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Deep Learning and Machine learning Techniques in Advanced Non-Destructive Testing

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Abstract— There has been considerable evidence of the effectiveness of machine learning (ML) and artificial intelligence (AI) algorithms as numerical tools; some of their applications include computational fluid dynamics, control and automation, signal processing, and materials engineering. Recent advances in ML and AI can directly benefit non-destructive testing, one of the most important industrial applications. With AI, data analysis can be improved and better harnessed. NDT uses electromagnetic waves or material-based methods to acquire information from a specimen. ML algorithms can interpret multiple signals or images to analyze, inspect, and examine the integrity of the materials structure. An overview of the foundations and current applications of ML techniques in advanced NDT is presented in this paper. In addition to explaining ML techniques, the most recent advances in ML and AI, including deep learning, are also discussed.
Index Terms— Deep learning, Machine learning, Non-destructive testing, NDT

Introduction

Non-destructive testing plays an essential role in making sure that costs of all operations are highly minimized. NDTs ensure that there is protection of mechanisms used in the entire operation such as railways, power generations, and petrochemical processes. In manufacturing industry, for instance, they are used to detect flaws, such as cracks, gaps, leaks, pores, and fractures which are mostly caused by stress, contraction, processing, and hammering on the surface or inside of materials, while maintaining durability and originality after inspection. In addition, non-destructive tests use physical principles to identify and evaluate faults or destructive defects. The field of NDT or NDE is cost effective methods of testing materials and are being used to identify and characterize damages on the surface and inside of materials without cutting apart or otherwise altering the material [1, 2]. In general NDT uses electromagnetic waves or material-based methods to acquire information from a specimen. These methods can be categorized based on the factors that are evaluated. Some significant recent inspections with non-destructive testing methods have been summarized and listed in Table 1.

The era of big data has already begun. Existing IT and computing technologies and algorithms are challenged by big data. A traditional definition of big data is an enormous amount of data (in excess of 1 terabyte) produced at high velocity with high variety and veracity [22]. In data generation, velocity indicates how fast data is generated, and the type of collected data is known as variety. The volume of the data can range from several petabytes (10^{15} bytes) to several exabytes (10^{16} bytes). This data deluges are driving the need for automated data analysis, which ML offers.

Table 1: Category of NDT methods based on the detecting factors [2, 3]

Inspection Type	NDT Method
Residual stresses in materials Aircraft composites assessment Health monitoring of aerospace composite structures	Ultrasonic Testing [4, 5] Shearography [6] and Thermographic Testing [7, 8], Vibration Methods [7, 9]
Renewable energy and industrial assets	Ultrasonic Testing, Thermography, Acoustic emission [10]
Evaluation of compressive strength in the structure	Rebound Hammer (RH) and Ultrasonic Pulse Velocity (UPV) [11, 12]
Structural Health Monitoring (SHM)	Ultrasonic Testing [13, 14]

Additive manufacturing	Optical (laser, LED), Penetrant inspection, Ultrasonic testing, Acoustic emission Radiographic techniques Electromagnetic techniques Thermographic techniques [15, 16]
Auto-detection of impact damage in carbon fiber composites Characterizing damage in CFRP structures	Thermographic Testing [17, 18] Radiography [19]
Impact damage in glass/epoxy with manufacturing defects	Infrared Thermography [20]
Multiple Cracks Detection [21]	Neutron Radiography [21]

ML is a subset of AI and computer science based on a set of statistical tools that focus on developing models with data learning and training that can predict new data in the future. In general, ML is a set of related algorithms and processes that create relationships between datasets. In particular, it is a method of automatically detecting patterns in data and then predicting future data, or making other decisions under uncertain conditions based on the uncovered patterns [23]. There are many ways in which uncertainty can present itself in ML, such as determining the best model for explaining some data; or based on past data, what is the best prediction for the future. It is common for NDT specialists to make mistakes during interpretation of signals and analysis of large amounts of data, resulting in defects being missed, and the sizing of the defect being incorrect, or the defect not being identified. In any NDT technique, consistency and reliability of the results are strongly influenced by the personnel conducting the inspections and evaluating the results. With AI, data analysis can be improved and better harnessed. By addressing the challenges posed by large data analysis and processing, this innovation will reduce the amount of time that advanced NDT methodologies must invest in a single analysis. The role of NDT becomes ever more important as industrial work and discovery increases and materials are used beyond their physical limits. Thus, testing methods themselves are evolving [24].

ML Algorithms Categories

Each ML algorithm develops a model that is equivalent to a set of experiences. The following five categories can be used to categorize ML algorithms:

a. Supervised Learning Algorithms: Labeled data is used to train the algorithm. Supervised learning algorithms are used when both predictors (inputs X) and outcomes (outputs Y) are present in the training data set.

b. Unsupervised Learning Algorithms: A training algorithm that uses unlabeled data. Unsupervised learning algorithms are used when training data contain only predictor variables (X) and without outcome variables (Y).

c. Semi-Supervised Learning Algorithms: In terms of learning method, semi-supervised learning is somewhere between supervised learning and unsupervised learning. A dataset may either have no labels for all observations in unsupervised learning or may have labels for all observations in supervised Learning. Since labeling requires skilled human experts, the cost to label is quite high in many practical situations. Therefore, semi-supervised algorithms are the best candidates for model building when labels are absent from most observations but present in a small part.

In NDT, supervised learning algorithms are the go-to methods for prediction, relying on labeled data to classify new datasets [25], while unsupervised learning is more suitable for detecting anomalies, dealing with unlabeled data for pattern recognition [26]. NDT can utilize supervised learning to detect severity and types of damage through input and output [27], and unsupervised learning to detect damage via clustering of structural response data. Combining both of these approaches leads to semi-supervised learning, aiming to combine labeled and unlabeled data for data classification [28].

d. Reinforcement Learning Algorithms: It is common for the input variable X as well as the output variable Y to be uncertain (for instance, predictive keyboards or spell check). Through an iterative learning process, reinforcement learning algorithms (called agents) continuously learn from their environment. The method automates the process of determining an ideal behavior within a specific context, thereby maximizing its efficiency. A sequential decision-making scenario can also be modeled using these algorithms.

e. Evolutionary Learning Algorithms: Algorithms that mimic the learning process of humans and animals. Prescriptive analytics is their most common application. Evolutionary algorithms (EAs) are a subset of evolutionary computations, which are generic metaheuristic optimization algorithms based on populations [29]. In EA, mutation, recombination, reproduction, and selection are some of the mechanisms inspired by biological evolution. Genetic algorithms and colony optimization are examples of these techniques [30].

Here is an overview of some of the types of algorithms and techniques used in ML (Figure 1).

I. Deep Learning (DL)

Deep learning is a subfield of ML that focuses on training and utilizing artificial neural networks with multiple layers to learn and extract intricate patterns and representations from complex data. It is inspired by the structure and functioning of the human brain's neural networks. Deep learning models, also known as deep neural networks, are designed to automatically learn hierarchical representations of data [31]. DL has achieved remarkable success in various domains, including computer vision, natural language processing, speech recognition, and recommender systems. Its ability to automatically learn features and representations from raw data, without the need for manual feature engineering, has revolutionized many fields and led to breakthroughs in tasks such as image classification, object detection, machine translation, and more. DL has various applications in NDT, offering improved accuracy and efficiency in defect detection [32, 33], classification [34, 35], and predictive maintenance [36].

ML and DL techniques have been highly successful in extracting features, providing better performance than many other techniques. Therefore, they are highly valued in many scientific fields. For example, Artificial Neural Networks (ANNs) were employed to analyze fiber orientation in composite materials using neurons as connecting elements [37], a single hidden-layer feedforward neural network (SLFN) was utilized for defect classification [38], convolutional neural network (CNN) models were implemented for inner damage analysis and evaluation [39, 40], Support Vector Machine (SVM) automatic classification model was utilized to monitor microcracks using multi-sensor measurements [41], and k-means clustering method was used for automatic defect detection and classify signal sources [42].

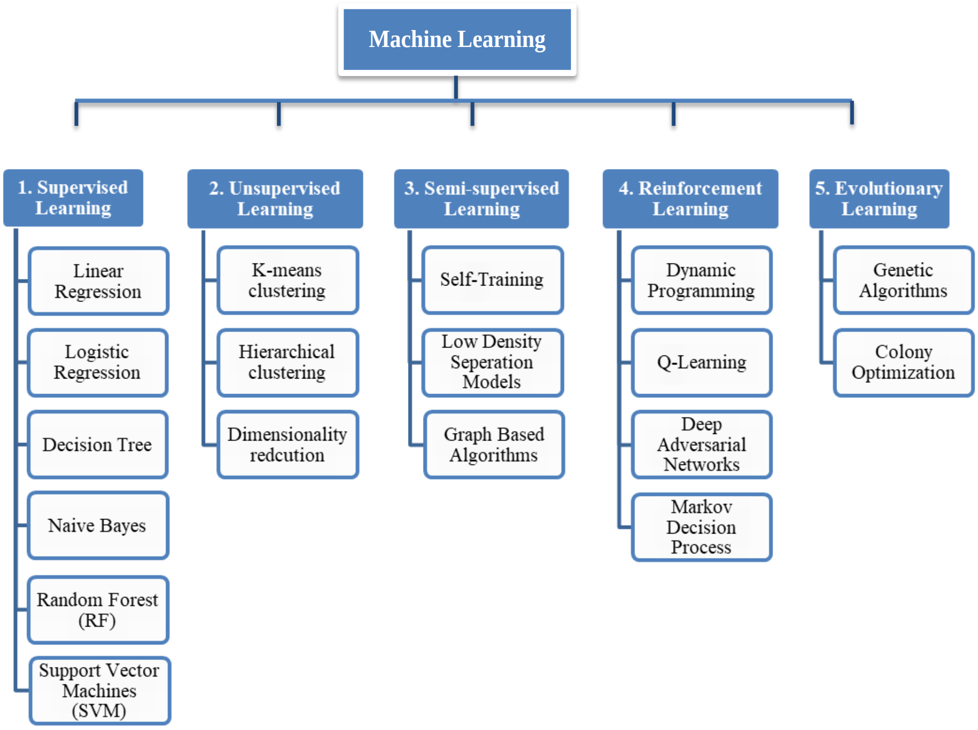

Figure 1: Common types of algorithms and techniques used in ML

Other ML algorithms have been applied in various fields, such as object recognition [43], speech recognition [44], Probabilistic neural network (PNN) [45], Least square support vector machines (LSSVM) [46].

II. The Application of ML and DL in NDT

ML and DL in NDT refers to the application of ML and DL techniques and algorithms to analyze NDT data, extract patterns, and make predictions or classifications related to the integrity, quality, and performance of materials, components, or structures. ML and DL algorithms can learn from historical data and use that knowledge to improve defect detection, classification, predictive maintenance, and decision-making processes in NDT. In the context of NDT, ML algorithms are trained on labeled datasets that consist of NDT data, such as images, waveforms, or sensor readings, along with corresponding annotations or outcomes. The ML models learn to recognize patterns, relationships, and characteristics in the data through a process called training. Once trained, the ML models can analyze new, unseen data and make predictions or classifications based on what they have learned. DL enables the construction of highly flexible and powerful models that can learn complex patterns and make accurate predictions from large-scale, high-dimensional data [47]. DL models are composed of multiple layers of interconnected artificial neurons, known as nodes or units. Each layer receives inputs from the previous layer, performs computations, and passes the outputs to the next layer. The layers closer to the input are responsible for learning low-level features, while deeper layers learn high-level representations and abstractions. ML and DL have found several applications and offers several advantages in the field of NDT:

A. Automated Defect Detection and Defects Classification

ML algorithms can be trained to automatically detect and recognize defects in NDT data, such as images or sensor readings, and identify defects or anomalies automatically. There are some studies that focus on leveraging ML algorithms to analyze NDT data and identify defects in an automated manner. These automations reduce the reliance on manual inspection, speed up the process, and enhance the accuracy and the efficiency of defect detection processes. For example, in radiographic testing, ML models can analyze X-ray images and identify the presence and location of cracks, voids, or other anomalies [48-50]. Valavanis and Kosmopoulos [51] developed a method for weld defect detection and classification through the use of texture measurements and geometrical features as inputs for a Support Vector Machine (SVM) and an Artificial Neural Network (ANN). With this system, SVM and ANN correctly identified 62%, 59%, and 78% of the cracks, lacks of fusion, and non-defects respectively. Contemporary research endeavors focus on creating an automated system for the interpretation of weld defects, and such a system can be segmented into three components: image processing, feature extraction, and pattern recognition. Silva and Mery [52] comprehensively reviewed image processing. Over the past few decades, numerous imaging and detection techniques have been utilized in the domain of diagnostic radiology. Presently, the commonly used modalities in medical centers and hospitals include radiography, fluoroscopy, computed tomography (CT) scans, ultrasound, magnetic resonance imaging (MRI), and positron emission tomography (PET) [53].

ML techniques can also classify and categorize different types of defects or flaw patterns based on training data. This helps in accurately identifying and characterizing defects, improving the reliability of NDT inspections. For example, ML can distinguish between different types of corrosion or classify different types of surface cracks [54-58]. Such classification enables better understanding of defect types and facilitates appropriate remedial actions. For instance, K-means clustering was applied by Du et al. [59] to classify acoustic emission signals obtained from the analysis of stress-corrosion-cracking (SCC) on 304 stainless steel. The authors conducted experiments with three clusters (k = 3) that represented the types of damages encountered in steel (crack propagation, pitting, and bubble break-up). Saenkhum et al. [60] classified corrosion using acoustic emission and Artificial Neural Networks (ANNs). Testing phase of neural networks indicated very little misclassification rate and a very effective generalization capability with a training accuracy of 96.41% and testing accuracy 94.35%. Risheh et al. [61] used K-means clustering algorithm for defect detection in thermal images of industrial materials, while Sophian et al. [62] utilized the same algorithms for defect detection using pulse eddy currents and Shrifan et al [63] used it in microwave NDT to detect defect.

Similarly, in ultrasonic testing, ML can analyze waveforms and identify specific flaw patterns [64, 65]. Fei et al. [66] and Vaclav et al. [67] have demonstrated the effectiveness of Support-Vector Machines (SVMs) in classifying ultrasonic signals. Both shallow neural networks and SVMs have achieved a high degree of accuracy for A-scan. However, due to the necessity of feature engineering, these methods are not suitable for broader applications. Niu et al. [68] proposed the use of Surface Defect-Generation Adversarial Network (SDGAN) for generating defect images to enhance deep-learning-based surface defect recognition, addressing the limitations of insufficient and costly labeled defect data. The SDGAN is applied to expand the commutator cylinder surface defect image data sets, both with labeled data (CCSD-L) and without labeled data (CCSD-NL). For anomaly recognition, an error rate of 1.77% and a relative improvement (IMP) of 49.43% for the CCSD-NL defect data set was reported. In terms of defect classification, an error rate of 0.74% and an IMP of 57.47% for the CCSD-L defect data set were achieved. Munir et al. [69] utilized deep neural networks (autoencoder) to mechanize the ultrasonic weldment defect classification system to identify and remove the noise from the counterbore, planer, and volumetric weldment defect signals. Results revealed that the autoencoder was successful in reducing noise from ultrasonic weldment defect signals which in turn improves the classification accuracy of deep learning classifiers. A typical defect detection study and test method of comparative analysis is shown in Table 2.

B. Predictive Maintenance (PdM), Condition and Real-time Monitoring

ML models can analyze historical NDT data, sensor readings, and other relevant parameters to predict the likelihood of future defects or failures, or the remaining useful life of components or structures. By considering patterns and trends in the data, ML algorithms can estimate when and how defects or failures might occur. This enables proactive maintenance planning and minimizes the risk of unexpected equipment or component failures, scheduling repairs or replacements before failures happen, and optimizing maintenance resources.

In predictive maintenance, diagnostics and prognostics play an important role. Diagnostics and prognostics fall into three categories: i) the reliability data-driven approach that consist of determining the expected lifetime of the average component under historically average conditions [79], ii) Stress-driven models that estimate the lifespan of components in a particular environments [80], iii) In Condition-based, the component's lifetime is determined based on its operating environment [81, 82]. Figure 2 demonstrates a broad spectrum of diagnostic and prognostic techniques, as well as different steps in data driven diagnostics and prognostics.

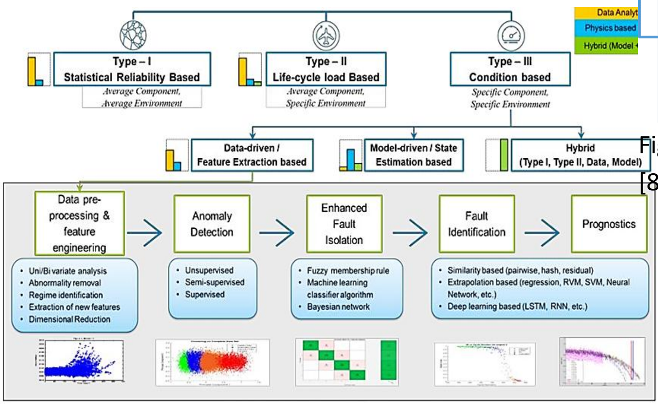

Figure 1: Data driven diagnostics & prognostics: broad categories & steps [81]

The numerous research works on PdM can be classified into three approaches [83]:

Physical models: Through physical model methods, system degradation is mathematically described based on prior system knowledge [84, 85]. Despite being easy to understand on a physical level, they are difficult to implement on a complex level.

Data-driven models: As explained above, data-driven methods are used to predict the state of a system by analyzing historical data and learning from it. Due to the fact that they do not need to know how complex systems work, they are suitable for complex systems. ML algorithms [86] and deep learning algorithms [87] have been extensively used in data-driven PdM in industrial manufacturing. A detailed description of the implementation process for the data-driven PdM can be found in [88], which follows the design methodology. In general, there are four stages in the process: operational assessment, data acquisition, feature engineering, and modeling (Figure 3).

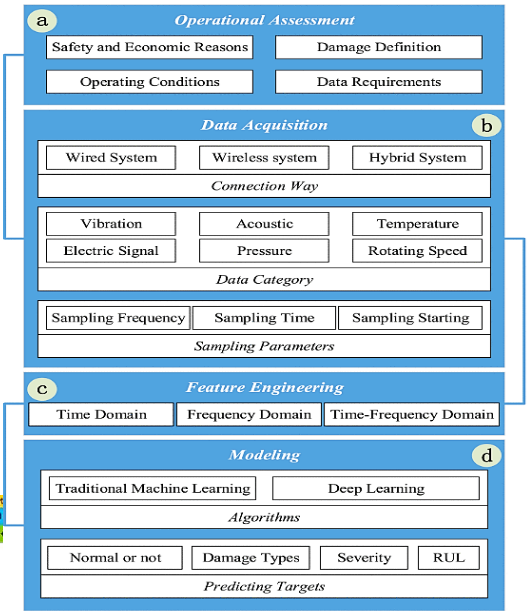

Figure 2: Data driven PdM implementation process [89]

Table 1: Defect detection, test methods and analysis

Application	Defect detections technique	Precision	DL defect detection technique	Precision
Manufacturing and industries	Optical Quality Control (OQC) and machine vision	98.2%	Deep convolutional neural network	99% [70]
Steel materials	Visual Inspection System	87%	Artificial Neural Networks (ANN)	98% [71]
Concrete	Ultrasonic wave propagation	90%	Deep Learning (AlexNet, ResNet)	96% [72]
	Automatic optical detection	95%	Deep convolutional neural network	98% [73]
Composite materials	Granular crystal sensor - highly nonlinear solitary waves (HNSWs)	89.3%	Convolutional neural network (CNN)	90% - 92% [74]
	-	-	Convolutional neural network (CNN)	92% [75]
Rail	-	-	Deep convolutional neural network	90% and 95% [76] 92% [77]
Road	-	-	Deep convolutional neural network	87% [78]

Hybrid models: Hybrid approaches combine the two approaches outlined above [83]. The development of accurate PdM models in complex systems is now possible through data-driven and deep learning methods due to improvements in machine data collection. Figure 4 illustrates the frameworks of three different machine health monitoring systems (MHMS) including Physical Models, Conventional Data-driven Models and Deep Learning Models.

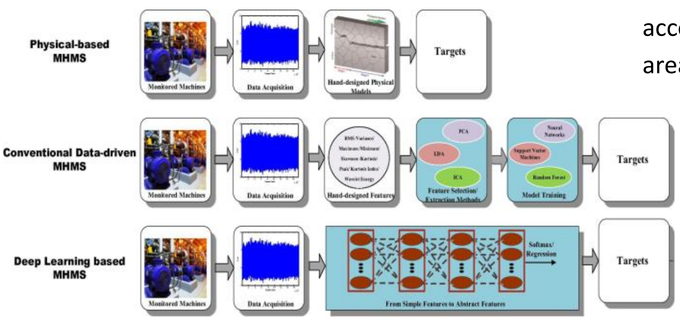

Figure 3: Frameworks of three different machine health monitoring systems (MHMS) [90]

The prognostics stage of Structural Health Monitoring (SHM) is used in predictive maintenance to predict the future evolution of the defect or degradation. Originally, SHM systems utilized wired sensor networks [91]. Wireless sensor networks (WSNs) are a viable option platform for SHM systems because of their superior trustworthiness and low installation and maintenance costs [92, 93]. As part of the assessment of structures with SHM systems, cracking, displacement, temperature, corrosion, force, fatigue, tilt, settlement, vibration, strain, and water level and wind are taken into account [94]. Figure 5 depicts the SHM systems areas, methods, techniques and algorithms.

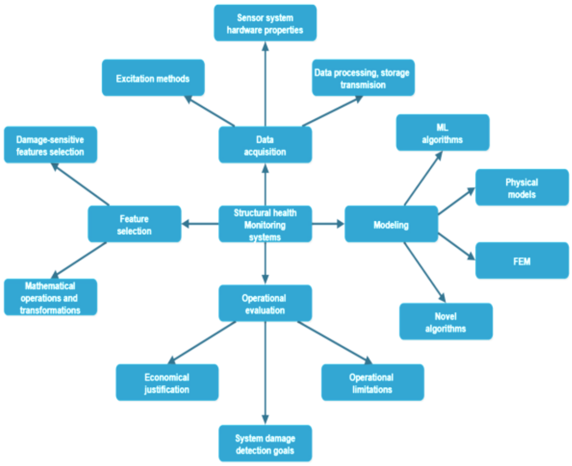

Figure 4: Diagram of structural health monitoring systems areas [95]

ML in SHM is used to construct models or representations for mapping input patterns in measured sensor data to output targets to assess damage at various levels [96]. Gholizadeh et al. [96] evaluated damage progression under fatigue loading on glass fiber reinforced polyester composite materials using acoustic emission (AE) with different approaches of ML; ensemble learning methods namely; XGboost, LightGBM, and CatBoost, and unsupervised learning k-means clustering. XGboost was found as a most reliable technique with the accuracy of 95%. Abhishek et al. [97] investigated the SHM of Wind Turbine Blade (WTB) using convolutional neural network (CNN) for image classification. Accuracies of 94.94% of binary fault classification and 91% of multiple class fault classification were achieved. Gomez et al. [95] focused on the process of features extraction and patterns recognition by SHM systems used in bridge construction. An evaluation of ML algorithms in SHM systems for reinforced concrete bridges was conducted by Fan et al. [98]. ML algorithms are explored in the areas of structural design, construction quality management, bridge engineering, and inspection. To identify, locate and predict structural health, feature extraction can be implemented using signal processing techniques [99, 100]. Additionally, ML algorithms have also been employed in the field of pattern recognition [101-104]. The use of machine learning algorithms has been demonstrated in the variety of applications throughout the life cycle of structures, including design optimization, maintenance, performance assessment, SHM, damage detection and construction. [105-107].

As the name implies, condition-based maintenance (CBM) plans maintenance based on condition monitoring (CM) data such as temperature, vibration and currents. As part of CBM, several disciplines are involved, such as failure analysis, on-line diagnostics, interpreting diagnostic data and so forth. Widod and Yang [108] investigated machine condition monitoring and fault diagnosis using support vector machine (SVM). SVM has demonstrated excellent generalization performance with high classification accuracy for machine condition monitoring and diagnosis. Bakar et al. [109] developed failure root causes database using CBM actual site data of 33 kV switchgears. Multiple methods were used to obtain the CBM data, including ultrasound, thermoscanning, and transient earth voltage (TEV). Based on the sequence of failures in the database with the highest percentages, the root cause was identified. On the basis of the highest percentage of occurrences, the ultrasonic method successfully identified most root causes of failure. An induction motor fault diagnosis model based on convolutional discriminative feature learning has been proposed by Sun et al [110]. A back-propagation-based neural network (BPNN) was used to pre-learn local filters in a feed-forward convolutional pooling architecture as shown in Figure 6. In the next step, SVM was used to classify fault conditions based on the learned representation. Based on the BPNN-learned local filters, the following convolutional pooling architecture could extract invariant and discriminative features quickly from the raw vibration data. Since the input data was a 1D vibration signal, their work was also considered as a 1D CNN. Ben Ali et al. [111] used an ANN-based model to monitor and diagnose rolling bearing conditions. Empirical mode decomposition and energy entropy were used to extract features. As a result, the proposed method demonstrated that an ANN can be effectively used by itself without human intervention as a tool for assessing bearing degradation.

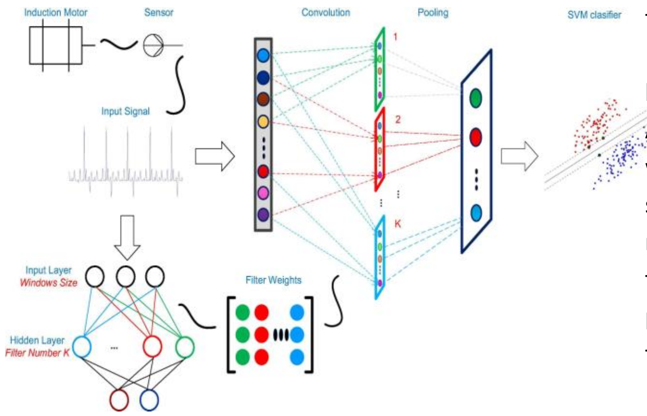

Figure 5: Illustrations of the induction motor fault diagnosis using proposed unsupervised CNN [110]

ML models can also be deployed for real-time monitoring of NDT data streams. By continuously analyzing incoming data, such as sensor readings or streaming images, and compare it to established baselines or thresholds, ML algorithms can quickly detect deviations, anomalies, or potential defects, enabling timely interventions or alerts to operators. Real-time monitoring enhances safety, reduces downtime, and supports proactive maintenance strategies.

An important research topic is time series analysis, which involves two aspects: (1) identifying the nature of the phenomena represented by the time series of observations[112], and (2) predicting future values of the time series variable based on historical data [113]. The preprocessing of time series data, the extraction of features, and the customization of algorithms are critical to predictive maintenance. Prognostics have been approached as a time series prediction problem by some researchers and forecasting methods have been proposed such as: Artificial Neural Networks (ANNs) [114], Auto Regressive Integrated Moving Average (ARIMA) [115], Exponential smoothing model (ETS) [116], Support vector Regression (SVR) [117]. Auto-Regressive Integrated Moving Average (ARIMA), and Support Vector Regression (SVR) are categorized as statistical models for anomaly detection [81]. Sfar et al. [118] investigated SHM of a tube via ultrasonic guided waves by utilizing two models based on Empirical Mode Decomposition (EDM)- ARIMA to realize high-precision predictions, and predict components; and Auto-Regressive Neural Networks (ARNNET) technique to estimate functions based on a huge volume of training data. EMD-ARIMA provides better results than ARIMA for both modes. In the study by Hongzhan et al. [117], ARIMA was used to forecast linear basic load, whereas SVMs were used to forecast non-linear sensitive load, and a hybrid model of both. The result showed that the hybrid ARIMA-SVMs realized the mutual supplement with each other and performed better than the two separate models of themselves with lowest error of 3.85%.

Deep learning has emerged as one of the most popular techniques in the past years to detect anomalies in time series data, delivering state-of-the-art results for a range of unsupervised and supervised tasks due to its capability of learning high-level representations automatically from data; its higher accuracy, greater flexibility, stronger generalization, and its lower dependency on domain knowledge [119]. long short-term memory (LSTMs) and recurrent neural networks (RNNs) are now the deep learning models of choice for learning long-range patterns in sequential and temporal data [120, 121].

Yuan et al. [122] investigated three RNN models for aeroengine fault diagnosis and prognostics, including vanilla RNN, LSTM and GRU. The LSTM and GRU advanced RNN models outperformed vanilla RNNs. Interstingly, LSTM performance was not improved by the ensemble model of the three RNN variants above. A tool wear test utilizing LSTMs was presented by Zhao et al. [123]. In the applied LSTM model, raw sensory data was encoded into vectors and tool wear was predicted according to those vectors. Zhao et al. [124] Further, Zhao et al incorporated CNN and LSTM to formulate a more complicated deep learning model called the Convolutional Bi-directional Long Short-Term Memory Network (CBLSTM). The robust local features of the sequential input were extracted with CNN, as shown in Figure 7. In the sequential output of CNN, bi-directional LSTM was adopted to encode temporal information. The final step was to predict the target value by adding fully-connected stacked layers and using a linear regression. Compared with several baseline approaches, including conventional LSTM models, the proposed model excelled at tool wear tests. A LSTM-based encoder-decoder structure was developed by Malhotra et al [125], in which a LSTM-based encoder transformed a multivariate input sequence to a fixed-length vector, and then the LSTM decoder produced the target sequence from the vectors. To predict RUL, their assumptions state that the model the model can initially be trained unsupervised on raw signals corresponding to normal behavior. After that, the reconstruction error is used to calculate a health index (HI) that can be used to estimate RUL.

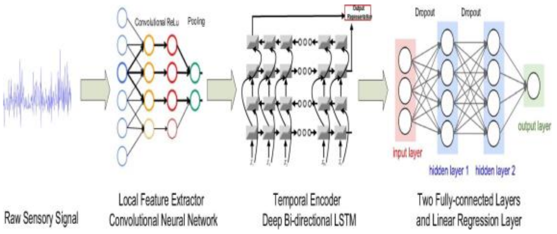

Figure 6: Illustrations of the proposed Convolutional Bi-directional Long Short-Term Memory Networks [124]

A real-time anomaly detection system was described in Numenta [126], Aggarwal et al [127-129]. A potential breakthrough developed by Numenta is Hierarchical Temporal Memory (HTM) [126], a biologically inspired machine intelligence system that mimics neocortex processes and architecture. HTM stood out as a promising real-time predictive maintenance approach. Kukjin et al. [130] provided a broad explanation of how DL can be applied to anomaly detection.

CONCLUSION

ML and DL represents power tools that can lead to significant improvements in NDT and related fields. Overall, ML and DL in NDT empowers industries to leverage the power of data analysis and pattern recognition to enhance inspection capabilities, increase accuracy and efficiency, enable and optimize predictive maintenance strategies, support data-driven decision-making in various industries and ultimately contributing to safer and more reliable systems and structures. The rapid advancement of NDT technologies and automation necessitates the urgent need for a precise assessment of test signals, data, images, and patterns. In order to fulfill this requirement, an AI-powered knowledge-based system is desired to process the NDT testing data and generate a comprehensive output in the form of classified and systematic interpretation.

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