Transfer Learning based Evolutionary Deep Neural Network for Intelligent Fault Diagnosis

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Abstract—The performance of a deep neural network (DNN) for fault diagnosis is very much dependent on the network architecture. Also, the diagnostic performance is reduced if the model trained on a laboratory case machine is used on a test dataset from an industrial machine running under variable operating conditions. Thus there are two challenges for the intelligent fault diagnosis of industrial machines: (i) selection of suitable DNN architecture and (ii) domain adaptation for the change in operating conditions. Therefore, we propose an evolutionary Net2Net transformation (EvoNet2Net) that finds the best suitable DNN architecture for the given dataset. Nondominated sorting genetic algorithm II has been used to optimize the depth and width of the DNN architecture. We have formulated a transfer learning-based fitness evaluation scheme for faster evolution. It uses the concept of domain adaptation for quick learning of the data pattern in the target domain. Also, we have introduced a hybrid crossover technique for optimization of the depth and width of the deep neural network encoded in a chromosome. We have used the Case Western Reserve University dataset and Paderborn university dataset to demonstrate the effectiveness of the proposed framework for the selection of the best suitable architecture capable of excellent diagnostic performance, classification accuracy almost up to 100%.

Index Terms—Intelligent Fault Diagnosis, Multi-objective Optimization, Transfer Learning, Deep Neural Network, Automatic Architecture Search

I. INTRODUCTION

WITH the advent of modern industrial machinery, fault diagnosis and monitoring has become a major concern to ensure the reliability and smooth operation of various systems. Preventive maintenance also called condition based monitoring (CBM) is an essential requirement of today’s industries to avoid any catastrophic accident. Therefore, the research on fault diagnostic techniques has gained much attention from many researchers and organizations [1]–[4]. The development in the area of fault diagnosis can be divided roughly into three stages: (i) traditional methods which rely on experience with the machine running conditions, (ii) fault diagnosis based on signal processing and analysis, and (iii) intelligent fault diagnosis. Signal processing based methods rely on analysis of change in the specific pattern of the machine signals like current, vibration, temperature, acoustic transmissions, etc. [5]–[8]. In these methods, complex signal analyses are required to be performed for the assessment of the machine’s health condition. Therefore, these methods are computationally uneconomical and not suitable for continuous monitoring. In recent decades, machine learning-based intelligent fault diagnosis has been the most investigated method due to their learning capability of non-linear complex patterns [9]–[14]. In these methods, a diagnostic model is trained to learn the data patterns which represent the health state of the machine. The trained model is employed for the health diagnosis of the machine using data recorded for testing. Support vector machine (SVM) was proposed by Vapnik [15] as a method of statistical learning theory. SVM has been reported with outstanding performance for various applications of pattern recognition [10]. However, it fails to perform well for big data classification with high sparsity. For such problems, applications of deep neural network (DNN) have been reported to be very effective [11]–[14]. It is highly capable for hierarchical feature transformation of raw data to obtain linearly separable features. However, the performance of DNN is much dependent on the selection of its hyperparameters. Therefore, with any change in the machine working conditions, a new DNN is required to be trained using the new dataset which is an uneconomical and time-consuming task.

The motivation behind this work is to design a learning mechanism for DNN which can quickly adjust its architecture and the weight parameters to classify accurately with new data domain. The concept of transfer learning accelerated the training process of DNN for the new data domain by initializing the weight parameters using knowledge of pre-trained model on the source data [16], [17]. If there is a significant shift in the data distribution, the fine-tuning on the target data may overfit the network. To solve the problem of domain shift, domain adaptation based on transfer component analysis was introduced in 2011 by S.J. Pan [18]. Later, the concept of domain adaptation using minimization of Maximum Mean Discrepancy (MMD) gained much attention by the various researchers [19]–[26]. Long et. al. [19] used the principle of structural risk minimization and regularization theory to obtain a mechanism of adaptation regularization for cross-domain learning. In the domain adversarial neural network (DANN) [20], labeled source data and unlabeled target data are required to learn the target domain. L. Wen et. al. [22] suggested a fine-tuning method by minimization of the classification loss and the MMD term calculated for labeled source data and the labeled target data. Li et.al. [23] suggested a deep generative neural network to train a generator model and generate fake labeled target data to train the model in the target domain and then employ it for testing in the target domain.

Model architecture in most of these methods plays a vital role for the acceptable classification accuracy on the new dataset. Therefore, applications of these methods for the target data from an industrial machine require (i) selection of suitable network architecture and (ii) quick training using the data in

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the new domain. The concept of function preserving based network transformation gives a breakthrough for transforming the existing model to a new model [26]–[28]. The network transformation method proposed in [26] provides a way to quickly train a new model for the new target dataset through a network to network knowledge transformation. But, there remains a challenge for the selection of the best suitable architecture for the given dataset.

Various methods for the neural architecture search have been reported in literature [29]–[36]. [29]–[31] suggested the use of random search and greedy sequential algorithm for the optimization of hyperparameters of neural network and deep belief network. Random search or sequential search algorithms explore all possible architectures in a given search space. Therefore, exploration for the best suitable architecture takes too long. Baker et. al. [32] introduced a guided search algorithm using a Q-learning agent for the automatic selection of CNN architecture. In recent decades, genetic algorithms (GA) have gained much attention for hyperparameter optimization due to their multi-constraint optimization capabilities [33]–[36]. However, the application of GA to modern deep learning techniques is a complex problem due to a large number of constraint variables and a time-consuming fitness evaluation process. Y. Sun et. al [36] designed a variable-length gene encoding technique to encode the CNN architecture and adopted the fitness evaluation strategy of training a CNN model for a few iterations to find the best of the generation. Each individual (CNN model) in the population is initialized based on Gaussian distribution and trained from scratch. Again, this method requires the training of CNN models from scratch at each generation to evolve for the best suitable architecture of CNN. Also, the application of CNN on fault diagnosis data for variable working conditions of machines is computationally uneconomical. To solve the problem of long training in architecture search, we propose an automatic search of DNN architecture with a quick fitness evaluation framework using knowledge transfer from generation to generation. Our main contributions are summarized below:

i) A knowledge transfer based automatic deep neural network architecture search using multi-objective optimization.

ii) A variable-length gene encoding to carry the architectural information of DNN

iii) Quick fitness evaluation framework based on knowledge transfer with domain adaptation. An Initial (source) model trained on the source data drawn from a laboratory test machine is used to initialize the new model followed by fine-tuning.

iv) A hybrid crossover technique for the alteration of both depth and width of the DNN architecture encoded in genes of a chromosome.

The organization of the rest of the paper is as follows. Section II defines the problem objective of automatic architecture search. Section III briefly introduces the theoretical background of evolutionary algorithms, multi-objective optimization, DNN, and knowledge transfer from a DNN to another through function preserving principle. Section IV describes the proposed EvoNet2Net. Section V discusses the effectiveness of the proposed framework and its comparison with state-of-the-art methods on (i) Case Western Reserve University (CWRU) dataset [2] and Paderborn university dataset [3] under different operating conditions. Finally, Section VI concludes the work.

II. PROBLEM STATEMENT

Let $W^s$ be the teacher (source) model trained on a dataset $D^s = (X^s, Y^s)$ from the source domain and $D^{tr} = (X^{tr}, Y^{tr})$, $D^{val} = (X^{val}, Y^{val})$, & $D^{te} = (X^{te}, Y^{te})$ are the training dataset, the validation dataset, & the test dataset respectively from the target dataset $D^t = (X^t, Y^t)$. The objective of fault diagnosis via automatic DNN architecture search can mathematically be expressed as

$$P = G(W^s)$$

$$W^{best} = H(P, D^{tr}, D^{val})$$

$$Y^{te} = F(W^{best}, X^{te})$$

where $G(\cdot)$ generates a set ($P$) of DNN model with different architecture by transforming the model $W^s$. $H(\cdot)$ is the function to search and find the best model $W^{best}$ with optimal parameters and $F(\cdot)$ is the feed-forward sequential function of the DNN to predict the fault class $Y^{te}$ for the given test data $X^{te}$.

III. THEORETICAL BACKGROUND

A. Multi-objective Genetic Algorithm

Multi-Objective Genetic Algorithm (MOGA) is a heuristic search-based optimization technique under multi-constraint to find multiple optimal solutions called Pareto-optimal solution. A number of MOGAs have been reported in various literature [37]–[42]. The non-dominated sorting genetic algorithm (NSGA-II) [41] has gained much attention due to its fast sorting methodology. K. Deb [42] further proposed a framework of NSGA-III for the handling box constraints based on a given reference point. Our problem consists of unconstrained optimization of depth & width of a DNN architecture for maximum diagnostic performance. Therefore, we have considered NSGA-II framework for the evolution of DNN architecture considering the objectives (i) to maximize the validation accuracy and (ii) minimize the total number of weight matrices. The building blocks of NSGA-II from [41] has been illustrated in Fig.1.

B. Deep Neural Network (DNN)

A DNN is a multi-layered neural network formed by stacked auto-encoder (SAE) [43] with softmax classifier as output layer. DNN has the capability of highly non-linear function approximation. Each layer of SAE is trained by a greedy layer unsupervised learning mechanism followed by stacking together to form SAE. Now, SAE with softmax classifier at the output layer is fine-tuned by gradient descent using a labeled dataset. Fig. 2 shows a general structure of DNN with softmax classifier as output layer.
C. Net2Net Transformation

Network to Network (Net2Net) transformation is based on the function preserving principle introduced by [27]. We have used this concept to transform the network architecture as depicted in Fig. 3. If the teacher (source) network has the weight matrix $\Omega$, it can be transformed to another network with different architecture (having weight matrix $\Omega'$) provided that condition in Eq. 4 is satisfied.

$$\forall x, \quad y = F_1(x; \Omega) = F_2(x; \Omega')$$  \hspace{1cm} (4)

where, $x \in X$ is the input variable, $y \in Y$ is the output variable. The concept of Net2Net transformation enables us to initialize the a DNN with new architecture using the knowledge gained previously. That is, a roughly trained model with new architecture is generated which requires little fine-tuning on the target data only for a few iterations. The mathematical generalization of Net2Net transformation can be found in [26].

D. Domain Adaptation

If the target datasets have different distribution from the source data, the DNN trained on the source data fails to classify correctly on the target data. [21]. The diagnostic model trained on the source data needs to be fine-tuned using the target data to shift the classifier shown in Fig. 4.

Maximum Mean Discrepancy (MMD) minimization is the most popular method for the domain adaptation to the change in distribution. It measures the non-parametric distance for the domain shift on the reproducing kernel Hilbert space (RKHS). [44]. The Ref. [26] has suggested a method for quick training of a new DNN model for the target data using the model trained on source data via classification loss plus MMD term minimization.

IV. PROPOSED METHODOLOGY

Here, we have discussed the proposed methodology of evolutionary Net2Net transformation (EvoNet2Net) in detail. Let $\Psi^s, \Psi^t, \mathcal{D}^s = (X^s, Y^s)$, and $\mathcal{D}^t = (X^t, Y^t)$ be the initial (source) DNN model, the target DNN model, source dataset, and the target dataset respectively, the main framework of the NSGA-II based evolution and training of the DNN architecture is formulated as in Algorithm 1. Detailed discussions on the implementation procedure for each step are presented in the following sections.

A. Gene Encoding and Population Initialization

For optimal architecture search, both the depth and width of the DNN architecture have to be optimized. Each chromosome should be of variable length and contains the information of (i) depth: number of hidden layers ($n_h$) and (ii) width: number of nodes in each layer ($h_1, h_2, h_3, ...$). The gene encoding with different length has been illustrated in Fig. 6. The length of the chromosome represents the depth of the network and the value of each gene represents the number of hidden nodes in each layer. Since the size of the chromosomes is variable, information about the network architecture is encoded using the real-coded approach. The procedure for population initialization is provided in Algorithm 2. The population size, maximum range for depth of the network, maximum range for number of nodes in a hidden layer, and minimum number of nodes in a hidden layer are $N$, $n_h \in [n_{min}, n_{max}]$, & $h \in [h_{max}, h_{min}]$ respectively.
Algorithm 1 Main Framework of the EvoNet2Net

1: Inputs ← ($\Psi^s$, $\Psi^t$, $\mathcal{D}^s$, $\mathcal{D}^t$)  // $\Psi^s$ be the initial model and ($\mathcal{D}^s$ & $\mathcal{D}^t$) be the source & target datasets respectively.
2: Gen ← 0  //Set generation count = 0;
3: $P_0$ ← PopulationInitialization($N_p$)  //Initialize $N_p$ populations using the proposed method in section IV-A.
4: $P_{fit}$, $\Psi_{best}$ ← EvalFitness($P_0$, $\Psi^s$, $\mathcal{D}^s$, $\mathcal{D}^t$)  //Evaluate fitness of each individual in $P_0$ using the Algorithm 3.
5: $P_{rank}$ ← NonDominatedSorting($P_{fit}$)  //Assign rank using non-dominated sorting [41].
6: $P$ ← SelectParents($P_0$, $P_{rank}$)  //Select parents by proposed binary tournament selection (Algorithm 4).
7: $Q$ ← CrossOverMutation($P$)  //Apply crossover and mutation on $P$ using CP & MP (Section IV-D).
8: $\Psi^t$ ← $\Psi_{best}^t$  //Set current best model as initial (source) model for the next generation.
9: while Gen $\leq$ MaxGeneration do
10: $R$ ← $(P \cup Q)$  //Combine the parent population ($P$) & the child population ($Q$).
11: $R_{fit}$, $\Psi_{best}$ ← EvalFitness($R$, $\Psi^s$, $\mathcal{D}^s$, $\mathcal{D}^t$)  //Evaluate fitness for each individual in $R$.
12: $R_{rank}$ ← NonDominatedSorting($R_{fit}$)  //Assign rank using non-dominated sorting
13: $R_{crowd}$ ← CrowdingDistances($R$, $R_{rank}$, $R_{fit}$)  //Find crowding distances of individuals in population set $R$ [41].
14: $P$ ← SelectParents($R$, $R_{crowd}$, $R_{rank}$)  //Select parents by crowding distance and rank.
15: $Q$ ← CrossOverMutation($P$)  //Apply crossover and mutation on $P$ using CP & MP (Section IV-D).
16: $\Psi^t$ ← $\Psi_{best}^t$  //Set current best model as initial (source) model for the next generation.
17: Gen ← Gen + 1  //Update the generation counter
18: end while
19: Return: Best Model ← $\Psi_{best}^t$  //Best model of last generation.

Algorithm 2 Population Initialization for EvoNet2Net

1: Inputs ← ($N$, $[n_{min}, n_{max}]$, $[h_{max}, h_{min}]$)
2: $H$ ← Generate $N$ random integers between $[1 \rightarrow N_h]$.
3: for $p$ = 1:N do
4: $h$ ← $H(p)$ : depth of $p^{th}$ chromosome
5: $P_{\{p\}}$ ← generate $h$ random integers $\in [h_{min}, h_{max}]$
6: end for
7: Return $P$

B. Evaluate Fitness

The fast evolution for the network architecture requires quick fitness evaluation of individuals (DNN models) in the population at each generation. Our proposed method of fitness evaluation is based on network (Net2Net) transformation followed by fine-tuning on the target dataset. Since the initial (source) model has been trained on the source data from a different domain, the cost function for fine-tuning should include classification loss as well as the MMD term to adapt to the domain shift [26]. The fitness evaluation strategy has been illustrated in Fig. 5. Optimal weight matrices are obtained by minimizing the cost function in Eq.(5) based on Limited-Broyden-Fletcher-Goldfarb-Shanno (LBFGS) [45] algorithm.

$$\mathcal{J} = \mathcal{J}_c(W^f_1, W^c_1) + \gamma \mathcal{J}_{MMD}(W^f_1)$$  \hspace{1cm} (5)

where, $\mathcal{J}_c(W^f_1, W^c_1) = \text{classification loss of DNN}$ and $\mathcal{J}_{MMD}(W^f_1) = \text{MMD term}$ with $W^f_1 \in \Psi^t$ & $W^c_1 \in \Psi^t$ be the weight matrices of the DNN feature extractor and the softmax classifier respectively. $\gamma$ is positive fractional value and represents the trade off between the regularization term and the MMD term. The term $\mathcal{J}_c(W^f_1, W^c_1)$ and $\mathcal{J}_{MMD}(W^f_1)$ are calculated using feed-forward DNN function and softmax classifier function on training data from the source domain and the target domain. [26]. Once the DNN model is trained for the target data, classification accuracy (CA) is evaluated on the validation data from the target domain. Similarly, CA for all the models in the population ($P$) is evaluated and stored as fitness vector $P_{fit}$.

C. Parent Selection using Rank and Crowded Distance

Selection of parents is required to create the population for next generation. Algorithm 4 presents the parent selection procedure assuming that each individual in the combined population $R = (P \cup Q)$ is assigned with (i) non-dominating rank ($r_p \in R_{rank}$) and (ii) crowding distance ($d_p \in R_{crowd}$).

D. Crossover and Mutation

The processes of crossover and mutation are required for local search and global search respectively for the optimal search. Due to the variable length chromosomes, crossover is one of the major challenges for the DNN architecture...
Algorithm 3 Fitness Evaluation for EvoNet2Net

1. \textbf{Inputs} \leftarrow (P, \Psi^*, D^*, D^f).
2. \(N_p \leftarrow \) population size //number of individuals in \(P\).
3. for \(p = 1 : N_p\) do
4. \(\Psi^t \leftarrow \) Net2Net(\(\Psi^t\)) //Transform the source network to target network (\(p^{th}\) model in \(P\)) as depicted in Fig. 3.
5. Fine-tune the target network (\(\Psi^t\)) to minimize Eq. (5).
6. \(P_f(p) \leftarrow \) classification accuracy (\(CA\)) of the final network on the validation data.
7. end for
8. \(\Psi_{best} \leftarrow \) Best model // Find the model with maximum CA and minimum number of model parameters.
9. Return \(P_f, \Psi_{best}\)

Algorithm 4 Parent Selection using \(R_{rank}\) and \(R_{crowd}\)

1. \textbf{Inputs} \leftarrow (R, R_{crowd}, R_{rank}) //Maximum number of possible Pareto-front.
2. \(N_pf \leftarrow\) length(unique(\(R_{rank}\))) //Maximum number of set Pareto-front at 1
3. \(p_f \leftarrow 1 /\)set Pareto-front at 1
4. \(p \leftarrow 0 /\)solution counter \(p\) at zero.
5. while \(p_f \leq N_pf\) do
6. if \(p + \sum(R_{rank} == pf) \leq N_p\), then \(n = \sum(R_{rank} == pf)\);
\(P\{p + 1 : p + n = R_{rank} == pf\}\);
\(p = p + \sum(R_{rank} == pf)\);
7. else \(q = N_p - p /\)number of rest of the members in \(P\).
\(q_f = R_{rank} == pf\); //The rest members in \(P\)
\(d_{qf} = R_{crowd}(R_{rank} == pf)\); //distance 
\(index = sort(d_{qf}, \text{“descend”});\)
\(q_f = q_f(index);\)
\(P\{p + 1 : p + q\} = q_f(1 : p)\);
\(p = p + q;\)
8. end if
9. \(p_f = p_f + 1\)
10. end while
11. Return \(P\)

evolution. The proposed method of crossover has two steps: (i) single point depth crossover for depth variation and (ii) common depth simulated binary crossover for gene variation. The process of crossover is illustrated in Fig. 6. The offspring generation by crossover and mutation is summarized in Algorithm 5:

V. EXPERIMENTAL RESULTS AND DISCUSSION

We have demonstrated the effectiveness of the proposed frameworks on two different datasets under various working conditions. The datasets are taken from (i) CWRU fault diagnosis bearing data [2] and (ii) Paderborn university (PBU) dataset [3] under various working conditions as described in the following sections.

A. Setup Description

1) CWRU Bearing Data [2]: The CWRU dataset was provided by Case Western Reserve University (CWRU) Bearing Data Center. The details of the experimental setup of the bearing test rig can be found in [2]. Three types of faults (inner raceway, rolling element (i.e. ball), and outer raceway) were created on the drive-end (DE) and fan-end (FE) bearings. Faults were artificially seeded on the bearings with fault diameters ranging from 0.007 to 0.028 inches (7 to 28 mil) using the electro-discharge machining process. The vibration signals were recorded under various operating conditions (motor loads 0, 1, 2, & 3 hp and motor speed varying from 1730 to 1797 RPM). The recorded signals represent the three types of faults in the bearing: (i) inner race (IR) fault, (ii) outer race (OR) fault, and (iii) rolling ball element (B) fault. The signal recorded in healthy state represents the normal (N) state of the machine.

2) PBU Dataset [3]: C. Lessmeier et. al. [3] provided a benchmark dataset for condition based monitoring of electrical rotating machines running under a wide variety of motor load and rotational speed conditions. The machine is operated in four settings of load and rotational speed (abbreviated as L.S.). These are (i) \textbf{LS1: N09_M07_F10} (speed = 900 rpm, torque = 0.7 Nm & radial force = 1000 N) (ii) \textbf{LS2: N15_M01_F10} (speed = 1500 rpm, torque = 0.1 Nm & radial force = 1000 N) (iii) \textbf{LS3: N15_M07_F04} (speed = 1500 rpm, torque = 0.7 Nm & radial force = 400 N) and (iv)
LS4: N15_M07_F10 (speed = 1500 rpm, torque = 0.7 Nm & radial force = 1000 N). Experiments were conducted on 32 different bearings: 6 healthy bearings, 12 artificially damaged bearings, and 14 bearings damaged by accelerated life-time tests. The dataset from each experiment contains phase current, vibration signal, radial forces, torque, and bearing temperature. From each experiment, 20 measurements, each of 4 seconds were taken for each of the load settings LS1, LS2, LS3, and LS4. The measurement data represents two faulty states of the machine (i) inner race (IR) fault and (ii) outer race (OR) fault. Experiments were conducted with different level of damages called the extent of damage.

B. Data Processing

The recorded are the time-series signals usually contaminated with outliers and noises that make the data unstructured and unsuitable for training a diagnostic model. Since outliers may carry some necessary information, data should be normalized with z-score normalization technique: $x = (x - \mu)/\sigma$, where $\mu$ and $\sigma$ are mean and standard deviation of the data $x$ respectively. But, z-score normalization does not scale down the data into a common scale. If the information in the outliers is not so important for the diagnosis, data is scale down to [0 1] scale by using min-max normalization technique: $x = (x - x_{min})/(x_{max} - x_{min})$, where $x_{min}$ and $x_{max}$ are the minimum and maximum value of the dataset $x$.

Since the measurement data is a time-series signal with a huge number of data points, it is not suitable to be directly used for training. Therefore, the signal is segmented into samples with a segment length of approximately a quarter of the sampling period. For CWRU, the time-series signal is segmented with a segment length of 100 data points. For example, a signal with a length of 121200 points is converted into 1212 X 100 samples. Similarly, PBU data is segmented using a segment length of 400 data points. Now, the source dataset and the target dataset are prepared for evaluation of the performance of the proposed framework described in the following subsection.

C. Evaluation Scheme

For the demonstration of the quick architecture search, we choose a source dataset and a number of target dataset. The evaluation scheme is divided into two cases:

Case-1: CWRU dataset: The source dataset and the target dataset are prepared as follows and summarized in Table I.

| Fault Name | Source (CWRU-DE) | Target-1 (CWRU-FE) | Class Label |
|------------|-----------------|--------------------|-------------|
| N          | 1200 0 hp       | 400                | 0           |
| IR         | 1200 0 hp       | 400                | 1, 2 & 3 hp |
| B          | 1200 0 hp       | 400                | 1, 2 & 3 hp |
| OR         | 1290 0 hp       | 400                | 1, 2 & 3 hp |

D. Evaluation metrics

Classification performance of a diagnostic model is measured in term of classification accuracy (CA) as widely accepted in literature [19], [21], [22].

$$CA = \frac{|x : x \in X_{te} \land y = F(x)|}{|x : x \in X_{te}|} \times 100\%$$

where, $X_{te}$ is the test data, $F(x)$ and $y$ are the predicted and the true labels. Also, the improvement analysis of the proposed method with respect to a baseline method is described in term of transfer improvement ($TI$). $TI$ is calculated as $TI = CA - CA_{baseline}$, where, $CA$ is the average $CA$ for dataset under various operating conditions.

E. Implementation and Training Parameters

The proposed evoNet2Net as described in the Algorithm 1 requires an initial DNN model ($\Psi^*$) termed as teacher model. Therefore, first a teacher model with any architecture (we choose DNN model with 3 hidden layers 80 – 40 – 20) is trained on the source dataset. The proposed framework is applied to the target dataset mentioned in table I & II. The initial parameters for the evolutionary algorithm are chosen (i) population size ($N_p$) = 100, (ii) probability of cross-over ($P_c$) = 0.8, (iii) probability of mutation ($P_m$) = 0.2, and (iv) the
number of maximum generation = 20. The maximum ranges for the number of hidden layers and nodes are selected as $n_h \in [1, 8]$ and $h \in [4, 400]$ respectively. The best models obtained for each of the cases of the target dataset (T1, T2, & T3) are tested on the test data. Performances in term of $CA$ are tabulated in tables III & IV.

For better analysis, the performance of the proposed framework is compared with the state-of-the-art method most popularly used for fault diagnosis of rotating machines. The selected algorithms are support vector machines (SVM) [10], deep neural network (DNN) [13], deep transfer learning (DTL) based on sparse autoencoder [22], Deep neural network for domain Adaptation (N2N) [26], and evolutionary deep CNN (EvoDCNN) [36]. The architecture for DNN, DTL, and DAFD is kept same as source network. The population size and the maximum number of generations for EvoDCNN is kept same as the proposed method. All these models are trained on the same data as described in section V-C using the methods suggested in the cited references. The classification accuracy are are tabulated in tables III and IV.

The $TI$s of average accuracies for the four cases: (i) CWRU dataset with 400 samples/class, (ii) PBU dataset with 400 samples/class, (iii) CWRU dataset with 40 samples/class, and (iv) PBU dataset with 40 samples/class.

### Table II: Evaluation Scheme on PBU Dataset [3] Description

| Class Name | Source (Artificial Damage) | Target-2 (T2) | Target-3 (T3) | Class label |
|------------|---------------------------|---------------|---------------|------------|
| N          | K001                      | 5000          | K001          | None       |
| OK         | K001                      | 5000          | K004          | None       |
| IR         | K16                       | 5000          | K16           | 3          |

### Table III: CA for Target-1 Dataset and for Very Limited Samples of Target-1 Dataset

| Target | F.D. | Load | SVM [10] | DTL [22] | DAFD [21] | N2N [26] | EvoDCNN [36] | EvoNet2Net |
|--------|------|------|----------|-----------|-----------|----------|---------------|------------|
| T1     | DE   | 7 mil| 1hp      | 88.1      | 96.7      | 96.6     | 97.9          | 98.9       | 98.9       | 99.6       | 100.0      |
| T1     | DE   | 14 mil| 2hp     | 98.1      | 95.9      | 93.4     | 96.1          | 97.1       | 98.1       | 99.6       | 100.0      |
| T1     | DE   | 21 mil| 3hp     | 99.6      | 98.8      | 98.8     | 98.4          | 99.4       | 99.4       | 99.7       | 100.0      |
| T1     | DE   | 7 mil| 2hp     | 99.7      | 96.9      | 96.7     | 97.2          | 99.2       | 99.7       | 100.0      | 100.0      |
| T1     | DE   | 14 mil| 3hp     | 99.5      | 96.9      | 94.7     | 97.6          | 99.3       | 98.6       | 98.4       | 100.0      |
| T1     | DE   | 21 mil| 2hp     | 98.8      | 95.9      | 92.2     | 95.7          | 97.7       | 98.7       | 98.1       | 99.1       |
| T1     | DE   | 7 mil| 3hp     | 96.9      | 98.6      | 84.7     | 89.6          | 95.6       | 96.6       | 93.8       | 98.8       |
| T1     | DE   | 14 mil| 2hp     | 88.4      | 85.3      | 82.2     | 86.7          | 90.7       | 90.7       | 90.1       | 95.4       |
| T1     | DE   | 21 mil| 3hp     | 92.2      | 86.6      | 79.4     | 88.1          | 91.1       | 92.1       | 92.8       | 95.8       |
| T1     | DE   | 7 mil| 1hp     | 78.1      | 90.6      | 90.6     | 90.6          | 90.6       | 90.6       | 93.8       | 93.8       |
| T1     | DE   | 14 mil| 3hp     | 96.9      | 90.6      | 90.6     | 91.5          | 90.6       | 93.6       | 99.6       | 100.0      |
| T1     | DE   | 21 mil| 1hp     | 95.0      | 93.8      | 93.8     | 94.8          | 93.8       | 94.2       | 94.4       | 97.4       |
| T1     | DE   | 7 mil| 2hp     | 87.5      | 68.8      | 68.8     | 69.8          | 68.8       | 70.8       | 90.0       | 97.4       |
| T1     | DE   | 14 mil| 3hp     | 75.0      | 65.6      | 65.6     | 67.6          | 65.6       | 70.6       | 96.9       | 96.9       |
| T1     | DE   | 21 mil| 3hp     | 93.8      | 65.6      | 65.6     | 67.6          | 65.6       | 70.6       | 96.9       | 98.9       |
| T1     | DE   | 7 mil| 2hp     | 87.5      | 65.6      | 65.6     | 66.6          | 65.6       | 75.6       | 96.9       | 100.0      |
| T1     | DE   | 14 mil| 3hp     | 90.6      | 68.8      | 68.8     | 70.0          | 68.8       | 70.8       | 95.0       | 100.0      |
| T1     | DE   | 21 mil| 3hp     | 89.4      | 12.60     | 12.60    | 12.16         | 12.60      | 10.52      | 5.45       | 2.12       |

### Discussion

Following points can be observed from the diagnostic results shown in tables III & IV and Fig.’s 7 & 8.

1) The proposed framework enables us to obtain the best suitable DNN architecture for a dataset that can provide diagnostic accuracy up to almost 100%, a very
much improved over the most popular methods used fault diagnosis (tables III & IV). Therefore, the network architecture greatly affects the performance of DNN.

2) TI in Fig. 7 under four cases of dataset reveals that performance of various methods may be poorer than the baseline method SVM depending upon the dataset. But, the proposed method performs better in all cases. For very limited target data samples, SVM performs better than most of the popular fault diagnostic methods because of insufficient labeled data samples. However, the proposed method can find a suitable architecture that can perform very well even under very limited data samples.

3) Fig. 8 shows the fitness growth of the best model obtained at each generation during the evolution process. It can be observed that the best model at each generation gets better with evolution. Since exploitation by the crossover and exploration by the mutation perform both local and global search, the final model obtained has the best possible DNN architecture.

4) Further, it can be observed that EvoDCNN [36] also performs better than the other state-of-the-art methods because it finds the best CNN model for the corresponding dataset. The comparison of CA also reveals that the best DNN model by the proposed framework performs better than the best CNN model.

Therefore, the proposed framework is the effective solution to ensure accurate fault diagnosis in variable operating conditions through the evolution of the best diagnostic model.

VI. CONCLUSIONS

This article proposed the framework of evolving Net2Net transformation of DNN architecture to find the best suitable architecture for a given dataset. The DNN architecture to be optimized is encoded as real-coded chromosomes in the population initialization. An initial (source model) is used to train the individuals at $0^{th}$ generation based on domain adaptation. Now, the knowledge of the best model obtained at each generation is transferred to the next generation. Thus, the training of the individuals gets faster with the generation. Therefore, the proposed framework proves to be a very effective solution for fault diagnosis with very high accuracy up to almost 100%. The validation on various target datasets under different operating conditions justifies the suitability of the proposed method for real-time industrial applications. Also, the proposed method has a big transfer improvement over the baseline method (SVM). This work can further be extended for faster evolution using an agent (meta-reinforcement) based population initialization with guided population size. The limited size of the population will accelerate the evolution process.
