Knowledge Transfer 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 (EvoN2N) that finds the best suitable DNN architecture for the given dataset. Non-dominated sorting genetic algorithm II has been used to optimize the depth and width of the DNN architecture. 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 formulated a knowledge transfer-based fitness evaluation scheme for faster evolution. The proposed framework can obtain the best model for intelligent fault diagnosis without the need for a long-time taking search process. We have used the Case Western Reserve University dataset, Paderborn university dataset, and gearbox fault detection 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, Knowledge Learning, Deep Neural Network, Automatic Architecture Search,

I. INTRODUCTION

With the advent of modern industrial machinery, fault diagnosis and monitoring have become a major concern to ensure the reliability and smooth operation of various systems. Therefore, preventive maintenance also called condition-based monitoring (CBM) is an essential requirement of today's industries and has gained much attention from researchers worldwide [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.

In signal processing-based methods, complex signal analyses are required to obtain the specific change in the machine signals like current, vibration, temperature, acoustic transmissions, etc. [5]–[8]. Therefore, these methods are computationally uneconomical and not suitable for continuous monitoring. In recent decades, intelligent fault diagnosis has been the most investigated method due to the learning capability of machine learning models [9]–[14]. The machine learning-based diagnostic model is trained to learn the specific pattern in the machine signals. The trained model is used for the health diagnosis of the machine using the data recorded for testing. Support vector machine (SVM) [10] has been reported with outstanding performance for intelligent pattern recognition. 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]. DNN is highly capable for hierarchical feature transformation of raw data to linearly separable features. Recently, a number of feature extraction methods using genetic algorithm have been reported, [15]–[17]. However, the performance of DNN in fault diagnosis is much dependent on the selection of its hyperparameters. Therefore, with change in the machine working conditions, training a new DNN for the new dataset is an uneconomical and time-consuming task.

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 [18], [19]. However, due to the significant shift in the data distribution, the fine-tuning on the target data may overfit the network with limited number of training samples. To solve the problem of domain shift, domain adaptation based on transfer component analysis was introduced in 2011 by S.J. Pan [20]. Later, the concept of domain adaptation using minimization of Maximum Mean Discrepancy (MMD) gained much attention by the various researchers [21]–[28]. Long et al. [21] 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) [22], labeled source data and unlabeled target data are required to learn the target domain. L. Wen et al. [24] 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. [25] 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. The performance of all these methods is greatly affected by the selection of model architecture. Therefore, fault diagnosis under variable operating conditions of machines demands a fast network architecture search method capable of finding the best suitable model for the given working condition using a small amount of labeled data.

The motivation behind this work is to develop a learning mechanism for DNN which can optimize its architecture with quick model training to classify accurately in the new data domain. 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 deep learning algorithms is a complex problem due to a large number of constraint variables and a time-consuming fitness evaluation (training and testing) 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. However, this method requires the training of CNN models from scratch at each generation. Therefore, the evolution for the best suitable architecture of CNN is a time-consuming process.

Since most of the architecture search methods rely on training and evaluating DNN with different architecture and concluding to a best model, the major challenge in the architecture search process is the quick fitness evaluation strategy. The concept of function preserving based network transformation gives a breakthrough for transforming the existing model to a new model [28], [37], [38]. The network transformation method proposed in [28] provides a way to quickly train a new model for the new target dataset through a network to network knowledge transformation. Based on [28], we propose an evolutionary DNN architecture with a quick fitness evaluation framework using knowledge transfer from generation to generation. Since the architecture of fully connected network (DNN) involves depth (number of hidden layers) and width (number of nodes in each hidden layer), we adopt a multi-optimization strategy for the architecture search. Our main contributions are summarized below:

i) An evolutionary deep neural network with quick fitness evaluation methods for automatic architecture optimization.

ii) Architecture optimization of a fully connected network involves width and the depth of the network

iii) The quick fitness evaluation framework is 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 using a limited number of samples of target dataset.

iv) A hybrid crossover technique for the optimization of both depth and width of the DNN architecture encoded using variable-length gene encoding method [36].

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 EvoN2N. 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], (ii) Paderborn University (PBU) dataset [3], and (iii) gearbox fault detection dataset [39] 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

\begin{equation}
P = G(W^{s})
\end{equation}

\begin{equation}
W^{t}_{\text{best}} = H(P, D^{tr}, D^{val})
\end{equation}

\begin{equation}
\hat{Y}^{te} = F(W^{t}_{\text{best}}, X^{te})
\end{equation}

where $G(.)$ generates a set ($P$) of DNN model with different architecture by transforming the model $W^{s}$, $H(.)$ is the function to search and find the best model $W^{t}_{\text{best}}$ with optimal parameters and $F(.)$ is the feed-forward sequential function of the DNN to predict the fault class $\hat{Y}^{te}$ 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 set of multiple solutions is obtained, out of which, any one solution can not be said to be better without some additional information. For such problems, a number of MOGAs have been reported in various literature [40]–[46]. The non-dominated sorting genetic algorithm (NSGA-II) [44] has gained much attention due to its fast sorting methodology. Our problem consists of unconstrained optimization of depth & width of a DNN architecture for maximum diagnostic performance keeping the number of total trainable parameters to be minimal. Therefore, we have considered the architecture optimization as multi-objective optimization problem instead of single objective optimization problem. We have selected 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.

B. Deep Neural Network (DNN)

A DNN is a multi-layered neural network formed by stacked auto-encoder (SAE) [47] 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. 1 shows a general structure of DNN with softmax classifier as output layer.

![Fig. 1: General structure of DNN with softmax classifier](image)

**C. Net2Net Transformation**

Network to Network (Net2Net) transformation is based on the function preserving principle introduced by [37]. We have used this concept to transform the network architecture as depicted in Fig. 2. 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.

$$\forall x, \ y = F_1(x; \Omega) = F_2(x; \Omega') \quad (4)$$

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 little fine-tuning on the target data only for a few iterations. The mathematical generalization of Net2Net transformation can be found in [28].

![Fig. 2: Net2Net transformation: new nodes and connecting weights are shown in red color](image)

**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. [23]. The diagnostic model trained on the source data needs to be fine-tuned using the target data to shift the classifier shown in Fig. 3.

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). [48]. The Ref. [28] 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 (EvoN2N) in detail. Let $\Psi^s$, $\Psi^t$, $D^s = (X^s, Y^s)$, and $D^t = (X^t, Y^t)$ 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. 5. 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.

**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. The first step of the fitness evaluation strategy is the network transformation as illustrated in Fig. 4(a). Since at the first generation, the initial (source) model trained on the source data has been
Algorithm 1 Main Framework of the EvoN2N

1. Inputs ← (Ψ*, D* , Dt) //Ψ* be the initial model and (D* & Dt) be the source & target datasets respectively.
2. Gen ← 0 //Set generation count = 0;
3. P0 ← PopulationInitialization(Np) //Initialize Np populations using the proposed method in section IV-A.
4. Pfit, Ψbest ← EvalFitness(P0, Ψ*, D*, Dt) //Evaluate fitness of each individual in P0 using the Algorithm 3.
5. P_rank ← NonDominatedSorting(Pfit) //Assign rank using non-dominated sorting [44].
6. P ← SelectParents(P0, 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. Ψ ← Ψbest //Set current best model as initial (source) model for the next generation.
9. while Gen ≤ MaxGeneration do
   10. R ← (P ∪ Q) //Combine the parent population (P) & the child population (Q).
   11. Rfit, Ψbest ← EvalFitness(R, Ψ*, D*, Dt) //Evaluate fitness for each individual in R.
   12. R_rank ← NonDominatedSorting(Rfit) //Assign rank using non-dominated sorting
   13. R_crowd ← CrowdingDistances(R, R_rank, Rfit) //Find crowding distances of individuals in population set R [44].
   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. Ψ ← Ψbest //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 ← Ψ

Algorithm 2 Population Initialization for EvoN2N

1. Inputs ← (N, [nmin, nmax], [hmax, hmin])
2. H ← Generate N random integers between [1 → Nh].
3. for p = 1:N do
   4. h ← H(p) : depth of pth chromosome
   5. P[p] ← generate h random integers ∈ [hmin, hmax]
4. end for
5. Return P

transformed, the cost function for fine-tuning should include classification loss (Jc) as well as the MMD term (JMMD) [28]. For the given C class problem, Jc and JMMD are defined as

\[ J_c = \frac{1}{N} \sum_{i=1}^{N} \sum_{t=1}^{C} I[y_{jt} = C] \log \frac{\left(\hat{y}_{jt}^{T} \hat{y}_{jt}\right)}{\sum_{t=1}^{C} \left(\hat{y}_{jt}^{T} \hat{y}_{jt}\right)} \] (5)

\[ J_{MMD} = \sum_{i=1}^{C} \left[ \frac{1}{N_i} \sum_{p=1}^{N_i} f(x_{i,p}) - \frac{1}{N_t} \sum_{q=1}^{N_t} f(x_{t,q}) \right]_2^2 \] (6)

where, f(·) = h-level features output of DNN, N_t and N_i are the number of samples in the i-th class of X_t and X_i respectively, y_{jt} be the source label and [w_t, b_t] be the weight and bias connecting i-th node in the output (softmax) layer.

Let W_f ∈ Ψf & W_c ∈ Ψc be the weight matrices of the DNN feature extractor and the softmax classifier respectively, then the cost function minimization objective by Limited-Broyden-Fletcher-Goldfarb-Shanno (LBFGS) [49] algorithm can be expressed as in Eq.(7).

\[ \min_{W_f, W_c} J = \min_{W_f, W_c} \left[ J_c(W_f, W_c) + \gamma J_{MMD}(W_c) \right] \] (7)

where, γ is positive fractional value and represents the trade off between the regularization term and the MMD term. 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 ∪ Q) is assigned with (i) non-dominating rank (r_p ∈ R_rank) and (ii) crowding distance (d_p ∈ 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 EvoN2N
1: Inputs ← (P; Ψ*, D*, Df).
2: Np ← population size //number of individuals in P.
3: for p = 1 : Np do
4: Ψt ← Net2Net(Ψ*) //Transform the source network to target network (Ψth model in P) as depicted in Fig. 2.
5: Fine-tune the target network (Ψt) to solve Eq. (7).
6: Pfit(p) ← classification accuracy (CA) of the final network on the validation data.
7: end for
8: Ψbest ← Best model // Find the model with maximum CA and minimum number of model parameters.
9: Return Pfit, Ψbest.

Algorithm 4 Parent Selection using R_rank and R_crowd
1: Inputs ← (R, R_crowd, R_rank)
2: Npf ← length(unique(R_rank)) //Maximum number of possible Pareto-front.
3: pf ← 1 //set Pareto-front at 1
4: p ← 0 //solution counter p at zero.
5: while pf ≤ Npf do
6: if p + \sum R_rank = pf ≤ Np then
7: n = \sum R_rank = pf;
8: P[p + 1 : p + n] = R_Rank = pf;
9: p = p + \sum R_rank = pf;
10: else
11: q = Np − p; //number of rest of the members in P.
12: qf = R_Rank = pf; //The rest members in P
d_qf = R_crowd (R_rank = pf); //d = distance
13: index = sort(d_qf, “descend”);
14: qf = qf(index);
15: P[p + 1 : p + q] = qf(1 : p);
16: p = p + q;
17: end if
18: pf = pf + 1
19: end while
20: Return P

Algorithm 5 Offspring Generation: Crossover and Mutation
1: Inputs : P= Parent Population, p_c = Crossover Probability, p_m = Mutation Probability, N_p = Population Size.
2: I_c = indices of random p_c * 100% members from P.
3: while I_c in not empty do
4: Select P_1 = P_{i_1} & P_2 = P_{i_2}, where, (i_1, i_2) = two random indices from I_c.
5: (C_1, C_2) = apply crossover operator on (P_1, P_2). //as illustrated in Fig. 5.
6: Replace (P_{i_1}, P_{i_2}) by (C_1, C_2).
7: Remove i_1, i_2 from I_c.
8: end while
9: P_m = generate N_p, new populations using Algorithm 2.
10: I_m = indices of random p_m * 100% members from P_m.
11: P_{I_m} = P_m_{I_m}.
12: Return P

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) LS1: N09_M07_F10 (speed = 900 rpm, torque = 0.7 Nm & radial force = 1000 N) (ii) LS2:
N15_M01_F10 (speed = 1500 rpm, torque = 0.1 Nm & radial force = 1000 N) (iii) 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.

3) Gearbox Fault Detection (GFD) Dataset [39]: A SpectraQuest’s Gearbox Fault Diagnostics Simulator has been used to record the gear vibration signals. The dataset contains four vibration signals recorded using four sensors installed in four different directions. The recorded signals represent two different states of gear conditions namely healthy/normal (N) and broken tooth (BT). The dataset for each state of gear fault contains 10 files of vibration signals recorded under various load conditions from 0 to 90%.

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: \( z = \frac{x - \mu}{\sigma} \), 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: 
\[
x_n = \frac{(x - x_{\text{min}})}{(x_{\text{max}} - x_{\text{min}})},
\]
where \( x_{\text{min}} \) and \( x_{\text{max}} \) 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 × 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. Also, for the gear box fault dataset, each signals are segmented using 400 data points. Therefore, 104 signals having 3600 samples in each class is converted into 936 × 400 samples.

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:

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

Table I: Evaluation Scheme on CWRU Dataset [2]

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

i) Source Data: The time-series signals recorded at 12 Hz DE with a motor load of 0 hp and speed of 1796 RPM are segmented to create 1200 × 100 samples per class. After merging the segmented dataset from each class (N, IR, OR, and B), the it contains a total of 4800 × 100 samples.

ii) Target-1: The time-series signals recorded at 12k Hz FE with motor loads of 1, 2, & 3 hp, fault diameter (F.D.) varying from 7 to 21 mil and the speed of 1772 RPM are used to prepare the dataset for target-1 (T1) under nine different cases with F.D.’s and motor loads as shown in table I.

Case-2: PBU dataset: The source dataset and the target dataset with three classes (N, OR, & IR) are prepared as follows and summarized in table II.

i) Source Data: The time-series signal recorded for artificially damaged bearing fault with the motor running under the load setting of L1 is used prepare source dataset. Since each measurement contains approx 2,56,001 data points, the segmented samples of size 5000 × 400 per class with segment length 400 are prepared using 10 measurement files from each class.

ii) Target-2 & 3: Two different sets of target dataset (target-2 (T2) & target-3 (T3)) are created by considering different level of damages (extent of damage) as given in table II. For each case of T2 and T3, four L.S.’s of LS1, LS2, LS3, & LS4 are considered to study the diagnosis in a total of eight cases. For each case, the target dataset is prepared using a number of data points to generate 400 × 400 samples per class.

Case-3: Gearbox fault dataset recorded at zero load is used to create a source dataset. 80000 sample points from the file corresponding to zero load and the sensor ‘1’ is segmented to convert into 800 × 100 samples per class. Now, target-4 (T4) is created by using the recorded signals from the files corresponding to 30, 60, &90 % of load. Thus, it contains three case study corresponding to three different load conditions. For each case, a small amount of sample points 30000 are used to created a segmented dataset of 300 × 100 samples per class. The evaluation scheme for gearbox fault diagnosis is summarised in Table III.

Each of the target datasets is split into train, test, and validate datasets using the random sampling method. 20% of the available target samples are kept for testing, 16% for validation, and 64% for training.
Table II: Evaluation Scheme on PBU Dataset [3]

| Class Name | Source (Artificial Damage) | Target-2 (T2) | Target-3 (T3) | Class label |
|------------|-----------------------------|---------------|---------------|-------------|
|            | Bearing name | Extent of damage | Sample/Class | Bearing name | Extent of damage | Sample/Class | Bearing name | Extent of damage | Sample/Class |
| N          | K001        | 5000            | K001 None     | 400          | K002 None     | 400          | 0            |
| OK         | K001        | 5000            | K004 1        | 400          | KAX16 2       | 400          | 1            |
| IR         | KI01        | 5000            | KI16 3        | 400          | KI18 2        | 400          | 2            |

Table III: Evaluation Scheme on GFD [39]

| Class Name | Source Dataset | Target- (T4) | Class label |
|------------|----------------|---------------|-------------|
|            | Load (%) | Sample/Class | Load(%) | Sample/Class |
| N          | 800     | 30,60,90     | 300     | 0            |
| BT         | 800     | 30,60,90     | 300     | 1            |

D. Evaluation metrics

Classification performance of a diagnostic model is measured in term of classification accuracy (CA) as widely accepted in literature [21], [23], [24].

\[ CA = \frac{|x : x \in X_{te} \land y = F(x)|}{|x : x \in X_{te}|} \times 100\% \] (8)

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 \(TI = \frac{CA}{CA_{baseline}}\), where, \(CA\) is the average CA for dataset under various operating conditions.

E. Implementation and Training Parameters

The proposed EvoN2N as described in the Algorithm 1 requires an initial DNN model (\(\Phi_s\)) termed as teacher model or the source model. Therefore, first a source model with any architecture (we choose DNN model with 3 hidden layers \(80-40-20\)) is trained on the source dataset (as mentioned in section V-C for three datasets) using back-propagation gradient descent.

Now with this source network, the proposed framework 1 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 IV & V.

The performance of the proposed framework is compared with the state-of-the-art method most popularly used for intelligent fault diagnosis. The selected algorithms are support vector machines (SVM) [10], deep neural network (DNN) [13], deep transfer learning (DTL) based on sparse autoencoder [24], Deep neural network for domain Adaptation in Fault Diagnosis (DAFD) [23], Net2Net without domain adaptation (N2N_WDA) [28], Net2Net with domain adaptation (N2N_DA) [28], 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 accuracies are are tabulated in tables IV and V. Fig. 8 shows the transfer improvement \((TIs)\) of average accuracies for the three cases: (i) CWRU dataset, (ii) PBU dataset, and (iii) GFD dataset.

F. Discussion

Following points can be observed from the diagnostic results shown in tables IV & V and Fig.’s 8 & 6.

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
Table IV: CA for CWRU bearing fault data (T1) recorded at Fan End (FE) with three fault diameter (F.D.)

| Target F.D. | Load | SVM [10] | DNN [13] | DTL [24] | DAFD [23] | N2N [28] | EvoDCNN [36] | EvoN2N |
|-------------|------|----------|----------|----------|----------|----------|--------------|--------|
| T1 FE 7 mil | 1hp  | 88.1     | 96.7     | 96.6     | 97.9     | 98.9     | 98.9         | 99.6   | 100.0 |
|            | 2hp  | 98.1     | 95.9     | 93.4     | 96.1     | 97.1     | 98.1         | 99.6   | 100.0 |
|            | 3hp  | 99.6     | 98.8     | 98.8     | 98.4     | 99.4     | 99.4         | 99.7   | 100.0 |
| T1 FE 14 mil | 1hp | 99.6     | 94.8     | 96.9     | 97.2     | 99.2     | 99.7         | 100.0  | 100.0 |
|            | 2hp | 98.8     | 95.3     | 92.2     | 95.7     | 97.7     | 98.7         | 98.1   | 99.1  |
|            | 3hp | 99.7     | 96.9     | 94.7     | 97.6     | 99.3     | 98.6         | 98.4   | 98.8  |
| T1 FE 21 mil | 1hp | 96.9     | 86.6     | 84.7     | 89.6     | 95.6     | 96.6         | 98.4   | 100.0 |
|            | 2hp | 88.4     | 85.3     | 82.2     | 86.7     | 90.7     | 90.7         | 90.1   | 95.4  |
|            | 3hp | 92.2     | 86.6     | 79.4     | 88.1     | 91.1     | 92.1         | 92.8   | 95.8  |

Standard Deviation 4.80 5.30 7.10 4.70 3.50 3.30 3.7 1.80

Table V: CA for PBU Dataset (T2 & T3) with different level of fault and different load setting (L.S.)

| Target L.S. | SVM [10] | DNN [13] | DTL [24] | DAFD [23] | N2N [28] | EvoDCNN [36] | EvoN2N |
|-------------|----------|----------|----------|----------|----------|--------------|--------|
| T2 L1      | 96.3     | 97.9     | 97.9     | 97.9     | 99.6     | 99.9         | 100.0  |
|            | 90.0     | 94.6     | 95.0     | 94.6     | 95.1     | 96.1         | 99.6   | 99.8  |
|            | 89.2     | 92.9     | 93.3     | 92.1     | 94.4     | 94.4         | 97.5   | 97.7  |
|            | 89.2     | 93.8     | 93.8     | 94.2     | 97.2     | 95.3         | 100.0  | 100.0 |
| T2 L2      | 99.6     | 99.6     | 99.6     | 100.0    | 100.0    | 100.0        | 99.2   | 100.0 |
|            | 95.8     | 97.9     | 97.5     | 96.7     | 96.3     | 96.6         | 98.6   | 100.0 |
|            | 95.8     | 94.2     | 93.3     | 94.2     | 95.7     | 96.8         | 97.2   | 100.0 |
| T3 L4      | 93.3     | 93.3     | 95.0     | 95.8     | 95.7     | 95.7         | 93.3   | 100.0 |

Standard Deviation 4.18 2.58 2.54 2.69 2.16 2.16 1.15 0.86

Table VI: CA for Gearbox Fault Detection Dataset (T4) with 30, 50, 70, 90% of Load

| Target Load (%) | SVM [10] | DNN [13] | DTL [24] | DAFD [23] | N2N [28] | EvoDCNN [36] | EvoN2N |
|-----------------|----------|----------|----------|----------|----------|--------------|--------|
| T4 30.0%       | 83.3     | 90.0     | 93.3     | 93.3     | 95.0     | 95.0         | 98.3   | 100.0 |
| 50.0%          | 87.5     | 90.8     | 90.8     | 93.3     | 93.3     | 95.8         | 95.8   | 100.0 |
| 70.0%          | 87.5     | 95.0     | 91.7     | 92.5     | 92.5     | 93.3         | 95.0   | 99.2  |
| 90.0%          | 89.2     | 93.3     | 93.3     | 91.7     | 93.3     | 95.0         | 99.2   | 100.0 |

Standard Deviation 2.49 2.30 1.25 0.79 1.05 1.05 1.98 0.41

Fig. 8: Transfer Improvement (TI) of average CA (CA) on the (i) CWRU dataset, (ii) PBU dataset, and (iii) GFD dataset.

3) TI in Fig. 8 for the three types of dataset reveals that performance of some method may be poorer than the baseline method SVM depending upon the dataset. But, the proposed method performs better in all cases.

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.

improved over the most popular methods used intelligent fault diagnosis (Tables IV & V). Therefore, the network architecture greatly affects the performance of DNN.

2) Fig. 6 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.

3) TI in Fig. 8 for the three types of dataset reveals that performance of some method may be poorer than the baseline method SVM depending upon the dataset. But, the proposed method performs better in all cases.
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.

G. Complexity Analysis

The complexities of the proposed algorithm 1 is defined based on the worst complexity in each epoch. One epoch of the entire algorithm has worst complexity contributed by fitness evaluation, non-dominated sorting, parent selection based on crowding distance and rank, and crossover and mutation process. Out of all these steps, fitness evaluation and non-dominated sorting has the worst complexity to contribute.

The fitness evaluation of DNN model involves the parameter optimization by L-BFGS with complexity of \( O(N_f \times n^2) \), where \( n \& N_f \) be the total number of parameters and number of iterations required to fine-tune the DNN model. The complexity of non-dominated sorting is given by \( O(MN_p^2) \), where \( M \& N_p^2 \) represents the number of objective and the population size respectively. Since the number of objective \( (M) \) is usually very less compared to the population size \( (N_p) \), the complexity of the proposed algorithm (EvoN2N) can be approximated as \( O(N_fN_pn^2) \) where, \( N_p \) be the population size, \( N_f \) be the number iteration for the model training in fitness evaluation step, \( n \) be the number of parameters in a DNN model.

VI. CONCLUSIONS

This article proposed the framework of evolving Net2Net transformation for DNN architecture search. The DNN architecture to be optimized is encoded as real-coded chromosomes (individuals) in the population initialization. An initial (source model) is used to train the individuals at \( 0^{th} \) generation based on domain adaptation. Now, the best model obtained at each generation is transferred to the next generation for the initialization of individuals. Thus, the training of the individuals gets faster with the evolution. 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.

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