Lightweight and Self Adaptive Model for Domain Invariant Bearing Fault Diagnosis

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Keywords: Condition Based Monitoring, Self Adaptation, Resource Constrained Computing, Bearing Fault Diagnosis, Domain Invariance.

Abstract: While the current machine fault diagnosis is affected by the rarity of cross conditional fault data in practice, efficient implementation of these diagnosis models on resource constrained devices is another active challenge. Given such constraints, an ideal fault diagnosis model should not be either generalizable across the shifting domains or lightweight, but rather a combination of both, generalizable while being minimalistic. Preferably being uninformed about the domain shift. Addressing these computational and data centric challenges, we propose a novel methodology, Convolutional Auto-encoder and Nearest Neighbors based self adaptation (SCAE-NN), that adapts its fault diagnosis model to the changing conditions of a machine. We implemented SCAE-NN for various cross-domain fault diagnosis tasks and compared its performance against the state-of-the-art domain invariant models. Compared to the SOTA, SCAE-NN is at least $6-7\%$ better at predicting fault classes across conditions, while being more than 10 times smaller in size and latency. Moreover, SCAE-NN does not need any labelled target domain data for the adaptation, making it suitable for practical data scarce scenarios.

1 INTRODUCTION

Cloud computing is one of the major facilitators of data analytics and intelligent decision making for industrial processes and machines. Although the combination of IoT and cloud computing provides infinite computing and storage resources for the previously remote machines, few challenges exist in fully centralizing the computation on the cloud (Wang et al., 2020). Some critical challenges in the context of Industrial IoT are, limited bandwidth, latency and reliability of the connection. While IoT enabled devices can continuously gather data from the machines and their environments, their bandwidth availability limitations cannot accommodate high data throughput. This in combination with the latency of the data/ decision communication and connection reliability to the cloud might lead to a catastrophe. Contrary to the cloud, computing on the edge not only brings the latency to *ms* scale but also reduces the overall operational costs by reducing the volume of data that has to be migrated across the networks (Qiu et al., 2020). With computing brought to the edge, the data is readily available for knowledge extraction and faster decision making.

While edge computing can aid many time critical applications, bearing fault diagnosis is one major field that can readily benefit from the low latency computing at the edge. The components of a rotating machinery like a motor often fail, leading to complete machine downtime or production quality reduction. According to Salah et al. (Salah et al., 2019), up to 90% of small motors' downtime is due to bearing faults, and 40-44% for large motors. Real-time characterization and detection of such frequently occurring faults may allow the stake-holders to take an appropriate and in-time action to avoid catastrophic scenarios.

Summarizing the bearing fault diagnosis literature, the current State-Of-The-Art (SOTA) is majorly

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Kancharla, C., Vankeirsbilck, J., Vanoost, D., Boydens, J. and Hallez, H.
Lightweight and Self Adaptive Model for Domain Invariant Bearing Fault Diagnosis.
DOI: 10.5220/0011822700003482
In *Proceedings of the 8th International Conference on Internet of Things, Big Data and Security (IoTBDS 2023)*, pages 29-38
ISBN: 978-989-758-643-9; ISSN: 2184-4976

concentrated on deep learning models (Gawde et al., 2022; Shan et al., 2022; Zhao et al., 2020). While some of these proposed methods show impressive performance, they ignore the fact that the data distribution in practice may not always be the same as the one used during the training (Pan and Yang, 2009). The changing conditions of a machine, environmental noise, sensor deviation, etc can introduce domain shift in the data. That is, the properties of the data do not remain consistent across the training phase and the real world inference. Thus leading to a deteriorated diagnostic model performance over the time. Considering the above discussed restrictions, an exemplary domain invariant model has to be efficient for the shifting domains while using as low computational resources as possible.

This article answers these aspects by:

- First, benchmarking the state-of-the-art domain invariant methods for their performance, accuracy, latency and model footprint.
- Second, proposing a novel self adaptive fault diagnosis model and comparing it to the SOTA models for both cross conditional efficiency and computational resource usage.

The article is organised as follows. We briefly discuss the background of domain invariance in section 2. Section 3 provides necessary details to understand the experimental setup. Section 4 discusses the benchmark results. Which is followed by the proposed methodology in Section 5. Section 6 and 7 summarizes the experimental results and conclusions respectively.

2 BACKGROUND

There are predominantly three different research areas that investigate the domain invariance. They are, learning domain invariant features from single-source data, learning domain invariant features from multiple-source data and lastly, domain adaptation methods that re-adjust their prediction models to the new domain.

If we consider that the data D^k of an application is available from three different domains $k = 1,2,3$, the data available for training in the form of source data $D_s = {D_s}^{\{k\}}$ is what will define these areas of diagnostic model generalization research. Single-source domain generalization is where one domain's data ($D_s = D^{1|2|3}$) is used for model training and extracting domain invariant features that are generalizable across the other two respective domains ($D_t = D^{!1|!2|!3}$). Here | implies 'or' and ! is 'not'. The effectiveness of this strategy can be understood from works like Yang et al., where they proposed a data augmentation strategy to learn a generalizable deep neural network, and our previous work, where we presented the usage of latent features of a Convolutional Auto-encoder as generalizable features across domains (Yang and Li, 2021; Kancharla et al., 2022).

Though the above discussed articles show the effectiveness of the single-source based generalization models, Zheng et al. and An et al. suggest that the multi-source domain based models are a practical necessity (Zheng et al., 2021; An et al., 2019). Multi-source generalization involves considering multiple source data ($D_s = D^{1\&2|2\&3|3\&1}$) to train and test generalizability performance on the left out domain data ($D_t = D^{3|1|2}$). Here & represents 'and'. Various research results favor the argument of multi-source domain generalization, but the fact that the data is a scarce resource limits these methods in practice (Zheng et al., 2021; An et al., 2019; Zhang et al., 2021; Zhao and Shen, 2022; Li et al., 2022).

To overcome the shortcomings of the single- and multi-source generalization, domain adaption is proposed. The domain adaptation method is where the model trained with source domain data is adapted to the other domains through model fine tuning or distribution alignment strategies in the feature space. Liu et al. proposed an effective Domain Adversarial Neural Network (DANN) that can adapt to real world data whilst being trained only with simulated bearing fault data (Liu and Gryllias, 2022). Another study by Li et al., studied the effectiveness of Central Moment Discrepancy (CMD) based domain adaptation where the target domain data is assumed available but without the class labels (Li et al., 2021). Maximum Mean Discrepancy (MMD) and adversarial learning based feature space adaptation (Wu et al., 2022) and Multi Kernel-MMD based (Wan et al., 2022) strategies are also effective and considered state-of-the-art. Assessing the lack of uniformity and ease of comparison, Zhao et al. studied various state-of-the-art domain adaptation methods in their comparative analysis (Zhao et al., 2021).

Whilst being relatively high on data demand, domain adaptation can be considered more resilient and safer option for achieving domain invariance as it adapts rather than assumes. Which is not the case with single and multi-source domain generalization models, they assume that domain invariant features exist across new unknown conditions.

Even though the domain adaptation models are relatively more employable in practice, it's challenging to use them for two reasons. Firstly, the current domain adaptation models for bearing fault diagnosis use labelled target domain data to adapt. Which is infeasible to obtain in practice. The other reason is that the adaptation process involve deep model relearning which is computationally expensive. Whereas the real world use cases necessitate implementation closer to the edge, meaning low computational resource availability. These restrictions necessitate a new genre of domain adaptation methodology that is accurate across changing conditions whilst being computationally efficient. More importantly, it should not require labelled target domain data for the adaptation.

Addressing the above mentioned restrictions, we first analysed the SOTA models for their cross conditional efficiency and resource utilization. A new domain adaptation model is proposed based on Convolutional Auto-encoder and Nearest Neighbours (CAE-NN). The proposed model is computationally efficient compared to SOTA models. It has low latency predictions, achieves better accuracy across conditions by self adaptation and more importantly its simplistic domain adaptation routine has negligible computational overhead compared to its inference.

3 EXPERIMENTAL SETUP

In this section we discuss the experimental setup used for this investigation. First, various domain adaptation methodologies from the literature that are worthwhile in terms of accuracy are introduced. Second, various open source data-sets used for the performance bench-marking are discussed. Finally, the details of the resources used for the experimentation are provided.

3.1 Domain Invariant Models for Comparison

Low data dependency during training is the major consideration for choosing models for comparison in this article. i.e., keeping the use-case as close to the real-world as possible, we restricted this selection to the models that use just the single-source data during the training process. They are single-source domain generalization models and single-source domain adaptation models.

3.1.1 Domain Generalization Models

From the literature, we consider two domain generalization methods. While a Neural Network trained on the data augmented samples proved to be domain invariant in the case of (Yang and Li, 2021), the proposal of Kancharla et al. was to use the latent features of a CAE along with a K-Nearest Neighbors approach as a domain invariant model (Kancharla et al., 2022). Considering the provided results in the respective articles, both approaches are considered for comparison in this work.

3.1.2 Domain Adaptation Models

As discussed in Section 2, there are numerous proposals and variations for domain adaptation, each for a specific use-case or an application. Reproducing and comparing them against each other was hard until Zhao et al.'s work, where the authors compared compared various domain adaptation strategies with a uniform data setting and model backbone. From their benchmark study we understand that their are a few competitive methodologies for different variations of DA applications. Particularly for label consistent DA, i.e., where labels in the source and target domain are homogeneous, there are four methods that have considerable performance. Multi kernel-Maximum Mean Discrepancy (MK-MMD) is one of them, which reduces the marginal distributions of the source and the target domains in the reproducing Hilbert Kernel Space. Unlike MMD, MK-MMD uses multiple kernels to embed the feature space and minimize the distance between the marginal distributions of the source and the target domain (Gretton et al., 2012). The other feature alignment method is based on adapting the model to the target domain by reducing both the marginal and conditional distributions between the source and target domains, it is referred to as Joint MMD (JMMD) (Long et al., 2016). While the models mentioned above were competitively placed in terms of performance, the domain adversarial loss minimization based methods like Domain Adversarial Neural Network (DANN) and Conditional Domain Adversarial Network (CDAN) demonstrated overall best mean performance (Zhao et al., 2021). They respectively introduce and minimize marginal and joint adversarial loss of the Neural Network model training through a domain discriminator. The reduced loss thus results in a model that is domain agnostic.

An important aspect of these domain alignment or adversarial models is having an appropriate feature extractor, also referred to as the backbone model. A good backbone leads to a better feature representations and eventually better domain adaption possibilities.

3.1.3 Backbone Model

Although numerous deep neural network architectures exist, we restricted this study to just two deep models to compare the above selected methods. Thus, four best performing adaptation methods in combination with two different deep feature extractors will be used to benchmark and compare. We included the results of both standard Convolutional Neural Network (CNN) and RESNET_18 backbones in this study to quantify and appropriately discuss the trade-off between the model size and the efficiency of domain adaptation. The same CNN architecture is used for the shadow label based domain generalization evaluation to remove any architectural advantage. Whereas, the model architecture of the CAE from CAE-NN is consistent to the original paper as it is an unsupervised feature learner and is different to the other methods considered here (Kancharla et al., 2022). The summary of the architectures used and their respective Floating Point Operations (FLOPs) necessary for inferring one input of size (1,256) is presented in Table 1. We can see from Table 1 that CAE network used for inference is much shallower compared to the CNN and RESNET, making the concept of architectural advantage irrelevant.

Table 1: Backbone models' architecture and FLOPs for a 256 input size.

Model	Architecture	MFLOPs
RESNET	$18^{\circledast};1^{\ddagger};1^{\star}$	46.19
CNN	$4^{\circledast};2^{\ddagger};4^{\urcorner};3^{\star}$	4.37
CAE	$2^{\circledast};2^{\ddagger};2^{\star}$	0.32

$^{\circledast}$*convolution layers*; ‡*pooling layers*;
**fully connected/dense layers*;
$^{\urcorner}$*batch normalization layers*

3.2 Datasets

Various open-source bearing fault datasets are ideal for algorithmic evaluation (Zhao et al., 2020). In this paper, we will use two datasets with extensive vibration data, the Case Western Reserve University dataset (CWRU) and the Paderborn University dataset (PU) (Lessmeier et al., 2016; Smith and Randall, 2015). While the (CWRU) dataset is frequently used in the studied literature, (PU) is also widely referred.

With four different conditions (load = 0,1,2,3 Hp) and 10 different faulty and non-faulty classes, the CWRU dataset can be considered relatively easy to diagnose (Zhao et al., 2020). While the provided data files consist of vibration data sampled at 12 kHz and 48 kHz from both the motor's driving and fan end, only the drive end data collected at 12 kHz is used in this study.

Whereas, the PU dataset has a unique combination of machine conditions that vary in multiple dimensions. Rotating speed (1500 and 900 RPM), applied Radial force (1000 and 400 N) and Load torque (0.7 and 0.1 Nm). With four different combinations of the three variables as mentioned above, PU dataset entails 6 healthy classes, 12 artificial fault classes and 14 natural run to failure fault classes. Each of these class' data is collected for four seconds at 64 kHz for 20 times. Given the large amount of data for the PU dataset, randomly selected five files of each class were used for training and testing. Notably, the average accuracies across some of the state-of-the-art domain adaptation methodologies on PU dataset is very low (Zhao et al., 2021). This makes it one of the most complex datasets currently available to validate domain invariance.

3.2.1 Experimental Tasks

Given four different conditions in CWRU and PU datasets each, there are 12 different experimental tasks possible individually. Each experimental task is defined as, one condition's data within a dataset as training data and another condition's data within the same dataset as test data. While all the 24 tasks have been experimented with, we summarize the results with one critical task from each dataset to reduce the overwhelming amount of information. The critical task here is defined by the transfer of information across majorly different conditions. According to our experiments and the benchmark study (Zhao et al., 2021) these critical tasks are C3-C0 and P2-P0 from CWRU and PU datasets respectively. C3-C0 refers to CWRU load condition 3 Hp as source/ train data and load condition 0 Hp as target/ test data, similarly, P2-P0 is PU dataset condition 2 (1500 RPM, 0.1 Nm and 1000 N) as source/ train data to condition 0 (900 RPM, 0.7 Nm and 1000 N) as target/ test data. Thus in this study the results of these two tasks will be discussed.

3.2.2 Model Inputs and Pre-Processing

Frequency-based features have been proven to be good in modelling the data for domain adaptation and generalization characteristics (Zhao et al., 2021; Kancharla et al., 2022). Following that understanding, we used frequency transformed data as the model inputs. As the considered data is continuous in nature and assuming each sample window contains at least one spindle rotation's information, the selected sample windows for CWRU and PU data files are chosen to be 512 and 2048 sample points respectively. Fast Fourier Transform has been applied on these windows and absolute values of the positive spectrum are retained. Finally, they are introduced to the appropriate models as inputs (256 and 1024 for CWRU and PU respectively). Whereas its outputs are 10 class labels of

CWRU (1 normal and 9 faulty) and 14 class labels of PU (1 normal and 13 faulty), are also provided to the model during training and target labels as inputs while domain adaptation with CNN and RESNET backed methods. Training and testing data from both source domain and target domain are split into 80-20. All the training and retraining happen with the 80 split data while the testing is done on the 20 split.

3.2.3 Performance Evaluation Metrics

Model efficacy was measured and evaluated based on the general accuracy, i.e. the amount of correctly predicted samples out of all samples across conditions. Whereas, the model computational efficiency was mostly measured by various parameters like model size, number of operations performed, and inference latency. Model size was measured in terms of the memory consumed by the trainable and non-trainable parameters involved in model inference. Number of Floating Point Operations (FLOPs) per inference were also gathered to understand the computational complexity of the models. Additionally, per sample inference latency was measured, i.e, time taken for inferring each randomly selected sample. Except for data pre-processing, this latency measure includes all the steps for per sample feature extraction and classification. Moreover, for each model evaluated in this study, these metrics were collected from 3 separate experiments to eliminate any bias due to randomness.

3.3 Experimental platform

Both model characterization of the selected SOTA methods and preliminary analysis of the proposed self adaptive method have been performed on a computer with Intel® i7-8850H CPU running at 2.60GHz, equipped with 32GB RAM. Please note, as the experimental platform does not represent a constrained device, we infer and discuss the computational efficiency of the SOTA models based on the acquired computing parameters from the experiments. None of the acquired computational parameters vary across devices, except for the latency.

4 RESULTS OF MODEL BENCHMARKING

We first performed an end to end benchmark study for the various SOTA models upon the experimental tasks discussed above. As mentioned previously, the end to end performance study involved analyzing parameters like model footprint, FLOPs, accuracy and per sample inference latency. From Table 2, we can observe that the RESNET backed domain adaptation models are in general 15-30% more accurate than the CNN features based models. But there is a large difference in the FLOPs, model size and the latency of inference between them. While the aggregate number of operations performed by CNN based models are approximately 4.37 M and 18.1 M for both the cases respectively, for the same tasks the RESNET model needs to perform approximately 10 times more FLOPs. On the other hand, latency of RESNET models is .approximately 4 times to that of CNN models within the dataset. Inference latency and FLOPs of similar models are different across the datasets because of the change in the number of inputs. As discussed in the previous section, CWRU has 256 inputs while PU has 1024 inputs, which are 4 times more compared to CWRU, leading to more computations performed. Whereas, the trainable parameters and model size does not change across the tasks as they are architectural parameters and are independent of the input size.

As opposed to RESNET and CNN based models, the single domain generalization model, CAE-NN is competitively placed in terms of accuracy whilst having smaller space requirements, lower number of performed operations and inference latency. It's the second best performing model with CWRU task and better than the CNN models for the PU task. When compared to CAE-NN, RESNET backed models are slightly effective at cross domain adaptation, but CAE-NN is several orders less complex. It is 100 times lower on number of FLOPs and approximately 10 times low on prediction latency compared to RESNET models. Overall, even though it is a single-source domain generalization model, it's evident that CAE-NN has the best accuracy over inference latency and FLOPs ratios out of all the domain invariant SOTA models.

Summarizing the SOTA domain invariant models for resource constrained implementation, we found that the data augmentation based method showed the least cross-domain generalization capability. Whereas the labelled target data based domain adaption of CNN models' performance is mediocre. Finally, RESNET backed models are the best performing for the considered tasks and show very high adaptability to the changing conditions. But this is at the cost of *labelled target data*, which is scarce in practice as discussed in the previous section. The next best model CAE-NN does this generalization without any prior knowledge of the feature distribution in the target domain. Additionally, the number of trainable parameters that have to be accommodated on a com-

Table 2: Cross conditional bearing fault diagnosis models' performance and their corresponding computational metrics.

Model	Accuracy (%)	Latency (ms)	FLOPs (Million)	Model size (MB)	Params (Thousand)
	Task: CWRU C3-C0; input size: 256				
CAE-NN	92.2	**0.2**	**0.42**	**0.20**	**26.61**
C-Shadow	69.5	0.5	4.37	0.93	232.90
C-CDAN	82.6	0.6	4.37	0.93	232.90
C-DAN	79.7	0.7	4.37	0.93	232.90
C-MKMMD	74.3	0.6	4.37	0.93	232.90
C-JMMD	79.1	0.6	4.37	0.93	232.90
R-CDAN	**93.5**	3.0	46.19	15.91	3977.80
R-DAN	89.9	3.0	46.19	15.91	3977.80
R-MKMMD	84.7	3.0	46.19	15.91	3977.80
R-JMMD	83.1	3.0	46.19	15.91	3977.80
	Task: PU P2-P0; input size: 1024				
CAE-NN	41.8	**0.3**	**1.66**	**0.80**	**98.61**
C-Shadow	34.6	1.2	18.10	0.93	233.93
C-CDAN	39.2	1.1	18.10	0.93	233.93
C-DAN	39.3	1.0	18.10	0.93	233.93
C-MKMMD	43.2	1.2	18.10	0.93	233.93
C-JMMD	41.0	1.3	18.10	0.93	233.93
R-CDAN	53.6	4.3	184.39	15.91	3978.83
R-DAN	48.1	4.0	184.39	15.91	3978.83
R-MKMMD	58.7	4.0	184.39	15.91	3978.83
R-JMMD	**78.2**	4.0	184.39	15.91	3978.83

$C-/R-Prefix\ denotes\ backbones\ used,\ C: CNN;\ R: RESNET\_18.$

putational platform is an unfair comparison between the RESNET backed models and CAE-NN. Trainable prameters of RESNET are approximately 20 times more compared to CNN and more than 40 times compared to CAE-NN.

5 PROPOSED SELF-ADAPTATION STRATEGY

Taking advantage of the generalization prowess of CAE-NN we devised a self adaptive strategy as vrepresented in Figure 1. From the benchmark experiments conducted on CAE-NN, there is enough evidence to consider that the source domain (D_s) and the target domain (D_t) share similar feature distribution or at least have a close proximity in the latent space L. This is valid for the two tasks considered here that are very different in their conditions and for the majority of the 24 cases from both CWRU and PU tasks. We can observe that a considerate amount of samples are accurately classified across the domains. Thus, we propose to use this new found information from across the domain to retrain the existing CAE-NN. And the so re-trained CAE-NN will be called SCAE-NN (Self adapted CAE-NN).

But, taking into account the low computational resource availability at the edge, our proposal will consider re-training the classifier alone, KNN in this case.

The proposal involves three simple steps,

- Inferring a new sample.
- Pseudo label the strong predictions.
- Retrain the KNN with pseudo labelled predictions.

In other words, if a sample X_t^i, an i^{th} sample of the target domain D_t is predicted with probability above a threshold, it will be considered a strong prediction. The latent features of this strong prediction i.e, l_t^i acquired from the encoder will be pseudo labelled as Y_t^i. As a retraining step, this pseudo labelled set of (data, label $\{l_t^i\ Y_t^i\}$) pair will be added to the KNN training set KNN_s.

As we are using the KNN with brute force approach, the retraining phase of the KNN in the proposed SCAE-NN is simply appending the new (data, label) pair to the existing pairs. This means, the proposed re-training method of SCAE-NN can be implemented with a negligible amount of computational overhead compared to the inference of CAE-NN. While the KNN re-training can be performed with the similar cost of inference, its trade-off will be elaborated in the next section.

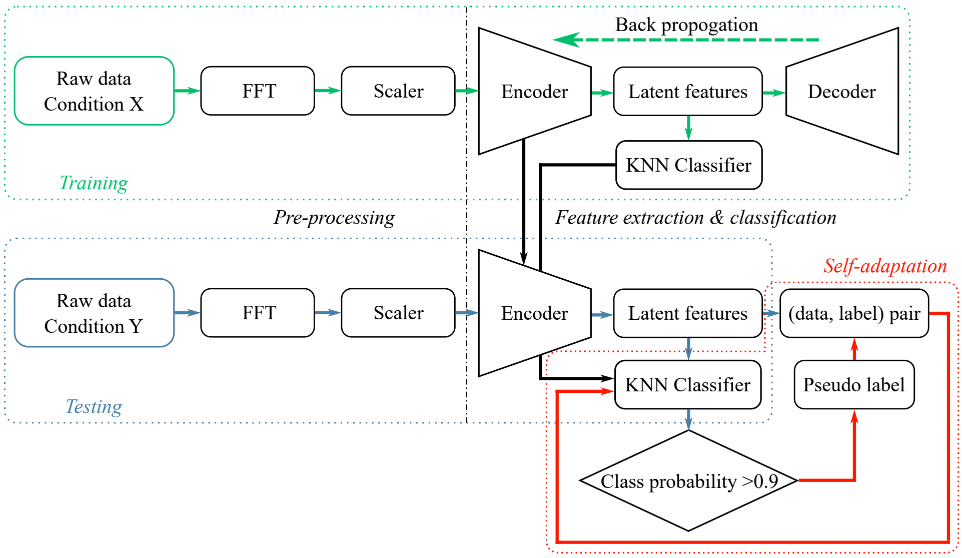

Figure 1: Block diagram describing the proposed self-adaptation strategy utilizing the generalizability of CAE-NN and pseudo labelling.

Probability Threshold

In general, the final prediction of KNN is based on the maximum number of K closest neighbours in the feature space. Whereas for the re-learning purpose we pseudo label only the strong predictions. Strong predictions here mean the samples that are predicted with over certain probability threshold. Although the threshold selection is dynamic and subjective to domain adaptation use case, in this article we chose probability over 0.9 for pseudo labelling a sample. This in some cases might not produce high rate of adaptation, but restricts negative learning by considering only the strong positive predictions.

6 RESULTS

As mentioned in the experimental setup section, all the performance evaluation metrics for the proposed SCAE-NN were also acquired from 3 individual experiments for each task and mean values are reported. Figure 2 compares the SOTA domain invariant models discussed in the previous section to the self-adaptive model proposed in this article SCAE-NN. Starting with the improvement over CAE-NN, self-adaptive version is approximately 8-9% more accurate for C3-C0 task and an impressive 35-40% higher for the P2-P0 task. Empirical results suggest that the proposed SCAE-NN is capable of adapting to the new conditions much better than the SOTA domain adaptation models. It adapts 6-7% better than best performing RESNET backed models for C3-C0 task and 2-3% for P2-P0. This is a significant improvement over the SOTA models in terms of accuracy.

Moreover, the model sizes of SCAE-NN compared to the RESNET based models are substantially low. It is approximately 33.4 and 9.3 times smaller for (1,256) and (1,1024) respective inputs of the CWRU and PU tasks. While the model size does not change with the inputs in the case of RESNET or CNN models, SCAE-NN's does vary. As can be seen from Figure 3, the effect of SCAE-NN retraining is relatively high on the model size, latency of prediction and floating point operations. This is more drastic in the case of model size compared to the latency and FLOPs.

Both the input size and the number of samples used during training and re-training affect the model size of SCAE-NN because of the KNN. While KNN does not fit any function to the data during training, it searches its feature space during every inference. KNN evaluates the new data point's distance from every other data point in the training set during inference. Thus, after the retraining of SCAE-NN, newly added pseudo samples lead to increased model size and introduce extra computations during inference.

The increased computational overhead during inference is reflected by the increased Latency and FLOPs of SCAE-NN. While the average FLOPs count was 0.41 and 1.62 Million with CAE-NN for CWRU and PU tasks respectively, with SCAE-NN it has increased by up to 0.1-0.2 Million for both the tasks. Also a similar increase on the latency of per sample inference can be observed. Figure 4 shows periodic increase in the accuracy and the inference time

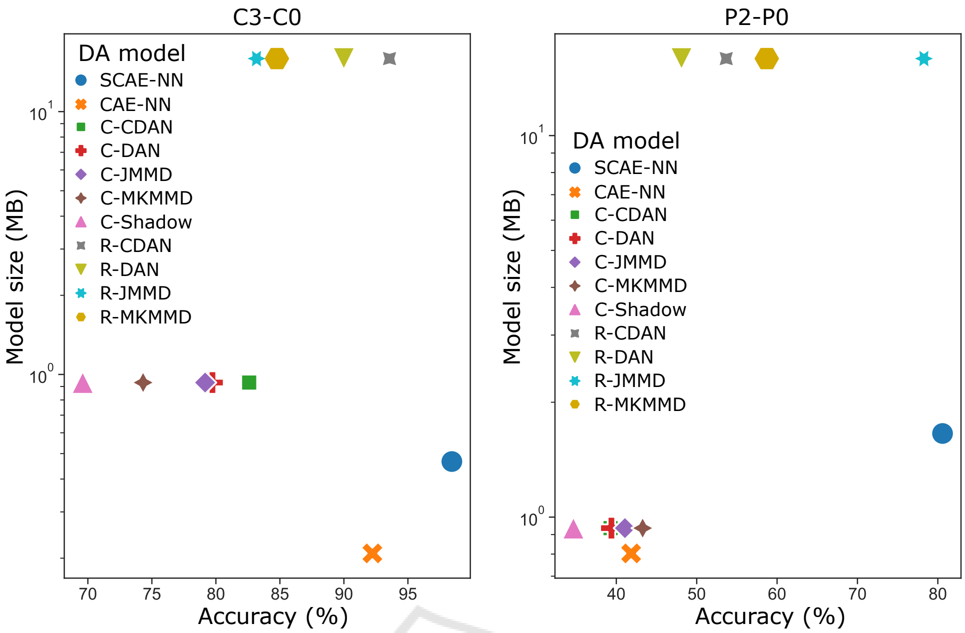

Figure 2: Comparison of the domain invariant models for their model sizes against the accuracies. With considerably low model size, SCAE-NN is at par or sometimes better than RESNET based domain adaptation models.

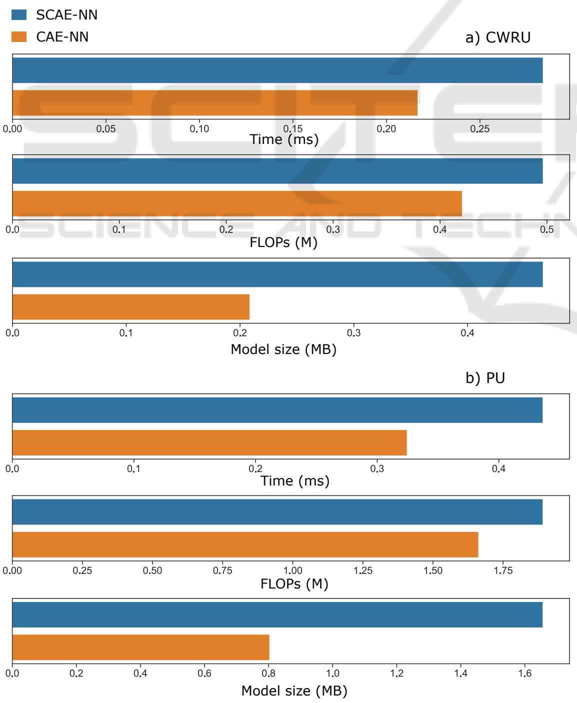

Figure 3: Across CAE-NN and SCAE-NN, we can observe an exponential increase in the model size compared to the linear increase in the latency and number of operations.

with changing number of new observations used in retraining.

From Figure 4, we can see that about 80-90% of the adaptation is due to the first 40-50% of the new observations. Particularly, for the PU task this adaptation is around 90% by the 40% mark. The accuracy gain after that point is a trade-off with the increased model size and latency. Nevertheless, summarizing the results from Figures 2 and 3, with better accuracies, lower number of FLOPs, low latency of inference and lower model size than the RESNET models, SCAE-NN is the best choice for any application that is resource constrained or not.

The adapted fault diagnosis model of CWRU task is very close to being perfect. Whereas, the PU task still has some room for fault diagnosis adaptation. Figure 5 represents the confusion matrix of PU task after SCAE-NN adaptation, It is clear that all the normal classes i.e, label number '13' from the figure are predicted correctly. Most of the other faulty classes are also appropriately classified. Even though the miss classifications amongst the faulty classes doesn't affect the overall fault predictability. The frequently occurring and note worthy confusion is between class number 4, KA30, generated by 'plastic deformation: indentation' and the normal class. It has to be understood well to further improve the cross conditional bearing fault diagnosis performance. The next important case that needs further understanding is between class numbered 6, originally KA24 generate by fatigue pitting and the normal class. While the KA30 is non severe fault case, the KA24 is a severe one with faults on both inner race and outer race. While the general expectations are that these strong fault cases are classified apart from normal classes, it is unclear of why these two classes are confused with the nor-

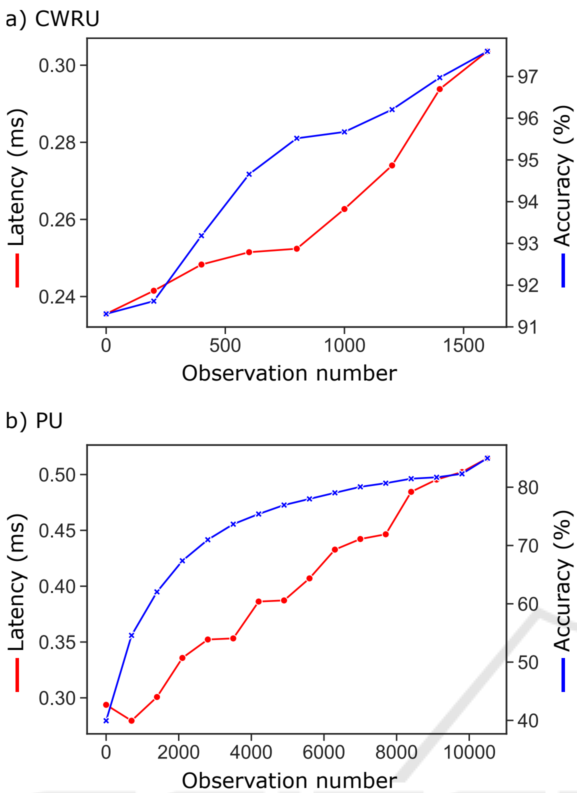

Figure 4: Periodic increase in the accuracy with the new observation based KNN retraining. We also observe the increasing per sample inference latency due to the increased KNN samples.

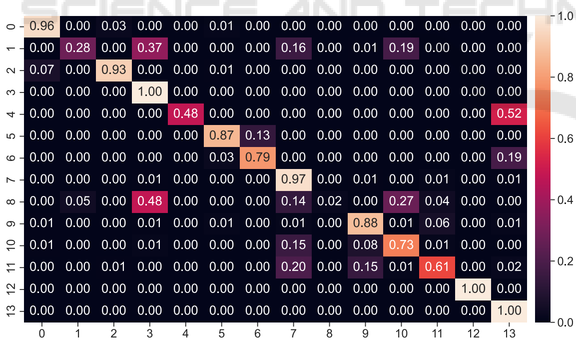

Figure 5: Confusion matrix of PU task after the self adaptation with SCAE-NN.

mal ones. Might be a case of negative learning, and need to be further investigated.

For the readers interested in the class labels as mentioned in the original PU dataset paper (Smith and Randall, 2015), the chronological order of 0-12 classes mentioned in Figure 5 are 'KA04', 'KA15',' KA16', 'KA22', 'KA30', 'KB23', 'KB24', 'KB27', 'KI14', 'KI16', 'KI17', 'KI18', 'KI21' and all the six non faulty classes are label 13.

7 CONCLUSIONS AND FUTURE WORK

In this article, we first analysed various SOTA models of bearing fault diagnosis for domain invariance. This was particularly performed from the perspective of resource deficient implementation. Different metrics concerned with cross conditional fault classification performance and implementability were used to benchmark them. First, from the benchmark study it is evident that the current models are limited either based on their performance or computational complexity. Overall, domain adversarial methods and distribution alignment methods based on RESNET features were the best performing. Whereas the same strategies with features from less complex CNN architecture were competitively placed after RESNET models. Relative to CNN and RESNET based models, CAE-NN, an Auto-encoder and K-Nearest Neighbors based domain generalization model was computationally efficient while exhibiting promising cross fault diagnosis accuracies.

Additionally, a new self adaptation methodology SCAE-NN based on CAE-NN has been proposed. Its performance evaluation for cross conditional domain adaptation was conducted and the results were reported. The proposed novel methodology demonstrated impressive self adaptive nature. While other performance metrics like inference latency, model size and FLOPs were relatively high compared to the non adapted model CAE-NN, the accuracy improvements were at least 8%-40% higher for the evaluated tasks. What is more impressive is that the SCAE-NN is self-supervised, whereas the compared models are supervised. Despite the fact that it is unfair, the authors chose to compare it to supervised adaptation models because they are the SOTA for domain invariant fault diagnosis.

Although SCAE-NN is several orders less complex than the next best method, there is a scope to further improve it in terms of resource utilization efficiency and will the subject of our future work. Additionally, future implementation and characterization of SCAE-NN will be performed using microcontrollers, which are the epitome of resource constrained edge.

ACKNOWLEDGEMENT

This work is supported by the VLAIO-PROEFTUIN "Industry 4.0 Machine Upgrading" (Project number:180493).

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