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Review

A review on the application of deep learning in system health management

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ABSTRACT

Given the advancements in modern technological capabilities, having an integrated health management and diagnostic strategy becomes an important part of a system's operational life-cycle. This is because it can be used to detect anomalies, analyse failures and predict the future state based on up-to-date information. By utilising condition data and on-site feedback, data models can be trained using machine learning and statistical concepts. Once trained, the logic for data processing can be embedded on on-board controllers whilst enabling real-time health assessment and analysis. However, this integration inevitably faces several difficulties and challenges for the community; indicating the need for novel approaches to address this vexing issue. Deep learning has gained increasing attention due to its potential advantages with data classification and feature extraction problems. It is an evolving research area with diverse application domains and hence its use for system health management applications must been researched if it can be used to increase overall system resilience or potential cost benefits for maintenance, repair, and overhaul activities. This article presents a systematic review of artificial intelligence based system health management with an emphasis on recent trends of deep learning within the field. Various architectures and related theories are discussed to clarify its potential. Based on the reviewed work, deep learning demonstrates plausible benefits for fault diagnosis and prognostics. However, there are a number of limitations that hinder its widespread adoption and require further development. Attention is paid to overcoming these challenges, with future opportunities being enumerated.

Contents

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1. Introduction

Health management is described as the process of diagnosing and preventing system failures, whilst predicting the reliability and remaining useful life (RUL) of its components [1]. The past few decades have experienced a proliferation of system health management research to help with all kinds of failures occurring at component level and up to the systems level [2] and Lee et al. [3]. However, even though these concepts have been studied extensively [4,5], most methods often require triggering mechanisms that are intelligent enough to collect enough data about the failing component, the nature of the fault, and its severity on the overall system performance. Consequently, efforts are being concentrated on the integration of anomaly, diagnostic and prognostic technologies across systems and related platforms. Such capability to predict and isolate impending failures can help maintain system performance in a cost-effective manner; whilst identifying ongoing issues to mitigate potential risks. Another consequence is the increase in the amount of data collection as an essential component in modern engineering systems. Compared to the typical top-down approaches[1], data-driven methods offer a new paradigm of bottom-up solutions for health management of system failures and prediction. This has made data analytics within diagnostic technologies a high priority research topic.

As the aerospace industry continuously strives to improve its performance[2]; operational pressures expect to reduce the time required for any diagnostic investigations. Here, there is value of having many data collection sources that can be used to provide rich information, e.g. operating variables, environmental conditions, etc., if a disruption occurs during operation. However, most often data sources are disparate. With the ever-increasing size of big data produced by modern systems, coupled with the complexities of contextual components for correlating information; can create barriers that were not anticipated by design engineers during the design phase of the system life-cycle. This eventually results in higher levels of uncertainty during the diagnosis process [6]. In this context, novel approaches are required which can configure applications, as well as mechanisms for making better decisions at the system-level. In the nominal environment, such problems warrant advanced capabilities to monitor in-service operations, record and share expert knowledge, and address critical aspects of on-board software. To address this issue, diagnostic systems based on conventional techniques are being replaced by AI-based ones which can increase the efficiency of the monitoring technology. AI-based approaches can be categorised into (1) knowledge-driven (knowledge-based) approaches including expert system and qualitative-reasoning, and (2) data-driven approaches including statistical process control, machine learning approach and neural networks[3]. Fig. 1 illustrates some of the AI approaches that have been used for system health monitoring applications over the years. One notable development is the application of deep learning. These architectures aim to model high level representations of data and classify (predict) patterns by stacking multiple layers of information processing modules in hierarchical structures. There are advantages of using them, but since it is an evolving research area, its applicability for diagnostic applications must been researched with an aim to increase overall system resilience or potential cost benefits for maintenance, repair, and overhaul activities. The computing science communities have accelerated their research efforts on deep learning in the past few years. However, its knowledge transfer within engineering communities has been scarce [7].

This article provides an overview of AI techniques and focuses its efforts on the application of deep learning methods that have been used for system health management. Deep learning has been applied for fault diagnosis and prediction in the past few years. To date, this expansion has extended from mechanical equipment monitoring to electrical systems, power installations and aerospace disciplines. This includes solutions on electromechanical equipment fault diagnosis, classifying degradation and pattern recognition, and predicting of RUL of components. The presented state-of-the-art is a synthesis of articles that have been reviewed during an ongoing research project on the application of deep learning. The authors have adopted a pragmatic approach and concentrated their efforts on the system health management discipline; rather than providing a comprehensive survey on deep learning. Fortunately, there are other much detailed literature publications that have carried out rigorous reviews on deep learning with the commuting science community (e.g. see [8], LeCun et al. [9], Schmidhuber

[1] These are traditional physics based models whose realisation is often obfuscated by noisy environments and system complexities.
[2] By delivering more reliable assets, with a higher availability.
[3] Some approaches, such as probabilistic reasoning (e.g., Bayesian networks), may belong to both categories, because reasoning and learning cannot be distinguished. Yet, many of them are dependent on obtaining accurate (and sometimes complete) data on system models.

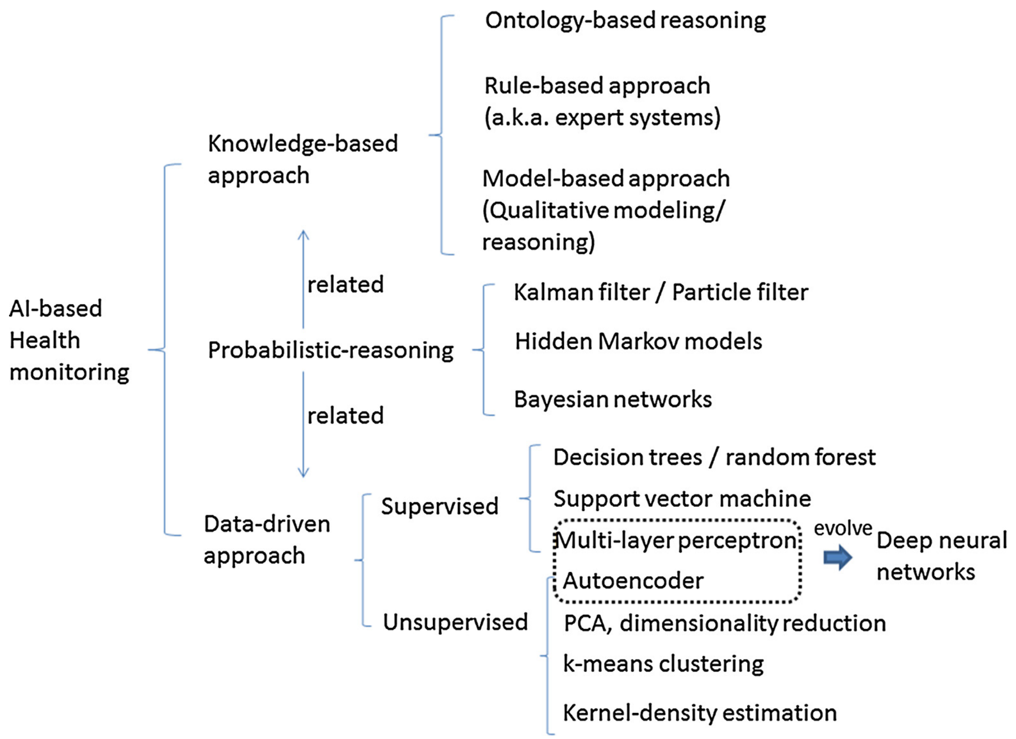

Fig. 1. Categorisation of AI based methods used in system health monitoring applications.

[10] and Najafabadi et al. [11]). Yet, this article should be of general interest to design engineers and researchers who are working in the areas of testability, diagnostic algorithm design and health monitoring technology within the context of artificial intelligence research. It can be used to introduce the concept of deep learning and understand where it is being used. The paper also presents some issues when considering current implementation technology. Even though the focus is mainly centred upon solutions being developed for aerospace applications, other disciplines should be able to find the contents of this paper appropriate. The aims of this work can be summarised to:

- Analyse current trends in the state-of-the-art towards the application of deep learning within system health management,
- Develop a cohesive understanding of deep learning in supervised (e.g., classification) and unsupervised (e.g., pattern analysis) manners;
- Develop an appreciation of the core merits of deep learning through a sector-wise view of the technology.

1.1. Challenges

If a system can resolve issues autonomously, it can result in significant reduction of operational costs and increase in operational uptime; as the asset will not be taken out for corrective maintenance. These would rather become evidence-based scheduled maintenance tasks which will reduce inspection costs, the required number of skilled labours, system down time, life-cycle cost of the system and emergency unscheduled maintenance. But effective identification of system faults (including the ones that have already occurred and that which are approaching) is still an open question. Some notable system diagnostic challenges that have persisted over the past few decades include:

- Definition of a single diagnostic procedure for identification and isolation of any type of faults [5],
- Insensitivity to operating conditions,
- Low-dimensional visualization,
- Robust separation of faults,
- Noisy sensor readings and missing data,
- Reliable fault detection in time-varying conditions;
- It is difficult to accurately model many physical processes – many of which are non-linear and time varying in nature [12],
- Health degradation trends [13],
- Interdependence of large system processes [14],

- The influence of noise and process uncertainty during implementation; including parameters which cannot be measured [3],
- Lack of expert knowledge [6].

Of course, the above list is not inclusive, but it does indicate the two benefits that can be achieved by addressing them. Firstly, there will be improvement in the safety aspects. Since failures can be diagnosed and assessed quickly, the remaining life of safety critical components can be regulated before they can cause any serious damage during operational service. Secondly, ongoing maintenance costs can be reduced with an increase in system availability. These two driving forces inevitably influence operational performance and the amount of maintenance required; a consequence of the design and the problems encountered during service. A direct consequence of these factors has contributed to the development of new technologies and techniques – which adds additional layers of complexities [15]. Practitioners can gain general knowledge on these topics from several resources e.g. training, books, etc., but because of the availability of so many different algorithms and health monitoring solutions, it becomes difficult to rationalise this information. This leaves a gap as the number of solutions available require making choices that engineers might not be equipped to make. This article attempts to discuss this gap.

The advent of health monitoring methods and related diagnosis technologies within aerospace applications is a significant achievement due to the environment these assets operate in. Within the supervision of equipment, diagnostic systems based on conventional computing techniques[4] have been replaced by new systems based on AI techniques which can increase efficiency of the monitoring technology. Traditionally, AI concepts have not been too concerned with real time processing largely due to the complexities associated with its successful implementation. However, its need was finally realised with the emergence of reactive systems [16]. The aim has been to study how intelligent agents react to changing environmental conditions, and to establish a balance between the agent reaction time and the time required to allow the adaptive reasoning of the actions that are to be performed. As a result, AI approaches are effectively being used to carry out fault analysis and to make system level decisions based on information collected from a combination of sources[5]. But because of the uncertainty in predicting performance and the cost of scheduling tasks, several limitations appear which are associated with the complexities of real time processing.

Typically, most health management methods make use of a priori expert knowledge and deductive reasoning process, e.g. expert systems and model-based reasoning. While these knowledge-intensive approaches have evidently performed much better than the classical methods, e.g. limit checking, it can often be costly and time-consuming to prepare the knowledge-base or model [17]. In contrast, other inductive reasoning techniques (i.e. data-mining or machine learning technologies) have drawn much attention as alternative approaches to the health and usage monitoring problems in various fields. These methods often make use of large amounts of past data for model training purposes, to appropriately update parameters contained in the diagnosis models[6]. But, AI has been used in the past to build heuristic models based on empirical data, e.g. collected from sensors, actuators, experts. The ideas are centred on learning system behaviours by observing variations from nominal operating conditions that indicate faulty states; extrapolating this information to determine the RUL of some components. Some of the most commonly used learning approaches that have been used for these purposes include neural networks, support vector machines, Bayesian networks, association rule mining, regression models, clustering, hidden Markov models and fuzzy logic. Some of these concepts, and their related developments, in the context of system health management will be covered in this article, but the bigger question is: can deep learning be used to solve these challenges which have plagued the industry for decades?

1.2. Contributions

The article provides a structured and a broad overview of deep learning research on system health management, which spans multiple application domains. Existing papers on the topic either focus on a particular application domain or on a single research area. For each technique, the authors provide its basic form, and then show its different variants. Literature developments are discussed accordingly. This template provides an easier and succinct understanding of these techniques, taking note of their strengths and limitations. While some the existing work concentrates its efforts on image processing applications, there is an increase interest from the electro-mechanical domain. This paper lists which applications these techniques that have been used. However, many of the reviewed papers do not provide any discussion on the computational complexity of these techniques, which is an important aspect of real-time applications. The authors have noted that most deep learning implementations in this field are application or equipment specific, and as such there seems to be no clear way to select, design or implement a deep learning architecture. Therefore, a key goal for future deep learning implementations is to proliferate fault diagnosis and prognosis towards lower design levels so that detections or predictions can occur closer to the actual event and therefore localisation becomes possible. There is also a lack of developed end-to-end solutions and appropriate benchmarking of the results. Since these techniques often require a lot of parameter and framework tuning,

[4] This article will not be discussing the conventional approaches in detail, unless they are being used in context to any AI approaches. Instead, the authors would like to recommend the works by Johnson et al. [68] and Roemer et al. [59], who have covered these concepts with much detail.

[5] Here, the use of the term AI incorporates various techniques such as expert systems, neural networks, support vector machine, fuzzy logic, and fuzzy-neural networks, that can be used autonomously or into each other to improve their efficiency and effectiveness.

[6] These are either given by experts or acquired through rules, patterns, and other past application models.

it is not always clear as to which architecture will work better for particular applications. Finally, it is useful to draw out the key contributions from the paper:

- This paper provides a systematic review of burgeoning literature on the application of deep learning in system health management;
- There is a growing interest in deep learning based fault diagnosis, however most approaches are application or equipment specific and as such there is no clear way to select, design or implement a deep learning architecture;
- This paper provides an overview for the engineering community of the various deep learning architectures and challenges associated with its successful implementation;
- There is a lack of understanding towards: application complexity, end-to-end learning solutions, appropriate benchmarking and evaluating the cost of implementing the architecture.

1.3. Research methodology

One of the goals of this study is to understand the current research of deep learning in system health management. This is accomplished by investigating existing published material that yield insights of potential applications and academic interests on the major trends, significant works, and future directions. Therefore, the authors have attempted to compile a systematic reference point for burgeoning literature of this emerging field. As research within this area is of practical importance, the scope of this investigation covers the period between 2013 and 2017. To accomplish the study aims, this research is based on reviewing a variety of journal articles and conference papers, all of which are directly related to system health management concepts and its deep learning application. Due to the scope and diversity of these methods, articles are found to be scattered across a range of sources, and thus a literature search was conducted using the electronic databases including: Science Direct, IEEE Xplorer, Scopus and IET Digital Library. The primary descriptor used is "deep learning", grouped with the following: "system health management", "condition monitoring" and "fault/failure detection".

The authors have written this article in a way, that can allow readers with a non-computing science background to gain an understanding of the deep learning philosophy. Also, even though the selected period spans over the last five years; the last two years are believed to be the most productive from a research point-of-view. Following the database searches, articles were then reviewed and assessed against the inclusion criteria as outlined in Table 1.

In total, the authors identified 38 published journals have been published specifically on deep learning and system health management applications. Some additional 25 conference papers were also selected to assist with the underlying study throughout the review process. In addition, Table 2 lists the journals that have been targeted for publication of the short-listed articles. An interesting observation is the lack of review papers on the topic. The authors have identified only two survey publications: one a conference paper by Zhao et al. [18] and another as a preprint by Zhao et al. [19]. This provides a unique opportunity for this article to act as a reference point of the relevant publications on the topic to date. Finally, a notable observation is regarding the research demographic of the publications. About 70% of them are affiliated with Asian universities; predominantly China.

1.4. Taxonomy

Over the past two decades, there have been several attempts to define some of the following terms; although, these descriptions may vary from discipline to discipline. The following are a list of terms (and their descriptions) often associated with this subject area.

Anomaly detection: Deciding if there is any unexpected performance of intended function. An anomaly is any point in time where the behaviour of a system is unusual and significantly different from past behaviour, and does not necessarily imply a fault or failure.

Artificial intelligence: Artificial intelligence aims at making machines perform tasks in a manner like an expert. The intelligent machine will perceive its environment and take actions to maximise its own utility. The central problems in artificial intelligence include deduction, reasoning, problem solving, knowledge representation, and learning [58].

Table 1
Inclusion and exclusion criteria for articles.

Inclusion	Exclusion
Published in 2013 and later	Published as non-English articles
Included application for system health monitoring: fault diagnosis, isolation, prognosis, RUL estimation, degradation, condition monitoring	Published only as abstract
Included some form of deep learning architecture implementation	Published as an editorial, commentary, poster, book chapter or report
Included some form of experimental results	Existed as multiple publications from the same authors
	Published as a description with no results

Table 2
Breakdown of the targeted journals for the identified 38 articles published since 2013.

Journal	No of articles	References
Shock and vibration	4	Tao et al. [20], Liu et al. [21], Chen et al. [22], Guo et al. [23]
Mechanical Systems and Signal Processing	3	Jia et al. [24], Gan and Wang [25], Ahmed et al. [26]
IEEE Transactions on Instrumentation and Measurement	3	Ding and He [27], Chen and Li [28], Ma et al. [29]
Neurocomputing	3	Li et al. [30], Gao et al. [31], Wu et al. [32]
IEEE Transactions on Industrial Informatics	2	Wang et al. [33], Liu et al. [34]
Sensors	2	Zhao et al. [35], Li et al. [36]
Journal of Sound and Vibration	2	Janssens et al. [37], Abdeljaber et al. [38]
IEEE Transactions on Industrial Electronics	2	Liao et al. [39], Ince et al. [40]
Measurement	2	Sun et al. [41], Guo et al. [42]
IEEE Transactions on Cybernetics	1	Javed et al. [43]
Expert Systems with Applications	1	Tran et al. [44]
IEEE Transactions on Industry Applications	1	He and He [45]
IEEE/ASME Transactions on Mechatronics	1	Janssens et al. [46]
IEEE Transactions on Neural Networks and Learning Systems	1	Zhang et al. [47]
International Journal of Prognostics and Health Management	1	Liao et al. [48]
Frontiers of Information Technology and Electronic Engineering	1	Feng et al. [49]
IET Science	1	Xia et al. [50]
IMeche, Part C: Journal of Mechanical Engineering Science	1	Mao et al. [51]
CIRP Annals-Manufacturing Technology	1	Weimer et al. [52]
IEEE Access	1	Li et al. [53]
IEEE Transactions on Systems, Man, and Cybernetics: Systems	1	Deutsch and He [54]
Signal Processing	1	Lu et al. [55]
Reliability Engineering and Safety Systems	1	Tamilselvan and Wang [56]
Journal of Vibroengineering	1	Chen et al. [57]

Availability: Availability is the probability that the system or equipment used under stated conditions will be in an operable and committable state at any given time [15].

Expert system: An intelligent computer program that uses knowledge and inference procedures to solve problems that are difficult enough to require significant human expertise for their solution.

Diagnostics: It is a classification of anomalous behaviour to known fault conditions. While generic algorithms are sometimes capable of performing diagnostics, faults must be identified a priori within an integrated modelling architecture that links anomalous conditions to failure modes.

Fault: A fault is the inability or incorrect functioning of an entity. It can be an inherent weakness of the design or implementation, and can result in a failure.

Failure: A failure is defined as the state or condition of not meeting a desired or intended objective, e.g. a service stops performing its required operation.

Feature extraction: Reducing the amount of resources required to describe a large dataset.

System Health management: This integrates component, subsystem and system level health monitoring strategies, consisting of anomaly/diagnostic/prognostic technologies, with an integrated modelling architecture that addresses failure mode mitigation and life cycle costs. These will include various failure mode diagnostic and prognostic approaches ranging from generic signal processing and experience-based algorithms to the more complex knowledge and model-based techniques [59].

Prognostics: It is the ability to predict a future condition. Inherently probabilistic or uncertain in nature, prognostics can be applied to system/component failure modes governed by material condition or by functional loss.

Real-time systems: These are reactive systems that consist of a series of complex, heterogeneous and critical processes. They are closely coupled systems, consisting of a physical system part and a control computer system part. While the physical part reacts to the control signals from the computer, the control computer part and its software must interact with the dynamic properties of the physical part.

2. Research motivation

2.1. Application requirements

Modern health management systems exist to offer *basic* monitoring. The word 'basic' emphasises the fact that, even though there have been various developments in the field of fault detection and isolation, there have been technological limitations for real-time decision-making at the systems level. Despite ongoing advances in model based techniques and algorithm design, novel health management schemes are still required to warrant safety margins. This is due to operational uncertainties, to allow a maximum number of flight cycles, and the lack of considerations often given to all faults/failures that can occur during service, e.g. no fault found issues [15]. The fact is that even though modern systems are reliable and safe, they are getting more expensive to operate and maintain. As a result, maintenance techniques are being optimised and incorporated into the design phase of both military and civilian aircraft. The grounds for this begin by defining the maintainability goals. These must include quantifiable measures for the repair process, as well as a quantitative description of the way in which repairs are to be undertaken. For example, it is necessary to determine which components will need to be repaired rather than discarded or replaced, the level of repair, test equipment and skills required and the maintenance scheduling. There will always be a financial trade-off whilst carrying out these activities and therefore will reflect the resources needed to support maintenance. In recent years, globalisation and technological innovation have changed the way a system is maintained, via techniques such as condition monitoring, Built-In-Tests, and integrity monitoring systems, which offer maintenance staff early indications of both impeding and actual failures. Communication and documentation are now being recognised as vital elements for successful troubleshooting and cost justification [60].

Achieving near zero downtime, whilst integrating more sophisticated health management systems into existing designs introduces new challenges that affect cost, design periods, availability of experts, etc. To the customer, this will guarantee that all operational equipment remains functional. It is the key to avoiding unnecessary processes and helps making informed decisions to avoid or mitigate the consequences of a failure. However, no matter how well a maintenance system is designed, there are always deficiencies due to decisions and trade-offs in design that can lead to difficulties in the quality of service. This is because there are always inherent weaknesses in systems which only become evident once the system is in operation [6]. Technologies such as on-board diagnostics and built-in tests, can be employed to reduce this disparity between expectations and what is happening during operation in terms of faults and operating conditions.

Traditionally, systems had been developed based on deterministic models (model-based systems) which can consider different fault conditions. These can simulate a wide range of operating conditions. But their implementation within a single application often leads to complexities which are difficult to maintain and to manage. This leads the discussion towards the need to introduce on-board intelligence to future aerospace assets so that they can operate with lower costs whilst maintaining reliability. The solution can be extended to include self-aware, resilience and coordinate together from past knowledge, expert opinions, and system predictions. This idea was discussed by Merrill and Lorenzon [61], who studied the need of AI for diagnostic functionalities. The authors envisaged that expert system based decision making in real-time will eventually be realised once technological developments can improve computing times and implementation architectures. The next section attempts to review how this has evolved in the past few decades; to reach the capability of making system level decisions to the discussed problems.

2.2. AI based diagnostics

In general, if the mathematical model of the system, in addition to different fault models and their progression are available, model-based approaches are more accurate and effective. However, it can be difficult to find the explicit mathematical model as the system complexity and uncertainties increase. Thus, the accuracy of the results will eventually decrease. This problem is especially highlighted for the case of gas turbine engines, where the complexity of the system makes it challenging to have an accurate mathematical model. In this case, data-based techniques have proven to be useful as the measured data have captured system's relation as well as the uncertainties [62], random error, and unbiased sensor error that are present in the system. The results from these methods can only account for the modes through which the system is operating, but they are very practical methods for complex systems. Yet, there does not exist a method that can outperform others in every aspect and there is a trade-off between generality and accuracy of the method. Over the years, many tools and techniques have been developed for identifying the guaranteed results from the resources available. As complexity increased the problem of resource limitations became apparent and hence systems were required to adapt to their changing environments. For example, monitoring avionics of an aircraft must deal with a variety of things including fluctuating temperatures, humidity, atmospheric radiation, etc. This monitoring system needs to constantly, and sometimes autonomously, work with unknown failure modes which may have not been realised during system design. Because of this uncertainty, it is difficult to isolate such problems to their root cause and hence require a wide range of reasoning tasks to resolve the issue. Fortunately, such topics[7] have been investigated in artificial intelligence.

In large applications, the AI element is only a part of a much larger system. It is expected to provide increased autonomy, to enable the system functions to become self-diagnostics and adaptable, in response to cope with various deadlines. This alludes towards the capability to rectify faults/failures and achieve mission goals; even with resource limitations. To understand the role an AI approach plays in today's health monitoring practices, it might be helpful to examine some of the historical developments over the years. Although a complete chronology of their use is beyond the scope of this text, the authors have tried to capture some of the significant advances. The rise in interest in developing AI solutions is a consequence of improving processor performance and their reducing costs [63]. Hence, applications of expert systems, fuzzy systems and neural networks have progressively developed. To address several implementation challenges, the discipline of software engineering has been promoted to accommodate the development of interacting systems. Unfortunately, from an engineering point-of-view, this indicates that a system's design has become more intricate and complicated. Any diagnostic analysis or prediction may require an even more rigorous procedure to elicit reliable and dependable system models. This illustrates the dichotomy within the use of AI for health management: improved capability is achieved through added com-

[7] Including reasoning, adaptability, general and flexible intelligent behaviour.

plexity, which consequently reduces system reliability[8]. Yet, AI based diagnostics hold many benefits when compared to conventional approaches. For example, they help improved performance with minimal human effort, they can be easily extended and modified, and they can adapt according to new data, as it becomes available.

In the past few decades, many AI approaches have been integrated into health management systems, but emphasis has been placed on mathematical rigour. An early recognition of a diagnostic systems based on AI was for expert systems application [64]. As research advanced, many other techniques were incorporated, replacing almost completely the conventional techniques. However, these mathematical models are heavily dependent on the quality of the captured data. This leads to the rise of novel systems that were based on fuzzy logic and Bayesian networks to overcome the limitations of heuristic approaches in the old models [65]. The focus remained on decision making – including definitions and rules for knowledge-based systems. This lead to further progresses in symbolic (or concept) oriented learning. These learning mechanisms aimed to meet performance requirements of predetermined set of actions, eventually resulting in knowledge-intensive learning systems with an emphasise of various methods of learning.

With the wide spread use of neural networks, practitioners started adopting them to carry out diagnosis to make health management decisions. The idea of having an AI based health management system become popular. The classical ''if–then and do" commands can be utilised to carry out most complex actions[9]. The major advantage is of retrieving and processing signals; and the knowledge-base which contains all the possible models corresponding to the considered fault modes. This knowledge based can be used as an account for various attributes needed by the models, and hence can compute and store tables or curves of diagnostic indexes for different faults, whilst working in different operating conditions. This can also archive heuristic rules and expert knowledge[10] coming from on-field experience to overcome some of the limits of incomplete system models. However, the major issue is associated with the cost of such systems. The development of a complete health management system that is integrated into the entire system architecture can be expensive. Also, the problem remains as more data is required to train a network. Using artificial data is not ideal and can result in incorrect performance attributes of real world applications. Anomalous behaviour can affect undesirably both the system function, e.g. aero engine performance, and the mission, e.g. air transport. At this point, it should be noted that despite the current drive towards industry 4.0 and autonomous applications [3,66], the role of the human user still has substantial influence in the process. Similarly, the human users must be supported by relevant tools and methodologies which can enable them to control and integrate a system effectively.

3. System health management

The aim of health management is to collect (relevant) data from various sensor sources and carry out the necessary processing including the extraction of key features, fault diagnosis and prediction. Based on this analysis, the system will be able to recommend further actions according to user requirements. This phase plays an important role in adding resilience to the overall solution and regulating availability during service operation. Finally, some recommended actions will be issued including for fault alarms, alternatives to maintain availability and in-service feedback. Depending on the recommendation, the human operator will either choose to delay any action – if the failure can be tolerated until the next scheduled maintenance, or take an immediate action e.g. in the case of failures that can affect safety.

This process has been illustrated in Fig. 2. Some key aspects that can be noted include:

- Any recommended decisions are only good as the data that was collected to represent the current state of the system operation. There is always some uncertainty in the raw data collected by the sensor sources. This can be a challenge as the implementation algorithms may not take such factors into account.
- False alarms have been identified as a major annoyance during maintenance activities [60]. These are fault calls when no actual fault exists, or a call for a maintenance action when none was needed. System level false alarms can send serviceable components for repair; or if the result is questioned, the predefined system level tests are repeated to gain confidence in the initial conclusions. Such difficulties are associated due to a lack of knowledge on the extent of degradation of a system's components whilst in operation.
- System models and related algorithms need to be updated from time-to-time in order to account for any unanticipated conditions. Typically, once a system model is developed it would remain unchanged, therefore the ability to adapt models and algorithms according in-service performance is important.
- Recording and storing acquired on-field knowledge for future application developments and improvements.
- There are often problems to collate meaningful information and analyse of all the acquired knowledge to improve diagnosis and resilience. The used of data and knowledge fusion strategies have been under development to address this issue.
- There might be several problems with acquired data including: missing attributes, where several parameters may not have been measured during failure manifestation, improper data format, corrupt data, bad sensors or even the human operator errors.

[8] Within the field of reliability engineering, a system will be designed with certain reliability attribute/levels during the design phase. These attributes/levels can only be maintained, and cannot be further enhanced, once the system is operational – reliability can only decrease due to degradation/ageing. Unless some design changes are introduced; which adds to the overall cost of increasing system reliability.

[9] such as programs execution, file management, etc.

[10] The symptom to fault map can be stored to identify the 'healthy' state of a system.

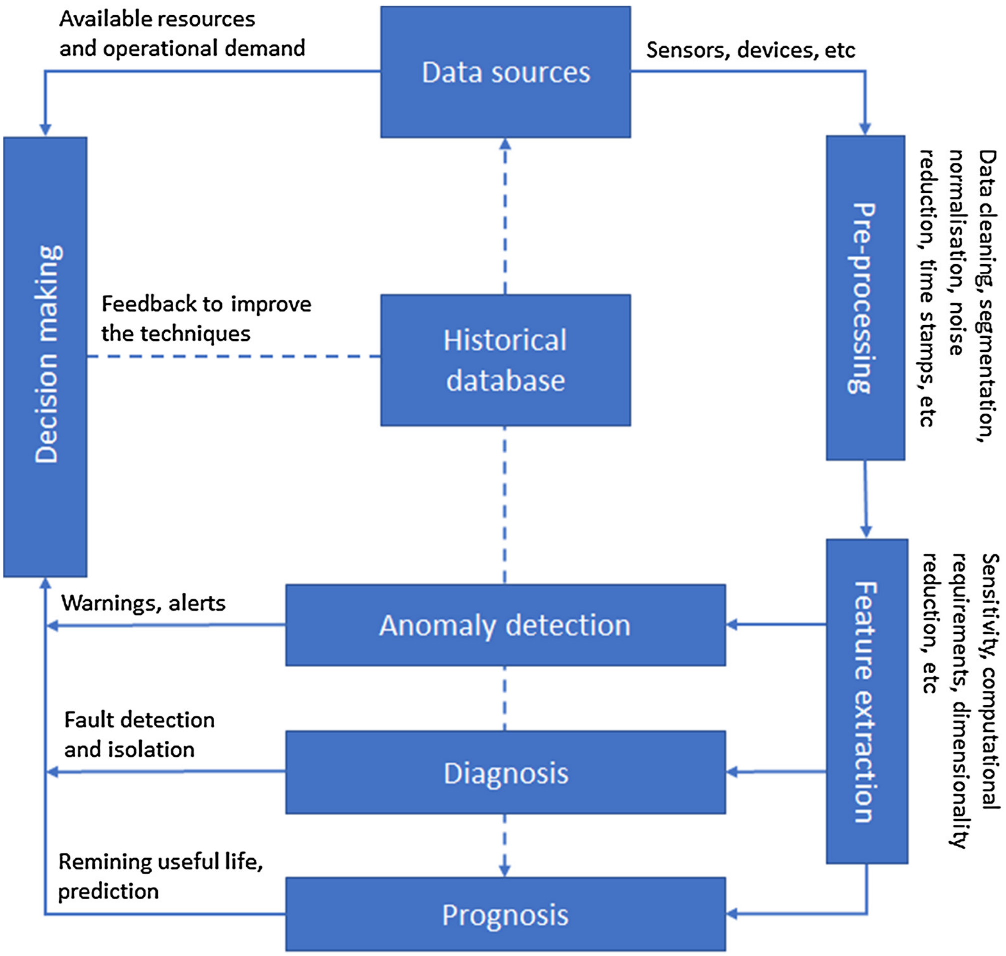

Fig. 2. The system health management architecture adapted from Bonissone et al. [67].

It can be argued that the essential components for the identification of anomalies and faulty conditions include condition monitoring, detection, diagnosis, and prognosis. **Condition monitoring** is when parameters are monitored for anomalies, whereas the **detection** mechanism would enable to detect these abnormalities. The **diagnostic** process will be carried out to determine where that abnormality is located, so that it can be actioned accordingly. Finally, **prognosis** is a process of predicting and estimating the RUL of the system based on its performance. Of course, uncertainties play a large role in the overall process which will influence the predictive results. Therefore, it is common to define some minimum specifications for the health management system in operation. This can include details of the operating environment, sensor tolerance, confidence levels, etc. Additionally, a number of techniques can be employed for processing all the information: optimisation algorithms such as genetic algorithms, artificial immune systems, Monte Carlo methods, learning algorithms such as artificial neural networks and support vector machines, and reasoning algorithms such as fuzzy logic systems, clustering algorithms, particle filtering algorithms, wavelet analysis algorithms, and principal component analysis algorithm. All these methods can be used in data pre-processing, feature extraction and feature selection [68].

Keeping within the scope of this article, a limited number of research papers have appeared to have discussed the challenges associated with embedded system health management implementations. Traditionally, health management systems were designed for component level fault analysis [59]. These systems would reason during operation only and would not consider any analysis at the system level. However, when managing large systems, e.g. a fleet of aircraft, it is important to effectively detect faults before they can affect safety levels and system costs. But there always are going to be faults which were not considered during the system design phase. The aim now is to mitigate these through real-time fault detection and isolation techniques. For example, most modern aircraft gas turbine engines have electronic engine controls units that can carry out these activities including limit checks, parameter tolerance and simple analytical tasks to validate sensor measurements [69]. There is usually built-in sensor redundancy, whilst control software is used to regulate fault modes. Upon the detection of specific faults, the control unit might opt to reduce performance, yet maintaining the core capabilities required to carry out the mission until corrective maintenance takes place. The use of AI to automate these processes does present a challenge; but is beneficial for diagnosing system health, whilst providing a level of analytical resilience.

3.1. Data driven approaches

Machine learning algorithms are usually classified into three categories: supervised, semi-supervised and unsupervised. In the supervised case, the operating user may have complete data of all failures modes and expected behaviours. In the semi-supervised case, the user has access to limited data, e.g. often only healthy data is available. In the worst-case scenario, within unsupervised learning, the system is already operating and there is no knowledge about its condition. In this situation, to enable fault detection, system failures need to categorised according to certain attributes; e.g. failure may be a single fault or related with certain boundary conditions. Once it is categorised into a combination of failures where similar anomalies can be included. Many techniques of that enable this that have been used in many disciplines include health management. Some of them, e.g. neural networks hidden Markov models, etc., can even be used to model highly non-linear problems. However, most methods require large amounts of training data, which may not always be available in practice. There do exist other solutions e.g. the Kalman filter) that can be used with less training data, but in such cases, detailed knowledge of the system processes is required [70].

Table 3
Use of various data driven techniques used in system health management.

Technique	Strengths	Limitations	References
Supervised learning			
Decision trees	Decision using branches Easy to understand Non-parametric Good visualisation	Previous knowledge of systemMay over fit dataIt can get stuck in local minimaHeuristic	Ash et al. [71], Rao et al. [72], Spina et al. [73], Bajwa and Kulkarni [74]
Random forest	Improved performance to decision treesFast and scalable Generally, trains faster than SVM	Increase in bias	Yan [75], Yang et al. [76]
Naïve Bayes	Simple Require less data	Does not allow for rich hypothesisAssumptions of attribute independence can be too constrainingFeatures need to be correlated	Muralidharan and Sugumaran [77], Elangovan et al. [78], Zhang et al. [79], Kumar et al. [80], Ng et al. [81]
[a]Bayesian networks	Probabilistic models Reduces no of parameters to learn Easy to visualise dependency links	Previous knowledge of system Learning unknown structure is complex	Hu and Hao [82], Weber et al. [83], Zaidan et al. [84]
Support vector machines	High accuracy Robust against noise Efficient for large datasets	Requires training data labels Previous knowledge of system Results can be incomprehensible Fundamentally a binary classifier Memory intensive No standard for choosing the kernel function	Fuertes et al. [85], Salem et al. [86], Li et al. [87]
[b]Neural networks (multilayer perceptron)	Small number of parameters needs to be optimised for training Adaptive system	May require greater computational resources Prone to overfitting No standard to determine network structure	Jakubek and Strasser [88], Kobayashi and Simon [89], Marsland [90], McDuff et al., [91], Zhang and Ganesan [92]
Unsupervised learning			
Clustering (k-means)	Short training times	Prior knowledge is needed i.e. the number of cluster, K, must be determined before hand	Soualhi et al. [93]
Adaptive resonance theory	Short training times Ability to model non-linear shaped clusters Robust against outliners	Less suitable for function fitting May require suitable data pre-processing scheme	Lei et al. [94], He et al. [95]
Self-organising maps	Data mapping is easily interpreted Capable of organising large complex data sets	Difficult to determine what input weights to use, mapping can result in divided clusters Requires that nearby points behave similarly	Prabakaran et al. [96], Lacaille et al. [97], Tibaduiza et al. [98], Cho et al. [99]
Hidden Markov models	Statistical models Scalable	Previous knowledge of system, can become complex Large amount of data needed for developing an accurate model	Yu [100], Zhou et al. [101]

[a] The concept of Bayesian networks is very broad, and they are not necessarily supervised. For example, HMM and Kalman Filter can be considered as special cases of Bayesian networks.
[b] Neural networks have both supervised and unsupervised types.

Data-driven techniques are based on collecting experimental data and extracting meaningful features to determine if the system is normal (healthy condition) or are there any symptoms of failure. If the latter is true, the failure must be classified and categorised to identify the fault and determine its severity. Depending on the application, data (such as vibration profiles, acoustic estimations, temperature data, oil analysis, etc.) can also be used to develop a history of the system on which qualitative (such as rule-based or fuzzy logic) and quantitative methods can be applied for further investigation. Over the years, it has been applied to many domains; and can be used to diagnose and isolate faults (see Table 3).

4. Application of deep learning—a review

Many techniques in Table 3 have progressively developed over the past few decades. But some have become more popular in recent years which is largely attributed to an increase in computation power and big data. Deep learning is one of them, which essentially is a *re-branding* of neural networks. It is typically described as an application of neural networks to learning tasks that contain more than one hidden layer. The focus is to model high-level abstractions in data to determine a high-level meaning, that can either be applied as supervised, partially supervised, or unsupervised learning. In theory, a neural network with more than two layers i.e. input and output, can be classified as a deep architecture, however it is not just about the number of layers, but rather the idea of automated construction of more complex features on every step. This means that stacking other algorithms (such as a random forest) several times, use probabilities instead of class labels, and this can be considered as deep learning too. Back-propagation[11], which has existed for decades, theoretically allows to train a network with many layers. Prior to technological advances in computation power, researchers did not have widespread success training neural networks with more than 2 layers simple because of the many calculations that would be required to adjust the weights in the network. This also suffered from a problem of vanishing and exploding gradients[12]. The network architecture was typically initialised using random numbers, and used the gradient of the network's weights with respect to the network's error.

Deep learning has been adopted in various areas such as computer vision, automatic speech recognition, natural language processing, audio recognition and bioinformatics. Considering its wide application and potential, it is an ideal candidate to be used for system health monitoring applications. AI techniques warrant hand-selected features that can best describe the system conditions. Manually designing these and optimising it usually requires great effort. A deep learning architecture is capable to extract hierarchical representation of the data automatically and then utilised the rest of the stacked layers to learn complex features from the simpler ones. In addition, such an approach can be used to achieve an end-to-end system that can automatically learn features from its raw inputs and be able to process accordingly. Fig. 3 illustrates this concept for autoencoders. In contrast to conventional machine learning, deep learning may not require extensive human interaction and knowledge for feature design. In fact, some architectures can be used to learn a model of the input distribution from which one can generate samples. They can also be seen as unsupervised feature learning algorithms and hence be used to pre-train features from labelled or unlabelled data. Such features can then be used as initialisation for supervised networks. A limited number of them has been used for health monitoring. The authors have summarised the various papers reviewed in Table 4.

4.1. Autoencoders

An autoencoder is a neural network that is trained to attempt to copy its input to its output and is often used for unsupervised feature extraction. Fig. 4(a) illustrates the architecture and Fig. 4(b) describes its operation:

- A single layer is used to find initial parameters for the first hidden layer. The approach uses the input data/vector to predict itself. By doing this, the layer learns something intrinsic about the data without the help of an output or label vector – that is often created by the human operator. The learned information is stored as the weights of the network for that layer.
- The next layer uses the output from the first hidden layer to find initial weights for the second layer. The process is repeated for the rest of the layers.
- Finally, a softmax classifier[13] (logistic regression) is used to find initial parameters for the output layer.

Now that all the layers have been initialised, through this pre-training process, to values that are more suitable for the data, the network can now be trained using gradient descent techniques without the problem of vanishing/exploding gradients. Of course, the field has moved forward since this initial breakthrough, and many practitioners now argue that

[11] Backpropagation or *backward propagation of errors* is a method to calculate the gradient of the loss function with respect to the weights. It is often used in conjunction with an optimisation method such as gradient descent. Evaluating the gradient involves using the chain rule and the need to multiply each layer's weight and gradients together across all the layers in the network.

[12] In a neural network, if most of the weights across its (many) layers are less than 1 and they are multiplied many times, then eventually the gradient just vanishes into a machine-zero and training stops i.e. vanishing gradient. On the other hand, if most of the weights across its (many) layers are greater than 1 and they are multiplied many times, then eventually the gradient explodes into a huge number and the training process becomes intractable i.e. exploding gradient.

[13] Softmax is a generalization of logistic regression that can be used for multi-class. In contrast, the standard logistic regression can be used for binary classification tasks.

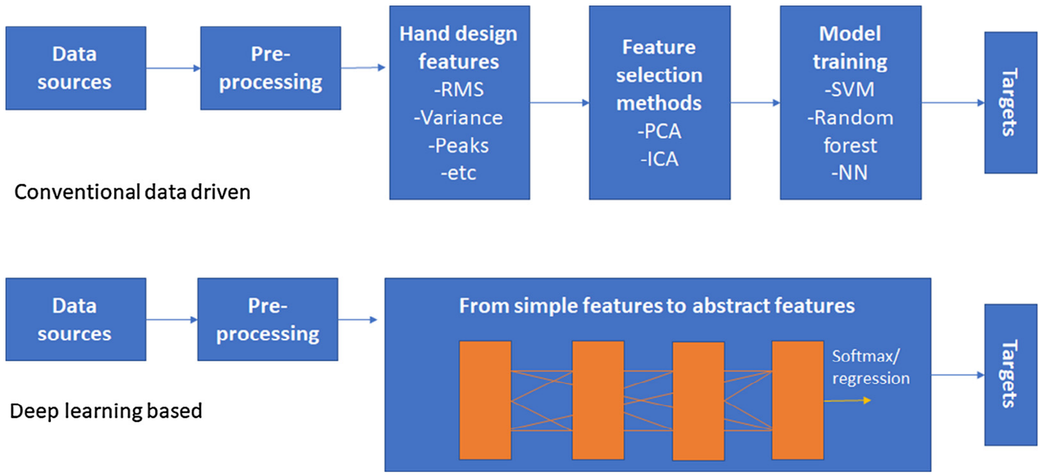

Fig. 3. A top level view of conventional vs deep learning.

pre-training is not always necessary[14]. But even without pre-training, reliably training a deep network requires some additional sophistication, either in the initialisation or training process beyond the older training approaches of random initialisation followed by standard gradient descent.

How many layers? It was mentioned earlier that deep learning works because of the architecture of the network, but more importantly, the optimisation routine applied to that architecture. As can be noted in Fig. 4, each hidden layer is connected to many other hidden layers within the overall network. When an optimisation routine is applied to the network, each hidden layer can become an optimally weighted, non-linear combination of the layers below it. As the size of each sequential hidden layer keeps decreasing, each hidden layer becomes a lower dimensional projection of the previous one. So, the information from each layer is being summarised in each subsequent layer of the deep network by a non-linear, optimally weighted, and lower dimensional projection. None-the-less, the training process can be a challenging and lengthy task when the network has many layers and multiple connections between layers and neurons; but nowadays many researchers are implementing this training phase in graphical processing units to leverage the power of parallel processing and reduce training time. However, once trained, classifying information becomes straightforward and fast to complete.

There have been applications of autoencoders to classify induction motor faults with just one hidden layer [41]. However, most of the literature makes use of multiple autoencoders that are stacked together. Ahmed et al. [26] proposed an unsupervised feature learning algorithm using stacked autoencoders to learn feature representations from compressed measurements. The experimental results demonstrate higher accuracy levels as compared to existing techniques, even with extremely compressed measurements. Lu et al. [55] presented a detailed empirical study of stacked denoising autoencoders with three hidden layers for fault diagnosis. This autoencoder variant uses multiple corruption/noise levels within all its layers and the network is trained it to reconstruct a clean *repaired* version of the input – making it more robust. In addition, Tao et al. [102] studied different structures of a two-layer network designed by varying the hidden layer size, and evaluated for its impact in fault diagnosis. It should be noted that the input dimensionality in these publications was over 100; which indicated concerns towards the large computation requirements and potentially overfitting problems due to so many parameters. As a result, a common practice which can be observed from literature is that most researchers are focusing on readily extracted features as input.

E.g. Galloway et al. [104] and Jia et al. [24] utilised the frequency spectrum to extract features for their fault diagnosis applications. In contrast, Junbo et al. [108] used a digital wavelet frame and nonlinear soft threshold method to process vibration signals and used an autoencoder on the preprocessed signal to carry out roller bearing fault diagnosis. Lu et al. [103] proposed to extract a meaningful representation from signal data. The results defined the bearing signal data accurately. Huijie et al. [109] extracted features after doing a Fourier transform for a hydraulic pump application. The developed algorithm makes use of a rectified linear unit activation function and a dropout technique which are known to overcome the gradient vanishing problem and prevents overfitting, respectively. In Liu et al. [21], a Short Time Fourier Transform of a sound signal was used for fault diagnosis. Li and Wang [107] made use principal component analysis for spacecraft fault diagnosis, and Guo et al. [23] made use of multiple features extracted from time-domain, frequency domain and time-frequency domain. Verma et al. [106] also proposed a similar approach for fault diagnosis but for an air compressors application.

[14] Pre-training helps to achieve two goals: further optimise layers and reduce overfitting. But if the initialisation of weights is done correctly, pre-training is not always needed. This is because pretraining will require many training samples and a lengthy training window (the first few layers will change slowly). This reduces the usefulness of the approach.

Table 4
Use of deep learning in system health management.

Technique	Strengths	Limitations	Application	References (includes conference publications)
Autoencoders				
Autoencoder	Can be modified to learn richer representations Easy to implement Dimensionality reduction Easier to track the loss/cost function that is being minimised by backpropagation	Training can require a lot of data, processing time and fine tuning It learns to capture as much information as possible rather than as much relevant information. It might not be able to determine what information is relevant.	Bearing fault diagnosis Diagnosis of tidal turbine vibration data Fault diagnosis of rotating machinery Motor fault classification Transformer fault diagnosis Condition based monitoring of rotating machines Classification of multi class signals of spacecraft Roller bearing fault diagnosis based on wavelet transform Fault diagnosis of hydraulic pump Anomaly detection in large flight data	Tao et al. [102], Mao et al. [51], Lu et al. [103], Liu et al. [21], Chen and Li [28] Galloway et al. [104] Jia et al. [24] Sun et al. [41] Wang et al. [105] Verma et al. [106] Li and Wang [107] Junbo et al. [108] Huijie et al. [109] Kishore et al. [110]
Denoising autoencoder	Better for denoising (or compression/ feature extraction) because they are deterministic Implicitly designed to form a generative model	Randomly inserts noise at input level	Fault diagnosis in health prognosis applications Fault diagnosis of rotary machinery components Anomaly detection in gas turbine combustors	Thirukovalluru et al. [111] Lu et al. [55] Yan and Yu [112]
Variational autoencoder	Learns what noise distribution to insert at code level It is possible to generate data using distributions Explicitly designed to form a generative model	Can be difficult to optimise Can be difficult to implement	RUL estimation	Yoon et al. [113]
RBM	Generative models as they can learn a probability distribution over its set of inputs Ability to create patterns if there are missing data	Can be difficult to train Difficult to track the loss/cost function	RUL estimation	Deutsch and He [114], Liao et al. [39]
DBM	Can learn very good generative models It retains much of the desired data found in DBN Parameters of all layers can be optimised jointly It incorporates uncertainty about ambiguous inputs	Training can be slower compared DBN. This makes the joint optimisation of parameters impractical for large datasets. Approximate inference is slower reducing the appeal of using DBM's for extracting feature representations	Gearbox fault diagnosis Fault diagnosis for rotating machinery	Li et al. [30] Li et al. [36]
DBN	Good for one dimensional data Can extract the global feature from data Can steadily achieve high performance on the raw vibration signal without too much data preparation Can be seen as a more powerful tool than PCA in separating the data, when used to reduce data dimensionality	Training can be very slow and inefficient	Bearing degradation assessment Fault diagnosis of reciprocating compressor valves Induction motor fault diagnosis Feature extraction of health prognosis applications Aircraft fuel system fault diagnosis Classification in health prognosis applications Bearing fault diagnosis Bearing rotor system diagnosis	Ma et al. [115] Tran et al. [44] Shao et al. [116] Fu et al. [117] Gao et al. [31] Tamilselvan and Wang [56] Tao et al. [20], Chen et al. [57] Oh et al. [118]

(*continued on next page*)

Table 4 (*continued*)

Technique	Strengths	Limitations	Application	References (includes conference publications)
Convolutional neural networks				
CNN	Good for multi-dimensional data Good performance in local feature extraction	More complicated and hence requires more training time	Bearing fault diagnosis	Lee et al. [119], Ding and He [27], Guo et al. [42]
			Fault detection for rotating machinery	Janssens et al. [37]
			Estimation of RUL	Babu et al. [120]
			Real-time motor fault detection	Ince et al. [40]
			Automated feature extraction in defect detection	Weimer et al. [52]
			Real-time vibration-based structural damage detection	Abdeljaber et al. [38]
			Gearbox fault identification and classification	Chen et al. [22]
Recurrent neural networks				
RNN, LSTM and GRU	Good for sequential data Can detect changes over time	Can be difficult to train and implement	Fault diagnosis and RUL estimation	Yuan et al. [121], Gugulothuet al. [13]
			Machine health monitoring	Zhao et al. [35]
			Prognostics using an unsupervised health index	Malhotra et al. [122]

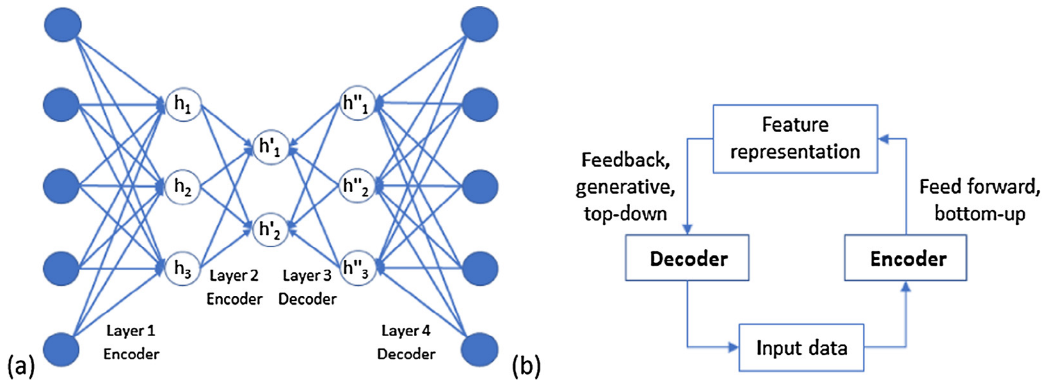

Fig. 4. (a) Adjusting the weights for each layer of an autoencoder (b) encoding of the inputs and recovering the original data as accurately as possible.

Autoencoders have also been used to learn time series data representations from multiple sensors by Kishore et al. [110] and Chen and Li [28]. Statistical features in time and frequency domains are extracted from vibration signals and realised for pattern classification purposes. Other researchers have taken this a step further and investigated the use of integrating autoencoders with other machine learning algorithms. Thirukovalluru et al. [111] made use of autoencoders to extract frequency domain features and then applied standard classifiers such as support vector machines and random forest to carry out classification. Handcrafted features based on Fast Fourier Transform and wavelet packet transform were used as inputs to the autoencoder. After some initial pretraining and supervised fine-tuning, the authors present experiments carried out on five datasets that include data from air compressor monitoring, drill bit monitoring, bearing fault monitoring and steel plate monitoring. This shows the generalization potential of deep leering based health monitoring systems.

It quickly becomes clear that there is a lot of effort being put into the applying autoencoders to a number of applications. Wang et al. [105] proposed a novel autoencoder as an unsupervised feature learning algorithm that is used to change the gradient direction and prevent over-fitting for transformer fault recognition application. Mao et al. [51] made use of another modification of an autoencoder for fault diagnosis called an extreme learning machine that is noted for producing better results and have a very fast learning speeds as compared to conventional forms. To make an autoencoders more robust, researchers have also explored the use of denoising and variational autoencoders. In the denoising version, its input is corrupted before being passed to the network but is being trained to reconstruct the original input. Thirukovalluru et al. [111] and Lu et al. [55] have used them for fault diagnosis, whilst Yan and Yu [112] have applied it for anomaly detection. These authors acknowledge that representation learning can be a power tool for health management applications and demonstrated it potential by comparing handcrafted and deep learned features. In the variational version, an autoencoder's inputs, its hidden representations, and its reconstructed outputs are treated as probabilistic random variables. This allows mapping the encoder inputs to (approximate) posterior distributions; the decoder becomes a generative network, capable of mapping arbitrary information back to distributions over the original data. Since the variational autoencoder can learn sufficient independent factors from the training data, it can generalise new combinations of the factors it has not seen before, making it ideal of missing data problems. Unfortunately, only one publication has been identified that has applied them for system health management application. Yoon et al. [113] used it for RUL estimation and advocate that it is an effective architecture for dealing with the problem of insufficient labels in future reliability prediction.

A notable variant of autoencoders is called the Restricted Boltzmann Machine (RBM). These are a simplification of Boltzmann Machines (BM), with restrictions in between nodes within a group; see Fig. 5. A simple BM comprises of two parts –

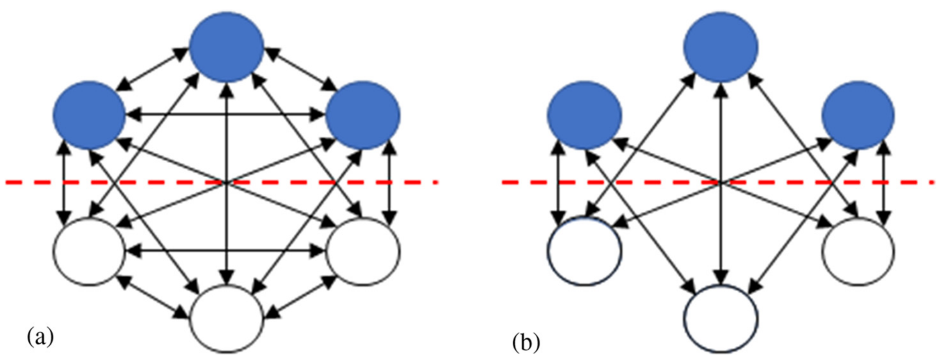

Fig. 5. (a) Boltzmann machine (b) restricted Boltzmann machine.

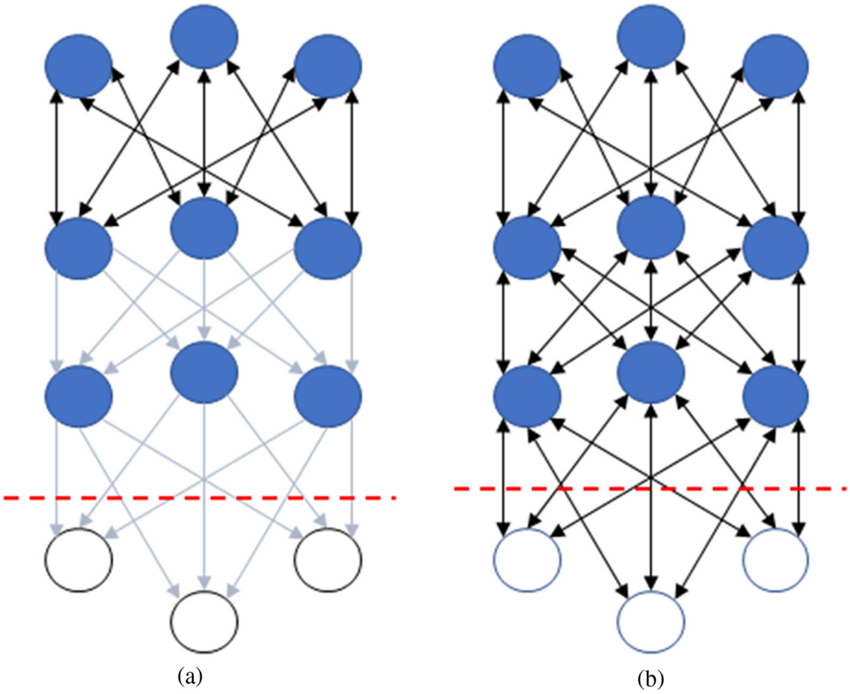

Fig. 6. (a) Deep belief network (b) deep Boltzmann machine.

the hidden and the visible. The red dotted line in the figure highlights this separation. On the other hand, an RBM places restrictions amongst the layers. These are generative models as they can learn a probability distribution over its set of inputs and can randomly generate observable data values, given some hidden parameters. The advantage of using them is the ability to create samples that look like they come from the distribution of the input data. But more importantly they can be used for pattern completion i.e. if there are any missing inputs. The primary disadvantage of RBMs is that they are difficult to train well. Also, it is a challenge to track the loss function. In contrast, the simple autoencoder, it is easier to track the loss that is being minimized by backpropagation. For health monitoring applications, Deutsch and He [114] made use of RBMs for predicting the RUL of bearings. The prediction was computed by using the predicted root mean square value and the total time of the bearings' life. Liao et al. [39] proposed a novel RBM for predicting the RUL of systems. A new regularization term was introduced that models the *trendability* of the hidden nodes. This was integrated with an unsupervised self-organising map algorithm and was applied to transform the representation to a health value that can used utilised to predict RUL via a similarity-based life prediction algorithm.

There are two further variations of RBM – DBN and DBM. What is the difference between Deep belief networks (DBN) and Deep Boltzmann Machines (DBM)? They extend the use of RBMs and are essentially probabilistic models consisting of stacked layers of RBMs[15]. The difference however, is in how their layers are connected (see Fig. 6). Some researchers have considered using these variations for system health management. E.g., Tamilselvan and Wang [56] had proposed a multi-sensory DBN-based health state classification model, which was verified in benchmark classification problems. Tran et al. [44] demonstrated an application for diagnosing reciprocating compressor valves using DBN. Gan and Wan [25] built a hierarchical DBN based diagnosis network for fault pattern recognition. In Fu et al. [117], three different feature sets were used. These included the raw vibration signal, the Mel-frequency cepstrum coefficient and the wavelet features. These were used by a DBN to achieve robust performance on the raw vibration signal without too much feature engineering.

Chen et al. [57], used a feature vector consisting of load and speed measurements. The authors used this data for extracting time domain features and frequency domain features to be fed into DBN-based network for gearbox fault diagnosis. Ma et al. [115] proposed a DBN based method for degradation assessment under a bearing accelerated life test. In Shao et al. [116], the authors proposed a DBN for induction motor fault diagnosis with the direct usage of vibration signals as input. Rather than opting for a principle component analysis, a t-SNE algorithm[16] was adopted to visualize the learned representation. Tao et al. [20] proposed a DBN based multisensory information fusion scheme for bearing fault diagnosis. Furthermore, Oh et al. [118] preprocessed vibration inputs to generate an image. A histogram of gradients was generated from image and the learned features was fed into a DBN for automatic diagnosis of bearing rotor systems. Furthermore, Zhang et al. [123] proposed

[15] For more information on these architectures, see Wang et al. [130].

[16] t-distributed stochastic neighbour embedding t-SNE) is a machine learning algorithm for dimensionality reduction developed by Maaten and Hinton [129].

an ensemble of DBNs with multi-objective evolutionary optimisation for fault diagnosis with multivariate input. DBNs with various architectures are base classifiers and an optimisation routine was introduced to adjust the ensemble weights to achieve a trade-off between accuracy and diversity. The authors further extended this work to estimate the RUL of a mechanical system in Zhang et al. [47].

In contrast to DBNs, publications on the use of DBMs seems to be limited in literature. Li et al. [30] had proposed a multimodal deep support vector classification where the authors extract time, frequency and time-frequency features from vibration signals. This is followed by the application of Gaussian-Bernoulli DBM to each of the three features. A support vector classification framework was used to fuse the three outputs to make the final prediction. Moreover, Li et al. [36] focused on data fusion and adopted a two-layer DBM to learn representations of statistical parameters of the wavelet packet transform of sensor data for gearbox fault diagnosis. The authors concentrated their efforts on data fusion and implemented two DBMs on acoustic and vibratory signals.

4.2. Convolutional Neural Networks (CNN)

Feature extraction can be designed by experts. But it often requires a significant amount of cost and time while it yields an inconsistent level of performance. A technique that has gain a lot of attention for high-dimensional data, such as images and time-series data, is CNN. CNNs are composed of special kinds of neural networks that include the feature extractor within its training process and the weights are determined via the training process. The fact that CNNs turned the manual feature extraction design into an automated process is its primary feature and advantage. They are simply, neural networks that use a convolution operation in place of general matrix multiplication.

Fig. 7 depicts the training concept. The input data enters the feature extraction network. The extracted feature signals enter the classification neural network. The classification (or regression) neural network then operates based on the features of the data and generates the output. The feature extraction neural network consists of piles of the convolutional layer and pooling layer pairs. The convolution layer, as its name implies, converts the data using the convolution operation. It can be thought of as a collection of digital filters. The pooling layer is used as a threshold and dimensionality reduction layer. The primary use of CNNs is in image processing; therefore, the operations of the convolution and pooling layers are conceptually in a two-dimensional plane. This is one of the differences between CNNs and other neural networks.

The way to use CNNs within system health management applications requires to automatically learn the features of the data by making use of the data's time and frequency representation images. This information is then going through a feedback loop for a *deep* CNN architecture for classification and fault diagnosis. Such a methodology can be used on several data sets. Other time and frequency analysis methods such as the short-time Fourier transform, wavelet transform, and Hilbert-Huang transform, etc., can also be explored for their representation effectiveness.

In literature, CNN architecture has successfully been applied for time series prediction and speech recognition problems. In Janssens et al. [37], the authors made use of CNNs for rotating machinery condition monitoring. The input to the network was a discrete Fourier Transform of the two accelerometers. Similarly, Babu et al. [120] built a CNN to predict the RUL of a system. The input was time series data from sensors. Since RUL is a continuous value, a regression layer was added. The authors where able to conduct a series of experiments and demonstrate how a CNN based regression model can be used to outperform three other regression methods i.e. the multilayer perceptron, the support vector regression, and the relevance vector regression. Ding and He [27] demonstrated a deep CNN in which a wavelet packet energy image is used as an input for bearing fault diagnosis. Other health monitoring related research has been carried out by Guo et al. [23] for bearing fault diagnosis, Chen et al. [22] for gearbox fault diagnosis, defect detection by Weimer et al. [52], and motor fault detection by Ince et al. [40].

Vibration analysis was carried out by Abdeljaber et al. [38] who proposed CNNs that perform vibration based damage and structural damage detection in real-time. The advantage of this approach is its ability to extract optimal damage-sensitive features automatically from the input without any additional processing. In addition, Lee et al. [119] investigated the use of CNNs for analyzing noisy acoustic signals. The authors were motivated by the fact that most existing signal analysis methods are largely dependent on the physical behaviour/characteristics of the system being analyzed, which warrants regular re-tuning of algorithms for new acoustic profiles. Although, training for a deep learning system can be slow; but in testing

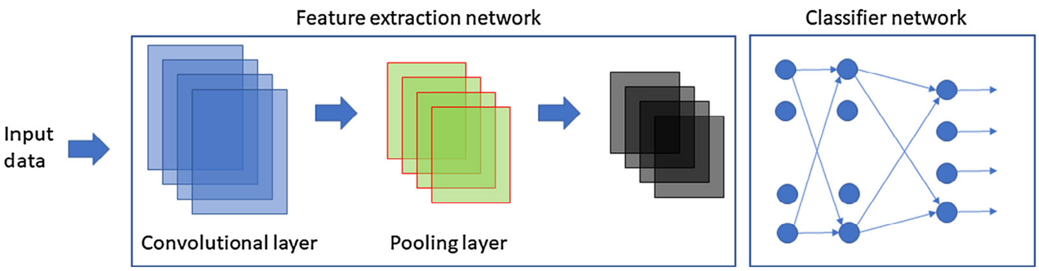

Fig. 7. Typical architecture of CNN.

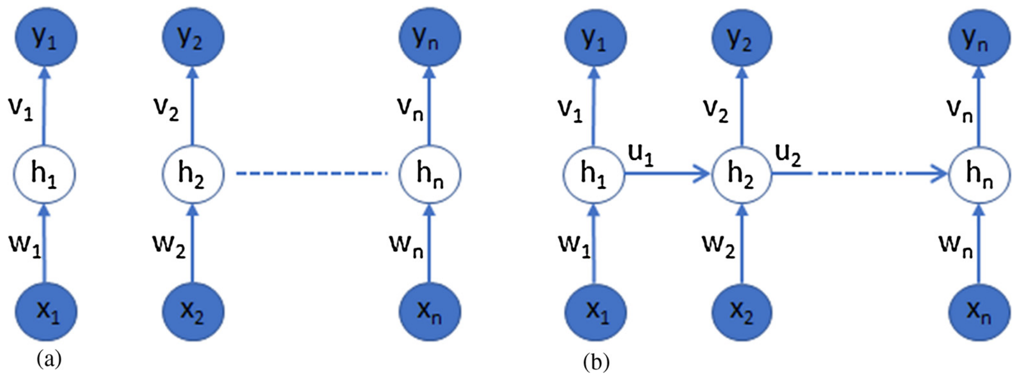

Fig. 8. (a) Sequential structure independence in a simple neural network (b) the RNN structure allows previous inputs to be kept in the networks internal memory.

(running) time these systems are usually quite fast when run on GPUs. Traditional methods can be much slower than deep learning methods during test time. It should also be noted that recently organizations have been focusing on optimising neural based computations, and are expected to see silicon chips that are designed especially for these systems.

4.3. Recurrent Neural Networks (RNN)

The RNN is a framework for dealing with *sequential* data, which makes it an ideal candidate for health management systems due to their time series nature. They overcome the limitations of simple neural nets by using information from the past network results to produce the output as illustrated in Fig. 8. Since a typical NN structure does not take into account the sequential structure in data for any observation $x_1, x_2, \cdots, x_n$; their corresponding hidden states $h_1, h_2, \cdots, h_n$ are independent of each other. In contrast, within an RNN, the hidden state at each step depends on the hidden state of the previous:

$$h_n = f(Wx_n + Uh_{n-1})$$

where U is like a transition matrix and f is some nonlinear function (e.g., tanh). It should also be noted in Fig. 8(b) that it is possible to use the same transition function f with the same parameters (i.e. W, U and V) at every time step.

Many RNN variations can be found in literature; the two more popular ones are networks that incorporate Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU). These variations were introduced to address the vanishing or exploding gradient problem in RNNs. Some authors advocate that these variations are better than traditional RNNs due to their ability to store long-term dependencies and nonlinear dynamics in time series data; making them ideal for time series sensor) data processing and health monitoring. More information on their implementation theory can be found in Jozefowicz et al. [128].

Like other architectures, RNN can also be extended to have more than one hidden layer that can connect its hidden states across many observations, and propagate information along the sequence. A limited number of deep RNN related publications have appeared for system health management. For example, Zheng et al. [124] studies LSTMs for RUL estimation. Yuan et al. [121] have successfully compared three different RNN variations: the simple RNN, LSTM and GRU for fault diagnosis and prognostics of aero engines. Zhao et al. [125] carried out an empirical evaluation of a health monitoring system using LSTMs, where the authors predicted the tool wearing. This research work was followed by further designing an integrated architecture using a CNN and a LSTM [35]. This integrated architecture can outperform several state-of-the-art baseline approaches, including conventional LSTM. Malhotra et al. [122] introduced another structure for predicting the RUL. This comprise of a LSTM-based encoder-decoder structure which would transform the input into a fixed-length vector and use the LSTM decoder to produce the target sequence. The assumption had been that this setup can be trained in using normal behaviour data in an unsupervised way. The reconstruction error can then be utilised to compute the health index where a large reconstruction error indicates corresponds an unhealthy condition.

5. Critique and further developments

This article has provided a systematic review for burgeoning deep learning based health management literature. It can be concluded that there has been a lot of interest in using simple autoencoders and DBN for fault diagnosis purposes. There has also been some limited work on end-to-end target prediction. CNN and RNN are more complex structures to learn representations from health data. However, regardless of which architecture is used, its theoretical formulation requires expert human knowledge for its successful realisation. And despite the positive outcomes from the reviewed material, there are many open questions.

Whilst deep learning based approaches depend heavily upon a system's feature representation data, acquiring it for any given asset can be an exceedingly expensive effort. This is due to the labelling process that requires expert knowledge, and is generally time consuming. However, what should be recognised is that deep learning architectures are desirable and can technically produce good results. Yet, to enable widespread adoption of these architectures within engineering applications, such as system health management, it will require a much more systematic methodology that should categorically address the two driving forces discussed at the paper outset, i.e., system safety and implementation cost. This indicates that even though deep learning is a useful tool for unsupervised feature learning, it will be difficult to replace common techniques such as SVM and random forest, for system health monitoring applications. This is because, these methods have excellent performance in generalization that produce high accuracy for classification and regression for machine condition monitoring and diagnosis.

The key challenges with the reviewed developments so far are:

- Most of the approaches are application or equipment specific and as such there is no clear way to select, design or implement a deep learning architecture:

Some authors, e.g., Thirukovalluru et al. [111], Lu et al. [55] and Yan and Yu [112] have not discussed the reasons why they have preferred to implement their solution using their selected architecture. This could be a result of a drive within research communities to ensure that these learning algorithms function as logically and accurately as possible – which is good for machine learning. Yet, this creates a disparity within academic knowledge regarding the subject area where deep learning, itself, is considered as an unsolved problem. This is because, deep learning methods are often looked at as a black box solution, at least in the computing discipline, where most confirmations are empirical rather than a mathematical solution to a learning problem. For example, why did some authors preferred using CNN or RNN for their application? (Yuan et al. [121] and Babu et al. [120] for estimation of RUL) Or how deep should these architectures be designed? This makes it difficult to understand the reasons why a trained network would predict certain results. Due to such ambiguities, some researchers have considered deep learning to be more of an improved computation effort rather than a research product, which is brought about due to big data; in contrast to better algorithms [126]. Its successes are therefore attributed to advances made in modern GPUs that enable parallelization of computational problems.

- At the moment, many deep learning architectures are being used and applied to solve specific diagnostic problems. Researchers have not explained, nor documented, the reasons as to why or how these architectures have been selected:

From Table 4, it is evident that autoencoders, denoising autoencoders, DBM, DBN, CNN and RNN has been used for fault diagnosis applications. This could be due to the specific fault diagnosis problem the authors are attempting to solve. But should there be any difference in the result, regardless of the selected architecture? Such comparative studies are non-existent, and this could be attributed to how health management systems are designed. Modern designers aim to build complete ecosystems within their final solutions with built-in sensors, cloud technology, monitoring software and communication mechanism which act as a feedback with operating and performance data to various stakeholders including the original equipment manufacturers, integrators, etc. Analysing this information can help to identify incipient faults and early signs of equipment degradation. Evidently, the use of big data is being used to provide an integrated system that can not only monitor various high value assets and their related components, but also account for interdependencies within subsystems and make design decisions. Therefore, the interrelations of these subsystems, their design specifications, their history, and their current conditions should all be considered when assessing operational conditions and maintenance needs; or when evaluating operations on an engineering level. Deep learning is an ideal candidate for such problems, which require end-to-end learning. The concept to automatically learn internal representations of the necessary processing steps, such as detecting useful component features, environmental impact, anomaly detection, etc. is an important one, yet there is no study which provides credence on one architecture over another for any particular problem.

- There is a lack of appropriate benchmarking of the results:

Limited research has attempted to benchmark results. Some authors such as Reddy et al. [127] and Jia et al. [24] have applied their deep architectures and compared its output to decision trees, backpropagation or their single layer counterparts to produce favourable training results. This can be misleading because stacking multiple layers of information processing modules in hierarchical structures will almost certainly provide an improved outcome. The issue here is evaluating the computational effort of the solution. The behaviour of any large system does not only depend on the system response, but also on the time it takes to compute the logic and its implementation. Adopting a deep learning approach for classification may yield a much robust and reliable conclusion, yet, for health management, the implementation architecture must warrant a controlled system performance under all conditions for safety reasons – indicating a deterministic system response. Any loss of information can be critical to the stability of the system; on the other hand, any delay in processing information can result in inaccuracies. This needs to be benchmarked to discover what is the best performance being achieved.

- Not much emphasis is being place on the cost of implementing the architecture:

Many authors in literature seem to have extracted features before-hand and then implemented their expected algorithm, such as Galloway et al. [104] used frequency spectrum, Junbo et al. [108] used wavelets, Li and Wang [107] made use of PCA, etc). The purpose for this is to be able to reduce the training time required, computational power and possibly processing cost. Yet, this can introduce a bias in the early training of an algorithm that can lead to unreliable results. It can also be argued that this goes against the philosophy of deep learning i.e. to discover unknown patterns in datasets and provide an end-to-end learning solution.

- Lack of understanding towards application complexity:

In contrast to other disciplines that make use of deep learning (e.g., image processing and speech recognition), the issue in system health management is rather complex. This is because faults and failures can be heterogeneous and vary according to different environments. Problems such as No Fault Found issues, are known to be difficult to diagnose using standard test equipment and hence contributes to the inability to correctly localise the suspected units [6,60]. A black box solution might be the answer to the problem, but this still requires a lot of research effort from both an industrial and academic viewpoint.

5.1. Future opportunities

For the engineering community, deep learning has opened a plethora of future research; the key questions centring around the impact of deep learning based innovation. The highlighted key challenges give way to a number of future research opportunities. With the continued research interest, the eventual goal is to develop an overall solution with several interacting components. Therefore, the questions that need to be speculated are: "do the benefits of using deep learning for health monitoring out-weight the efforts required for its realisation on current applications? If so, is there a systematic approach to design and implement the solution?". As seen in this review, deep learning approaches do offer adequate results; which makes its more attractive. As our society becomes more automated and technology efficient, the need to implement more effective health monitoring algorithms becomes important for its maintenance. However, these advances are dependent on high quality data from multiple sources, often located at different geographical locations, to predict the behaviours of the system operation and make corrective responses. The goal is to appreciate the limitations that deep learning brings to the application and then attempt to simplify the problem. Understanding these trade-offs is an on-going motivation of this work, and hence there are several opportunities that exist for fundamental advancement in this area:

- There is a need to pay attention to the structure of the computation to minimise complexity:

A limit needs to be imposed to control the number of computations involved with various deep learning architectures. Emphasis should be placed on acquiring as many features as possible from the health data. Data integration from disparate sources and how to enable it into a deep learning solution is an important research topic. In fact, to the best of the authors' knowledge, the reviewed material does not offer any research that is looking to integrate various types of disparate data sources using deep learning.

- Factoring in uncertainties:

The learning architecture should consider uncertainties within the data. This can be achieved by making use of Bayesian methods that use probabilities to represent uncertainty and confidence in its output. This information can be propagated throughout the network to improve predictions, that now take into account the consequences of plausible misclassifications and act accordingly. To date, the authors were not able to identify any publication that is studying uncertainty in this review.

- Selecting criterion for acceptable solutions:

The assumption here is to satisfy the requirement rather than to find an optimal solution. These satisfying solutions can take the form of using heuristic problem-solving techniques and is only useful if non-optimal solutions exist for a problem. Yet, whichever solution is selected, there is a need to gain confidence in the new strategy from a practical point-of-view. Machine learning techniques often require a lot of parameter and framework tuning, and it is not always clear as to which architecture will work better. This can be frustrating for engineering academics, who may be beginners to deep learning concepts.

- The role of variational autoencoders:

The work by Yoon et al. [113] demonstrates the applicability of variational autoencoders for health management applications. Since these autoencoders work with generative models, they can efficiently be used to regularize any complex system model whilst achieving high prediction accuracy that is far less sensitive to the availability of health status information. This makes it ideal for health management applications for anomaly detection and failure prediction problems in noisy environments. Also, the idea to detect unseen faults can be categorised as unsupervised fault detection that can detect anomalies from unlabelled data under the assumption that most of the instances in the data are normal by looking for instances that seem to fit least to the remainder of the data. Yet, there is limited research being undertaken to further its potential application.

- Combining expert knowledge for troubleshooting:

Existing expert knowledge in health management system problems is essential for not only availability requirements, but also system safety. Integrating expert knowledge into the deep learning solution can help lead towards an adequate solution that is cost feasible. These are situations in which unlabelled data is abundant but manually labelling is expensive (e.g. intermittent faults). In such a scenario, learning algorithms should actively query experts for labels. This type of iterative supervised learning is called *active learning*.

- Justification of resource costs:

Funding calls influence current academic research directions, who need to spend time write grants, sit on committees, etc. Currently funding bodies are paying scant attention to deep learning techniques for maintenance applications, which currently warrants some fundamental work – perhaps even below technology readiness level 4. Perhaps a good way to foster interest in the area is to collaborate with the aerospace industry, who should take a lead and partner in the development of technology.

6. Conclusions

Several AI approaches have been used for health monitoring over the years, with interest to the aerospace industry and related applications. Many approaches that have emerged are difficult to implement exclusively with the software, mechanical and electrical domains and hence cross domain strategies must be devised. As the device fabrication process continues to improve, failure rates of hardware components have steadily declined over the years to the point where non-hardware failures are emerging as more dominant issues. Yet, with the increased scale of system designs, there is more emphasis now to reduce troubleshooting complexities and the time-to-fix problems when investigating failures with health monitoring systems. Artificial intelligence techniques have helped with some of these aspects. But efforts seem to concentrate on increasing fault detection at lower design levels. Of course, when detections occur closer to the actual fault event, isolation becomes possible. However, on the system level, decision making should be carried out based on a range of learning processes; hence health monitoring for high-value assets will improve downtime and cost implications. It is important to recognise that, despite the view which is prevalent among academic researchers, from a practical industrial viewpoint achieving efficient and effective implementations of any AI method for health monitoring applications is not completely solved. There are therefore many sub categories for exploration, both relating to designing algorithms for processing and the computing architectures.

Deep learning has been applied successfully in a variety of domains. Even though, the focus of deep learning (for unsupervised learning) has been in the image processing domain, this article has reviewed the emerging research relating to deep learning of system health management. These methods are known to overcome the vanishing gradient problem; which was severely limiting the depth of neural networks. It is as simple as that. Typically, simple neural nets were trained using back-propagation gradient descent where the weights were updated for each layer as a function of the derivative of the previous layer. However, there were limitations to this approach if the network architectures increased and hence, practitioners often only used a single hidden-layer. But now, as there is the possibility to implement larger networks, it opens a door of opportunities to techniques such as auto-encoders for unsupervised problems, CNNs for classification, RNNs for time series, etc. It should be acknowledged from literature review that there is a growing interest in applying deep learning architectures in system health monitoring; but there appears to be no clear way to select, design or implement a deep learning architecture. Another criticism is regarding the absence of an end-to-end learning solution that can jointly train all aspects of the system from the data source, through to prediction/classification, and eventually, making a decision. This would be a successful platform of system health management as it will enable each data source to form a representation that is optimised according to the desired activity – which is the purpose of deep learning.

At this point in time, there are more questions than answers regarding the capabilities of deep learning for health management applications. Even though this article presented some of the requirements and recent advances of the engineering community, the authors were not able to evaluate the effectiveness of these approaches. This makes it difficult to assess whether deep learning will be at the academic frontier in upcoming years – as academic research now-a-days tends to have a short shelf-life and get replaced by new ideas and trendy topics. Collecting more data does not necessary mean better results. But due to recent industrial efforts, the machine learning field is moving quickly, and perhaps a few years from now may look nothing like what is call *deep learning*. That being said, there is an unprecedented interest from a number of technology organizations, other academic disciplines, and even the general public, on the topic. Despite the hype and how academics perceive it, deep learning seems quite valuable in the monetary sense. It has enabled an array of real-world commercial products and services that were not technologically feasible before and hence it could prove useful for the system health management community.

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