, being limited primarily to linear data models makes them encounter bottlenecks when facing the non-linear nature of many industrial processes.

One of the significant challenges in traditional FDD methods is dealing with the high-dimensional, nonlinear, and time-varying nature of process data [11]. The inherent limitations in capturing complex relationships between variables and the inability to adapt to evolving process conditions have often led to suboptimal fault detection performance. Additionally, the expansion in process scale and data volume has outpaced the capabilities of these traditional techniques, necessitating more advanced analytical methods [12].

The advent of deep learning, a subset of machine learning characterised by deep neural networks [13], has marked a paradigm shift in FDD. Deep learning algorithms, capable of automatic feature extraction and handling vast amounts of data, have shown superior performance in detecting and diagnosing faults in complex industrial systems. Techniques represented by convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have been particularly effective in processing time-series data and images, which is common in industrial monitoring systems. These deep learning models can learn hierarchical representations and offer enhanced accuracy, efficiency, and adaptability in fault diagnosis processes.

The rest of the study is structured as follows. Section 2 presents a comprehensive review of the traditional machine-learning techniques for FDD. Section 3 reviews the emergence and development of deep learning methods applied to FDD. Section 4 argues the techniques based on deep learning to process FDD. Challenges and future directions are drawn in Sect. 5.

2 Traditional Machine Learning Techniques for FDD

Traditional FDD methods, such as Principal Component Analysis (PCA) and Independent Component Analysis (ICA), were pivotal in the early stages of industrial process monitoring. PCA was particularly significant in reducing data dimensions while preserving the most critical variance aspects, making it an indispensable tool for visualising complex datasets in simpler forms [14]. This method helped highlight correlations in variables and detect outliers and anomalies in process data. However, the linear nature of PCA meant that it was less effective in handling complex, nonlinear relationships common in industrial processes. ICA, another statistical tool, worked to decompose a multivariate signal into independent non-Gaussian signals. It was helpful in identifying hidden factors in data but, like PCA, struggled with non-linear relationships [15]. Data often exhibits non-normal distributions and nonlinear behaviours in real-world industrial scenarios due to the complex interactions of various process variables. This discrepancy led to the limited applicability of these traditional methods in diverse industrial settings. The need for methods that could account for such complexities became increasingly apparent.

Advancements in statistical methods led to the development of kernel-based techniques such as Kernel PCA (KPCA) and Kernel ICA (KICA) to address the non-linearity in data. KPCA, an extension of PCA, utilised kernel functions to project data into a higher-dimensional feature space where linear methods could be more efficacious [16]. This method allowed for capturing nonlinear relationships in data, which was a significant step forward from traditional PCA. Similarly, KICA extended the capabilities of ICA using kernel methods, enhancing its ability to find independent components in nonlinear data [17]. Despite these advancements, kernel-based methods faced their own set of challenges. One major issue was model overfitting; these methods could become too tailored to the specific training data, losing their generalizability to new data [18]. Another significant challenge was computational inefficiency. Industrial processes often generate large datasets, and kernel-based methods require high computational power, making them less feasible in real-time applications [19]. These limitations highlighted the need for more advanced methods to handle large-scale data efficiently.

Gaussian Mixture Models (GMMs) were introduced to address the complexities in data distribution [20]. GMMs are probabilistic models that assume data is generated from a mixture of several Gaussian distributions. This approach effectively models data with complex, multimodal distributions often encountered in industrial scenarios. GMMs were particularly adept at clustering and identifying different states or behaviours in process data [21]. Alongside GMMs, Hidden Markov Models (HMMs) added a temporal dimension to FDD. HMMs are statistical models representing systems with hidden states, which are helpful in sequential and time-dependent data modelling [22]. This made HMMs particularly valuable in scenarios where the state of a process changes over time, such as in predictive maintenance. Despite the strengths of GMMs and HMMs, they faced challenges in handling high-dimensional data. Both methods often required significant preprocessing efforts, including dimensionality reduction and feature selection, to be effective. This preprocessing was time-consuming and required extensive domain knowledge, limiting their applicability in more automated settings.

Support Vector Data Description (SVDD) emerged as another robust method for anomaly detection in FDD. Unlike traditional methods that often relied on assumptions about data distribution, SVDD did not assume any specific distribution, making it particularly suitable for monitoring non-Gaussian processes [23]. This method worked by creating a boundary around the data representing the normal state of the process; anything falling outside this boundary was considered an anomaly, and along with SVDD, clustering techniques like K-means and Self-Organizing Maps (SOM) gained prominence in FDD. K-means clustering algorithm was widely used for its simplicity and effectiveness in grouping data into clusters based on similarities. SOMs, on the other hand, provided a visual representation of complex data, facilitating the more straightforward interpretation of process states and behaviours [24]. However, these techniques often required expert intervention for interpreting results and were sensitive to parameter selection, which could impact their effectiveness in different scenarios.

Despite the advancements in traditional machine learning methods for FDD, several challenges remained. One of the main challenges was the requirement of extensive domain knowledge for effective feature selection and model tuning [25]. The increasing volume and velocity of data generated in industrial settings, along with the growing complexity of manufacturing processes, began to outstrip the capabilities of these methods. They often could not handle large-scale data sets efficiently and struggled with automatic feature extraction.

This realisation led to exploring more advanced techniques for FDD in intense learning methods. Deep learning presented a promising alternative to traditional methods with its ability to automatically extract features and handle complex, high-dimensional data. These advanced techniques, capable of learning from large volumes of data and making sense of complex relationships without extensive human intervention, were seen as the future of FDD in industrial settings. The research on these methods marked a significant shift in the approach to FDD, paving the way for more efficient, accurate, and automated fault detection and diagnosis processes.

3 Emergence and Development of Deep Learning in FDD

3.1 Deep Learning: A New Era in Machine Learning

Inspired by the human brain's structure and function, deep learning uses multiple layers of artificial neural networks to learn from data [26]. Deep learning can automatically discover the hidden patterns and features in the data without human intervention or domain knowledge. Deep learning can also handle various data types, such as numerical, categorical, textual, image, audio, or video data, and integrate them into a unified framework [27].

The rise of deep learning coincides with advancements in computational power and data availability. Developments in GPU technology and parallel processing have enabled the training of deep neural networks, which require significant computational resources [28]. Computational power is a crucial factor determining the performance and scalability of deep learning models [29]. Deep learning models consist of multiple layers of artificial neurons that perform complex mathematical operations on the input data. These operations are often parallelisable and can be accelerated using specialised hardware, such as Graphics Processing Units (GPUs), Tensor Processing Units (TPUs), or Field Programmable Gate Arrays (FPGAs). GPUs, in particular, have been widely used for deep learning, as they offer high performance, low cost, and easy accessibility. GPUs can perform thousands of floating-point operations per second, essential for training large and deep neural networks.

Data availability is another crucial factor that influences the effectiveness and generalisation of deep learning models [30]. Deep learning models require large amounts of data to learn the hidden patterns and features representing the system's behaviour and fault characteristics. Data availability can be affected by various factors, such as data collection, storage, transmission, and privacy. The Internet of Things (IoT) in industrial settings has resulted in an explosion of data, providing the volume and variety necessary for deep learning algorithms [31]. IoT devices, such as sensors, actuators, cameras, or smart meters, can generate massive amounts of data that reflect the state and condition of industrial systems. These data can be used to train and test deep learning models for FDD tasks, such as anomaly detection, fault classification, or fault diagnosis [32]. Deep learning has achieved remarkable results in various domains, such as computer vision, natural language processing, speech recognition, and more[10]. It is also a promising direction for FDD in complex industrial systems. By leveraging the power of deep learning, FDD can achieve higher accuracy, robustness, and adaptability and provide more value and insight for industrial applications.

The transition to deep learning in FDD marked a significant shift in artificial intelligence. This evolution is driven by the increasing demand for advanced data analysis tools capable of handling the complexities and volumes of data generated by industrial processes. Industrial data, such as sensor measurements, process variables, and product quality indicators, contain rich information about the system's behaviour and fault characteristics [33]. Besides, these data are also characterised by high dimensionality, nonlinearity, multimodality, noise, outliers, and dynamics, which pose significant challenges for traditional FDD methods [34].

Deep learning excels in processing non-linear and high-dimensional data, overcoming the limitations of traditional machine learning methods like PCA and ICA, which require extensive preprocessing and manual feature extraction [35]. Deep learning can automatically discover the hidden patterns and features in the data without human intervention or domain knowledge. Deep learning can also handle various data types, such as numerical, categorical, textual, image, audio, or video data, and integrate them into a unified framework [36]. Its ability to learn from raw data has proven particularly valuable in industrial applications where data can be varied and complex. Industrial data, such as sensor measurements, process variables, and product quality indicators, contain rich information about the system's behaviour and fault characteristics. However, these data are also characterised by high dimensionality, nonlinearity, multimodality, noise, outliers, and dynamics, which pose significant challenges for traditional FDD methods. Deep learning can effectively address these challenges and improve FDD performance and robustness [37].

Deep learning can use CNNs to learn spatial features from image data, such as thermal, infrared, or X-ray images, that can indicate faults or defects in industrial systems. Deep learning can also use RNNs or Long Short-Term Memory (LSTM) networks to learn temporal features from sequential data, such as time series, signals, or videos, that can capture the dynamic changes or trends in industrial processes. Deep learning can also use autoencoders (AEs) or variational autoencoders (VAEs) to learn latent features from unlabeled data, such as sensor data, that can represent the average or abnormal states of industrial systems [38].

3.2 Feature Learning and Its Impact on Industrial FDD

Feature learning is one of the core concepts in deep learning, and it significantly impacts industrial fault detection and diagnosis (FDD). Traditional FDD methods typically require manual feature extraction, which relies on domain experts' knowledge and experience, making it time-consuming and labour-intensive, especially for complex industrial systems. However, deep learning can automatically learn features from the data and uncover hidden patterns and characteristics without human intervention or domain knowledge [39].

Features are the attributes or characteristics of the data that can represent the system's behaviour and fault conditions [40]. Feature extraction transforms the raw data into a lower-dimensional, more informative representation that can facilitate FDD tasks, such as anomaly detection, fault classification, or fault isolation. Feature extraction is a crucial step in FDD, as it can affect the performance and robustness of the FDD models [41]. Deep learning models have shown superior performance in feature extraction for FDD, as they can capture the data's non-linear, multimodal, and dynamic characteristics and identify the most relevant and discriminative features for fault detection and diagnosis. Deep learning models can adapt to changing conditions and environments and provide interpretable and explainable results [42].

In industrial settings, applying deep learning has significantly improved the accuracy and efficiency of FDD systems. These advancements have enhanced the reliability of FDD systems and enabled more proactive and predictive maintenance strategies. Proactive maintenance is preventing or mitigating faults before they occur or escalate. It uses FDD systems to monitor the system's condition and performance and to trigger appropriate actions, such as alarms, warnings, or interventions [43]. Predictive maintenance is forecasting the remaining useful life (RUL) of the system components using FDD systems to estimate the components' degradation or wear and schedule optimal maintenance plans [44]. Proactive and predictive maintenance can significantly benefit industrial applications by reducing downtime, increasing productivity, saving costs, improving quality, and extending lifespan.

For example, in the oil and gas industry, FDD systems based on deep learning can help detect leaks, corrosion, erosion, blockages, and equipment failures in pipelines, wells, refineries, and offshore platforms and prevent accidents, spills, or explosions

[32]. In the power generation sector, FDD systems based on deep learning can help monitor and diagnose faults in generators, turbines, transformers, and other components and prevent power outages, blackouts, or cascading failures [3]. In the renewable energy sector, FDD systems based on deep learning can help detect and diagnose faults in wind turbines, solar panels, batteries, and inverters and improve the reliability and availability of renewable energy sources [45].

4 Deep Learning Techniques in FDD

Deep learning has demonstrated excellent performance in fault detection and diagnosis (FDD), and a variety of methods have been developed for different targets. However, implementing these methods in industrial environments still presents challenges. Adaptive solutions have been proposed to address these challenges to make deep learning more accessible and effective in various industrial domains. This section reviews some of the methods used for applying deep learning in FDD and discusses the challenges and corresponding solutions currently faced.

4.1 Autoencoders (AE) and Their Variants

Autoencoders, a fundamental type of neural network in deep learning, are particularly suited for unsupervised learning tasks in FDD. They consist of an encoder that compresses the input and a decoder that reconstructs the output from this compressed representation. This architecture makes them excellent at learning efficient data representations, which is crucial for anomaly detection in industrial processes [46]. AEs and their variants are powerful and versatile tools for FDD in industrial systems, as they can learn from unlabeled data, handle noisy and complex data, and detect subtle and complex fault patterns.

Variants of AEs like Stacked Denoising AE (SDAE) and Distributed Ensemble Stacked AE (DESAE) have been successfully applied in complex industrial environments [47]. These models excel in extracting valuable features from noisy data, a common challenge in industrial settings. SDAE is an extension of AE that adds noise to the input data and trains the model to recover the original data from the noisy data. This way, the model can learn more robust and invariant features that can capture the system's normal behaviour and detect anomalies that deviate from it. SDAE can also be stacked with multiple layers of AEs to form a deep neural network that can learn more abstract and high-level features from the data [48]. DESAE is another extension of AE that combines multiple SDAEs to form an ensemble model that can improve FDD performance and reliability. Each SDAE in the ensemble is trained on a different subset of the data, and the outputs of the SDAEs are aggregated by a fusion layer that can learn the optimal weights for each SDAE. This way, the model can leverage the diversity and complementarity of the SDAEs and reduce the variance and bias of the FDD results [47].

4.2 Convolutional Neural Networks (CNNs)

CNNs, renowned for their prowess in image processing, have also found extensive applications in FDD [49]. Their ability to extract spatial hierarchies of features from images makes them ideal for analysing visual data from industrial inspection systems1. CNNs comprise multiple layers of artificial neurons that perform convolution operations on the input data, followed by pooling and activation functions. These operations can learn the local and global patterns in the images, such as edges, shapes, textures, and objects [50]. In FDD, CNNs have been used for tasks such as analysing images from visual inspection systems and processing multivariable sensor data. For example, CNNs have been used to detect and classify defects in steel surfaces, such as scratches, holes, cracks, and inclusions, using images captured by cameras or scanners [51]. CNNs have also been used to detect and diagnose faults in wind turbines, such as blade damage, gearbox failure, or generator malfunction, using images captured by drones or thermal cameras [52]. Moreover, CNNs have been used to process multivariable sensor data, such as temperature, pressure, flow, or vibration, by transforming them into image-like representations, such as spectrograms, recurrence plots, or Gramian angular fields, and applying convolution operations on them [53].

4.3 Recurrent Neural Networks (RNNs)

RNNs and their advanced variant Long Short-Term Memory (LSTM) are particularly effective in processing sequential and time-series data common in industrial sensor readings. They can capture temporal dependencies and patterns in data for critical FDD tasks[54]. RNNs comprise multiple units that can store information from previous inputs and pass it to the following units. This way, RNNs can learn from the sequential order and context of the data[2]. LSTM is a type of RNN that can overcome the problem of vanishing or exploding gradients, which occurs when the network is too deep, or the sequence is too long. LSTM can selectively remember or forget information over long periods using gates, such as input, output, and forget gates[55]. LSTMs have been employed in various FDD scenarios. [56]. LSTMs have also been used to detect and diagnose faults in semiconductor manufacturing processes, such as wafer defects, tool failures, or process deviations, by using data from sensors, such as optical, acoustic, or vibration sensors[57].

4.4 Deep Belief Networks (DBNs)

A DBN is a generative graphical model, or a class of deep neural network, composed of multiple layers of latent variables ("hidden units"), with connections between the layers but not between units within each layer[58]. DBNs, consisting of multiple layers of stochastic latent variables, are particularly useful in scenarios where the data has a high degree of variability and complexity[59]. DBNs are composed of multiple restricted Boltzmann machines (RBMs), which are generative models that can learn the joint probability distribution of the input data and the hidden variables. RBMs can be stacked and trained in a greedy layer-wise fashion to form a deep neural network that can learn more abstract and high-level features from the data [60].

In industrial FDD, DBNs have been applied for feature extraction and fault classification in processes with complex signal patterns. For instance, DBNs have been used to extract and classify features from vibration signals of rotating machinery, such as bearings, gears, or motors, that can indicate faults, such as cracks, wear, or misalignment

[61]. DBNs have also been used to extract and classify features from acoustic emission signals of metal cutting processes, such as turning, milling, or drilling, that can indicate faults, such as tool wear, breakage, or chatter [62].

5 Challenges and Future Directions in FDD

5.1 Challenges in Implementing Deep Learning for FDD

A significant hurdle in deploying deep learning for FDD is obtaining high-quality, labelled data for training. This is often challenging in industrial settings due to the costs and time required for data collection and labelling. It is affecting the deep-learning models' accuracy and robustness.

Deep learning models demand substantial computational resources, including powerful hardware, which raises concerns about energy consumption and operational efficiency. Deep learning models involve multiple layers of artificial neurons that perform complex mathematical operations on the input data. These operations require significant computational resources, such as GPUs, TPUs, or FPGAs, which may not be available or affordable in some industrial settings. Moreover, deep learning models may have long training and inference times, which may not be suitable for real-time FDD applications. Some solutions have been proposed to address this challenge, such as model compression, model pruning, model quantisation, model distillation, and model parallelisation.

Despite their effectiveness, deep learning models often lack transparency, making understanding the rationale behind their decisions difficult. This is particularly problematic in industrial settings where comprehending a model's reasoning is crucial for ensuring the reliability and safety of the industrial systems and the trust and confidence of the users and stakeholders. Some solutions have been proposed to address this challenge, such as explainable AI, visual analytics, attention mechanisms, saliency maps, feature visualisation, and influence functions.

Adapting deep learning models to fit into existing industrial systems and workflows can be challenging and require substantial technical and operational adjustments. For example, deep learning models may not be compatible with the legacy hardware or software of the industrial systems or may not conform to the existing standards or protocols of the industrial communication networks. Moreover, deep learning models may not be able to integrate with the existing FDD methods or tools or may not be able to leverage the industrial practitioners' existing domain knowledge or expertise. Some solutions have been proposed to address this challenge, such as edge computing, cloud computing, hybrid models, and transfer learning.

Future Directions in Deep Learning for FDD:

- Enhanced Model Interpretability: Developing techniques to improve the transparency of deep learning models is vital. This might involve integrating deep learning with rule-based systems or creating new architectures that offer more precise insights into their decision-making processes. For example, some studies have proposed using fuzzy logic or decision trees to interpret the outputs of deep learning models or, capsule networks or graph neural networks to capture the hierarchical and relational features of the data.

- Efficient and Scalable Models: There is a growing need for deep learning models that can manage large datasets without excessive computational costs. This might involve developing new algorithms or techniques that can reduce the complexity or size of the deep learning models or accelerate the training or inference of the deep learning models. For example, some studies have proposed using federated learning or online learning to distribute the computation tasks among multiple devices or nodes or using meta-learning or reinforcement learning to optimise the learning process of the deep learning models.
- Hybrid Models and Transfer Learning: Combining deep learning with traditional machine or statistical methods could balance performance and interpretability. This might involve developing new frameworks or models that can integrate the advantages of both types or that can transfer the knowledge learned from one domain to another. For example, some studies have proposed using ensemble methods or stacked models to combine the outputs of deep learning models and traditional FDD methods or to use transfer learning or domain adaptation to apply the deep learning models trained on one dataset or task to another dataset or task.
- Edge Computing and Real-time Analysis: Shifting towards edge computing for real-time FDD can enhance efficiency, reducing latency and bandwidth usage. This might involve developing new architectures or platforms that can deploy the deep learning models on the edge devices, such as sensors, actuators, or controllers, or that can perform the FDD tasks on the streaming data, such as sensor readings, signals, or videos. For example, some studies have proposed using edge AI or fog computing to implement the deep learning models on edge devices or using convolutional LSTM or attention-based models to process the streaming data.

5.2 Summarization of the Potential of Deep Learning in Transforming FDD

Revolutionizing Fault Detection: Integrating deep learning in Fault Detection and Diagnosis (FDD) has marked a significant milestone in industrial maintenance and operation. Deep learning's unparalleled ability to process and learn from vast and complex datasets has significantly enhanced the accuracy and efficiency of FDD systems. Deep learning models can detect subtle and complex fault patterns that traditional methods might miss, leading to earlier and more accurate fault detection[1]. Deep learning models can also predict potential faults before they occur, enabling more proactive and predictive maintenance strategies.

Despite its impressive advancements, deep learning in FDD still faces challenges like data scarcity, computational demands, and model interpretability. Addressing these challenges through continued research and development is crucial for further enhancing the efficacy of deep learning in industrial applications. Data scarcity refers to insufficient labelled data for training deep learning models, which can affect their performance and generalisation. Computational demands refer to the high computational resources and energy consumption required by deep learning models, which can pose environmental and economic challenges. Model interpretability refers to the transparency and understandability of the deep learning models, which can affect the users' and stakeholders' trust and confidence. Some of the solutions and opportunities that have been proposed to address these challenges are data augmentation, data synthesis, model compression, model pruning, model quantisation, model distillation, model parallelisation, explainable AI, visual analytics, attention mechanisms, saliency maps, feature visualisation, and influence functions.

Integrating deep learning with emerging technologies such as IoT, edge computing, and Industry 4.0, as well as advancements in model interpretability and efficiency, is expected to revolutionise FDD further. IoT devices, such as sensors, actuators, or cameras, can collect and transmit large amounts of data from industrial processes, which deep learning models can use for FDD. Edge computing can enable real-time and distributed FDD at the edge devices, such as sensors, actuators, or controllers, reducing latency and bandwidth usage. Industry 4.0 technologies, such as cloud computing, blockchain, or smart contracts, can provide the infrastructure and platform for deploying and executing deep learning models for FDD, ensuring the security and privacy of the data and models. Moreover, developing more efficient and interpretable models that can reduce deep learning models' energy consumption and carbon footprint without compromising their accuracy and robustness is an essential direction for FDD. Some techniques and methods that can achieve this goal are model compression, pruning, model quantisation, model distillation, model parallelisation, explainable AI, visual analytics, attention mechanisms, saliency maps, feature visualisation, and influence functions.

Further, the future outlook of deep learning in industrial FDD:

The evolution of FDD towards more predictive and proactive approaches, supported by deep learning, is anticipated to reduce downtime and maintenance costs in various industries significantly. Predictive maintenance allows equipment operators and manufacturers to assess the condition of machines, diagnose faults, and estimate time to failure. By analysing vast datasets, deep learning models can predict potential faults before they occur, reducing downtime in industrial operations. Predictive maintenance can benefit industrial applications by lowering costs, increasing productivity, improving quality, and extending lifespan. Deep learning is poised to catalyse transformation in industrial FDD, leading to more intelligent, efficient, and sustainable industrial operations.

Acknowledgments. H.C. appreciates Industrial Engineering And Business Information Systems (IEBIS) at Faculty of Behavioural, Management and Social sciences at University of Twente for supporting the research.

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