



ADVANCED DEEP LEARNING TECHNIQUES FOR INTELLIGENT FAULT DETECTION IN CHEMICAL PROCESS INDUSTRIES

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ABSTRACT

Human-friendly analysis of chemical process industries is a nonlinear dynamic system. This paper also points out a great research issue of smart and scalable monitoring methods as the traditional statistics-based and model-driven methods are often not sufficient in discovering complex relationships with high-dimensional data due to the gradual digitalization of industry. The purpose of this paper is to review and analyses existing work on deep learning-based methods for chemical processes monitoring and fault detection. This method provides an overview of approaches based on architecture like the autoencoder, CNN, RNN, and hybrid models and their deployment in benchmark scenarios or real industrial applications. The results indicate that deep learning models enhance fault diagnosis performance via automatic feature extraction, early anomaly detection and effective modelling of temporal dependencies. Hybrid and attention-based models fast-track robustness and diagnostic capability even further. Emphasizing the practical significance of deep learning that extends beyond traditional use cases, the study mentions areas such as predictive maintenance and process safety and operational optimization. It applies for United Nations Sustainable Development Goals (SDG 9, SDG 12, SDG 7), to realize any kind of industry with high efficiency and sustainability.



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I. INTRODUCTION

Monitoring understood chemical processes is a key factor in plant-safe operating, with under overhead monitoring being paramount to success. PD provides continuous observation of process variables to identify abnormalities, diagnose faults and prevent failures. (Advanced Fault Detection and Diagnosis) in detection of dangerous accidents and reducing economic damage. Modern-day industrial systems are becoming increasingly complex in nature and require more advanced methodologies for effective condition monitoring to be adopted, transitioning from traditional statistical techniques towards the usage of artificial intelligence (AI) which facilitates better fault detection and diagnosis measures [1].

In recent years, data-driven approaches are attracting increasing attention thanks to their ability to model complex non-linearity and temporal correlation of chemical processes [2], [3] which is difficult for the traditional model-based approach. Some of the correlations in modern industrial plants are highly nonlinear, making it impossible for classical linear techniques such as Principal Component Analysis to model complex dependencies [4], so this is essential. As a result, there has been an increasing number of studies demonstrating that deep learning architectures can outperform traditional approaches by autonomously deriving representative features and identifying complex patterns directly from high-dimensional process data [5]. These models are well-suited to address the most serious fault in conventional methods for examining chemical production, which is the dynamic and high-dimensional nature of chemical production where the complexity is embedded [6]. Deep learning in combination with machine learning methods like bidirectional long-term memory neural network, fully connected neural networks, and extra trees algorithms have been proven to increase fault detection rates of complex chemical processes like the Tennessee Eastman process [7]. The process used in this simulation is widely known as the Tennessee Eastman Process, which is a common benchmark for metrics of success in methods that deal with monitoring and control of processes as it models real-life chemical plant behaviors with complex dynamics under various fault scenarios which establish a good ground for validating techniques to implement advanced algorithms for fault detection and diagnosis [8], [9]. This platform includes a product condenser, reactor, vapor-liquid separator, product stripper and recycle compressor with 41 measured variables and 12 manipulated variables that produce highly time-varying, nonlinear, strong coupling effects data across 22 different health states consisting of 21 fault categories and normal operation for more stringent assessment [10]. The complexity of the Tennessee Eastman Process dataset, which encompasses a variety of fault scenarios and detail-rich interactions among the subtle dynamics of an operational plant, makes a robust procedure for fault detection and identification essential; deep learning models are increasingly showing great potential in fulfilling this role [11-13].

As a result, deep autoencoders and recurrent variational autoencoders have been successfully utilized in anomaly detection and fault diagnosis of this nature system with superior performance compared to traditional statistical methods [8], [14]. In addition, merged deep learning models with ensemble networks, like Autoencoder-assisted Feature Ensemble Net (AFE-Net), have shown superior performance in identifying the nascent fault which could be subtle inside process data and hard to identify [15], [16]. These measurements and changes are representative of nonlinear and nonstationary nature of the industrial processes where they are often used thus showcasing how these challenges make deep learning a powerful tool to address large-scale as well as high-dimensional data. Thus, this tutorial review will provide a systematic survey of the current state-of-the-art deep architecture and methodologies applied to chemical process monitoring and fault detection, critically addressing their potential applicability to real industrial cases. The highlight will be on how these methods are able to utilize the distinctive capabilities of deep architectures, like modeling sequential data and recreating nominal operating conditions [17], [18] as well as improve fault detectability and minimizing false alarms for intricate chemical systems. These trends include the exploration of quantum computing-based deep learning methods, which have the potential to provide unique solutions for addressing computational limits and improving fault diagnosis in industrial processes, such as that used in the Tennessee Eastman Process [19]. This assists in reducing time consumption such as training deep learning models on immense industrial datasets for fault detection classification. Classical methods like Principal Component Analysis (PCA) and model-based approaches rely on simplistic assumptions, failing to account for complicated nonlinear dynamics.

As data, such as those from the sensors and distributed control systems become more widely available process data-driven methods have received significant attention in particular deep learning. These sophisticated deep learning-based models have the power to automatically extract hierarchical features and detect more nuanced patterns which contain information about process anomalies, effectively addressing the challenges presented by traditional methods that struggle in dealing with noisy, correlated, and high-dimensional industrial processes. However, a major drawback of implementing deep learning models for fault diagnosis is the interpretability issue, also known as "black box," nature of deep learning models [20], making it difficult to identify the failure root. This results in limited use of these approaches in industrial settings where safety is an important parameter as revealing the underlying mechanism of a fault for prevention and system tuning is critical [21]. As a result, research increasingly focuses on interpretable deep learning models and explainable AI methods that allow us to understand the decision-making process inside these complex algorithms so as not only to increase trust towards their results but also make it easier for them to be used in industrial fault detection and diagnosis pipelines. Machine learning approaches benefit from automatic feature extraction, making deep learning a promising technique to achieve better fault classification performance for complex industrial systems. This survey will cover various deep learning architectures including convolutional neural networks, recurrent neural networks and their sophisticated variants exploring their respective contributions and feasibility of addressing the distinctive features presented in chemical process data for robust monitoring and fault diagnosis. A comparative summary of prominent deep learning and traditional techniques in the context of fault detection and diagnosis for chemical process monitoring is provided in Table 1.

Table 1: Deep Learning Techniques for Chemical Process Monitoring and Fault Detection.

Sr. No.	Technique / Method	Model Type	Key Application	Dataset / Process	Key Features	Advantages	Limitations
1	Principal Component Analysis (PCA)	Statistical Method	Fault detection	Industrial processes	Linear feature extraction	Simple and fast	Poor for nonlinear systems
2	Convolutional Neural Network (CNN)	Deep Learning	Fault classification	Chemical process data	Spatial feature learning	High accuracy	Needs large dataset
3	Recurrent Neural Network (RNN)	Deep Learning	Time-series monitoring	Dynamic processes	Sequential modeling	Captures temporal behavior	Vanishing gradient
4	Bidirectional LSTM (Bi-LSTM)	Advanced Deep Learning	Fault detection	Tennessee Eastman Process	Bidirectional sequence learning	High detection accuracy	High computation
5	Autoencoder (AE)	Unsupervised Learning	Anomaly detection	High-dimensional data	Feature compression	Detects unknown faults	Low interpretability
6	Variational Autoencoder (VAE)	Probabilistic Model	Fault diagnosis	Nonlinear systems	Latent variable modeling	Handles uncertainty	Complex training
7	Feature Ensemble Network (AE-FEN)	Hybrid Deep Learning	Incipient fault detection	Complex chemical plants	Feature fusion	Detects subtle faults	Model complexity

Source: Authors (2026).

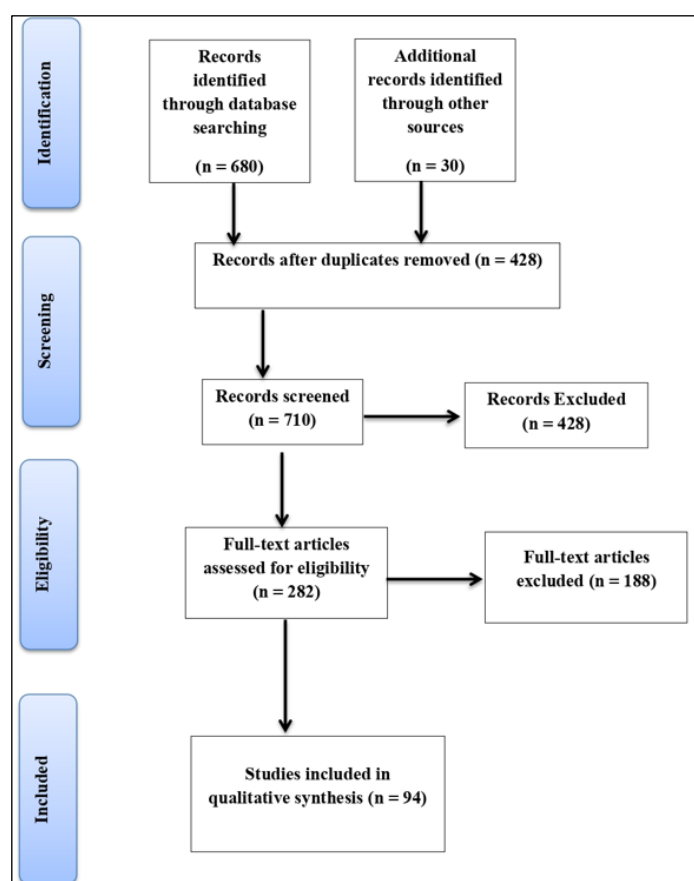


Figure 1: PRISMA flowchart for article selection process.

Source: Authors (2026).

The PRISMA diagram in figure 1 depicts the systematic selection of studies with initial inclusion from databases (n=680) and other sources (n=30), followed by removal of duplicates. From the 710 records screened, 428 were eliminated and 282 full-text articles were evaluated for eligibility. Ultimately, 94 high-quality studies underwent qualitative synthesis after the exclusion of a further 188 full-text manuscripts.

II. FUNDAMENTALS OF PROCESS MONITORING AND FAULT DETECTION

The overall structures of a process monitoring system, with data acquisition and feature extraction as input, followed by fault detection (FD), fault diagnosis (FDD), and root cause analysis (RCA), are depicted in figure 2. It also identifies the types of common faults that can occur in chemical processes, allowing for the systematic identification and mitigation of abnormal operating conditions.

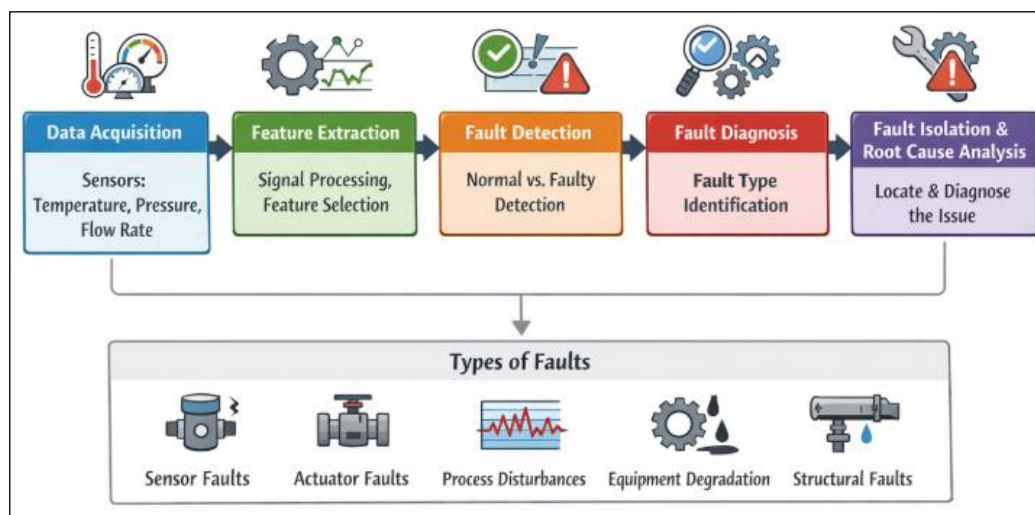


Figure 2: Process Monitoring and Fault Detection Framework.
Source: Authors (2026).

II.1 PROCESS MONITORING FRAMEWORK

A standard process monitoring architecture primarily contains a series of interlinked steps that provide reliable processing and timely detection of abnormal situations. The first step is Data acquisition that refers to data from real-time measurements such as temperature, pressure, and the flow rate taken using various sensors placed in the process. Raw data extracted from sensors is processed through feature extraction to derive indicators indicating system behavior. Using these characteristics, fault detection techniques are used to identify healthy and faulty operating conditions. When a fault is detected, fault diagnosis identifies and classifies the cause of the deviation. Here, fault detection is the identification of whether a fault occurs, and fault diagnosis is the determination of what specifically caused that error to occur so that it can be corrected appropriately. The increased reliance on reliable and timely Fault Detection and Diagnosis in the modern engineering systems for operational safety and resilience poses challenges, particularly in complex and data-intensive environments due to limitations of model-based or rule-based approaches [22]. Abnormal operation settings in such domains are still increasingly supplemented with intervention, which leads to a high number of production accidents. Data preprocessing, training PCA and LSTM autoencoder models, calculating monitoring statistics, determining thresholds, and marking anomalies if those thresholds are cancelled in the workflow shown in figure 3 [23].

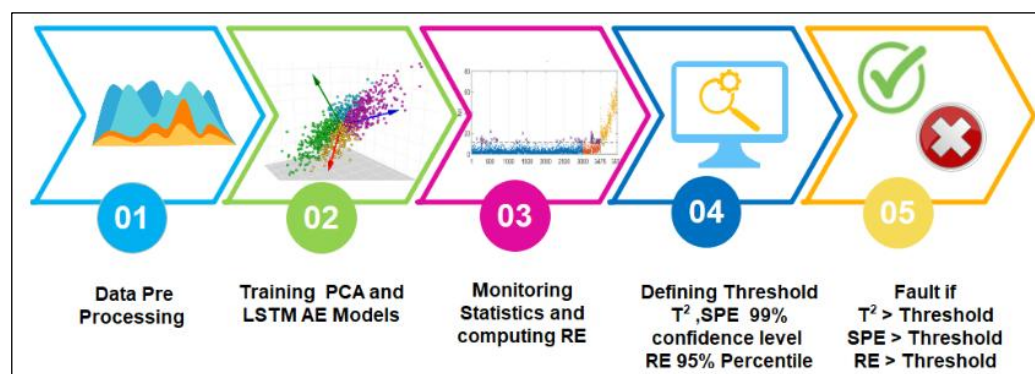


Figure 3: PCA–LSTM Autoencoder–based Anomaly Detection Pipeline.
Source: [23].

As a result, the implementation of a reliable automated system for detecting and diagnosing faults is critical to improving process safety as well as efficiency in modern-day industrial processes. Consequently, a process monitoring system should not only predict the next-step values of quality variables accurately but also efficiently to facilitate timely corrective intervention before considerable disturbances [24]. This highlights the performance of technologies predictive monitoring, which use a knowledge-based understanding approach to classify deviations based on analytical techniques [25]. These systems function by determining normal behaviors and subsequently detect deviations from it that may be an early indicator of failure [26].

II.2 TYPES OF FAULTS IN CHEMICAL PROCESSES

In these systems, faults may occur at smart sensors (e.g., faulty measurements) or control devices (e.g. faulty control actions), leading to compromised system performance. Sensor faults happen when measurement devices give wrong or noisy data because of calibration errors, drift, or failure, which results in incorrect information about the process. Actuator faults are relevant to control elements like valves, pumps or motors that fail to respond accordingly to the control signal. Process disturbances are external or internal deviations like variations in feed composition, changes in temperature, and environmental influences which interrupt the normal operation.

The gradual decline in the performance of a system due to wear, fouling corrosion or aging of components reducing the efficiency of a system is called equipment degradation. Finally, there are structural faults, either of material failure, leakage or blockage in the system infrastructure, which can severely impact safety and operations. As detailed, these distinct fault types require extensive monitoring approaches that can detect small deviations in several operational parameters to ensure system integrity and avoid significant failures [27]. Figure 4 shows one of model-based approach where outputs from the process compared with model predictions for detection, isolation and management of a fault in system [28]. A fault, in general terms, is defined as an unallowed alteration of at least one process parameter from a suitable state and may be organized to abruptness category type such as clear faults, intermittent and gradual [29]. The detection latency, which is the latent period before a fault materially influences the process, may widely vary with respect to fault types and will require complex models for accurate estimation of fault commencement and magnitude [30], [31]. The output of process monitoring in terms of fault detection, diagnosis and isolation as well as root cause analysis is a structured solution to these challenges. Detection indicates if we have abnormalities, diagnosis states what kind of fault we have, isolation points out at what component or subsystem we deal with, and root cause analysis gives us the deepest insight of the reasons that triggered the fault to apply appropriate corrective and preventive actions. In this context, a fault is an external register which makes the system behave differently than it was designed to do and can be classified based on its physical location as either component, actuator or sensor faults [32]. This delineation is important for developing targeted diagnostic strategies, as independent fault origins need separate remedial actions [33-35]. From a temporal viewpoint, faults could also be categorized as sudden or drift, which is based on if the parameter deviation is stepwise or progresses over time and usually drift behavior indicates equipment degradation [36]. The important stage of the process monitoring framework, fault types, and their role in secure and dependable industrial operation are summarized in Table 2.

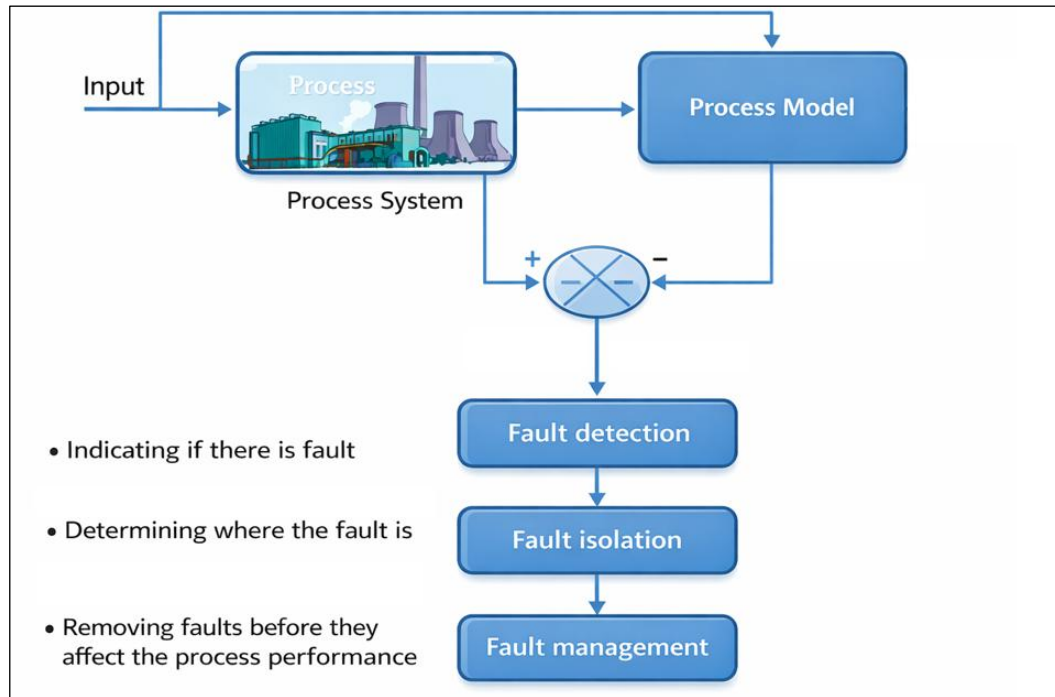


Figure 4: Model-Based Fault Detection and Diagnosis (FDD) Framework.
Source: [28].

Table 2: Process Monitoring Framework and Fault Types.

Stage / Fault Type	Description	Key Components	Significance
Data Acquisition	Collection of real-time process data	Sensors, instruments	Provides input for monitoring
Feature Extraction	Processing raw data into meaningful features	Signal processing tools	Improves detection accuracy
Fault Detection	Identification of abnormal conditions	Detection algorithms	Early warning of faults
Fault Diagnosis	Identification of fault type and cause	Classification models	Supports corrective action
Types of Faults	Sensor, actuator, disturbance, degradation	Process components	Affects safety and performance

Source: Authors (2026).

III. DEEP LEARNING TECHNIQUES FOR FAULT DETECTION

Key deep learning models for fault detection that can learn spatial, temporal and nonlinear patterns in the PID process data such as Autoencoders, CNNs, RNN/LSTM and hybrid architecture are illustrated in figure 5. Additionally, it emphasizes more sophisticated techniques like attention mechanisms and graph-related models that incorporate feature relevance consideration and relationship reasoning across the system to facilitate fault diagnosis.

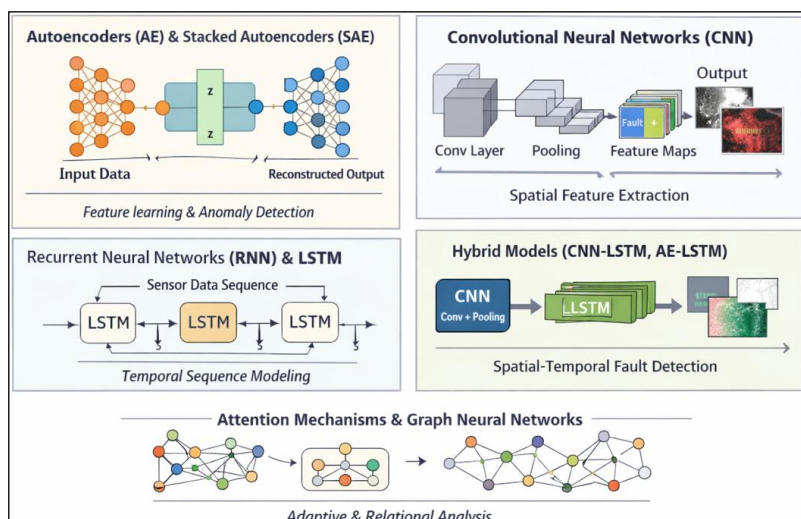


Figure 5: Deep Learning Techniques for Fault Detection in Chemical Processes.
Source: Authors (2026).

III.1 AUTOENCODERS (AE) AND STACKED AUTOENCODERS (SAE)

Autoencoders have proven valuable in chemical process monitoring, due to their ability for unsupervised feature learning and anomaly detection. These neural networks work by encoding the process data into a lower-dimensional latent space (via an encoder) and then reconstructing it back to original form (via a decoder), therefore learning compact and meaningful representation of process data. This allows the model to learn the normal operating patterns of the system during this process. The reconstruction error is then obtained and since the output can differ significantly from the input in case of fault it serves as an indicator. Autoencoders are a popular neural network architecture, which can compress input data into a latent representation of lower dimensionality and then decompress it, with anomalies being detected via an increased reconstruction error [7]. This mechanism exploits the fact that an autoencoder trained only on normal operational data will present a higher reconstruction error for anomalous inputs since they do not belong to the normal distribution of the learned data [37]. This diffuse nature of fault occurrence makes it very hard for human-noise systems to define conditions upon which faults will occur and their trigger rates [38]. This ability makes autoencoders highly applicable for unsupervised fault detection of chemical processes, which is non-linear and high dimensional, with the consideration that comprehensive labeled fault data is often not readily available. Since in classical Principal Component Analysis we performed an intrinsic linear transformation, it failed to adequately model nonlinear process variables [39]; therefore, defective detection might not be accurate when monitoring fault in more complex systems compared autoencoders were a more robust option for linear/nonlinear process monitoring [40].

Autoencoders can be used to work with incomplete and/or noisy datasets, which are often encountered in industrial environments. The stacked autoencoders which are formed by cascading linear transformation methods add more advantage over autoencoders by learning hierarchical and high-level features from the complex process dataset. Stacked autoencoders and their modified variants have received very good performance in industrial benchmark datasets, especially when adapting to missing or partially observed data as these methods can learn deeper spread representations that contribute positively towards fault detection. The basic architecture of an autoencoder is composed of an encoder that compresses the high-dimensional input data into a lower dimensional latent space, and a decoder that reconstructs the reconstructed data from this lower dimensional representation [4], [41]. The encoder compresses the data and maps from high-dimensional space to low-dimensional space, while the decoder generates original data from compressed code [42]. By learning the structure of the data, the network can identify anomalies as deviations from this learned structure [43]. Autoencoders are trained in an unsupervised manner, which makes them very suitable for cases where anomalous data can be heterogeneous and not necessarily annotated with explicit labels [44]. Variational autoencoders are another advancement of the autoencoder architecture that brings a probabilistic perspective to the latent space, allowing for generative modeling capabilities as well as regularization during training such that overfitting can be reduced. Figure 6 shows a deep learning pipeline that involves using autoencoders and classification models to process vibration data to detect faults, which is helpful for health index construction to discover the state of system monitoring. [45].

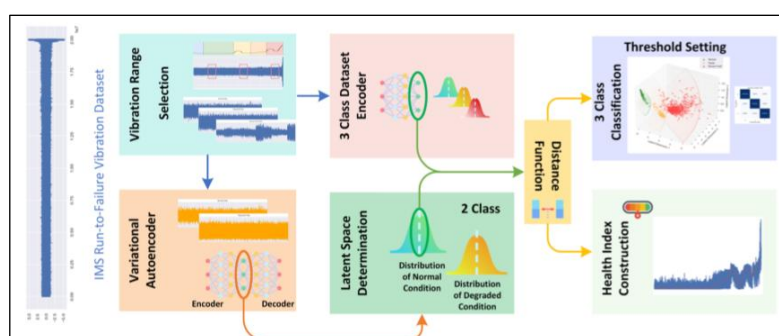


Figure 6: Deep Learning-Based Fault Detection and Health Index Construction Framework.
Source: [45].

Unlike regular autoencoders, stacked autoencoders have multiple layers where the output from one layer's autoencoder is fed as input to the next [46]. The deeper architecture, including more hidden layers in both encoder and decoder locations, makes stacked autoencoders capable of capturing relatively complex relationships within the data [18], which allows to represent high-dimensional features or nonlinearities on fault indications as well [47], [48].

III.2 CONVOLUTIONAL NEURAL NETWORKS (CNN)

Convolutional neural network (CNN) offers a feasible solution to fault detection in chemical processes owing to its strength in capturing spatial correlations among simultaneous process variables. Process data in multivariate systems often have structured relationships that are well suited for extraction by CNNs through convolutional operations. Such networks use filters to extract local patterns and return feature maps that provide an indication of the states of interest in the process. This property enables CNNs to handle high-dimensional data flows, their advantages lying in the ability to pick up on signals that powerful statistical tests might fail to detect, especially when temporal or image-like encodings of process variables are used [49]. CNNs are capable of automatically extracting the most important features, making them useful for anomaly detection from recurrence plots based on multisensory streams, and allowing them to diagnose faults in real time [50]. In addition, it is possible to combine advanced CNN architecture with other deep learning models, contributing to hybrid systems that improve robustness and interpretability in industrial fault diagnosis. Several deep learning methods have been applied to fault detection, with CNNs being one of the most prominent due to their high performance in terms of complex features and classification. Input images, illustrated in the figure7 CNN framework as requiring passes through convolution layer followed by pooling and fully connected layers to extract features from input data and perform their final classification [51]. CNNs take advantage of their hierarchical design to recognize patterns associated with faults through progressively abstracted features learned from raw process data and frequently show superior performance compared to more traditional machine learning algorithms when sufficiently large datasets are available.

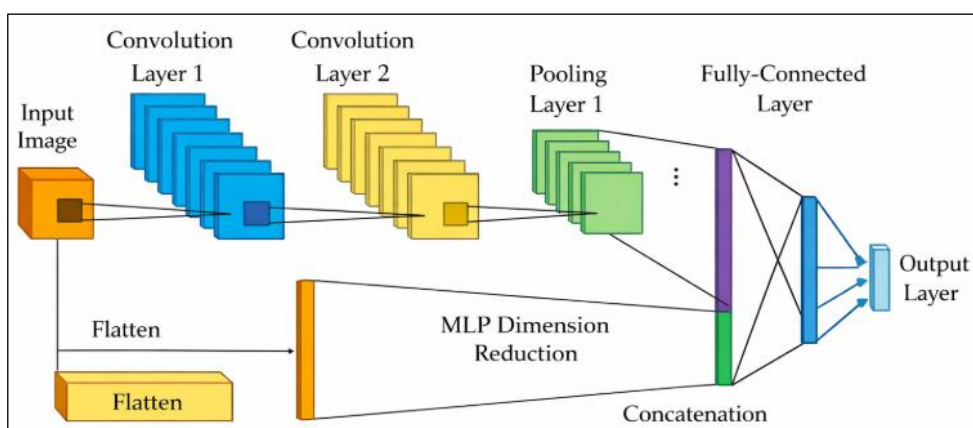


Figure 7: Convolutional Neural Network (CNN) Architecture for Feature Extraction and Classification.
Source: [51].

Learning these localized features significantly increases the accuracy of fault classification by CNN-based models, and as a result, enables robust discrimination between normal and faulty operating conditions. They are especially good at dealing with high-dimensional and multidimensional process data where traditional methods can struggle to find hidden correlations. This is one of the main reasons that, with better feature extraction ability by CNNs, performance-wise they provide a more reliable approach for monitoring and fault identification in chemical process systems. The basic structure of a CNN consists of convolutional layers that extract features via learnable filters and pooling layers that down-sample the data while maintaining most vital information [52]. Compared to other algorithms, CNNs are particularly suited for processing time-series features or imaging-based representations of process variables, as they create a processing chain with multiple layers that distinguish increasingly abstract levels of regularities in the series data [52]. The approach of CNNs to learn feature hierarchies purely from raw sensor data, avoiding the need for explicit feature engineering, has significant utility in complex industrial fault detection scenarios [53].

III.3 RECURRENT NEURAL NETWORKS (RNN) AND LSTM

Inherent to chemical processes that their systems are dynamic, with system behavior changing with time and depending on previous states. This makes Recurrent Neural Networks a natural candidate for those environments, since they are made to approximate temporal dependencies in sequential input. Because RNNs have internal memory, they can learn to model the relationships between current and previous observations, making them suitable for analyzing time-series blue-tooth sensor data. RNNs can learn time-varying patterns that may correspond to gradual increase of process anomalies or the incipient stage of faults, which is useful for proactive process monitoring [54]. More specifically, RNNs handle sequential inputs by using the output of a hidden layer from one temporal step as an input to the next hidden layer, allowing networks to learn and perform complex data transformations over long ranges of timesteps [55]. Due to the diminishing target problem in traditional RNNs when learning long-term dependencies, Long Short-Term Memory neural networks have become effective approaches for fault detection among RNN architectures [56]. Their advanced gating functionalities (input, output and forget gates) are what makes it possible, wherein input gate helps them in remembering past states and forget gate enables them to forget the state [57]. The specialized neural network architecture of Long Short-Term Memory (LSTM) networks overcomes the limitations of traditional RNNs regarding long-term dependencies.

LSTM networks are designed with memory cells and gate variables that enable them to keep significant information over longer time spans, as well as skip out on irrelevant details. In chemical processes, this ability is crucial to detect abnormalities where deviations could occur gradually or have a time-lag feature. In particular, the insertion of input, output and forget gates in LSTMs allows them to learn which features are important temporal behavior that needs to be retained in their memory cells, which significantly enhances reliability and accuracy where it comes to fault diagnosis. Figure 8 depicts the receiving of raw data from measurement signals to online processing and then uses a PdM analysis to detect, locate, and predict faults in rotating machinery systems [58]. This architecture enables LSTMs to mitigate the vanishing gradient issue that traditional RNNs face, helping to retain important information from time steps in earlier training cycles [59-61]. The internal memory and gating mechanisms allow RI-GEGRs to capture long-term temporal dependencies much more effectively due to greatly enhanced gradient flow [62].

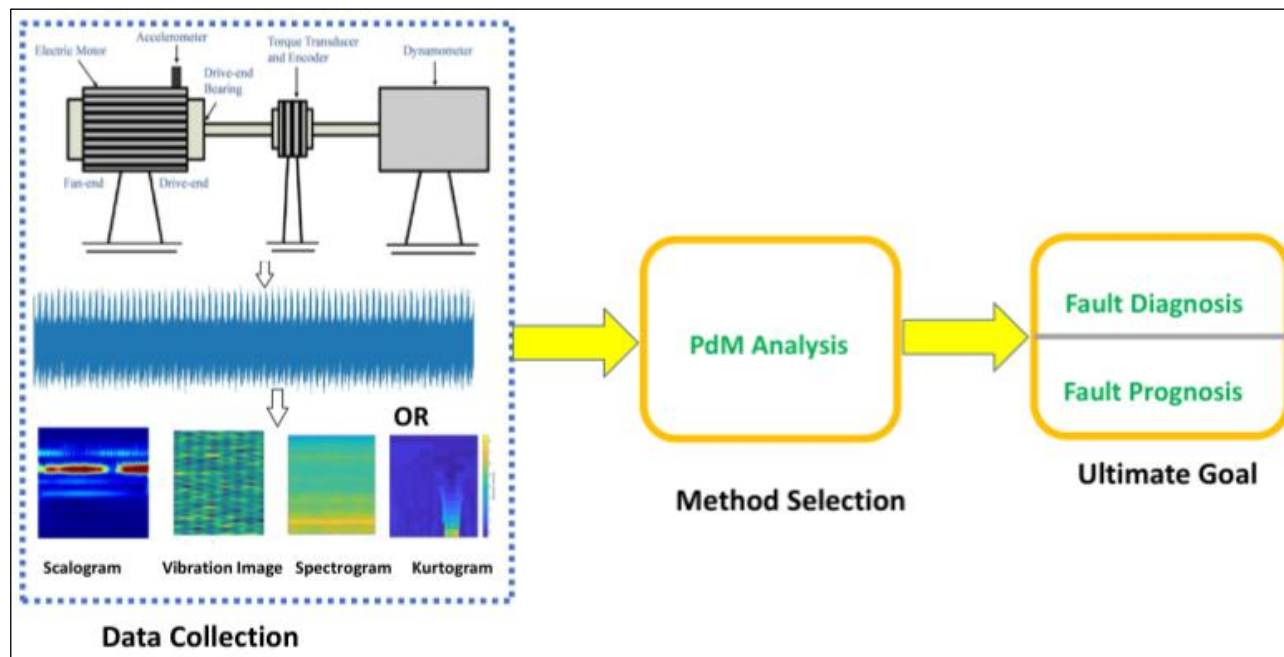


Figure 8: Predictive Maintenance Framework for Fault Diagnosis and Prognosis Using Vibration Signal Analysis. Source: [58].

Hybrid architectures, such as CNN–LSTM combine the strengths of both structures by using CNNs for spatial feature extraction and LSTMs for the temporal analysis. These models are based on the integrated approach, which can facilitate successful and effective detection of fault dynamics and time-delay effects in process and provide greater accuracy and reliability to monitoring systems. Although standard RNNs have demonstrated success in various tasks, challenges like vanishing or exploding gradients during the training process can significantly limit their performance with sequences of longer length [63], [64]. These limitations can be addressed with more advanced RNN variants, such as long short-term memory (LSTM) networks and Gated Recurrent Units, which use complex gating mechanisms to control information flow in the model more effectively, improving their ability to fit time-series data with long-range dependencies [65]. LSTMs specify an input gate, a forget gate and an output gate to regulate the transport of information which enables them to selectively save and recall information over long periods [66], [67]. This unique architecture allows LSTMs to remember important information over long sequences and avoid vanishing gradient problems, which often limit the effectiveness of traditional RNNs in learning long-term dependencies [68-70]. The forget gate decides what will be thrown away from the previous cell state, the input gate decides what new information should be saved in this cell, and the output gate controls what is sent to hidden state [71].

III.4 HYBRID DEEP LEARNING MODELS

To effectively model the complexity of chemical processes, recent trend in process monitoring is to adopt hybrid deep learning models that combine various architectures. These approaches typically integrate the advantages of various methods to incorporate both spatial and temporal features associated with process data. A common approach is to utilize CNN–LSTM frameworks for deriving spatial–temporal features, where convolutional layers capture local correlations and LSTM units model time-dependent dynamics. These combined strengths harness the CNN's ability to extract features in a hierarchical manner, along with LSTM's ability to learn long-range temporal dependencies, resulting in the establishment of a strong mechanism for decoding complex fault signatures from intricate process dynamics [72]. Additionally, kernel deep learning has been introduced in soft sensor context with hybrid variable-wise weighted stacked autoencoders [73]. Another potential direction of development related to emission monitoring systems can be found at the crossroads between explainable artificial intelligence (AI) and deep learning, aiming for more transparent and reliable algorithms catering to emissions-sensitive processes [74]. These hybrid methods typically combine anomaly detection and fault classification, employing aggregated feature representations resulting in higher diagnostic accuracy than standalone models. RRNNs help understand the spatio-temporal aspects of environmental data [75], hence, are suitable to develop hybrid deep approaches by aggregating CNN with RNN or LSTM for accurate detection and prediction of fault in complex industrial processes.

Likewise, hybrid systems such as Autoencoder–LSTM facilitate feature extraction and predictive functionality simultaneously, enabling early fault anomaly detection from learned data representations. Graph Neural Networks have also received attention in modeling process topology, where the connections between different units or variables are considered as interconnected nodes, providing a broader view of inter-system interactions. It has been shown that hybrid CNN-LSTM networks can achieve a better result about anomaly detection and fault prediction tasks in industrial applications on the premise of modeling both spatial and temporal information [76]. This is especially apparent in hydraulic systems, where integrated CNN and LSTM architectures outperformed traditional methods for anomaly detection [77]. Integrated frameworks which merge CNN, Autoencoders and LSTM network have shown improved performance on multi-class fault classification tasks. These diverse hybrid methods enhance feature extraction, improve detection accuracy, and rarefaction of a fault diagnosis more accurately in complex chemical processes.

III.5 ATTENTION MECHANISMS AND GRAPH-BASED MODELS

Attention mechanisms and graph based deep learning structures have also been integrated into these advanced models, highlighting their strengths in accurate fault detection and diagnosis for chemical processes. Attention mechanisms allow the model to exploit different importance levels of process variables by focusing on more significant features for fault identification. This weighted force fitting aids model interpretability and helps to emphasize which features contribute most towards unexpected behavior. To illustrate, Dual-Stage Attention RNN architectures can learn input-level attention weights as well as temporal attention weights simultaneously, allowing highlighting of relevant features and significant time steps while forecasting [78]. Likewise, the channel–spatial attention method can improve feature importance as well as reduce noise in CNN-LSTM for real-time sensor fault detection [79]. Additionally, the combination of these attention mechanisms with LSTMS allows us to forecast future patterns of important variables, providing good early prediction results in several fault cases [80]. Instead of focusing on a single feature among many, attention can be incorporated into hybrid deep learning architectures that dynamically emphasize important features for better risk recognition under changing operational scenarios [81]. This flexibility allows them to perform especially well in settings with skewed datasets, a frequent occurrence within fault identification approaches [82]. Graph-based approaches, including popular paradigms like Graph Neural Networks, show great potential in modeling the complex relationships between various process variables and sensors throughout a chemical plant. A four-stage approach of understanding the data, learning patterns, diagnosing faults and finally taking maintenance actions is shown in figure 9 which enhances reliability and performance levels of a system [83].

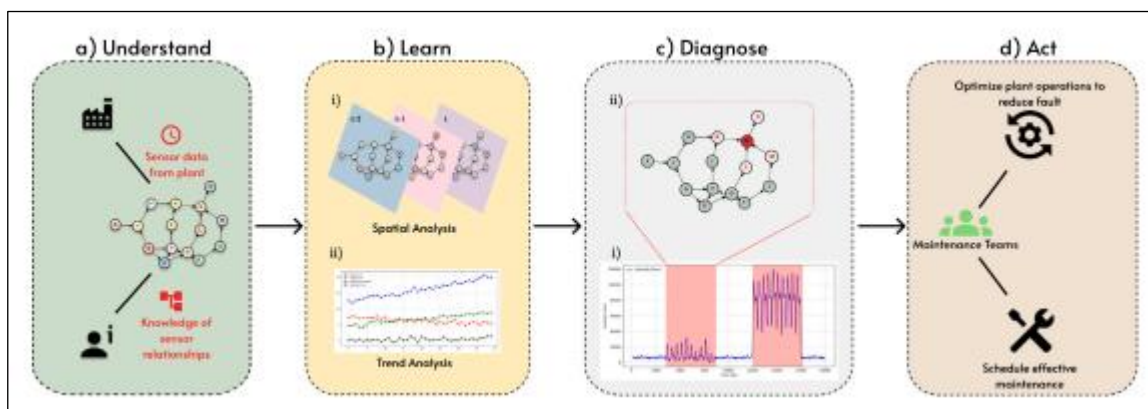


Figure 9: AI-Based Predictive Maintenance Workflow: From Data Understanding to Maintenance Action.
Source: [83].

This is an approach where the process is represented with graph models (a network of interconnected nodes and edges), and each node corresponds to a specific process variable or unit. These representations can effectively capture the complexities of relationships and interactions in the system. Graph Attention Networks (GAT) introduced attention heuristics along with the underlying graphical structures to better learn the spatial and temporal dependencies between variables in input data. At a deeper level, tailored graph neural networks such as EG-SAGCN further modify edge weights and use spatial attention to better learn local and global relationships in sensor networks [84]. This enables a more detailed understanding of how disturbances diffuse over interlinked systems. Considering their capability of naturally model relationships between entities, a characteristic that suits well for property modeling [85] and addresses challenges in traditional descriptor-based methods. In Table 3, a consolidated comparison of various prominent deep learning architectures tailored for fault detection in chemical process systems is provided, specifying their learning modes, characteristics and applications. It shows how different models based on data patterns can systematically improve the accuracy and reliability of detection using spatial, temporal, and relational patterns in process data.

Table 3: Deep Learning Techniques for Chemical Process Monitoring and Fault Detection.

Technique	Model Category	Learning Type	Key Application	Data Type	Key Features	Advantages	Limitations	Typical Use Case
Autoencoder (AE)	Neural Network	Unsupervised	Anomaly detection	High-dimensional	Reconstruction error	Detects unknown faults	Low interpretability	Industrial monitoring
Stacked Autoencoder (SAE)	Deep NN	Unsupervised	Feature extraction	Complex data	Hierarchical learning	High accuracy	High complexity	Missing data cases
CNN	Deep Learning	Supervised	Fault classification	Multivariate	Spatial features	High accuracy	Needs large data	Sensor systems
RNN	Deep Learning	Supervised	Time-series analysis	Sequential	Temporal modeling	Captures dynamics	Vanishing gradient	Process monitoring
LSTM	Advanced RNN	Supervised	Fault prediction	Time-series	Memory gates	Handles long-term data	High computation	Dynamic systems
CNN-LSTM	Hybrid	Supervised	Spatio-temporal	Time-series	Combined features	High reliability	Complex model	Real-time monitoring
Attention Model	Advanced DL	Supervised	Feature importance	Large datasets	Variable weighting	Better interpretability	Training complexity	Fault diagnosis
GNN	Graph-based	Semi-supervised	System modeling	Network data	Node relations	Captures dependencies	Complex implementation	Large plants

Source: Authors (2026).

The only existing effective methods are those that enhance spatiotemporal feature learning, promote diagnosis capability, and contextualize root cause analysis by identifying the most relevant variables and their interactions which make them increasingly suitable for complex large-scale chemical process systems.

IV. APPLICATIONS IN CHEMICAL PROCESS INDUSTRIES

Figure 10 summarizes the Tennessee Eastman Process (TEP) as a standard system for testing fault detection models with industrial real applications in processes such as petrochemical, polymer, pharmaceutical and wastewater. It emphasizes the primary advantages of deep learning — early fault detection, predictive maintenance, enhanced process safety, and efficient root cause analysis.

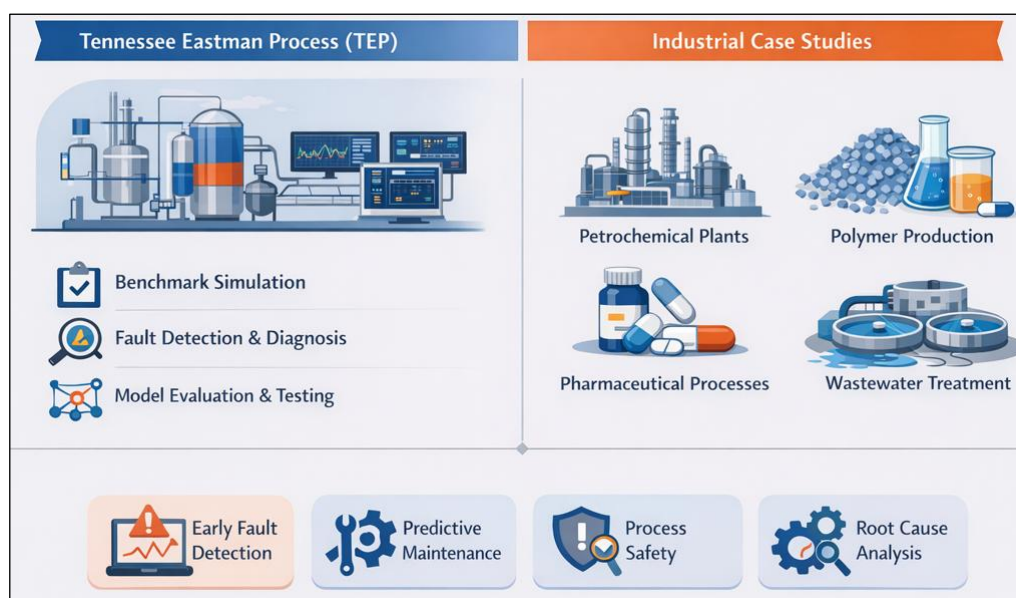


Figure 10: Applications of Deep Learning in Chemical Process Industries.

Source: Authors (2026).

IV.1 TENNESSEE EASTMAN PROCESS (TEP)

The Tennessee Eastman Process is one of the most widely used benchmark systems for process monitoring and fault detection techniques. It reflects a real industrial chemical process including complex reactions, recycle streams and multivariable control structures. Due to its nonlinear and dynamic characteristics, it can provide a test platform for advanced data-driven as well as deep learning-based methods validation. The dataset provides intact operation as well various fault cases that are very important to evaluate performance of a model in detection and diagnosis task, allowing standardized comparisons among different techniques. State-of-the-art results in the context of fault diagnosis on the Tennessee Eastman Process dataset have been reported for advanced GNNs (including with learnable adjacency matrices) over classical recurrent neural networks. As illustrated in figure 11 [86], an abnormal condition is detected based on analysis of these multi-sensor signals, as well as a specific type of fault is classified using a diagnostic model.

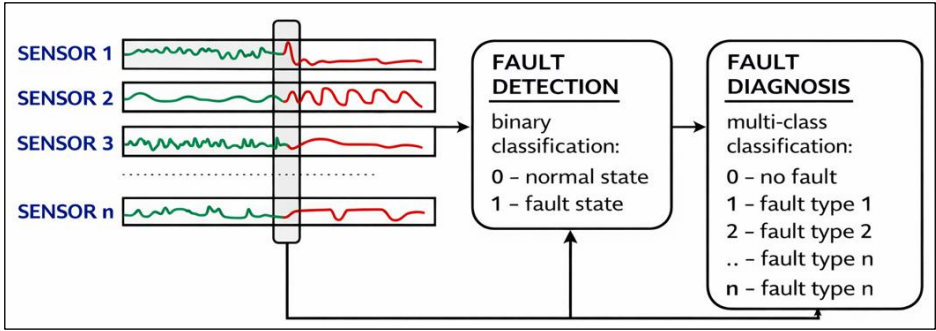


Figure 11: Sensor-Based Fault Detection and Diagnosis Framework.
Source: [86].

This is due to their capability of modeling complex spatial correlations and inter-relational dependencies among the variables that the process encompasses [87]. Yet the continuously changing relations between time series and different operational conditions are still challenging to model [88]. This indicates a need for further explorations to design GNN architectures that can flexibly respond and capture such changes, possibly via employing temporal graph learning methods or integrating physics-informed constraints to improve the generalizability across different operational scenarios [89], [90]. TEP is run over multiple different indicative operating conditions and predefined fault cases, allowing for the systematic evaluation of fault detection and diagnosis algorithms. This benchmark is widely used by researchers to assess model performance across detection accuracy, false alarm rate, robustness under noise and uncertainty. For example, a recent work proposed the new Twin Transformer architecture combined with the Gated Dynamic Learnable Attention mechanism to improve detecting and diagnosing different faults, trained on Tennessee Eastman Process Dataset independently process input data while dynamically adapting attention strategies [9]. Big advantages in accuracy and reliability of fault detection have been shown using deep learning applied to Tennessee Eastman Process. By employing techniques like autoencoders, CNNs, and hybrid architectures that can capture complex patterns inherent in the process data, these approaches have shown improved robustness and generalization by effectively handling multiple fault scenarios.

IV.2 INDUSTRIAL CASE STUDIES

Deep learning-based fault detection methods have been successfully applied to a wide variety of industrial chemical processes. These techniques are used in petrochemical plants and refinery operations to monitor complex reaction networks and dynamic separation units that feature multiple interacting species. Deep learning models are used to monitor reaction parameters for product quality in polymer production. In pharmaceutical processes, they are similarly valuable in providing necessary quality assurance by quickly finding anomalies in batch operations and continuous manufacturing systems. These applications exploit the ability of deep learning to handle high dimensional sensor data, allowing them to detect subtle anomalies that may propagate into significant equipment failures or excursions early, providing operational safety and efficiency. In addition, the use of deep learning in these industrial contexts has contributed to decreased unscheduled downtime and improved resource utilization by enabling proactive maintenance scheduling. Thus, this positive approach is significant in improving overall reliability and economic performance of the system. The efficacy of these approaches on features fusion and ensemble learning underscored that these methods have also been extensively validated to real-world datasets collected from industrial facilities such as wastewater treatment plants in which they are shown superior fault detection performance over single model-based setups [91-97]. There are many practical benefits of incorporating deep learning into process monitoring systems. It allows fault detection as early as possible by recognizing small changes in process behavior before these turns into serious failings. Forecasting equipment degradation and scheduling maintenance interventions can lead to improved predictive maintenance strategies that lower downtime and maintenance costs. It also makes process safety even better, since advanced models can detect abnormal conditions in real time and initiate preventive measures. Additionally, deep learning systems enhance the ability to conduct effective root cause analysis by identifying individual outlier occurrences along with their causative factors, thus allowing for continuous enhancement of chemical process operations [98-100]. Data-driven strategies are crucial to tackling the intrinsic complexities of chemical processes, where dynamic and non-linear interactions make it hard for conventional modelling approaches [101]. Table 4 provides a summary of various industrial applications for deep learning in chemical processes, including faults detection and monitoring, as well as operational efficiency improvement.

Table 4: Applications for Deep Learning in Chemical Process Industries.

Application Area	Process Type	DL Technique Used	Key Function	Benefits
Tennessee Eastman Process	Benchmark system	AE, CNN, LSTM	Fault detection	High evaluation accuracy
Petrochemical Plants	Continuous process	CNN, RNN	Process monitoring	Improved safety
Refineries	Separation units	CNN-LSTM	Fault diagnosis	Reduced downtime
Polymer Production	Reaction systems	Autoencoder	Quality monitoring	Product consistency
Pharmaceutical Industry	Batch process	LSTM, RNN	Anomaly detection	High precision
Wastewater Treatment	Environmental systems	Ensemble DL	Fault prediction	Better reliability
Smart Manufacturing	Industry 4.0	Hybrid DL	Predictive maintenance	Cost reduction
Cyber-Physical Systems	Automated plants	GNN, Attention	Fault & attack detection	Enhanced security

Source: Authors (2026).

In today's Industry 4.0 settings, the scope of deep learning-based approaches goes beyond typical monitoring tasks to recognize unseen defects and provide alerts for possible cyber threats in industrial control systems. This ability is critical for safe, reliable function within highly automated and interconnected chemical process industries.

V. ADVANTAGES OF DEEP LEARNING IN PROCESS MONITORING

Deep learning can hold significant benefits in process monitoring due to its ability to deal with nonlinear and high dimensional data, which are often encountered in complex industrial processes. It can automatically derive the stimulus-relevant feature from raw sensor data, thus removing the manual feature engineering step and lessening reliance upon domain-specific preprocessing unlike traditional methods. It reduces the number of false positives with deep learning models able to learn fine-grained differences and latent features in process data. Furthermore, these methods assist in near-real-time monitoring where persistent analysis of streaming data helps in timely abnormality detection. In predictive maintenance, deep learning can use raw sensor data to detect early signs of equipment failure and predict impending failures. Thus, deep learning methods outperform traditional ones in capturing dynamic connections and underlying processes.

VI. CHALLENGES AND LIMITATIONS

While deep learning has significant potential for chemical process monitoring, several practical challenges hinder its broad industrial application. These have to do with problems concerning data availability, interpretability of models, computational demands and suitability across processes. Since this technique is still in its initial phases, knowing its limitations will help avoid the implementation pitfalls and provide directions for developing efficient and robust fault detection systems.

VI.1 DATA-RELATED ISSUES

One of the significant challenges to applying deep learning in monitoring chemical processes is data. Labeled fault data are limited in many industrial settings because faults happen rarely and do not follow any systematic documentation. For supervised learning, this results in a lack of training samples. Moreover, the datasets usually are heavily imbalanced where there is more amount of normal operating data than faulty conditions available which leads to models being biased towards normal predictions. Dealing with missing, incomplete and noisy sensor data introduces additional complexity in developing a model that accounts for the reliability and accuracy of feature extraction and learning processes.

VI.2 INTERPRETABILITY

Many deep learning systems are black boxes in nature, meaning they do not lend themselves to easy interpretation of internal workings or decisions. The present absence of such insight is particularly limiting in safety-critical industries like chemical processing, where knowing not just that a fault occurred but why it can be crucial. Due to the limited ability of such models to explain themselves, engineers and operators may be reluctant, if not downright fearful, to rely on them — especially in high-stakes environments that mandate very stringent regulatory compliance and accountability.

VI.3 COMPUTATIONAL COMPLEXITY

The implementation of deep learning models involves significant computational requirements. Training complex architectures, such as deep neural networks, requires high processing power and long training times, particularly when dealing with large-scale industrial datasets. In addition, these models typically require extensive datasets to achieve high accuracy, which may not always be available in real-world applications. This increases the cost and complexity of deployment in industrial settings.

VI.4 GENERALIZATION

Generalization remains a critical issue in deep learning-based fault detection systems. Models trained on a specific process or dataset may not perform effectively when applied to different processes due to variations in operating conditions, system configurations, and process dynamics. This limits the scalability and adaptability of such models across different industrial applications, requiring retraining or fine-tuning for each new environment.

VII. FUTURE RESEARCH DIRECTIONS

To address current constraints and improve the performance of those deep learning models, researchers are focused on novel methods and high-performance computer technologies. Future works will surely focus on enhancing the explainability of such models, decreasing dependency on annotated content, and coupling intelligent systems with modern industrial architectures. This will greatly enhance the robustness and practical reliability of deep learning within chemical process monitoring.

VII.1 EXPLAINABLE AI (XAI)

Explainable Artificial Intelligence is emerging as a critical research direction to address the lack of transparency in deep learning models. By incorporating XAI techniques, it becomes possible to interpret model predictions and understand the underlying reasoning behind fault detection and diagnosis. This improves trust and acceptance of AI systems in industrial environments, particularly in safety-critical chemical processes. In addition, explainability supports informed decision-making by providing engineers with actionable insights rather than only prediction outputs.

VII.2 TRANSFER LEARNING AND FEW-SHOT LEARNING

Transfer learning and few-shot learning approaches offer promising solutions to the challenge of limited labeled data in industrial applications. These techniques enable models trained on one process or dataset to be adapted to another with minimal additional data. This reduces the need for extensive data collection and labeling efforts. Such approaches are especially useful in chemical industries where fault data are rare, allowing models to generalize knowledge across different plants and operating conditions.

VII.3 INTEGRATION WITH INDUSTRY 4.0

The integration of deep learning with Industry 4.0 technologies is expected to significantly enhance process monitoring and fault detection capabilities. The use of IoT-based systems enables real-time data acquisition from sensors and equipment, facilitating continuous monitoring. Digital twins provide virtual replicas of physical systems, allowing real-time simulation, prediction, and optimization of process performance. Edge computing further supports rapid decision-making by processing data closer to the source, reducing latency and improving system responsiveness in industrial environments.

VII.4 SELF-SUPERVISED AND UNSUPERVISED LEARNING

Self-supervised and unsupervised learning methods are gaining attention as they reduce the dependency on labeled datasets. These approaches allow models to learn patterns and representations directly from raw data, making them suitable for large-scale industrial applications where labeled data are limited or unavailable. By leveraging unlabeled data, such methods enhance scalability and enable more efficient deployment of intelligent monitoring systems across diverse chemical processes. Deep learning has significantly transformed chemical process monitoring and fault detection by enabling accurate, data-driven analysis of complex industrial systems. Techniques such as autoencoders, CNNs, and LSTMs provide improved detection accuracy and adaptability compared to traditional approaches. Despite challenges related to interpretability and data availability, ongoing research in explainable and hybrid models is addressing these limitations. Future advancements integrating deep learning with Industry 4.0 technologies will further enhance the reliability, safety, and efficiency of chemical process industries.

VIII. CONCLUSION

Deep learning has emerged as a highly effective approach for chemical process monitoring and fault detection, offering clear advantages in handling nonlinear, high-dimensional, and dynamic industrial data. Techniques such as autoencoders, convolutional neural networks, recurrent neural networks, and hybrid architectures have demonstrated strong capability in extracting meaningful features, identifying subtle anomalies, and improving fault classification accuracy. These models significantly outperform conventional statistical and model-based methods, particularly in complex systems such as the Tennessee Eastman Process and real industrial environments. The study also highlights that deep learning enables real-time monitoring, early fault detection, and predictive maintenance, thereby improving process safety, reliability, and operational efficiency. Despite these strengths, several practical challenges remain, including limited labeled data, model interpretability, computational requirements, and generalization across different processes. Addressing these issues is essential for large-scale industrial adoption. Recent research trends indicate that the integration of explainable AI, transfer learning, self-supervised learning, and Industry 4.0 technologies will play a critical role in advancing this field. These developments are expected to improve model transparency, adaptability, and scalability across diverse industrial applications. Overall, deep learning-based process monitoring represents a transformative direction for modern chemical industries, supporting intelligent decision-making and enabling safer, more efficient, and data-driven operations in increasingly complex manufacturing environments.

IX. AUTHOR'S CONTRIBUTION

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Approval of the final text: All authors.

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