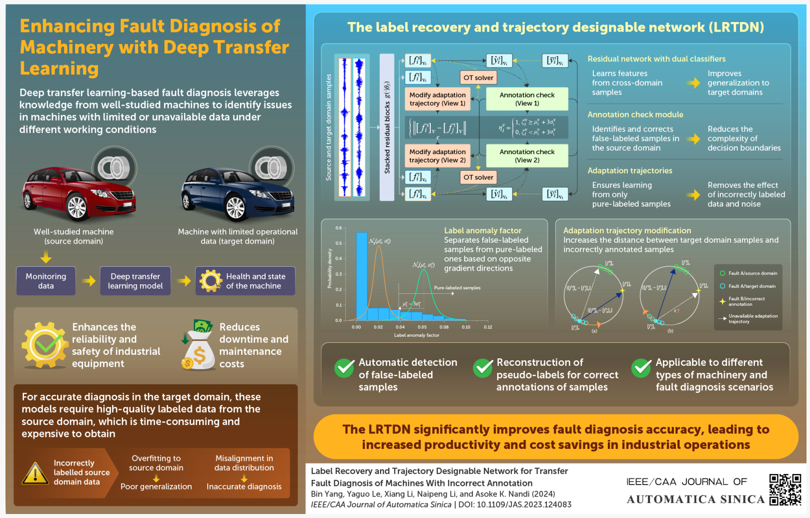
New Study Improves Fault Diagnosis Accuracy in Machines with Deep Transfer Learning

A label recovery and trajectory designable network addresses labeling challenges of input data to improve fault diagnosis in machines.



The LRTDN consists of a residual network with dual classifiers, an annotation check module, and adaptation trajectories. Together, these components enhance fault diagnosis by correcting incorrect labels in the source domain and aligning data distributions

BEIJING, CHINA, July 3, 2024 /EINPresswire.com/ -- Diagnosing faults with deep transfer learning allows knowledge transfer between machines to detect issues. However, it requires high-quality labeled data, which is hard to obtain. In this study, researchers developed the Label Recovery and Trajectory Designable Network to correct mislabeled data and align data distributions between the source and target domains for accurate fault diagnosis. This method can accurately diagnose faults in bearings under different working conditions and in different but related machines.

Maintaining machinery is a time-consuming, challenging task that often involves putting the machine out of operation as it is disassembled and inspected for faults. This not only causes significant downtime but is also prone to human errors. However, rather than relying solely on manual inspections, we are moving towards automated diagnosis where intelligent models can analyze vast amounts of data from sensors placed on machines to identify potential problems. This shift is made possible by advancements in deep transfer learning, a branch of artificial intelligence that allows diagnostic knowledge gained from analyzing well-studied machines (the source domain) to be applied to other machines operating under different conditions (the target domain). This innovative approach reduces the need for extensive data collection and training to build diagnosis models for each machine. However, for accurate fault diagnosis, these models require high-quality labeled data from the source domain, which is challenging to obtain.

To address this issue, researchers from Xi'an Jiaotong University, Hunan University of Science and

Technology in China, and Brunel University London in the United Kingdom have proposed a Label Recovery and Trajectory Designable Network (LRTDN). This method enhances the fault diagnosis process by correcting incorrectly labeled source data and ensuring better alignment of data distributions between the source and target domains. This prevents the model from overfitting to the source domain and allows for greater generalization to the conditions of the target domain. The paper was [published in the 2024 Issue 4 of the IEEE/CAA Journal of Automatica Sinica].

"Incorrect label annotation produces two negative effects: First, the complex decision boundary of diagnosis models lowers the generalization performance on the target domain, and secondly, the distribution of target domain samples becomes misaligned with the false-labeled samples. To overcome these negative effects, we propose LRTDN," says corresponding author Yaguo Lei, Professor at Xi'an Jiaotong University.

To understand how the network works, let us dive into how deep transfer learning identifies faults. Initially, the model learns to identify specific features associated with faulty parts using data from the source domain. It then categorizes the data into different groups based on its understanding of normal and faulty machine behavior, establishing decision boundaries. These decision boundaries are then utilized by the model to classify data in the target domain.

However, incorrect labeling in the source domain can lead to the misclassification of faulty parts as non-faulty. This occurs because the decision boundaries are influenced by these incorrect labels, resulting in inaccurate classification of data in the target domain.

The LRTDN addresses the issue of incorrect labeling using three key components: a residual network with dual classifiers, an annotation check module, and adaptation trajectories. Each component tackles specific challenges of deep transfer learning to enhance fault diagnosis.

The residual network with dual classifiers captures the nuances of features between the source and target domains. Machines vary widely in their design, operating conditions, and environmental conditions. These differences result in unique data profiles or feature distributions for each machine, making it challenging to apply a fault diagnosis model trained on the source domain directly to the target domain. By learning to distinguish these features, the model can adapt to the new patterns in the data, making it more accurate in diagnosing faults in the target domain.

The annotation check module identifies and corrects falsely labeled samples in the source domain. It uses a label anomaly factor that separates false-labeled samples from pure-labeled ones based on opposite gradient directions. By correcting these labels, the module ensures that the training data for the fault diagnosis model is more accurate.

The adaptation trajectories prioritize the fault detection model to learn from accurately labeled samples. It achieves this by increasing the distance between target domain samples and incorrectly annotated samples.

Using the proposed LRTDN method, researchers successfully diagnosed faults in bearings, even when the data in the source domain was incorrectly labeled. They conducted two tests: the first involved the fault diagnosis of new-energy vehicle bearings across different working conditions. In this test, transfer learning was used to transfer knowledge between bearings operating at different speeds to determine their health status. The second test focused on transfer fault diagnosis across different machine-used bearings. In both tests, the LRTDN outperformed other methods, achieving notably higher accuracy rates, with the highest average accuracy of 79.9% for the first test and 95% for the second test.

Such a method can enhance the reliability and safety of industrial equipment. “The ability to accurately diagnose faults despite incorrect annotations will lead to more reliable preventive maintenance strategies. This can prevent unexpected machinery failures, reducing downtime and maintenance costs,” says Prof. Lei. Furthermore, the method also finds use in other fields where transfer learning is useful such as such as medical diagnostics, financial fraud detection, and more.

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Reference
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