Fuzzy-membership-based labeling: a new labeling method for both classification task and regression task

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Abstract

In the machine learning and deep learning field, there are two main kinds of tasks: classification and regression. The label for the former is discrete, while for the latter is continuous. Due to the big gaps in labels, these two tasks are generally resolved separately, bringing low training efficiency and waste of computing resources. To this end, this paper proposes a new labeling method based on fuzzy membership. The main idea is to build an intermediate variable, which behaves between continuous and discrete variables. Then, the relation between the intermediate variable and the discrete label can be identified with fuzzy membership. Finally, the fuzzy membership is adopted for building labels to train the source model. After training, the source model can be transferred to achieve both classification and regression tasks. To validate the new labeling method, two typical tasks in the PHM field, aging stage classification and RUL prediction, are selected as the representative for classification and regression tasks, respectively. Furthermore, LSTM with two dense layers is chosen as the benchmark source model. With the C-MAPSS dataset, the superiority of the proposed fuzzy-membership-based labeling to improve the network's task transfer learning performance has been verified.

1. Introduction

In the data-driven PHM (predictive maintenance and health management) field, classification and regression are two main types of tasks. For the former, like fault classification (Zhao et al. [2022]), degradation stage recognition (Alfeo et al. [2022]), friction state identification (Mokhtari et al. [2020]), et al.; for the latter, including RUL (remaining useful life) prediction (Zhou et al. [2022]), wear loss estimation (Bote-Garcia et al. [2020]), health index evaluation (Djurdjanovic et al. [2003]), and so on. Due to the output labels for classification and regression tasks are different, one is limited discrete values, like "yes" and "no" for with and without fault, or 1, 2, and 3 standing for different fault positions, while the other is unlimited continuous values, like the RUL ranging between 0 and 100%, these two tasks are solved separately, with one model/network for one task. However, building and training two separate deep networks for these two kinds of PHM issues for one machine inevitably brings time consumption and waste of computing resources (Liu et al. [2019]). Moreover, in most cases, there is no sufficient data available to train such two networks.

Essentially, both kinds of tasks evaluate the machine's health state and are inherently related. This enables transfer learning to be a possible solution to this problem. Transfer learning concerns transferring a network from the source domain to the target domain (Weiss et al. [2016]). To date, the reported research mainly concentrates on either the transfer learning of one identical machine across different operating conditions, the transfer learning among different machines, or the one from the simulation model to a real machine, rarely addressing the transfer learning between different tasks (Lei et al. [2020]; Ruan, Chen, et al. [2022]). As shown in Fig. 1(a), for two tasks, task A and task B, at present, they are usually solved with two individual models. Task transfer learning aims to learn the knowledge shared by two tasks and then leverage it from one task to another (see Fig. 1(b)). Different from published research that focuses on structure development or hyperparameter optimization to improve the source model's transfer performance, this paper focuses on the labeling improvement of the source model and proposes a new task transfer learning framework with membership-based labeling. As demonstrated in Fig. 1(c), the main idea is to introduce the membership from fuzzy logic to build new labels, which behave between discrete and continuous variables. Then, the membership-based labels will be used to train the source model. After that, the source model can be transferred to realize both classification and regression tasks.

The remainder of this paper is structured as follows. Section 2 introduces the theory of fuzzy logic and membership as well as the methodology of fuzzy-membership-based labeling. Section 3 details the C-MAPSS dataset, feature selection, and two tasks preparation for task transfer learning. Section 4 elaborates on the LSTM (long short-term memory)-based source model and the construction of HI (health index). Section 5 presents the results and analysis. Finally, Section 6 concludes the whole paper.

2. Background theory

2.1. Fuzzy membership and membership function

In boolean logic, one variable belongs to a set or not, with a probability of either 100% or 0. On the contrary, variables in a fuzzy set belong to the set with a probability between 0 and 1. This probability is called membership degree and is defined as follows.

Definition 1 *A fuzzy set A in universe U means any element u ($u \in U$) has a corresponding number $\mu_A(u)$ ($\mu_A(u) \in [0,1]$), which is defined as the membership degree of u to A. The mapping μ_A is called as the membership function. It can be described as:*

$$\begin{aligned} &\mu_A : U \to [0,1] \, , \\ &\mu \to \mu_A(u) \, . \end{aligned} \tag{1}$$

Since the fuzzy set was first proposed by L.A. Zadeh in 1965 (Zadeh [1996]), it has been widely used in control, image processing et al. due to its superiority in describing the fuzzy relation that boolean logic cannot resolve. Table 1 summarizes the three main fuzzy membership functions (Mandal et al. [2012]), and they will be used in this study.

Table 1. Three kinds of membership functions

Membership	Formulation
Triangular	$\mu(x) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ \dfrac{c-x}{c-b}, & b \le x \le c \\ 0, & x \ge c \end{cases}$
Trapezoidal	$\mu(x) = \begin{cases} 0, & x \le a \\ \dfrac{x-a}{b-a}, & a \le x \le b \\ 1, & b \le x \le c \\ \dfrac{d-x}{d-c}, & c \le x \le d \\ 0, & x \ge d \end{cases}$
Gaussian	$\mu(x) = e^{-\frac{(x-\mu)^2}{2\sigma^2}}$

2.2. Membership-based labeling for transfer learning

Fig. 2 shows a fuzzy set with two categories, and the membership is characterized by a trapezoidal function. Any sample x_i belongs to either class A or/and class B, where $\mu_A(x_i)$ stands for the membership degree that the sample x_i belongs to class A, and $\mu_B(x_i)$ stands for the membership degree that the sample x_i belongs to class B. In the following, the membership-based labeling will be introduced based on this fuzzy set. This paper proposes two different labeling methods: single-labeling and multi-labeling. The binary classification in Fig. 2 is taken as an example, and Algorithm 1 outlines the methodology.

A. Single-labeling method

In single-labeling, each sample has only one label. The membership degrees $\mu_A(x_i)$ and $\mu_B(x_i)$ are taken as probabilities. When $\mu_A(x_i) = 1$, the sample x_i is labeled as class A; if $0 < \mu_A(x_i) < 1$, then the sample x_i is labeled as class A randomly with a probability of $\mu_A(x_i)$. Likewise, the labels for class B can be obtained.

B. Multi-labeling method

In multi-labeling, each sample corresponds to multi labels. For example, in a binary classification, there are two label values, including L_A and L_B for class A and B, respectively. For any sample x_i, its membership to class A and B is $\mu_A(x_i)$ and $\mu_B(x_i)$, then, its corresponding multi-label is a vector with two elements, namely, [$\mu_A(x_i) \times L_A$, $\mu_B(x_i) \times L_B$]. For classification tasks with more than two categories, it can be resolved with the same procedure.

Algorithm 1 Labeling based on membership

Require: Sample set X, $X = \{x_1, x_2, \cdots, x_N\}$; Label value set Y, $Y = \{L_A, L_B\}$; Labeling mode, 0 for single-labeling, 1 for multi-labeling;
 if Labeling mode = 0 **then**
  if $\mu_A(x_i) = 1$ and $\mu_B(x_i) = 0$ **then**
   Label sample x_i as class A, $Y(x_i) = L_A$;
  end if
  if $\mu_A(x_i) = 0$ and $\mu_B(x_i) = 1$ **then**
   Label sample x_i as class B, $Y(x_i) = L_B$;
  end if
  if $\mu_A(x_i) = q$, $0 < q < 1$ **then**
   Label sample x_i as class A with probability q and label sample x_i as class B with probability $1 - q$;
  end if
 end if
 if Labeling mode = 1 **then**
  if $\mu_A(x_i) = q$, $\mu_B(x_i) = 1 - q$ **then**
   Label sample x_i with two labels, one is $q \times L_A$, the other is $(1 - q) \times L_B$;
  end if
 end if

In the above methodology introduction, the variable X is as-

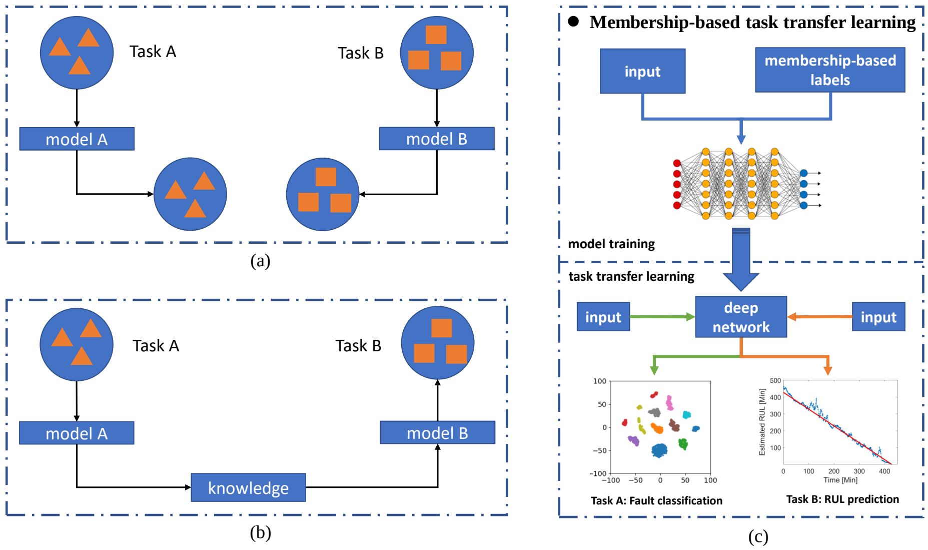


Figure 1. Fuzzy membership-based framework for task transfer learning.

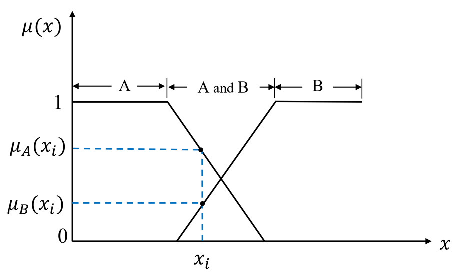


Figure 2. Diagram of membership-based labeling

sumed to have a fuzzy relation with the output label set. Once such a variable exists, membership-based labeling can be facilitated. However, in most practical applications, such a variable does not exist. Therefore, we should define a variable that satisfies the requirement, which is termed the health index in this study. As outlined in Fig. 3, four main steps are necessary to realize the membership-based labeling for task transfer learning, including HI construction, HI distribution analysis, membership function identification, and labeling. In the following, the implementation details will be introduced.

3. Dataset and Tasks for Transfer Learning

3.1. Introduction of experimental setup and dataset

The C-MAPSS dataset is used for validation in this study, which is collected from a high-fidelity aero-engine simulator provided by NASA. Fig. 4 shows the simplified diagram of the engine (D. Frederick & Litt [2007]). Different operating conditions and fault modes are defined in the simulation model to generate degradation data over cycles. These data are saved in four sub-datasets, as presented in Table 2. Each sub-dataset contains a training set, a test set, and a real RUL set, which is used to verify the corresponding test set.

Table 2. C-MAPSS Dataset

Dataset	FD001	FD002	FD003	FD004
Train Trajectories	100	260	100	249
Test Trajectories	100	259	100	248
Conditions	1	6	1	6
Fault Modes	1	1	2	2

The raw data representing the engine status is recorded as a $L \times S$ matrix, where each row in the matrix stands for a cycle, and each column represents an attribute that identifies the engine status. As illustrated in Table 3, there are a total of 26 columns, namely $S = 26$, where the 1st column is engine ID, the 2nd one represents current cycle number, the 3rd-5th columns are three parameters characterizing engine operating condition, the 6th-26th columns represent 21 sensor values, but the information about the sensor and measured variable is not accessible. Initially, the engine works normally and gradually grows into failure over running cycles. The service life of each engine varies from each other, which means the L differs among engines.

3.2. Data preprocessing and feature extraction

Though 21 sensor data are collected for each engine at every cycle, not all the sensor data contain useful information for engine fault diagnosis. As shown in Fig. 5, four sensor signals are randomly selected. We can find that sensor 1 and sensor 9 do not have much obvious tendency, while sensor 12 and 13 shows an overall exponential changing trend, which agrees with the aging process of the engine. Therefore, this study adopts two metrics to select appropriate sensor data for further diagnostic issues, including monotonicity and corre-

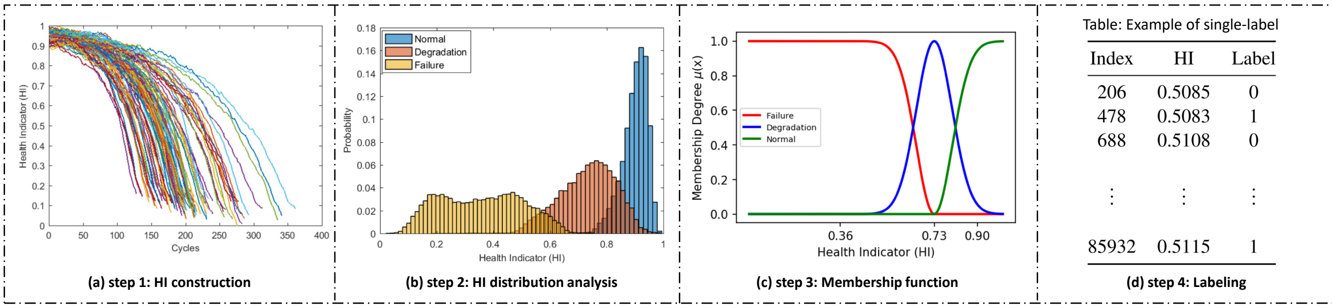


Figure 3. Flowchart of designing a membership function

Table 3. Data of #1 engine in FD001 training set

ID	Cycle	Condition 1	Condition 2	Condition 2	Sensor 1	Sensor 2	$\cdots$	Sensor 21
1	1	-0.007	-0.004	100	518.67	641.82	$\cdots$	23.4190
1	2	0.0019	-0.0003	100	518.67	624.15	$\cdots$	23.4236
1	3	-0.0043	0.0003	100	518.67	642.35	$\cdots$	23.3442
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	
1	192	0.0009	0	100	518.67	643.54	$\cdots$	22.964

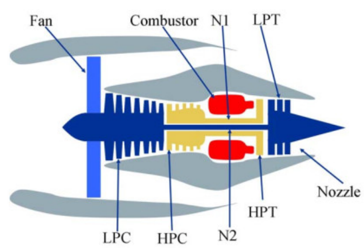


Figure 4. The engine test bench (D. Frederick & Litt [2007]).

lation with RUL (Ruan, Wu, et al. [2022]). With both metrics considered, eight sensors like 2, 3, 4, 7, 11, 12, 14, and 15 are determined. Additionally, to generate sufficient training data, a sliding window is used for data segmentation. As illustrated in Fig. 6, each sample contains 30 cycles with selected features, and the step size of the sliding window is defined as 3.

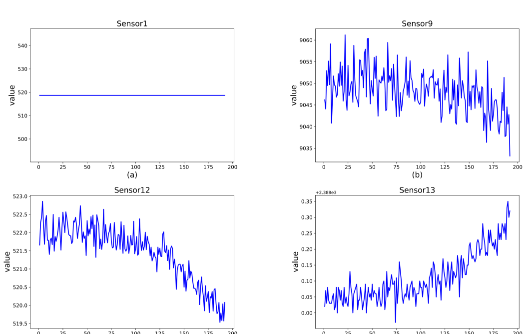


Figure 5. Four signals from sensors

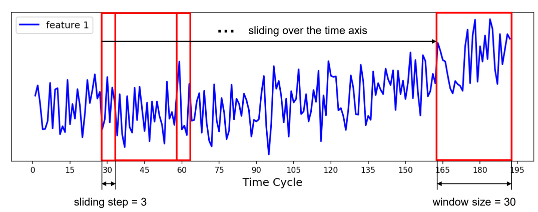


Figure 6. Data segmentation with time window

3.3. Two tasks for transfer learning validation

The purpose of this study is to explore fuzzy-membership-based labeling for task transfer learning. Therefore, two different tasks should be defined, including one of regression type and the other of classification type. For the former, the RUL prediction of the engine is naturally a regression task, while there is no ready classification task for the latter. Thus, this study will build a classification task based on the aging stage estimation. More details about the two tasks will be elaborated on in this section. As the input of two tasks is the same, the focus will be laid on the output labels.

A. Regression task: RUL prediction

The regression-type task is defined as RUL prediction. The output label is thereby the RUL values, which are defined as:

$$RUL_i^j = \max\{m^j - a_i^j, 130\} \ , \tag{2}$$

where RUL_i^j stands for the i-th sample of the j-th engine. m^j indicates the whole life-cycle of the j-th engine. a_i^j means the final cycle of the i-th sample for the j-th engine. The maximum RUL limit of 130 is defined due to that engine degradation in the early period is not obvious (Heimes [2008]).

B. Classification task: aging stage classification

Since the information about each engine failure is not given, labeling the samples with fault classes is not practical. Thus, the aging stage classification is defined as a substitute and taken as a representative fault diagnosis task (Ramasso & Saxena [2014]). To achieve this, the rows in the status-recording matrix of each engine are arranged in descending order of the operation cycle. Afterward, the first 20% data in the recordings are considered as failure phase and labeled with 2, the middle 20%-50% data are taken as degradation phase and labeled with 1, and the last 50% data are regarded as normal phase and labeled with 0. The labeling of the classification task is given in Table 4.

Table 4. Labels for degradation status

Cycle	0 - 50%	50% - 80%	80% - 100%
Label	0	1	2

4. Source model and HI construction

4.1. Source model structure and hyperparameters

LSTM is adopted to build the source model for task transfer learning. Fig. 7(a) shows the model architecture, where two LSTM layers are stacked for feature extraction and followed by two dense layers. The first LSTM layer has 32 LSTM cells, and the second one has 64 LSTM cells, while both dense layers have 16 neurons. Fig. 7(b) presents the structure of an LSTM cell. The dropout and recurrent dropout techniques are used in both LSTM layers to resolve overfitting, and Tanh is selected as the activation function. Regarding the last layer, when the model is used for RUL prediction, one neuron is adopted, while for the source model training or aging stage classification, a softmax activation function will be involved instead. In addition, the hyperparameters of the source model are optimized by the particle swarm optimization (PSO) (Ruan et al. [2021]).

4.2. Health index construction

As analyzed in the introduction, the precondition to achieve membership-based labeling is to build an intermediate variable that has a fuzzy membership relation with the discrete label set. Nevertheless, there is no readily available variable that meets the requirement. This paper achieves this by building a health index based on the linear weighting of features. Firstly, an initial health index is defined as Eqs. (3) and (4), where $\boldsymbol{x_{all}}$ represents the selected and normalized features of all data from each dataset. $HI_{initial}$ is defined as the proportion of current cycle i to its whole life cycles RUL_{max}.

$$HI_{initial} = \boldsymbol{\omega}^{\mathrm{T}} \boldsymbol{x_{all}} + b \tag{3}$$

$$HI_{initial}(i) = 1 - \frac{i}{RUL_{max}} \tag{4}$$

To identify the parameters $\boldsymbol{\omega}$ and b, a linear regression model from the feature vector $\boldsymbol{x_{all}}$ to $HI_{initial}$ is fitted for each dataset. After training, the values of $\boldsymbol{\omega}$ and b are determined and then substituted into Eq. (5) to obtain the HI curve for each engine, here $\boldsymbol{x_i}$ denotes the feature vector of the i-th engine, and HI_i stands for its reconstructed HI values.

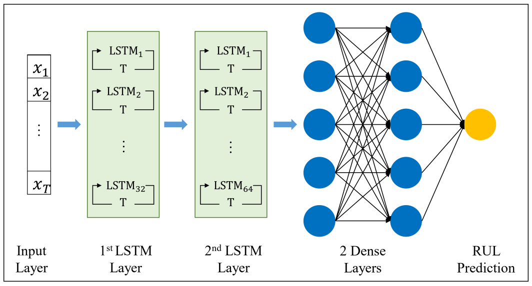
$$HI_i = \boldsymbol{\omega}^{\mathrm{T}} \boldsymbol{x_i} + b \tag{5}$$

Fig. 8 shows the trajectories of constructed HI from the engines in FD34 over cycles, which is a combination of FD003 and FD004. We can find that constructed HI shows good monotonicity. When the HI reduces from 1 to 0, it presents an exponential changing trend, which agrees well with the aero engine's degradation process.

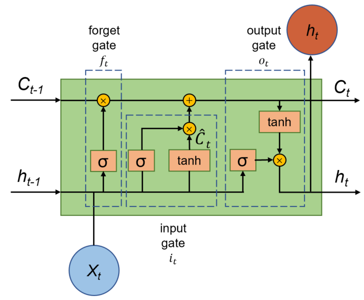
4.3. Membership function identification for HI and application in labeling

After building the HI, the next step is to identify a membership function characterizing the relation between HI and discrete labels through the HI histogram distribution analysis. Fig. 9 shows the histogram of HI values from all the samples in FD34. We can find that, on the one hand, the HI values are separated enough, which can obviously be grouped into three categories, corresponding to normal, degradation, and failure three stages. On the other hand, there exists overlapping between any two adjacent groups, indicating the HI values are continuous. In short, the constructed HI behaves as both discrete and continuous variables, which satisfies the requirement for the intermediate variable from the membership-based labeling.

Fig. 9 confirms the fuzzy-logic relation between the HI values and the classification task labels. For example, when the HI is smaller than 0.4, it belongs absolutely to the failure stage, while HI is between 0.5 and 0.7, it belongs to both the failure and degradation stages but with different probabilities. To accurately describe the fuzzy relation, the membership function can be applied. For example, we can use the Gaussian membership function to fitting the HI histogram distribution. Table 5 summarizes the identified mean and standard deviation of Gaussian membership functions. With the same method, the parameters of triangular and trapezoidal membership functions, when fitting with them, can also be obtained (Ruan, Wu, et al. [2022]).



(a) Structure of source model



(b) LSTM Cell

Figure 7. Source model structure for task transfer learning

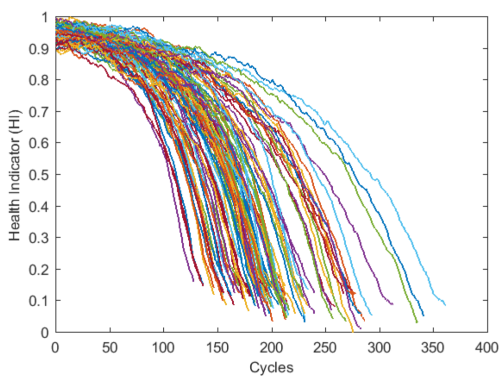


Figure 8. HI trajectory (Ruan, Wu, et al. [2022])

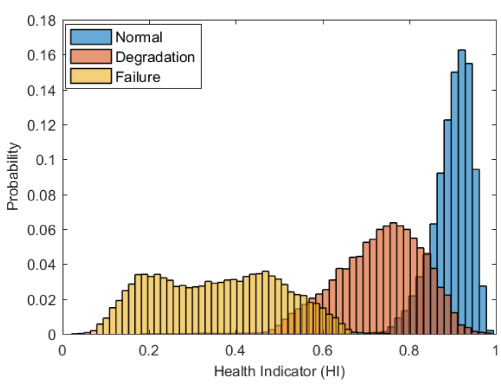


Figure 9. HI distribution under dataset FD34 (Ruan, Wu, et al. [2022])

Table 5. Statistic results of HI in dataset FD34

Status	Label	Mean	Standard deviation
Normal	0	0.90	0.05
Degradation	1	0.73	0.10
Failure	2	0.36	0.14

5. Results and discussion

To validate the proposed method, experimental data from the C-MAPSS dataset are applied. Firstly, the performance of the RUL prediction task is summarized in Table 6, where RMSE (root mean square error) is taken as the evaluation metric. We can find that the proposed method brings smaller RMSE compared with MLP, SVR, RVR, and CNN. Regarding the comparison between single-labeling and multi-labeling, takes the triangular membership as an example, the former performs better in FD002 and FD004 while the latter in FD001 and FD003, which means the single-labeling based source model has stronger adaptability across different working conditions and fault modes. As to the Gaussian membership function, single-labeling works better than multi-labeling on all four sub-datasets except FD002. When the source model is trained with trapezoidal membership-based labels, single-labeling outweighs multi-labeling in all cases. This confirms that single-labeling is better than multi-labeling when addressing task transfer learning.

After that, the different models are transferred to tackle the fault classification task. Compared with direct transfer learning (”RUL2Classification”), all the models trained with membership-based labels achieve higher accuracy among four cases, which confirms the effectiveness of the proposed transfer learning framework. In addition, based on the comparison between multi-labeling and single-labeling, we can find that single labeling with trapezoidal membership performs better, further validating the superiority of the single-labeling method.

6. Conclusion

In the data-driven fault diagnosis field, there are two main classes of issues. One is the classification-type task, like fault classification, aging stage identification, and friction state determination, where the output labels are limited and discrete values. The other is the regression-type task, such as RUL prediction, wear loss estimation, and health index evaluation, where the output labels are continuous values. In previous research, these two tasks are resolved separately. In this study, the transfer learning between these two different issues is termed task transfer learning. A new framework for task transfer learning is proposed by introducing a new fuzzy

Table 6. RMSE comparison of different source models for RUL prediction

Membership function	FD001	FD002	FD003	FD004
MLP	37.56	80.03	37.39	77.37
SVR	20.96	42.00	21.05	45.35
RVR	23.80	31.30	22.37	34.34
CNN	18.45	30.29	19.82	29.16
Triangular	17.44	24.95	20.41	29.76
Gaussian	15.87	26.39	19.14	29.82
Trapezoidal (10%)	16.04	25.49	20.00	29.95
Trapezoidal (20%)	17.50	25.86	19.02	31.47
Trapezoidal (25%)	15.97	25.70	21.61	30.43
Trapezoidal (30%)	17.23	26.42	21.19	30.17
Trapezoidal (15%)	15.80	25.73	18.34	30.40
Multi-label (triangular)	15.86	25.98	20.18	31.44
Multi-label (Gaussian)	16.72	26.20	19.89	31.61
Multi-label (trapezoidal)	16.55	26.95	20.28	33.87

Table 7. Transfer learning performance comparison

Method	FD001	FD002	FD003	FD004
RUL2Classification	0.90	0.73	0.86	0.66
Multi-label (triangular)	0.91	0.76	0.92	0.72
Multi-label (Gaussian)	0.91	0.77	0.91	0.72
Multi-label (trapezoidal)	0.90	0.75	0.89	0.72
Trapezoidal (15%)	0.91	0.78	0.92	0.72

membership-based labeling method. With the new labels, which behave between continuous and discrete variables, the source model can be trained to extract features for both classification and regression tasks. The C-MAPSS dataset of the aero engine is applied for validation, with two tasks constructed, one for aging stage classification and the other for RUL prediction. Experimental results confirm the feasibility and superiority of the proposed framework for task transfer learning.

REFERENCES

Alfeo, A. L., Cimino, M. G., & Vaglini, G. (2022). Degradation stage classification via interpretable feature learning. *Journal of Manufacturing Systems*, *62*, 972–983.

Bote-Garcia, J.-L., Mokthari, N., & Gühmann, C. (2020). Wear monitoring of journal bearings with acoustic emission under different operating conditions. *Spectrum*, *1010*, 49xx.

D. Frederick, J. D., & Litt, J. (2007). User's guide for the commercial modular aero-propulsion system simulation (cmapss). In *Technical manual tm2007-215026.* NASA/ARL.

Djurdjanovic, D., Lee, J., & Ni, J. (2003). Watchdog agent—an infotronics-based prognostics approach for product performance degradation assessment and prediction. *Advanced Engineering Informatics*, *17*(3-4), 109–125.

Heimes, F. O. (2008). Recurrent neural networks for remaining useful life estimation. In *2008 international conference on prognostics and health management* (pp. 1–6).

Lei, Y., Yang, B., Jiang, X., Jia, F., Li, N., & Nandi, A. K. (2020). Applications of machine learning to machine fault diagnosis: A review and roadmap. *Mechanical Systems and Signal Processing*, *138*, 106587.

Liu, R., Yang, B., & Hauptmann, A. G. (2019). Simultaneous bearing fault recognition and remaining useful life prediction using joint-loss convolutional neural network. *IEEE Transactions on Industrial Informatics*, *16*(1), 87–96.

Mandal, S. N., Choudhury, J. P., & Chaudhuri, S. B. (2012). In search of suitable fuzzy membership function in prediction of time series data. *International Journal of Computer Science Issues*, *9*(3), 293–302.

Mokhtari, N., Pelham, J. G., Nowoisky, S., Bote-Garcia, J.-L., & Gühmann, C. (2020). Friction and wear monitoring methods for journal bearings of geared turbofans based on acoustic emission signals and machine learning. *Lubricants*, *8*(3), 29.

Ramasso, E., & Saxena, A. (2014). Review and analysis of algorithmic approaches developed for prognostics on cmapss dataset. In *Annual conference of the prognostics and health management society 2014.*

Ruan, D., Chen, Y., Gühmann, C., Yan, J., & Li, Z. (2022). Dynamics modeling of bearing with defect in modelica and application in direct transfer learning from simulation to test bench for bearing fault diagnosis. *Electronics*, *11*(4), 622.

Ruan, D., Wu, Y., & Yan, J. (2021). Remaining useful life prediction for aero-engine based on lstm and cnn. In *2021 33rd chinese control and decision conference (ccdc)* (pp. 6706–6712).

Ruan, D., Wu, Y., Yan, J., & Gühmann, C. (2022). Fuzzy-membership-based framework for task transfer learning between fault diagnosis and rul prediction. *IEEE Transactions on Reliability*.

Weiss, K., Khoshgoftaar, T. M., & Wang, D. (2016). A survey of transfer learning. *Journal of Big data*, *3*(1), 1–40.

Zadeh, L. A. (1996). Fuzzy sets. In *Fuzzy sets, fuzzy logic, and fuzzy systems: selected papers by lotfi a zadeh* (pp. 394–432). World Scientific.

Zhao, H., Liu, J., Chen, H., Chen, J., Li, Y., Xu, J., & Deng, W. (2022). Intelligent diagnosis using continuous wavelet transform and gauss convolutional deep belief network. *IEEE Transactions on Reliability*.

Zhou, J., Qin, Y., Chen, D., Liu, F., & Qian, Q. (2022). Remaining useful life prediction of bearings by a new reinforced memory gru network. *Advanced Engineering Informatics*, *53*, 101682.