Combining Knowledge and Deep Learning for Prognostics and Health Management

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ABSTRACT

In the recent past deep learning approaches have achieved remarkable results in the area of Prognostics and Health Management (PHM). These algorithms rely on large amounts of data, which is often not available, and produce outputs, which are hard to interpret. Before the broad success of deep learning machine faults were often classified using domain expert knowledge based on experience and physical models. In comparison, these approaches only require small amounts of data and produce highly interpretable results. On the downside, however, they struggle to predict unexpected patterns hidden in data. This research aims to combine knowledge and deep learning to increase accuracy, robustness and interpretability of current models.

1. MOTIVATION AND RESEARCH QUESTION

Production halls are becoming more automated, efficient and flexible through the increasingly widespread adaption of the Industrial Internet of Things (IIoT). This provides the opportunity of working with minimal inventory and an optimal amount of work in progress. To guarantee the smooth sequence of operations nonetheless, requirements towards the functionality and reliability of machines are increasing. Additionally, all manufacturing companies are under the constant pressure of reducing costs. Therefore, state-of-the-art maintenance strategies for the ensured flow of processes and cost reduction are indispensable (Pawellek, 2016).

The basis for modern maintenance strategies is the rapid diagnosis and prognosis of faults using current machinery conditions, which makes it possible to base maintenance decisions on the expected remaining useful life (RUL). This is called predictive maintenance. In comparison to traditional maintenance strategies this approach can reduce machine down times by 35 % - 45 % and increase production by 20 % - 25 % (Selcuk, 2017). Prognostics and Health Management (PHM) provides the methods and techniques to analyze condition monitoring data and make predictive maintenance possible.

In the last years the advent of deep learning (DL) has shown remarkable results in diagnosing and predicting failures (Fink et al., 2020). Nevertheless, multiple obstacles remain if these algorithms are to be used in practice. One issue is the availability of correctly labeled data needed for training and the question on how models can work with limited or even nonexistent fault data. Many DL models have strong performance on specific data but deteriorate when confronted with minor domain changes. How to make models more robust is therefore a question worth exploring. A known issue with DL is the black box nature of the models. How the results can be explained nevertheless and if potential root causes can be inferred from these explanations are further open questions.

An attempt to tackle these issues in current state-of-the-art data driven DL models is the combination with knowledge. Hereby knowledge, which is formalized within a knowledge base, can consist of both physical models of fault processes and semantic knowledge describing the underlying system and relations. The resulting hybrid model is able to provide answers to the posed questions.

Consequently the overarching proposed research question for the PhD is the following: How can we improve state-of-the-art DL models for machinery fault classification and RUL prediction with the help of knowledge? The resulting methodology will be used to answer more specific questions: How can the amount of required labeled data be decreased? How can the explainability of black box DL approaches be increased and used for root cause analysis? How can DL models be made more robust towards outliers and minor domain changes?

2. STATE OF THE ART

Multiple approaches for detecting and predicting machinery faults exist. These can be grouped into experience-based, data-driven and physics-based models (Liao & Köttig, 2014). To create hybrid models these methods are combined to form new approaches, which alleviate the disadvantages of pure

models. Especially inducing data-driven models with knowledge based on experience and physics has been successful. Recent work in the PHM domain has shown to increase explainability and enable root cause analysis by taking into account input from human experts (Steenwinckel et al., 2021), make models more robust and decrease the amount of data needed through the simulation of data based on expert knowledge (Wang, Taal, & Fink, 2021), and increase overall performance by extending the feature space (Chao, Kulkarni, Goebel, & Fink, 2022).
Even though recent work in the direction of combining knowledge with data is promising, a lot of untapped knowledge in the shape of physical models (e.g. for rotating machinery (Cubillo, Perinpanayagam, & Esperon-Miguez, 2016)) and symbolic models, such as manufacturing ontologies (Cao, Zanni-Merk, & Reich, 2018), remains. Especially formal logic and semantic knowledge have not yet been studied in detail for mixing with DL in the PHM domain and provide fertile ground for further research.

3. Contribution

Two possible approaches towards combining PHM specific knowledge with deep learning will be explored.

3.1. Pretraining DL models based on knowledge

The first idea is to use knowledge based on physical and domain expertise as pretraining for a DL model. Through this approach one can mimic the process of human learning, where clear theoretical instructions are learned initially and are later fine tuned by practical experience. A first visualization of the possible process is given in Fig. 1. The idea aims to decrease the amount of necessary labeled data and make the optimal weight configuration of the resulting neural network more robust towards data anomalies and minor domain changes. For the correct implementation multiple questions need to be answered: What is the appropriate formalism for the knowledge base? Does an existing formalism have to be extended for this use case? How can the knowledge base be used for pretraining? Should data simulated with help of the knowledge base or observational data be used for teaching knowledge to the neural network? Can the intrinsic explainability of the knowledge base be maintained after fine tuning?

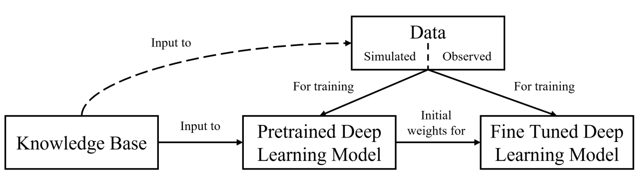

Figure 1. Potential high level process for pretraining with a knowledge base.

3.2. Splitting and combining DL tasks with knowledge

The second idea is to split the complex problem of failure diagnosis and prognosis into multiple sub-problems, which are solved via DL and are later combined to answer the initial question. Both the split into sub-problems and the combination of the outputs is done on the basis of underlying knowledge about the issue. For example, the occurrence of single known failure root causes can be predicted separately and later combined for possible fault inference. Or, different groups of features are defined, which are used to train different models independently, for which the combined output gives the final fault diagnosis. The proposed process is visualized in Fig. 2. By dividing the main problem into multiple sub-problems the amount of data needed is expected to decrease owing to the passing of explicit knowledge, which in turn does not need to be learned. Additionally, increased explainability due to the modular nature of the approach is achieved. Again, multiple questions arise when realizing the idea. How can the knowledge base be formalized? Does an existing formalism have to be extended for this use case? How can sub-questions be identified and inferred? How can the combination of different DL outputs be achieved?

Starting off, these two ideas will be examined in parallel and subsequently reflected on whether or not they should both be continued. In a later stage of research integrating the two streams is a possibility worth investigating.
In comparison to work in Sec. 2, where mainly physical knowledge was used to improve DL, the focus will be on additionally integrating symbolic knowledge for the union of different models and formalizing the knowledge base (both symbolic and physical) for wider reuse.

4. Work in Progress

In keeping with the first proposed idea, using knowledge for training neural networks in the domain of rolling element bearing fault detection is being examined in detail as an initial step. In the current (work-in-progress) paper a knowledge base for fault classification is created by deriving expected physical attributes of different faults through vibration signals. This knowledge is used to create a similarity function for comparing input signals to expected faulty signals. Afterwards the similarity measure is incorporated into a DL model using a Logic Tensor Network (LTN) (Badreddine, Garcez, Serafini, & Spranger, 2022). This enables logical reasoning in the loss function, in which the decision process of an expert analyzing the input data is to be imitated. The combination of the symbolic loss function and the underlying knowledge base enables better explainability of the classification results and achieves higher accuracy in comparison to the pure DL method, especially when using smaller fractions of the data, as shown in Fig. 3.

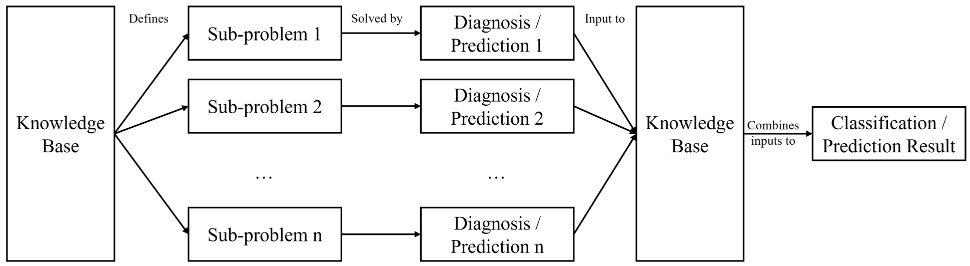

Figure 2. Process for splitting and combining DL tasks with knowledge.

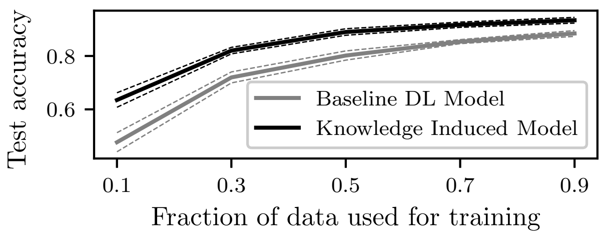

Figure 3. Results from the current (work-in-progress) paper, where we induce knowledge into DL models for bearing fault detection.

5. Conclusion

The proposed research direction for combining knowledge and DL for PHM has a lot of potential to improve current DL approaches in the PHM domain by taking the best of both worlds and alleviating the disadvantages of the individual approaches. The goal is to decrease the amount of labeled data needed, increase explainabilty and make models more robust towards outliers and minor domain changes. This year's European Conference of the Prognostics and Health Management Society further underlines the importance and high relevance of these ideas for the PHM community by conducting a special session for inducing physics and domain expert knowledge in DL algorithms for PHM applications.

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Biography

Maximilian-Peter Radtke studied business mathematics at the University of Mannheim, Germany and graduated in 2018. After his studies he worked as a data science consultant in various industries for two and half years before returning to academia. Since 2021 he has been working at the Technische Hochschule Ingolstadt (THI) as part of AIMotion Bavaria and the research group AI applications for innovative production and logistic systems. His research interests include the combination of symbolic and sub-symbolic AI approaches and the incorporation of knowledge into deep learning in the area of fault diagnostics and prognostics.

Jürgen Bock is a computer scientist, who graduated as Diplom-Informatiker from Ulm University, Germany, and as Bachelor of Information Technology with Honours from Griffith University, Brisbane, Australia, in 2006. He began his research career at the FZI Research Center for Information Technology in Karlsruhe, Germany, and received his PhD from the Karlsruhe Institut of Technology (KIT) in 2012. After 2 years as post doc and team leader at the FZI, he joined the corporate research department of KUKA Robotics in Augsburg, Germany as developer and later leader of the team Smart Data and Infrastructure. In 2020 he joined the Technische Hochschule Ingolstadt (THI) as research professor in the area of AI applications in innovative production and logistics systems.