A Survey on Ensemble Learning under the Era of Deep Learning

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Abstract

Due to the dominant position of deep learning (mostly deep neural networks) in various artificial intelligence applications, recently, ensemble learning based on deep neural networks (ensemble deep learning) has shown significant performances in improving the generalization of learning system. However, since modern deep neural networks usually have millions to billions of parameters, the time and space overheads for training multiple base deep learners and testing with the ensemble deep learner are far greater than that of traditional ensemble learning. Though several algorithms of fast ensemble deep learning have been proposed to promote the deployment of ensemble deep learning in some applications, further advances still need to be made for many applications in specific fields, where the developing time and computing resources are usually restricted or the data to be processed is of large dimensionality. An urgent problem needs to be solved is how to take the significant advantages of ensemble deep learning while reduce the required expenses so that many more applications in specific fields can benefit from it. For the alleviation of this problem, it is essential to know about how ensemble learning has developed under the era of deep learning. Thus, in this article, we present discussions focusing on data analyses of published works, methodologies, recent advances and unattainability of traditional ensemble learning and ensemble deep learning. We hope this article will be helpful to realize the intrinsic problems and technical challenges faced by future developments of ensemble learning under the era of deep learning.

1 Introduction

Ensemble learning (Dietterich 2000; Zhou 2009, 2012), a machine-learning technique that utilizes multiple base learners to form an ensemble learner for the achievement of better generalization of learning system, has achieved great success in various artificial intelligence applications and received extensive attention from the machine learning community. However, with the increase in the number of base learners, the costs for training multiple base learners and testing with the ensemble learner also increases rapidly, which inevitably hinders the universality of the usage of ensemble learning in many artificial intelligence applications. Especially when deep learning (LeCun et al. 2015) (mostly deep neural networks (He et al. 2016; Szegedy et

al. 2017; Huang et al. 2017b; Xie et al. 2017; Sandler et al. 2018; Zoph et al. 2018; Tan and Le 2021)) is dominating the development of various artificial intelligence applications, the usage of ensemble learning based on deep neural networks (ensemble deep learning) is facing severe obstacles.

Since modern deep neural networks (Rawat and Wang 2017; Liu et al. 2017a; Alam et al. 2020; Khan et al. 2020) usually have millions to billions of parameters, the time and space overheads for training multiple base deep learners and testing with the ensemble deep learner is far greater than that of traditional ensemble learning. Fast ensemble deep learning algorithms like Snapshot (Huang et al. 2017a), fast geometric ensembling (FGE) (Garipov et al. 2018) and stochastic weight averaging (SWA) (Izmailov et al. 2018; Maddox et al. 2019) have promoted the deployment of ensemble deep learning in some artificial intelligence applications to some extent. However, due to the large expenses compared with traditional ensemble learning, the deployment of ensemble deep learning algorithms still needs further advances in some specific fields, where the developing time and computing resources are usually restricted (f. e. the field of robotics vision (Yang et al. 2018, 2019)) or the data to be processed is of large dimensionality (f. e. the field of histopathology whole slide image analysis (Yang et al. 2020c, b)). In these specific fields, it is sometimes still difficult to deploy the traditional ensemble learning algorithms, which makes the deployment of ensemble deep learning even more challenging. Thus, an urgent problem needs to be solved is how to make full usage of the significant advantages of ensemble deep learning while reducing the expenses required for both training and testing so that many more artificial intelligence applications in specific fields can benefit from it.

To alleviate this problem, it is essential to know about how ensemble learning has developed under the era of deep learning. In this article, we achieve this by presenting discussions with our observations of various existing ensemble learning algorithms and related applications. Different from existing review articles (Sagi and Rokach 2018; Dong et al. 2020) that mostly discussed about traditional ensemble learning, reviews (Cao et al. 2020) that particularly discussed ensemble deep learning in bioinformatics, or specific technical innovations with ensemble learning introduced, such as GAN-Ensembles (Durugkar et al. 2017; Ghosh et al. 2018; Han et al. 2020), this article aims to reveal the intrinsic problems and technical challenges of deploying ensemble learning under the era of deep learning to a wider range of specific fields, with more fundamental discussions about the developing routes of both traditional ensemble learning and ensemble deep learning. First, through data analysis of published works, we show the prosperity of ensemble learning and the gap between ensemble deep learning and traditional ensemble learning. Second, we discuss the methodologies, recent advances and unattainability of traditional ensemble learning by analyzing existing well-known approaches, applications and giving some of our observations. Third, we discuss the methodologies, recent advances and unattainability of ensemble deep learning with analyses and observations in the context of usual and fast solutions. Finally, we discuss the whole paper, pointing out some possible future research directions.

2 Data Analysis of Published Works

In this section, we present some data analysis of published works to show the prosperity of ensemble learning (EL) and the gap between ensemble deep learning (EDL) and traditional ensemble learning (TEL).

2.1 Prosperity of EL

The research history of EL can be traced back to 1990 (Hansen and Salamon 1990; Schapire 1990). Due to its significant advantages in improving the generalization of learning systems, the research on the theoretical algorithms and applications of EL has always been a research hotspot. Dietterich (Dietterich 1997), an authoritative scholar in the field of machine learning, once listed EL as the first of four research directions in the field of machine learning in AI Magazine. In the past 30 years, the research of EL has made remarkable progress. As shown in Figure 1, the number of papers related to the topic of 'ensemble learning' and published in the core set of Web of Science from 1990 to 2019 has been increasing steadily year by year, which reflects an exponentially growing prosperity of EL.
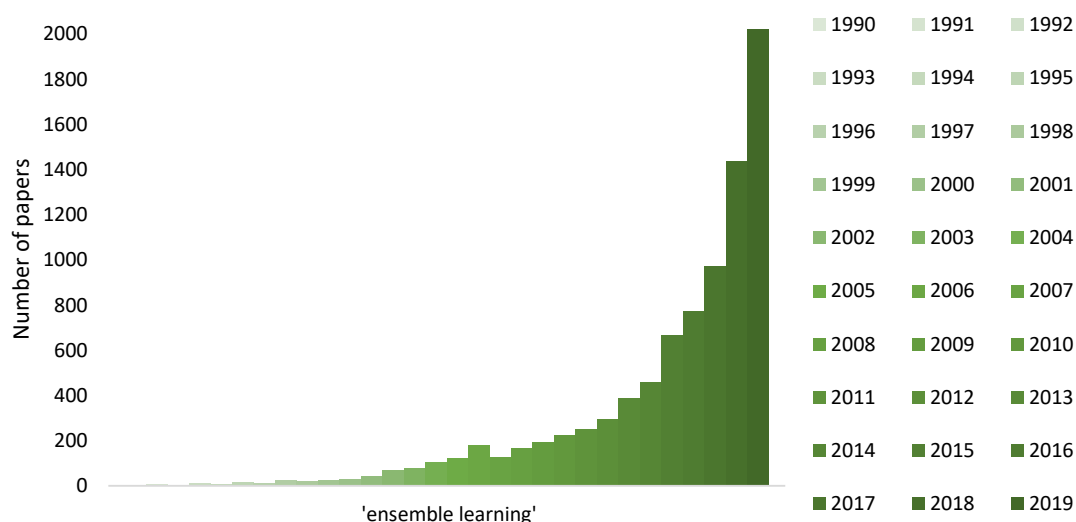

Figure. 1. The number of papers published in the core set of Web of Science from 1990 to 2019 for the topic of 'ensemble learning'.

2.2 Gap between EDL and TEL

The research history of ensembles of neural networks can be traced back to the early research stage of ensemble learning in 1990 (Hansen and Salamon 1990). However, the research progress of ensembles of deep neural networks (ensemble deep learning, EDL) had been very slow before 2014. Later benefited from the great success of deep neural networks with popularization of big data and high-performance computing resources, the research progress of EDL began to sprout rapidly. Figure 2 shows the comparison between the number of papers related to 'ensemble deep learning' or 'ensemble learning' not 'deep' (traditional ensemble learning, TEL) and published in the core set of Web of Science from 1990 to 2019. It can be noted from Figure 2 that a large gap exists between EDL and TEL. Compared with TEL, the

development of EDL is severely lagging behind. The primary reason for this phenomenon is that modern deep neural networks (Rawat and Wang 2017; Liu et al. 2017a; Alam et al. 2020; Khan et al. 2020) usually have parameters ranging from millions to billions which makes the time and space overheads for the training and testing stages of EDL much greater than that of TEL, which severely hinders the deployment of EDL in various artificial intelligence applications in specifical fields.
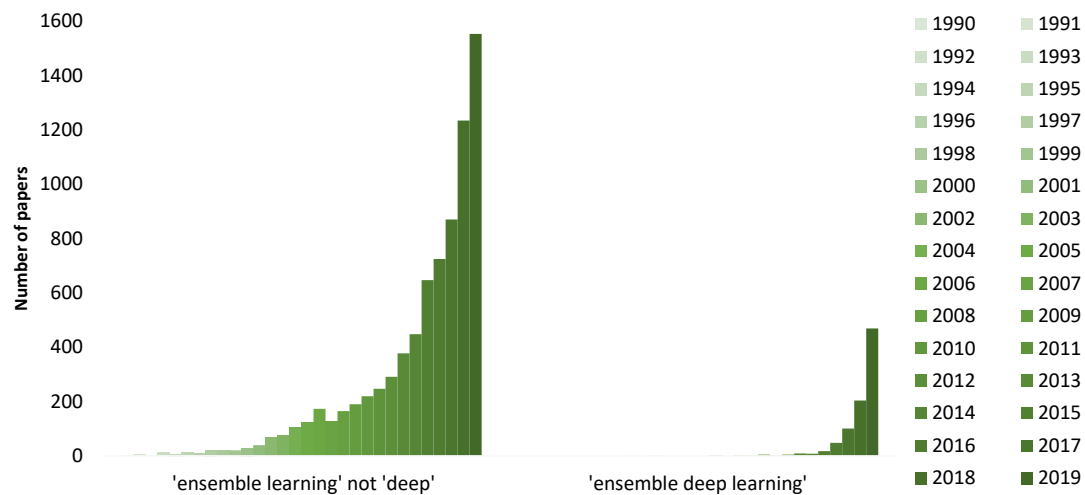

Figure 2. The comparison between the number of papers published in the core set of Web of Science from 1990 to 2019 for the topic of 'traditional ensemble learning' and the topic of 'ensemble deep learning'.

3 Traditional Ensemble Learning

Traditional ensemble learning (TEL) has been playing a major role in the research history of ensemble learning (EL). In this section, starting with the paradigm of usual machine learning (UML), we respectively present the methodology of TEL, well-known implementations for the methodology of TEL, recent advances of TEL and unattainability of TEL.

3.1 Preliminary

Let us first consider the paradigm of usual machine learning (UML), where a raw data set $D = \{d_1, \cdots, d_n\}$ and its corresponding target set $T = \{t_1, \cdots, t_n\}$ are given. Specifically, d_n is a raw data point of D and t_n is the target corresponding to d_n. In the UML paradigm, two components are normally essential: 1) feature extraction which converts raw data points into corresponding learnable representations; and 2) model development which evolves a learner that can map representations into corresponding targets.

The feature extraction consists of a number of extracting methods (Guyon and Elisseeff 2006), and a converting procedure. An extracting method is responsible for extracting a type of representations from raw data points; and the converting procedure is responsible for incorporating the results of extracting methods into learnable representations for the whole raw data set. The model development

component consists of a learning algorithm, a learning strategy, and an evolving procedure. The learning algorithm is responsible for the construction and optimization of a learner; the learning strategy is responsible for configurating rules to carry out the evolving procedure; and the evolving procedure is responsible for, under the learning strategy, updating the parameters of the learner to be appropriate for mapping representations into corresponding targets. The outline for the methodology of UML is shown as Figure. 3.
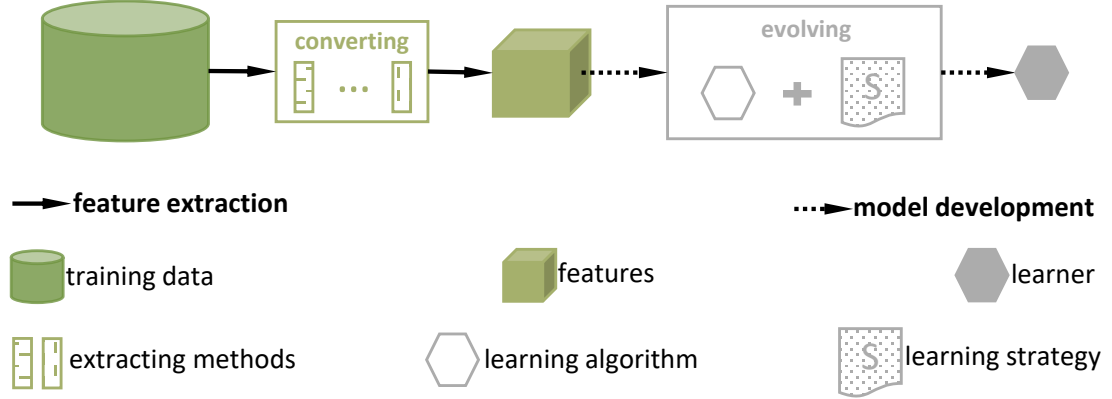

Figure. 3. The methodology of usual machine learning (UML), which consists of feature extraction and model development.

Formally, let $EM = \{em_1(*; \theta_1^{em}), \cdots, em_m(*; \theta_m^{em})\}$ denote various extracting methods. Particularly, $em_m(*; \theta_m^{em})$ signifies an extracting method $em_m(*)$ parameterized by θ_m^{em}. The feature extraction component can be expressed as

$$F = FeatureExtraction(D, EM) = \{f_1, \cdots, f_n\}.$$

Thereinto, f_n, which signifies the representation of d_n, is constructed by the converting procedure that can be more specifically expressed as

$$f_n = converting(d_n, EM)$$
$$= \{em_1(d_n; \theta_1^{em}), \cdots, em_m(d_n; \theta_m^{em})\}$$
$$= \{x_{n,1}, \cdots, x_{n,k}\} \quad s.t. \ k \geq m.$$

Formally, let $LA = \{l(*; \theta^l), opt(*,*; \theta^{opt})\}$ denote the learning algorithm and $LS = \{ls(\theta^{ls})\}$ denote the learning strategy. Specifically, $l(*; \theta^l)$ signifies the construction of a learner $l(*)$ parameterized by θ^l and $opt(*,*; \theta^{opt})$ signifies the learner's optimization procedure $opt(*,*)$ parameterized by θ^{opt} for updates of θ^l, and $ls(\theta^{ls})$ signifies a learning strategy ls parameterized by θ^{ls}. Note, here $opt(*,*)$ implicitly consists of an objective function constructed for classification or regression and corresponding optimization of the objective function. The model development component can be expressed as

$$L = ModelDevelopment(F, T, LA, LS) = \{l(*; \theta_u^l)\}.$$

Thereinto, $l(*; \theta_u^l)$ signifies the learner $l(*)$ parameterized by θ_u^l, which is updated by the evolving procedure that can be more specifically expressed as

$$\theta_u^l = evolving(F, T, l(*; \theta^l), opt(*,*; \theta^{opt}) \mid ls(\theta^{ls}))$$
$$= \arg\underset{\theta^l}{opt}\left(l(F; \theta^l), T; \theta^{opt} \mid ls(\theta^{ls})\right).$$

The developed learner $l(*; \theta_u^l)$ forms the mapping between representations F and corresponding targets T.

At testing, given a test raw data point d_{test}, the corresponding target t_{test} predicted by the evolved learner can be formally expressed as follows

$$f_{test} = \{em_1(d_{test}; \theta_1^{em}), \cdots, em_m(d_{test}; \theta_m^{em})\},$$
$$t_{test} = l(f_{test}; \theta_u^l).$$

Note, in the expressions of this subsection, each θ denotes the parameters corresponding to the implementation of respective expression.

3.2 Methodology of TEL

The paradigm of traditional ensemble learning (TEL) improves the paradigm of UML primarily differ in the model development. TEL improves UML by replacing the model development of UML with generating base learners and forming ensemble learner. Generating base learners is responsible for evolving multiple base learners that have diversity in mapping the extracted representations into corresponding targets. Forming ensemble learner is responsible for integrating the base leaners into an ensemble leaner that can achieve better generalization.

With appropriate learning algorithms (LA) and learning strategies (LS), generating base learners can be roughly divided into two categories: one is to use different types of learning algorithms to generate 'heterogeneous' base learners; and the other is to use the same learning algorithm to generate 'homogeneous' base learners. Forming ensemble learner consists of an ensembling criteria and an integrating procedure. An ensembling criteria is responsible for the construction and configuration of an ensemble learner. With the ensembling criteria, an integrating procedure is responsible for forming the final ensemble learner which is appropriate for mapping from predictions of base learners into corresponding targets. The outline for the methodology of TEL is shown as Figure. 4.

Formally, generating base learners can be expressed as

$$L_b = BaseLearnerGeneration(F, T, LA, LS) = \{l_1(*; \theta_u^{l_1}), \cdots, l_b(*; \theta_u^{l_b})\}.$$

Thereinto, $l_b(*; \theta_u^{l_b})$ signifies a base learner $l_b(*)$ parameterized by $\theta_u^{l_b}$, which is updated by the evolving procedure. More specifically, the details of generating 'heterogeneous' base learners can be expressed as follows

$$LA = \left\{\{l_1(*; \theta^{l_1}), opt_1(*,*; \theta^{opt_1})\}, \cdots, \{l_b(*; \theta^{l_b}), opt_b(*,*; \theta^{opt_b})\}\right\},$$

$$LS = \left\{ls_{hetero,1}(\theta^{ls_{hetero,1}}), \cdots, ls_{hetero,b}(\theta^{ls_{hetero,b}})\right\},$$

$$\theta_u^{l_b} = evolving\left(F, T, l_b(*; \theta^{l_b}), opt_b(*,*; \theta^{opt_b}) \mid ls_{hetero,b}(\theta^{ls_{hetero,b}})\right)$$

$$= \arg\underset{\theta^{l_b}}{opt}\left(l_b(F; \theta^{l_b}), T; \theta^{opt_b} \mid ls_{hetero,b}(\theta^{ls_{hetero,b}})\right).$$

And, the details of generating 'homogeneous' base learners can be expressed as follows

$$LA = \left\{\{l_0(*; \theta^{l_0}), opt_0(*,*; \theta^{opt_0})\}\right\},$$

$$LS = \left\{ls_{homo,1}(\theta^{ls_{homo,1}}), \cdots, ls_{homo,b}(\theta^{ls_{homo,b}})\right\},$$

$$l_b(*) = l_0(*),$$

$$\theta_u^{l_b} = evolving\left(F, T, l_0(*; \theta^{l_0}), opt_0(*,*; \theta^{opt_0}) \mid ls_{homo,b}(\theta^{ls_{homo,b}})\right)$$

$$= arg\ \underset{\theta^{l_0}}{opt}\left(l_0(F;\theta^{l_0}),T;\theta^{opt_0}\mid ls_{homo,b}(\theta^{ls_{homo,b}})\right).$$
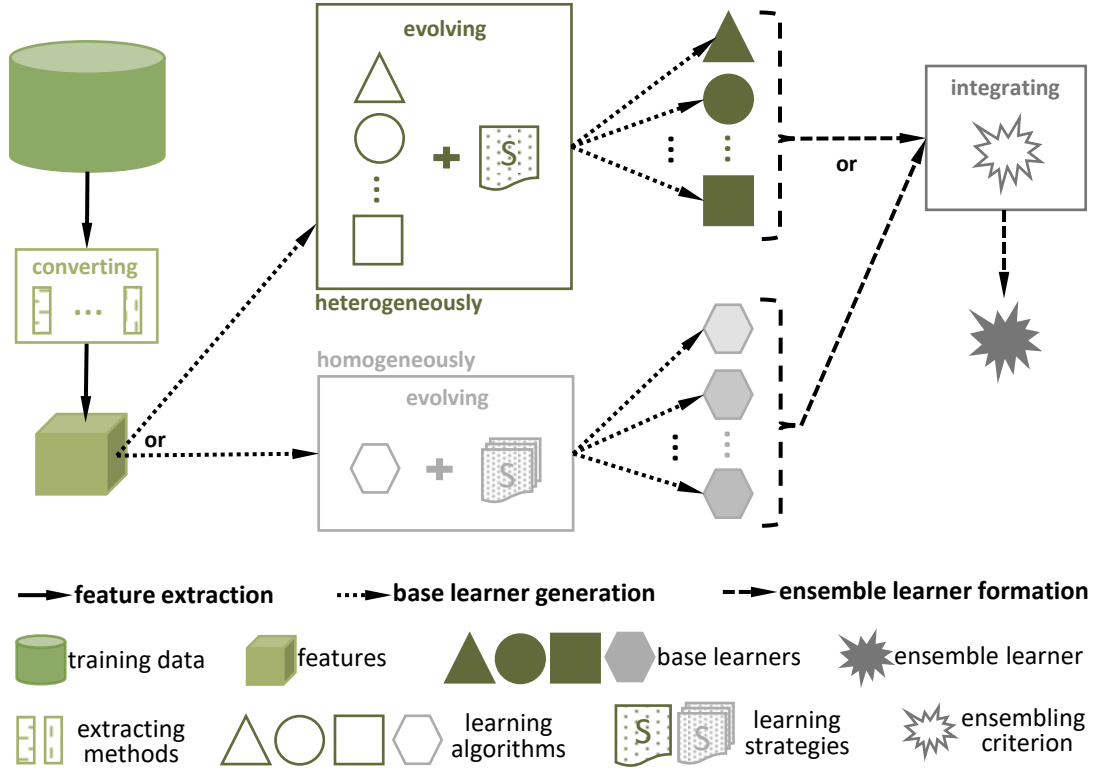

Figure. 4. The methodology of traditional ensemble learning (TEL), which consists of feature extraction, generating base learners and integrating base learners. In generating base learners, the learning strategy for evolving heterogeneous base learners is usually simpler than the learning strategy for evolving homogeneous base learners. In integrating base learners, building appropriate ensembling criteria is the key point to form the ensemble learner.

Let $EC = \{l_e(*;\theta^{l_e}), conf(*,*;\theta^{conf})\}$ denote the ensembling criteria for forming ensemble learner, and $\tilde{T} = \{\tilde{t}_1, \cdots, \tilde{t}_n\}, \tilde{t}_n = \{l_1(f_n;\theta_u^{l_1}), \cdots, l_b(f_n;\theta_u^{l_b})\}$ signify the predictions of the base learners. Specifically, $l_e(*;\theta^{l_e})$ signifies the construction of an ensemble learner $l_e(*)$ parameterized by θ^{l_e} and $conf(*,*;\theta^{conf})$ signifies the ensemble learner's configuration $conf(*,*)$ parameterized by θ^{conf} for updates of θ^{l_e}. Forming ensemble learning can be formally expressed as

$$L_e = EnsembleLearnerFormation(\tilde{T}, T, EC) = \{l_e(*;\theta_u^{l_e})\}.$$

Thereinto, $l_e(*;\theta_u^{l_e})$ signifies an ensemble learner $l_e(*)$ parameterized by $\theta_u^{l_e}$, which is configured by the integrating procedure. More specifically, the integrating procedure can be expressed as

$$\theta_u^{l_e} = integrating\left(\tilde{T}, T, l_e(*;\theta^{l_e}), conf(*,*;\theta^{conf})\right)$$
$$= arg\ \underset{\theta^{l_e}}{conf}\left(l_e(\tilde{T};\theta^{l_e}), T;\theta^{conf}\right).$$

At testing, given a test raw data point d_{test}, the corresponding target t_{test} predicted by the formed ensemble learner can be expressed formally as follows

$$f_{test} = \{em_1(d_{test};\theta_1^{em}), \cdots, em_m(d_{test};\theta_m^{em})\},$$
$$\tilde{t}_{test} = \{l_1(f_{test};\theta_u^{l_1}), \cdots, l_b(f_{test};\theta_u^{l_b})\},$$

$$t_{test} = l_e(\tilde{t}_{test}; \theta_u^{l_e}).$$

3.3 Well-known implementations for methodology of TEL

Since most existing well-known TEL approaches primarily focus on generating base learners and forming ensemble learner, here we weaken the descriptions for feature extraction (Guyon and Elisseeff 2006) since it is beyond the topic of the methodology of TEL. Particularly in discussion of generating base learners, we primarily elaborate on various learning strategies, as discussion of machine learning algorithms is a topic more appropriate in UML. The discussed well-known learning strategies and ensembling criteria for generating base learners and integrating base learners are summarized in Table. 1 and Table. 2.

Table. 1. Various well-known learning strategies (LS) for generating base learners

Category	Specific LS	
Manipulating at data level	Sampling data points	Bagging (Breiman 1996)
		Dagging (Ting and Witten 1997)
		Boosting (Freund and Schapire 1997)
	Weighting data points	Wagging (Bauer and Kohavi 1999)
		Multiboosting (Webb 2000)
Manipulating at feature level	Random Subspace (Ho 1998)	
Manipulating at both data and feature levels	Random Forests (Breiman 2001)	
	Rotation Forests (Rodríguez et al. 2006)	
Others	Negative correlation learning (Liu and Yao 1999)	
	ANN-based random initialization (Hansen and Salamon 1990)	

Table. 2. Various well-known ensembling criteria (EC) for forming ensemble learner

Category	Specific EC
Weighting methods	Majority voting / averaged summarization (Mendes-Moreira et al. 2012)
	Minimizing the objective (Mao et al. 2015)
Meta-learning methods	Stacking (Wolpert 1992)
	Mixture of expert (Masoudnia and Ebrahimpour 2014)
	Weighting-based learning (Omari and Figueiras-Vidal 2015)
Ensemble selection (Zhou et al. 2002) methods (many could be better than all)	Clustering based criteria (Bakker and Heskes 2003)
	Ranking-based criteria (Martinez-Muñoz et al. 2009)
	Selection based criteria (Dos Santos et al. 2008; Hernández-Lobato et al. 2009)

3.3.1 Base learner generation

It is generally believed that the base learners used for ensemble should have sufficient diversity and the prediction of a single base learner should be as accurate as possible (Granitto et al. 2005; Zhou 2009, 2012). While generating multiple base learners, the learning algorithm and the learning strategy have to be considered. The

learning algorithm used to generate the base learners can be a decision tree (DT) (Quinlan 1986), artificial neural network (ANN) (Rumelhart et al. 1986), support vector machine (SVM) (Chang and Lin 2011) or related variants. The used learning algorithm basically determines the upper limit of the predictive performance of the base learners. Generally, the predictive performance of the base learners is required to be at least better than random prediction, because, theoretically, a number of random predictions cannot be integrated to produce a well-regular prediction. The learning strategy that ensures the diversity of the base learners plays a decisive role in constructing the ensemble learner, especially when the accuracy of the base learners reaches certain limit. This is because, theoretically, a better ensemble learner cannot be summarized from a number of identical base learners. Usually, the learning strategy for generating base learners can be heterogeneous or homogeneous. When the learning strategy employs different learning algorithms to generate 'heterogeneous' base learners, the diversity of the base learners can be well ensured with very simple learning strategy like independently learning, because good diversity can exist among the base learners via the discrepancies of their diverse structures in addition to different parameters. However, when the learning strategy uses the same learning algorithm to generate 'homogeneous' base learners, the learning strategy to ensure the diversity of the base learners is the key point to success, because the diversity of the base learners is only kept in discrepancies of their parameters as they enjoy the same structure. Theoretically, both heterogeneous learning strategy and homogeneous learning strategy can be used at any time to generate base learners. However, the homogeneous learning strategy is the most commonly used, due to the fact that it only requires one learning algorithm to be implemented in practice. Thus, in the following contents of this subsection, we discuss various learning strategies for the diversity of 'homogeneous' base learners, respectively in the context of manipulating at data level, manipulating at feature level, manipulating at both data and feature levels, and others, which are summarized in Table 1.

(1) Manipulating at data level

Breiman et al. (Breiman 1996) and Freund et al. (Freund and Schapire 1997), ensured the diversity of the base learners by sampling or weighting the training set multiple times to generate new training sets for training different base learners. The two learning strategies are known as Bagging (Breiman 1996) and Boosting (Freund and Schapire 1997). Bagging uses the simple random sampling to generate new data sets for the training of base learners. A known variant of Bagging is Dagging (Ting and Witten 1997), which generates disjoint data sets by random sampling without replacement. Boosting starts with equal weights assigned to the samples of the training data and reweights the samples of the training data referring to the performance of previous base learner to focus on difficult data points. A known variant of Bagging is Wagging (Bauer and Kohavi 1999), which assigns random weights to the samples in the training data using Gaussian distribution or Poisson distribution. Combining Bagging and Wagging, Webb (Webb 2000) proposed Multiboosting, which firstly uses Boosting to assign weights to the samples in the training data, and then applies Wagging to update the weights of the assigned samples.

(2) Manipulating at feature level

Different from manipulating at the training data level (Breiman 1996; Freund and Schapire 1997; Ting and Witten 1997; Bauer and Kohavi 1999; Webb 2000), Ho (Ho 1998) upgraded the manipulation at data level to feature level (aka, Random Subspace) by sampling the features extracted from the training data and then using the sampled features as the input of the learning algorithm to generate various base learners.

(3) Manipulating at both data and feature levels

The two learning strategies of manipulating at data or feature level significantly promoted the development of ensemble learning. By combining the advantages of them, Breiman et al. (Breiman 2001) constructed a learning strategy by sampling the training data as well as the features extracted from the training data at the same time, and proposed the famous random forests (RF) ensemble learning approach, which is still widely used in various application fields. Later, Rodriguez et al. (Rodríguez et al. 2006) proposed rotation forests (RoF), the learning strategy of which first randomly splits the training features into several disjoint subsets and then principle component analysis (PCA) (Wold et al. 1987) is applied to each subset and axis rotation is employed to form new features for the training of base learners.

(4) Others

Another known learning strategy that can effectively ensure the diversity of base learners is to encourage negative correlation in the predictive error of base learners by complementary learning of the training data (Liu and Yao 1999). Besides, when artificial neural network (ANN) (Rumelhart et al. 1986) is employed as the learning algorithm, a commonly used learning strategy to obtain diverse base learners is training the ANN with different random initializations, which tends to differentiate the errors of the base learners (Hansen and Salamon 1990).

3.3.2 Ensemble learner formation

To form the ensemble learner from the based learners, an appropriate ensembling criterion is the key to success. Basically, known ensembling criteria for the ensemble learner formation can be roughly divided into three categories: weighting methods, meta-learning methods, and ensemble selection methods. In the following contents of this subsection, we respectively discuss these three categories, which are summarized in Table 2, and summarize corresponding usage.

(1) Weighting methods

The essence of the weighting methods for ensembling criteria is to combine the outputs of the base learners by assigning different weights to obtain better predictions. The majority voting rule commonly used for classification problem is the simplest implementation of the weighting method. The class with the most votes from the base learners will be taken as the final output of the ensemble learner. As for regression problem, the outputs of the base learners can be averaged (Mendes-Moreira et al. 2012) to produce the final output of the ensemble learner. Another commonly used weighting method is to assign the weight of a base learner in the ensemble learner according to its predictive ability on a validation data set. In addition, Mao et al. (Mao et al. 2015) used the error between the weighted output of multiple base learners and the true value as the objective function, where the weights of the base learners are

subject to $\sum \omega_i = 1$ and $-1 < \omega_i < 1$, and minimized the objective function to determine the weights of the base learners for the ensemble learner. Weighting methods are simple to use, but they may not be able to fully exploit the information of the base learners, especially when large amount of data is available.

(2) Meta-learning methods

Unlike the weighting methods which simply assign different weights to the base learners, the fundamental idea of meta-learning methods for ensembling criteria is by learning from the meta-knowledge that has been learnt by the base learners (i.e., the predictions of the base learners) and corresponding targets to further reduce the generalization error. Via learning to map the predictions of the base learners into corresponding targets, meta-learning methods can further reduce the generalization error when large amount of data is available, by fully exploiting the information of the base learners to overcome the limitation of weighting methods. As the essence of meta-learning methods follows the paradigm of machine learning, they are appropriate to form ensemble learners for both classification and regression problems. In 1992, Wolpert (Wolpert 1992) proposed the first meta-learning method Stacking to integrate multiple base learners. A popular variant of the Stacking method is the mixture of experts (ME) (Masoudnia and Ebrahimpour 2014), which first uses a divide-and-conquer strategy to split the problem into multiple sub-problems, and respectively trains an expert (base learner) for each sub-problem, and then use another machine learning algorithm to learn from the outputs of the base learners and corresponding ground-truths to further reduce the generalization error. Combining the advantages of both the weighting method and the meta-learning method, Omari and FIgueiras-Vidal (Omari and Figueiras-Vidal 2015) first weighted the outputs of multiple base learners to obtain an initial ensemble, and then used another machine learning algorithm to learn from the initial ensemble to further reduce the generalization error. Meta-learning methods can fully exploit the information from the base learners, but it will take much more expenses to evolve the ensemble criteria, especially when the number of base learners is relatively large.

(3) Ensemble selection methods

In the early research stage of ensemble learning, most ensembling criteria used all the generated base learners to form an ensemble learner. Although this simple selection strategy can obtain an ensemble learner that is significantly better than a single base learner with appropriate ensembling criterion, the prediction time and storage space of the ensemble learner increased rapidly with the increase in the number of base learners. To alleviate this problem, in 2002, Zhou et al (Zhou et al. 2002) proposed the concept of ensemble selection for the first time, affirming that using a small number of base learners can as well achieve better ensemble performance. This caused a strong focus in the community of ensemble learning and opened a new research direction of selective ensemble learning (Zhang and Zhang 2011). The strategies for selecting the base learner can be roughly divided into: clustering-based methods, ranking-based methods, and selection-based methods. The clustering-based method needs to consider how to measure the similarity between the prediction results of two base learners (subsets), which clustering algorithm to

choose, and how to determine the number of subsets for the base learners (Bakker and Heskes 2003). The ranking-based method first uses a certain measurement (such as accuracy) to rank the base learners, and then uses a suitable stopping criterion to select a number of base learners for ensemble (Martinez-Muñoz et al. 2009). The selection-based method leverages a certain selection strategy, such as greedy strategy (Jungnickel 1999) or dynamic programming (Kumar 2010), to select only a proportion of the base learners to participate in integrating (Dos Santos et al. 2008; Hernández-Lobato et al. 2009). Ensemble selection methods can favorably reduce the prediction time and storage space of the ensemble learner, but it may not achieve the optimal solution by ignoring the information of some base learners.

(4) Summarization of usage

In summary, there are no stationary rules for deciding which ensembling criterion is better than others. One has to construct the appropriate ensembling criterion by referring to specific situations. Theoretically, weighting methods can be used without any prerequisites. However, weighting methods may not be able to fully exploit the information of the base learners when large amount of collected data is available. In this situation, meta-learning methods are better than weighting methods. In addition, when the efficiency of the ensemble learner is a key factor to be considered, ensemble selection methods should also be united with weighting methods or meta-learning methods for a more appropriate ensembling criterion.

3.4 Recent advances of TEL

3.4.1 Material collection

Apart from the well-known implementation of TEL, in recent years, a lot of TEL advances have been proposed for various artificial intelligence applications (Behera and Mohanty 2019; Mohapatra et al. 2021). As the number of proposed TEL advances can reach up to hundreds or thousands in a single year, it is quite difficult for a survey to contain all of these advances. Thus, we propose to review a number of highly cited recent TEL advances and summarize corresponding key innovations to show some underlying trends of recent development of TEL. That highly cited recent advances are selected is based on one of the assumptions behind the PageRank (Page et al. 1998). In the case of this paper, that is the more citations a paper gets the more people agree with the approach presented in the paper. Thus, we consider summarizations from the review of the selection of highly cited recent TEL advances can more appropriately and stably reflect the primary underlying trends in recent development of TEL than the collection of all the recent TEL advances. The selected works for review of recent TEL advances were suggested by searching on Web of Science (accessed at February 3, 2021) with the filtering rules including being published in the last ten years and being highly cited or being a hotspot.

3.4.2 Review

Referring to the methodology of TEL presented in Figure. 4, but different from the discussion in Section 3.1 that focused more on learning strategies for generating base learners and ensembling criteria for forming ensemble learner, we add additional descriptions of extracting methods for feature representations as well as depictions of

learning algorithms for generating base learners, since they also provide essential basis for TEL approaches to be carried out in specific applications.

For the 3D human action recognition, Wang et al. (Wang et al. 2014) proposed an ensemble learning approach called actionlet ensemble. Actionlet was defined as a conjunction of the features for a subset of the joints of the human skeleton. The 3D joint position feature (3D-JPF) and local occupancy patter (LOP) were extracted from the training images, and further transformed into temporal patterns for training via the proposed Fourier temporal pyramid (FTP) (Wang et al. 2014). Multiple actionlet classifiers based on an support vector machine (SVM) (Chang and Lin 2011) were trained with a proposed data mining strategy which aims to discover discriminative actionlet classifiers on the training dataset. A convex linear combination of the pre-trained multiple actionlet classifiers were proposed to form the final actionlet ensemble classifier.

For the prediction of protein-protein interactions, You et al. (You et al. 2013) employed auto covariance (AC) (Guo et al. 2008), conjoint triad (CT) (Shen et al. 2007), local descriptor (LD) (Davies et al. 2008) and Moran autocorrelation (MA) (Xia et al. 2009) to extract features from protein sequences. The extracted features were used to train multiple base learners based on a single hidden layer feed-forward neural networks, extreme learning machine (ELM) (Ding et al. 2015; Huang et al. 2015), with different random initializations. Majority voting was employed to integrate the trained multiple base learners into the final ensemble learner.

For the identification of DNase I hypersensitive sites, Liu et al. (Liu et al. 2016a) proposed an ensemble learning algorithm entitled iDHS-EL. Multiple base learners based on the random forests (RF) algorithm (Breiman 2001) were trained using three types of features including Kmer (Lee et al. 2011), reverse complement Kmer (RC-Kmer) (Gupta et al. 2008) and pseudo dinucleotide composition (PseDNC) (Chen et al. 2013) that reflect the characteristics of a DNA sequence from different angles. The final ensemble learner was formed by employing the grid search strategy to integrate the pre-trained multiple base learners. For a similar task of identifying N6-methyladenosine sites, Wei et al. (Wei et al. 2018) proposed an ensemble learning algorithm named M6APred-EL. Three feature representation algorithms, including PS(kmer)NP, PCPs (Liu et al. 2016b), and RFHC-GACs (Chen et al. 2016), were used to extract diverse features from RNA sequences. The extracted features were respectively employed to train SVM (Chang and Lin 2011) for multiple base predictors to identify N6-methyladenosine sites. The obtained multiple base predictors were integrated by majority voting to form the ensemble predictor.

For the landslide susceptibility mapping, Chen et al. (Chen et al. 2017) proposed several ensembles using multiple base learners that were heterogeneously trained with artificial neural network (ANN) (Rumelhart et al. 1986), maximum entropy (MaxEnt) (Phillips et al. 2004) and SVM (Chang and Lin 2011). Based on previous studies, eleven landslide conditioning factors such as elevation, slope degree, aspect, profile and plan curvatures, topographic wetness index (TWI), distance to roads, distance to rivers, normalized difference vegetation index (NDVI), land use, and lithology were selected for training. The proposed ensembles include ANN-SVM, ANN-

MaxEnt, ANN-MaxEnt-SVM, and SVM-MaxEnt which were integrated by testing different basic mathematics (multiplication, division, addition and subtraction). For the same task, Pham et al. (Pham et al. 2017) assessed the application of the ensemble learning technique in the landslide problem, constructing several ensemble learners by combining the base classifier of multilayer perceptron (MLP) (Rosenblatt 1958) with Bagging (Breiman 1996), Dagging (Ting and Witten 1997), Boosting (Freund and Schapire 1997), Multiboosting (Webb 2000) and Rotation Forests (Rodríguez et al. 2006). The factors used for training were selected based on topography, physic-mechanical properties, locations and meteorology. The majority voting was employed to form the ensemble learner. In addition, Dou et al. (Dou et al. 2020) also constructed three types of ensemble learners for this task, combining SVM (Chang and Lin 2011) respectively with Bagging (Breiman 1996), Boosting (Freund and Schapire 1997) and Stacking (Wolpert 1992) ensembling strategies. The factors used for training were selected by referring to previous literatures, and the ensembling criteria employed to form the ensemble learner include majority voting and meta-learning.

For the short-term load forecasting, Li et al. (Li et al. 2020) proposed an ensemble learning algorithm based on wavelet transform (Daubechies and Bates 1993), extreme learning machine (ELM) (Ding et al. 2015; Huang et al. 2015) and partial least squares regression (PLSR) (Geladi and Kowalski 1986). Various wavelet transform specifications were used to generated different types of features from input load series. Each type of the generated features was individually leveraged to train multiple predictors based on extreme learning machine (ELM) (Ding et al. 2015; Huang et al. 2015). PLSR, which tackle the high degree of correlation between the individual forecast, was used to weight the multiple predictors to establish an accurate ensemble forecast.

For the multi-class imbalance learning, Bi et al. (Bi and Zhang 2018) proposed an ensemble learning algorithm named diversified error correcting output codes (DECOC) by introducing the error correcting output codes (ECOC) (Dietterich and Bakiri 1995) into the ensemble learning algorithm diversified one-against-one (DOVO) (Kang et al. 2015). ECOC is a decomposition strategy that builds a codeword for each class by maximizing the distance (such as Hamming distance) between various classes and, by selecting bits from the built codewords, divides the original problem into multiple sub-problems which can be further individually solved via machine learning. In original DOVO, one-vs-one (OVO) was employed to divide the original problem into multiple sub-problems which are further solved with a variety of learning algorithms. OVO is a decomposition strategy that build a sub-problem by only selecting instances for each pair of classes from the original data. DECOC is formed by replacing OVO of EOVO with ECOC, and the diverse learning algorithms that DECOC employs include SVM (Chang and Lin 2011), k-nearest neighbor (KNN) (Altman 1992), Logistic Regression (LR) (Cox 1959), C4.5 (Salzberg 1994), AdaBoost (AB) (Freund and Schapire 1996), Random Forests (RF) (Breiman 2001), and multilayer perceptron (MLP) (Rosenblatt 1958). The obtained multiple based learners were weighted by minimizing the error in favor of the minority classes to form the final ensemble learner. For experiments, 17 public datasets were used, which had clearly defined features, the number of which ranges from 3 to 128.

For the soil moisture forecasting, Prasad et al. (Prasad et al. 2018) proposed and ensemble learning approach based on ensemble empirical mode decomposition (EEMD) (WU and HUANG 2009) and complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) (Torres et al. 2011). EEMD and CEEMDAN are two improved variants of empirical mode decomposition (EMD) (Huang et al. 1998), which decomposes intact soil moisture time series into several intrinsic mode functions (IMFs) to extract instantaneous frequency features. Each of the IMFs and residual were separately processed by partial autocorrelation function (PACF) (Ramsey 1974) to help selecting features with statistically significant relationship. The processed IMFs and residual were used to train extreme learning machine (ELM) (Ding et al. 2015; Huang et al. 2015) and Random Forests (RF) (Breiman 2001) to generate multiple base learners. To form the ensemble learner, the generated multiple base learners were integrated via averaged summation.

For the flood susceptibility mapping, Shahabi et al. (Shahabi et al. 2020) proposed an ensemble learning algorithm which employed four types of k-nearest neighbor (KNN) classifiers as the base learning algorithm and utilized Bagging (Breiman 1996) strategy to generate sub-datasets for training multiple base learners. Ten task-related conditioning factors (Rahmati et al. 2016) were chosen for training, including distance to river, elevation, slope, lithology, curvature, rainfall, topographic wetness index (TWI), stream power index (SPI), land use/land cover, and river density. The employed four types of KNN classifiers include coarse KNN (Altman 1992) which defines the nearest neighbor among all classes as the classifier, cosine KNN (CoKNN) (Hu et al. 2016) which uses the cosine distance metric as the nearest neighbor classifier, cubic KNN (CuKNN) (Wu et al. 2008) which uses the cubic distance metric as the nearest neighbor classifier, and weighted KNN which uses the weighted Euclidean distance as the nearest neighbor classifier. The obtained multiple base learners were integrated by majority voting to form the final ensemble learner.

For the automatic detection of lung cancer from biomedical dataset, Shakeel et al. (Shakeel et al. 2020) employed generalized neural network (GNN) (Behler and Parrinello 2007) as the learning algorithm and trained multiple base learners using the ensemble learning process proposed in (Xia et al. 2017), which generated multiple base learners with subsets equally divided from the input features collected by examining lung cancer effects on people's genetic changes and other impacts. The obtained multiple base learners were integrated by majority voting to form the final ensemble learner.

For the hyperspectral image classification, Su et al. (Su et al. 2020) proposed two types of ensemble learners which employed the tangent space collaborative representation classifier (TCRC) (Su et al. 2016) as the learning algorithm and respectively utilized Bagging (Breiman 1996) and Boosting (Freund and Schapire 1997) to train multiple base learners. The features used for training were the narrow spectral bands captured by hyperspectral images. TCRC is an improved collaborative representation classifier (CRC) (Li et al. 2016), the principle of which is that a testing sample can be approximated by training samples. CRC classifies a testing sample by assigning it to the class whose labeled training samples provide the smallest

representation residual. TCRC improves CRC by using simplified tangent distance to take advantage of the local manifold in the tangent space of the testing sample (Su et al. 2016). The majority voting was employed to form the two types of ensemble learners.

For the wind power forecasting, Wang et al. (Wang et al. 2020) proposed a hybrid approach named BMA-EL based on Bayesian model averaging (BMA) (Hoeting et al. 1999; Wasserman 2000) and ensemble learning (EL). For training, the task-related features include wind speed, wind direction and ambient temperature. Artificial neural network (ANN) (Rumelhart et al. 1986), radial basis function neural network (RBFNN) (Borş and Pitas 1996), and SVM were employed as the learning algorithms. For generating more diverse base learners, the training set were divided into three subsets using clustering of self-organizing map (Vesanto and Alhoniemi 2000) and K-fold cross-validation (Bishop 2006). ANN, RBFNN and SVM were respectively optimized on the three generated subsets to produce three heterogeneous base learners. BMA was utilized to integrate the three base learners and the parameters of the BMA model were optimized on a validation dataset to form the final ensemble learner.

3.4.3 Summary

The information of the reviewed recent works of TEL is listed in Table. 3. The feature extraction methods adopted by the TEL approaches proposed in the reviewed works are listed in Table. 4. The learning algorithms and learning strategies employed to generate base learners are respectively listed in Table. 5 and Table. 6. The ensembling criteria utilized to integrate base learners are listed in Table. 7. Finally, referring to Table. 3-7, the key innovations of the TEL approaches proposed in the reviewed works are summarized in Table. 8.

Table. 3. The information of the applications in the reviewed recent TEL works (TA)

App.	Description		Citations	Published Year
TA1	3D human action recognition (Wang et al. 2014)		433	2014
TA2	Prediction of protein-protein interactions (You et al. 2013)		239	2013
TA3	Identification of hypersensitive sites	(Liu et al. 2016a)	191	2016
		(Wei et al. 2018)	91	2018
TA4	Landslide susceptibility mapping	(Chen et al. 2017)	176	2017
		(Pham et al. 2017)	290	2017
		(Dou et al. 2020)	70	2020
TA5	Short-term load forecasting (Li et al. 2020)		23	2020
TA6	Multi-class imbalance learning (Bi and Zhang 2018)		97	2018
TA7	Soil moisture forecasting (Prasad et al. 2018)		71	2018
TA8	Flood susceptibility mapping (Shahabi et al. 2020)		45	2020
TA9	Detection of lung cancer (Shakeel et al. 2020)		43	2020
TA10	Hyperspectral image classification (Su et al. 2020)		26	2020
TA11	Wind power forecasting (Wang et al. 2020)		24	2020

Table. 4. The methods for feature extraction (FE) of the TEL (TFE) approaches proposed in the reviewed works

Code	Description
TFE1	Temporal patterns transformed by Fourier temporal pyramid (FTP) (Wang et al. 2014)
TFE2	Auto covariance (Guo et al. 2008)
TFE3	Conjoint triad (Shen et al. 2007)
TFE4	Local descriptor (Davies et al. 2008)
TFE5	Moran autocorrelation (Xia et al. 2009)
TFE6	Kmer (Lee et al. 2011)
TFE7	Reverse complement Kmer (Gupta et al. 2008)
TFE8	Pseudo dinucleotide composition (Chen et al. 2013)
TFE9	PS(kmer)NP (Liu et al. 2016b)
TFE10	PCPs (Liu et al. 2016b)
TFE11	RFHC-GACs (Chen et al. 2016)
TFE12	Landslide related factors (Chen et al. 2017)
TFE13	Factors selected based on various properties of landslide (Pham et al. 2017)
TFE14	Factors selected by referring to previous literatures (Dou et al. 2020)
TFE15	Wavelet decompositions (Daubechies and Bates 1993)
TFE16	Factors predefined on public datasets (Bi and Zhang 2018)
TFE17	EEMD (WU and HUANG 2009) / CEEMDAN (Torres et al. 2011) followed with PACF (Ramsey 1974)
TFE18	Flood related factors (Rahmati et al. 2016)
TFE19	Factors of cancer effects (Shakeel et al. 2020)
TFE20	Narrow spectral bands of hyperspectral images (Su et al. 2020)
TFE21	Wind power related factors (Wang et al. 2020)

Table. 5. The learning algorithms (LA) of the TEL (TLA) approaches proposed in the reviewed works

Code	Abbr.	Description
TLA1	SVM	Support vector machine (Chang and Lin 2011)
TLA2	ELM	Extreme learning machine (Ding et al. 2015; Huang et al. 2015)
TLA3	RF	Random forest (Breiman 2001)
TLA4	ANN	Artificial neural network (Rumelhart et al. 1986)
TLA5	MaxEnt	Maximum entropy (Phillips et al. 2004)
TLA6	MLP	Multilayer perceptron (Rosenblatt 1958)
TLA7	KNN	K nearest neighbor (Altman 1992)
TLA8	LR	Logistic regression (Cox 1959)
TLA9	C4.5	An improved iterative Dichotomiser 3 (Salzberg 1994)
TLA10	AB	AdaBoost (Freund and Schapire 1996)
TLA11	CoKNN	KNN based on cosine distance (Hu et al. 2016)
TLA12	CuKNN	KNN based on cubic distance (Wu et al. 2008)
TLA13	WeKNN	KNN based on weighted Euclidean distance
TLA14	GNN	Generalized neural network (Behler and Parrinello 2007)
TLA15	TCRC	Tangent space collaborative representation classifier (Su et al. 2016)
TLA16	RBFNN	Radial basis function neural network (Borş and Pitas 1996)

Table. 6. The learning strategies (LS) of the TEL approaches proposed in the reviewed works

Code	Description
LS1	Discovering discriminative learner on the training dataset (Wang et al. 2014)
LS2	Training with randomly initialized parameters on the same dataset
LS3	Manipulating at both the data and feature levels with random selections (Breiman 2001)
LS4	Training multiple learners on the same dataset
LS5	Manipulating at the feature level with division
LS6	Manipulating at the data level with divide-and-conquer strategy
LS7	Manipulating at the data level with Bagging strategy (Breiman 1996)
LS8	Manipulating at the data level with Dagging strategy (Ting and Witten 1997)
LS9	Manipulating at the data level with Boosting strategy (Freund and Schapire 1997)
LS10	Manipulating at the data level with Multioosting strategy (Webb 2000)
LS11	Manipulating at both the data and feature level with axis rotation (Rodríguez et al. 2006)
LS12	Manipulating at the data level with self-organizing map (Vesanto and Alhoniemi 2000) and cross-validation (Bishop 2006)

Table. 7. The ensembling criteria (EC) of the TEL (TEC) approaches proposed in the reviewed works

Code	Description
TEC1	Linear combination
TEC2	Majority voting
TEC3	Grid search
TEC4	Basic mathematics
TEC5	Stacking (Wolpert 1992)
TEC6	Partial least squares regression (Geladi and Kowalski 1986)
TEC7	Minimizing the error in favor of the minority classes
TEC8	Averaged summation
TEC9	Bayesian model averaging (Hoeting et al. 1999; Wasserman 2000)

Table. 8. The key innovations of the TEL approaches proposed in the reviewed works

App.	FE	LA&LS		EC
		LA	LS	
TA1	TFE1	TLA1	Homo. by LS1	W. by TEC1
TA2	TFE2-5	TLA2	Homo. by LS2	W. by TEC2
TA3	TFE6-8	TLA1	Homo. by LS3	W. by TEC3
	TFE9-11	TLA3	Homo. by LS5	W. by TEC2
	TFE12	TLA1,4,5	Hetero. by LS4	W. by TEC4
TA4	TFE13	TLA6	Homo. by LS7-10	W. by TEC2
	TFE14	TLA7	Homo. by LS7,9	W. by TEC2 / M. by TEC5
TA5	TFE24	TLA2	Homo. by LS5	W. by TEC6
TA6	TFE16	TLA1,3,7-10	Hetero. by LS6	W. by TEC7
TA7	TFE17	TLA2,3	Homo. by LS5	W. by TEC8
TA8	TFE18	TLA7,11-13	Hetero. / homo. by LS7	W. by TEC2
TA9	TFE19	TLA14	Homo. by LS5	W. by TEC2
TA10	TFE20	TLA15	Homo. by LS7,9	W. by TEC2

| TA11 | TFE21 | TLA1,4,16 | Hetero. by LS12 | W. by TEC9 |

Based on these tables, we can summarize: The representations of data employed by the proposed TEL approaches of the reviewed works for training mostly were various hand-crafted features; The learning algorithms of these TEL approaches that were frequently employed are classic SVM, KNN, and neural networks (ELM, ANN, MLP and GNN); Manipulating at the data level and the feature level by resampling were the frequently learning strategies used by these proposed TEL approaches; While the majority of these proposed TEL approaches trained homogenous base learners, three of them trained heterogenous base learners; While the majority of these TEL approaches employed various weighting methods as ensembling criteria to form the final ensemble learner, only one of them tried meta-learning methods; And ensemble selection methods were rarely used, probably because the number of base learners was not massive enough to employ ensemble selection. These summarizations reflect the primary underlying trends for the recent development of TEL.

3.5 Unattainability

Based on the primary underlying trends of TEL summarized in the subsection 3.4.3, in this subsection, we discuss the unattainability of TEL. While most of recent advances of TEL focused on proposing solutions for specific applications based on combinatorial innovations by leveraging existing learning strategies for base learner generation and existing ensembling criteria for ensemble learner formation, few recent advances of TEL proposed new learning strategies for base learner generation or new ensembling criteria for ensemble learner formation. It seems that recent advances for the intrinsic problems of TEL have reached to a bottleneck, although TEL is still prosperously developing in various applications. Besides, the primary issue associated with the methodology of TEL comes from the nature of UML, which evolves a learner based on hand-crafted features which are usually difficult to design and not expressive enough.

4 Usual Ensemble Deep Learning

With the popularization of big data, computing resources, and deep learning (DL, mostly deep neural networks (He et al. 2016; Szegedy et al. 2017; Huang et al. 2017b; Xie et al. 2017; Sandler et al. 2018; Zoph et al. 2018; Tan and Le 2021)), which improves the paradigm of UML, has achieved unprecedented success in the field of machine learning. This will give birth to a huge number of approaches for ensembles of deep neural networks (ensemble deep learning, EDL) and promote the research of ensemble learning into a new era. The usual way to evolve the methodology of EDL (usual ensemble deep learning, UEDL) is directly applying DL to the methodology of TEL. In this section, starting with the paradigm of deep learning (DL), we respectively discuss the methodology, recent works and unattainability of UEDL.

4.1 Preliminary

Different from the paradigm of UML (Fig. 3), the paradigm of DL embeds the

feature extraction into model development to form an end-to-end framework, which is able to learn task-specifically oriented features that are more expressive when massive training data is available. The paradigm of DL is shown as Fig. 5.
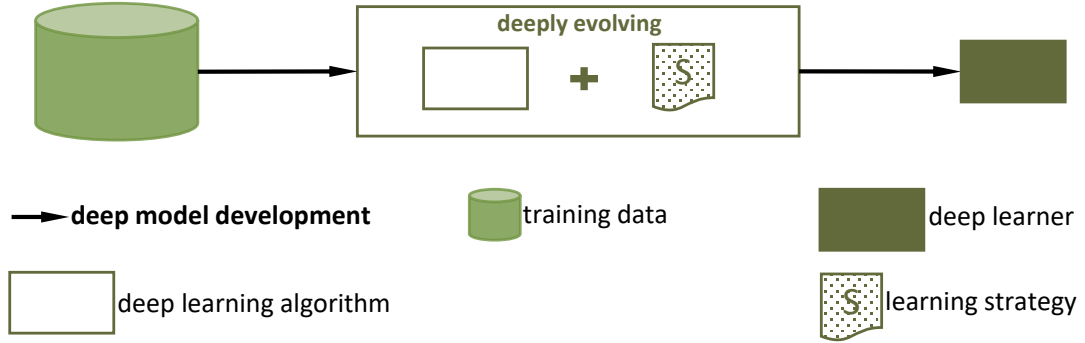

Figure. 5. The methodology of deep learning (DL), which embeds the feature extraction into deep model development to form an end-to-end framework.

Formally, let $DLA = \{dl(*; \theta^{dl}), dopt(*,*; \theta^{dopt})\}$ denote the deep learning algorithm and $LS = \{ls(\theta^{ls})\}$ denote the learning strategy. Specifically, $dl(*; \theta^{dl})$ signifies the construction of a deep learner $dl(*)$ parameterized by θ^{dl} and $dopt(*,*; \theta^{dopt})$ signifies the deep learner's optimization procedure $dopt(*,*)$ parameterized by θ^{dopt} for updates of θ^{dl}. Note, here $dopt(*,*)$ implicitly consists of an objective function constructed for classification or regression and corresponding optimization of the objective function. The deep model development component can be expressed as

$$DL = DeepModelDevelopment(D, T, DLA, LS) = \{dl(*; \theta_u^{dl})\}.$$

Thereinto, $dl(*; \theta_u^{dl})$ signifies the deep learner $dl(*)$ parameterized by θ_u^{dl}, which is updated by the deeply evolving procedure that can be more specifically expressed as

$$\theta_u^{dl} = deeply\_evolving(D, T, dl(*; \theta^{dl}), dopt(*,*; \theta^{dopt}) \mid ls(\theta^{ls}))$$
$$= arg \, \underset{\theta^{dl}}{dopt}\Big(l(F; \theta^{dl}), T; \theta^{dopt} \mid ls(\theta^{ls})\Big).$$

The developed deep learner $dl(*; \theta_u^{dl})$ forms the mapping between data D and corresponding targets T. Note the data D here can be raw data or features extracted from raw data.

At testing, given a test data point d_{test}, the corresponding target t_{test} predicted by the evolved deep learner can be expressed formally as follows

$$t_{test} = dl(d_{test}; \theta_u^{dl}).$$

Note, in the expressions of this subsection, each θ denotes the parameters corresponding to the implementation of respective expression.

4.2 Methodology of UEDL

Introducing DL to TEL, three basic patterns have emerged to evolve the methodology of UEDL. As shown in Fig. 6, the three basic patterns include: A) extracting features based on DL; B) generating base learners based on DL; and C) forming ensemble learner based on DL.

Let $DEM = \{dem_1(*; \theta_1^{dem}), \cdots, dem_m(*; \theta_m^{dem})\}$ denote various DL-based

extracting methods. Particularly, $dem_m(*; \theta_m^{dem})$ signifies a DL-based extracting method $dem_m(*)$ parameterized by θ_m^{dem}. Specifically, $\theta_m^{dem} = \{dl_m(*; \theta_u^{dl_m}), \theta_m^{em}\}$, which signifies that $dem_m(*)$ consists of a developed deep learner $dl_m(*)$ parameterized by $\theta_u^{dl_m}$ and a hyperparameter θ_m^{em} indicating what features to extract from $dl_m(*; \theta_u^{dl_m})$. The pattern A) can be formally expressed as

$$F = DeepFeatrueExtraction(D, DEM) = \{f_1, \cdots, f_n\}.$$

Thereinto, f_n, which signifies the deep representation of d_n, is constructed by a deeply converting procedure that can be more specifically expressed as

$$f_n = deeply\_converting(d_n, DEM)$$
$$= \{dem_1(d_n; \theta_1^{dem}), \cdots, dem_m(d_n; \theta_m^{dem})\}$$
$$= \{dx_{n,1}, \cdots, dx_{n,k}\} \quad s.t. \ k \geq m.$$

DL　deep learning

TEL　extracting features ...... generating base learners (hetero/homogeneously) ...... forming ensemble learner

UEDL　extracting features with deep learning ...... generating base learners with deep learning (hetero/homogeneously) ...... forming ensemble learner with deep learning

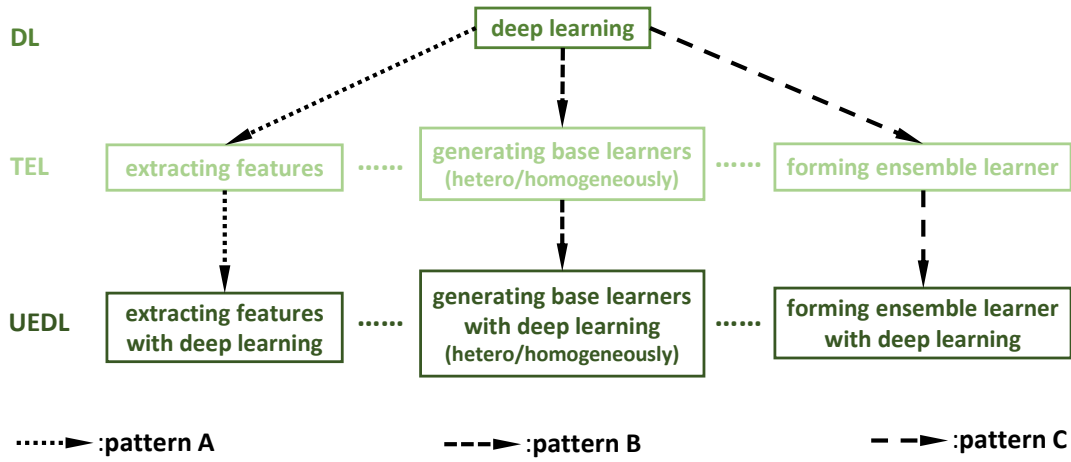······► :pattern A　 ---► :pattern B　 — —► :pattern C

Figure. 6. Three basic patterns to evolve the methodology of usual ensemble deep learning (UEDL) by applying DL to TEL.

With appropriate deep learning algorithms (DLA) and learning strategies (LS), the pattern B) can be formally expressed as

$$L_b = BaseDeepLearnerGeneration(D, T, DLA, LS)$$
$$= \{dl_1(*; \theta_u^{dl_1}), \cdots, dl_b(*; \theta_u^{dl_b})\}.$$

Thereinto, $dl_b(*; \theta_u^{dl_b})$ signifies a base deep learner $dl_b(*)$ parameterized by $\theta_u^{dl_b}$, which is updated by the deeply evolving procedure. Identically, the data D here can be raw data or features extracted from raw data. More specifically, the details of generating 'heterogeneous' base deep learners can be expressed as follows

$$DLA = \left\{\{dl_1(*; \theta^{dl_1}), dopt_1(*, *; \theta^{dopt_1})\}, \cdots, \{dl_b(*; \theta^{dl_b}), dopt_b(*, *; \theta^{dopt_b})\} \right\},$$
$$LS = \left\{ls_{hetero,1}(\theta^{ls_{hetero,1}}), \cdots, ls_{hetero,b}(\theta^{ls_{hetero,b}})\right\},$$
$$\theta_u^{dl_b} = deeply\_evolving\left(D, T, dl_b(*; \theta^{dl_b}), dopt_b(*, \right.$$
$$\left. *; \theta^{dopt_b}) \mid ls_{hetero,b}(\theta^{dls_{hetero,b}})\right)$$
$$= \arg_{\theta^{dl_b}} dopt\left(dl_b(D; \theta^{dl_b}), T; \theta^{dopt_b} \mid ls_{hetero,b}(\theta^{ls_{hetero,b}})\right).$$

And, the details of generating 'homogeneous' deep base learners can be expressed as follows

$$DLA = \left\{\{dl_0(*;\theta^{dl_0}), dopt_0(*,*;\theta^{dopt_0})\}\right\},$$

$$LS = \left\{ls_{homo,1}(\theta^{ls_{homo,1}}), \cdots, ls_{homo,b}(\theta^{ls_{homo,b}})\right\},$$

$$dl_b(*) = dl_0(*)$$

$$\theta_u^{dl_b} = deeply\_evolving\left(D, T, dl_0(*;\theta^{dl_0}), dopt_0(*,\right.$$

$$\left. *;\theta^{dopt_0}) \mid ls_{homo,b}(\theta^{ls_{homo,b}})\right)$$

$$= \arg_{\theta^{dl_0}} dopt\left(dl_0(D;\theta^{dl_0}), T;\theta^{dopt_0} \mid ls_{homo,b}(\theta^{ls_{homo,b}})\right).$$

Let $DEC = \{dl_e(*;\theta^{dl_e}), dconf(*,*;\theta^{dconf})\}$ denote the ensemble criteria for ensemble deep learner formation, and $\tilde{T} = \{\tilde{t_1}, \cdots, \tilde{t_n}\}$ signify the predictions of the base learners. Specifically, $dl_e(*;\theta^{dl_e})$ signifies the construction of a DL-based ensemble learner $dl_e(*)$ parameterized by θ^{dl_e} and $dconf(*,*;\theta^{dconf})$ signifies the DL-based ensemble learner's configuration $dconf(*,*)$ parameterized by θ^{dconf} for updates of θ^{dl_e}. Forming ensemble learning can be formally expressed as

$$L_e = EnsembleDeepLearnerFormation(\tilde{T}, T, DEC) = \{dl_e(*;\theta_u^{dl_e})\}.$$

Thereinto, $dl_e(*;\theta_u^{dl_e})$ signifies an ensemble deep learner $dl_e(*)$ parameterized by $\theta_u^{dl_e}$, which is configured by the deeply integrating procedure. More specifically, the deeply integrating procedure can be expressed as

$$\theta_u^{dl_e} = deeply\_integrating\left(\tilde{T}, T, dl_e(*;\theta^{dl_e}), dconf(*,*;\theta^{dconf})\right)$$

$$= \arg_{\theta^{dl_e}} dconf\left(dl_e(\tilde{T};\theta^{dl_e}), T;\theta^{dconf}\right).$$

At testing, given a test data point d_{test}, the corresponding procedures for the three individual patterns can be expressed formally as follows

$$f_{test} = \{dem_1(d_{test};\theta_1^{dem}), \cdots, dem_m(d_{test};\theta_m^{dem})\},$$

$$\tilde{t}_{test} = \{dl_1(d_{test};\theta_u^{dl_1}), \cdots, dl_b(d_{test};\theta_u^{dl_b})\},$$

$$t_{test} = dl_e(\tilde{t}_{test};\theta_u^{dl_e}).$$

Note, the three patterns of introducing DL into TEL can be further combined to produce more patterns for the construction of UEDL. No matter which pattern is employed to construct an UEDL approach, the final formed learner for testing is usually regarded as an ensemble deep learner.

4.3 Recent advances of UEDL

4.3.1 Material collection

Though many recent advances (Panda et al. 2021; Mohammed and Kora 2021; Das et al. 2022) have been proposed for UEDL, we follow the strategy presented for the material collection of recent advances of TEL in section 3.4.1. Thus, we review a number of highly cited recent works that are related to the topic of UEDL and summarize corresponding key innovations to more appropriately and stably reflect the primary underlying trends in recent development of UEDL. Identically, the reviewed works were suggested by searching on Web of Science (accessed at March 1, 2021) with filtering rules including being published in last ten years, and being highly cited or being a hotspot.

4.3.2 Review

Referring to the methodology of TEL presented in Figure. 6, in addition to learning

strategies for generating base learners and ensembling criteria for forming ensemble learner, we also add additional descriptions of extracting methods for feature representations as well as depictions of learning algorithms for generating base learners whenever they are necessary to provide essential basis for UEDL approaches to be carried out in specific applications.

For the probabilistic wind power forecasting, Wang et al. (Wang et al. 2017) proposed an ensemble deep learning approach based on different deep convolutional neural network (DCNN) (LeCun et al. 1998) architectures. Multiple base deep learners are independently trained using features extracted from raw wind power data by Mallat wavelet decomposition (Mallat 1989) and converted into 2D image. The employed DCNN architectures were different in terms of the number of hidden layers, the number of maps in each layer and the size of the input. For the training of each base deep learner, separated wavelet features were used. To form the ensemble deep learner, the predictions of the multiple base deep learners were fused by wavelet reconstruction (Daubechies and Bates 1993).

For the electricity load demand forecasting, Qiu et al. (Qiu et al. 2017) proposed a deep ensemble learning approach based on empirical mode decomposition (EMD) (Huang et al. 1998). First, via EMD, load demand time series were decomposed into several intrinsic mode functions (IMFs) and one residual which can be regarded as instantaneous frequency features extracted from the non-stationary and nonlinear raw data. Each of the IMFs and residual was separately used to train a deep belief network (DBN) (Hinton et al. 2006) which was composed of restricted Boltzmann machines (RBMs) (Hinton and Salakhutdinov 2006; Hinton 2012) and multilayer perceptron (MLP) (Gardner and Dorling 1998), resulting in a series of base deep learners. The base deep learners were integrated via averaged summation or weighted linear combination to form the ensemble learner.

For the sentiment analysis in social applications, Araque et al. (Araque et al. 2017) trained multiple base deep learners based on word2vec (Mikolov et al. 2013) / doc2vec (Le and Mikolov 2014) combined with logistic regression (word2vec/doc2vec-LR). Word2vec was used for representations of short texts and doc2vec was used for representations of long texts. The obtained base deep learners were integrated to form the final ensemble deep learner through weighting by majority voting or meta-learning by random forests (Da Silva et al. 2014; Zhang and He 2015).

For the melanoma recognition in dermoscopic images, Codella et al. (Codella et al. 2017) employed convolutional architecture for fast feature embedding (Caffe) (Jia et al. 2014) and deep residual network (ResNet) (He et al. 2016) pretrained on ImageNet (Deng et al. 2009) and convolutional network of U-shape (U-Net) (Ronneberger et al. 2015) pretrained on lesion segmentation task (Codella et al. 2018) for feature representations, in addition to several types of traditional feature representations including color histogram (CH) (Barata et al. 2014), edge histogram (EH) (Barata et al. 2014), multi-scale variant of color local binary patters (MSLBP) (Zhu et al. 2010) and a type of sparse coding (SC) (Mairal 2014). The deep CNN based feature representations and the traditional feature representations were respectively employed to train SVM (Chang and Lin 2011) for multiple base learners. The predictions of the obtained base

learners were averaged to form the final ensemble deep learner.

For the wind speed forecasting, Chen et al. (Chen et al. 2018) utilized long short-term memory (LSTM) (Hochreiter and Schmidhuber 1997; Sainath et al. 2015) to exploit the implicit information of collected wind speed time series. A cluster of LSTM with diverse number of hidden layers and neurons in each hidden layer were built to train multiple base deep learners on the collected raw data. A meta-learning strategy was proposed to form the final ensemble deep learner. The meta-learning strategy was composed of a support vector regression machine (SVRM) (Xu et al. 2017; Zhang et al. 2017) that took the forecasting results of the trained base deep learners as inputs and was optimized by extremal optimization (EO) (Boettcher and Percus 2000, 2001, 2002).

For the crude oil price forecasting, Li et al. (Zhao et al. 2017) formulated an ensemble deep learning approach named stacked denoising autoencoder bagging (SDAE-B). Employing the bagging strategy (Breiman 1996), multiple base deep learners were trained based on SDAE (Vincent et al. 2008, 2010). Referring to (Zagaglia 2010; Naser 2016), 198 factors, including price, flow, stock macroeconomic and financial series, were selected as exogenous variables for training. The predictions of the obtained base learners were averaged to form the final ensemble deep learner.

For the cancer prediction based on gene expression, Xiao et al. (Xiao et al. 2018) proposed to integrate multiple base learners using deep learning. The DEseq (Anders and Huber 2010) was employed to select informative genes from a given sequence for training. K nearest neighbor (KNN) (Altman 1992), support vector machine (SVM) (Chang and Lin 2011), decision tree (DT) (Quinlan 1986), random forests (RF) (Breiman 2001), and gradient boosting decision tree (GBDT) (Friedman 2001) were employed to train five base learners with model selection using K-fold cross-validation (Bishop 2006). To form the ensemble learner, a five-layer neural network (5-NN) was built as an implementation of the meta-learning strategy, which took the predictions of the five obtained base learners as inputs and output normal or tumor.

For the prediction of melt index (MI) in industrial polymerization processes, Liu et al. (Liu et al. 2018) proposed an ensemble deep kernel learning (EDKL) approach. A total of 11 factors correlated with MI were chosen for training, including the reactor pressure, reactor temperature, liquid level, and flow rate of the main catalysts. The deep belief network (DBN) (Hinton et al. 2006) comprising a series of individual restricted Boltzmann machines (RBM) (Hinton and Salakhutdinov 2006; Hinton 2012) was adopted to extracted features from the chosen factors in a unsupervised manner. With the extracted features, multiple base learners were trained based on a kernel learning soft-sensing model (KLSM) (Liu et al. 2013) by bagging (Breiman 1996). The predictions of the obtained base learners were averaged to form the final ensemble deep learner.

For the brain disease diagnosis based on MRI image, Suk et al. (Suk et al. 2017) as well proposed to integrate multiple base learners using deep learning. A series of techniques (details can be found in the preprocessing section) were employed to extract 93-dimensional volumetric features from an MRI image. Based on the extracted features, sparse regression model (SRM) (Wang et al. 2011; Zhang and Shen 2012) was utilized to train multiple base learners with different values of the

regularization control parameter. To form the ensemble learner, a six-layer convolutional neural network (6-CNN) was built as an implementation of the meta-learning strategy, which took the predictions of the obtained base learners as inputs and output disease diagnosis.

For the red lesion detection in fundus images, Orlando et al. (Orlando et al. 2018) formed an ensemble learning approach enhanced by deep learning. An unsupervised candidate lesion detection approach was proposed based on morphological operations to identify potential lesion areas. A five-layer convolutional neural network (5-CNN) was built to learn features from patches around the detected potential lesion areas. A 63-dimensional feature vector was as well extracted from lesion candidates using descriptors explored in related literature (Niemeijer et al. 2005; SB and Singh 2012; Seoud et al. 2016). Both convolutional and hand-crafted features are used by random forests (RF) (Breiman 2001) to form the ensemble learner.

For bearing fault diagnosis, Xu et al. (Xu et al. 2019) prosed an ensemble learning approach based on deep learning and random forests (RF) (Breiman 2001). Morlet, a type of continuous wavelet transform, was employed to convert raw vibration signals of bearing, which was one-dimensional in time-domain, into spectrum of abundant condition information, which was two-dimensional in time-frequency domain (LIN and QU 2000). A built five-layer CNN model, which consists of two convolutional layers, two pooling layers and one fully connected layer, was trained with the converted spectrums for feature extraction. The features of the two pooling layers and the fully connected layer were independently employed by RF (Breiman 2001) to produce three RF base learners. To form the ensemble learner, the outputs of the three base learners were integrated by the winner-take-all strategy (Guo et al. 2016). Ma et al. (Ma and Chu 2019) also proposed an ensemble learning approach for the same task. Employing a multi-objective evolutionary algorithm (MOEA/DD) (Li et al. 2015), multiple base deep learners were generated based on three deep learning architectures, including DBN (Hinton et al. 2006), ResNet (He et al. 2016) and deep auto-encoder (DAE) (Jia et al. 2016). The three architectures all have five layers (including three hidden layers). Regarding to the number of hidden neurons in each hidden layer and the learning rate for back propogation, MOEA/DD was leveraged to evolve a population of base deep learners with maximum accuracy and diversity simultaneously. Frequency spectrums calculated from the in-situ monitoring signals were used as input features for the training. To form the ensemble deep learner, the ensemble weights for the based learners were optimized by differential evolution (DE) (Storn and Price 1997) with the objective of average training accuracy and selected by a designed selection strategy with three constraints including: (1) prediction accuracy, (2) diversity and (3) training speed.

For vehicle type classification, Liu et al., (Liu et al. 2017b) constructed an ensemble deep learning approach based on three types of ResNet (He et al. 2016) architectures, including ResNet-50, ResNet-101, ResNet-152. With respective initializations pretrained on ImageNet (Jia Deng et al. 2009), the three architectures were independently trained on the same training set which had been augmented with balance sampling to obtain diverse base learners. The majority voting was employed

as the ensembling criterion to form the ensemble learner.

For vehicle type classification, Qummar et al., (Qummar et al. 2019) constructed an ensemble deep learning approach based on five deep CNN architectures, including ResNet-50 (He et al. 2016), Inception-v3 (Szegedy et al. 2016), Xception (Chollet 2017), Dense-121 and Dense-169 (Huang et al. 2017b). With respective pretrained initializations, the five architectures were independently trained on the same fundus images of Kaggle (https://www.kaggle.com/c/diabetic-retinopathy-detection/data) to generate five different base learners. To form the ensemble learner, Stacking (Wolpert 1992) was employed as the ensembling criterion.

For the prediction of neuromuscular disorders, Khamparia et al. (Khamparia et al. 2020) also proposed to integrate multiple base learners using deep learning. Bhattacharya coefficient was employed to select top gene features and the obtained coefficient was given as input to generate gene features related to muscular disorder. Based on the extracted features, KNN (Altman 1992), DT (Quinlan 1986), linear discriminant analysis (LDA), quadratic discriminant analysis (QDA), RF (Breiman 2001), variants of SVM (Chang and Lin 2011) was utilized to train multiple base learners. To form the ensemble learner, a five-layer convolutional neural network (5-CNN) was built as an implementation of the meta-learning strategy, which took the predictions of the obtained base learners as inputs and output disease diagnosis.

4.3.3 Summary

The information of the reviewed recent works of UEDL is listed in Table. 9. In addition to Table. 4, the feature extraction methods adopted by the UDEL approaches proposed in the reviewed works are listed in Table. 10. In addition to Table. 5 and Table. 6, the learning algorithms and learning strategies employed to generate base learners are respectively listed in Table. 11 and Table. 12. In addition to Table. 7, the ensembling criteria utilized to integrate base learners are listed in Table. 13. Referring to Table. 9-13, the key innovations of the UDEL approaches proposed in the reviewed works are summarized in Table. 14. Finally, referring to the paradigm of UEDL presented in Fig. 5, the basic patterns of applying deep learning to TEL to evolve the UEDL approaches proposed in the reviewed works are listed in Table. 15.

Table. 9. The information of the applications in the reviewed recent UEDL works (DA)

Code	Description	Citations	Published Year
DA1	Probabilistic wind power forecasting (Wang et al. 2017)	348	2017
DA2	Electricity load demand forecasting (Qiu et al. 2017)	229	2017
DA3	Sentiment analysis in social applications (Araque et al. 2017)	299	2017
DA4	Melanoma recognition in dermoscopic images (Codella et al. 2017)	295	2017
DA5	Wind speed forecasting (Chen et al. 2018)	144	2018
DA6	Crude oil price forecasting (Zhao et al. 2017)	162	2017
DA7	Cancer prediction based on gene expression (Xiao et al. 2018)	176	2018
DA8	Prediction of melt index in industrial polymerization processes (Liu et al. 2018)	113	2018
DA9	Brain disease diagnosis based on MRI image (Suk et al. 2017)	148	2017

DA10	Red lesion detection in fundus images (Orlando et al. 2018)	117	2018
DA11	Bearing fault diagnosis	(Xu et al. 2019)	65	2019
		(Ma and Chu 2019)	49	2019
DA12	Vehicle type classification (Liu et al. 2017b)	52	2017
DA13	Diabetic retinopathy detection (Qummar et al. 2019)	50	2019
DA14	Prediction of neuromuscular disorders (Khamparia et al. 2020)	45	2020

Table. 10. In addition to Table. 4, the methods for feature extraction (FE) of the UEDL (TFE/DFE) approaches proposed in the reviewed works

Code	Description
TFE22	Mallat wavelet decomposition (Mallat 1989)
TFE23	Empirical mode decomposition (EMD) (Huang et al. 1998)
TFE24	Color histogram (Barata et al. 2014)
TFE25	Edge histogram (Barata et al. 2014)
TFE26	Multi-scale variant of color local binary patters (MSLBP) (Zhu et al. 2010)
TFE27	Sparse coding (SC) (Mairal 2014)
TFE28	Raw wind speed series (Chen et al. 2018)
TFE29	Factors including price, flow, stock, macroeconomic and financial series (Zagaglia 2010; Naser 2016)
TFE30	DEseq (Anders and Huber 2010)
TFE31	Volumetric features extracted from MRI image (Suk et al. 2017)
TFE32	Volumetric features extracted from fundus images (Niemeijer et al. 2005; SB and Singh 2012; Seoud et al. 2016)
TFE33	Morlet wavelet transform (LIN and QU 2000)
TFE34	Frequency spectrums calculated from the in-situ monitoring signals (Ma and Chu 2019)
TFE35	Raw fundus images
TFE36	Raw vehicle images
TFE37	gene features related to muscular disorder (Qummar et al. 2019)
DFE1	Word2vec (Mikolov et al. 2013)
DFE2	Doc2vec (Le and Mikolov 2014)
DFE3	Caffe (Jia et al. 2014) pretrained on ImageNet (Deng et al. 2009)
DFE4	ResNet (He et al. 2016) pretrained on ImageNet (Deng et al. 2009)
DFE5	U-Net (Ronneberger et al. 2015) pretrained on lesion segmentation task (Codella et al. 2018)
DFE6	Unsupervised learning features from chosen factors via DBN (Hinton and Salakhutdinov 2006; Hinton 2012)
DFE7	Supervised learning features via convolutional neural network (Orlando et al. 2018)

Table. 11. In addition to Table. 5, the learning algorithms (LA) of the UEDL (TLA/DLA) approaches proposed in the reviewed works

Code	Abbr.	Description
TLA17	DT	Decision tree (Quinlan 1986)
TLA18	GBDT	Gradient boosting decision tree (Friedman 2001)
TLA19	KLSM	kernel learning soft-sensing model (Liu et al. 2013)
TLA20	SRM	Sparse regression model (Wang et al. 2011; Zhang and Shen 2012)

TLA21	LDA	Linear discriminant analysis
TLA22	QDA	Quadratic discriminant analysis
DLA1	DCNN	Deep convolutional neural network (LeCun et al. 1998)
DLA2	DBN	Deep belief network (Hinton et al. 2006)
DLA3	LSTM	Long short-term memory (Hochreiter and Schmidhuber 1997; Sainath et al. 2015)
DLA4	SDAE	Stacked denoising autoencoder (Vincent et al. 2008, 2010)
DLA5	ResNet	Deep residual network (He et al. 2016)
DLA6	DAE	Deep auto-encoder (Jia et al. 2016)
DLA7	Inception-v3	Rethinking the Inception Architecture for Computer Vision (Szegedy et al. 2016)
DLA8	Xception	Deep learning with depthwise separable convolutions (Chollet 2017)
DLA9	Dense	Densely Connected Convolutional Networks (Huang et al. 2017b)

Table. 12. In addition to Table. 6, the learning strategies (LS) of the UEDL approaches proposed in the reviewed works

Code	Description
LS13	Training with differently initialized values of regularization parameters (Suk et al. 2017)
LS14	Multi-objective evolutionary algorithm (MOEA/DD) (Li et al. 2015)

Table. 13. In addition to Table. 7, the ensembling criteria (EC) of the UEDL (TEC/DEC) approaches proposed in the reviewed works

Code	Description
TEC10	Wavelet reconstruction (Daubechies and Bates 1993)
TEC11	Random forests (Araque et al. 2017)
TEC12	Support vector regression machine optimized by extremal optimization (Chen et al. 2018)
TEC13	Winner-take-all (Guo et al. 2016)
TEC14	Differential evolution (Storn and Price 1997)
TEC15	Ensemble selection with constraints (Ma and Chu 2019)
DEC1	Five-layer neural network (Xiao et al. 2018)
DEC2	Six-layer convolutional neural network (Suk et al. 2017)
DEC3	Five-layer convolutional neural network (Khamparia et al. 2020)

Table. 14. The key innovations of the UEDL approaches proposed in the reviewed works

App.	FE	LA&S		EC
		LA	LS	
DA1	TFE22	DLA1	Hetero. by LS5	W. by TEC10
DA2	TFE23	DLA2	Homo. by LS5	W. by TEC1,8
DA3	DFE1,2	TLA8	Homo. by LS4	M. by TEC11
DA4	TFE24-27, DFE3-5	TLA1	Homo. by LS5	W. by TEC8
DA5	TFE28	DLA3	Hetero. by LS4	M. by TEC12
DA6	TFE29	DLA4	Homo. by LS7	W. by TEC8
DA7	TFE30	TLA1,3,7,17,18	Homo. by LS4	M. by DEC1
DA8	DFE6	TLA19	Homo. by LS7	W. by TEC8

DA9	TFE31	TLA20	Homo. by LS13	M. by DEC2
DA10	TFE32, DFE7	TLA17	Homo. by LS3	W. by TEC2
DA11	TFE33, DFE7	TLA3	Homo. by LS3	W. by TEC13
	TFE34	DLA2,5,6	Hetero. by LS14	W. by TEC14 / S. by TEC15
DA12	TFE35	DLA5	Hetero. by LS4	W. by TEC2
DA13	TFE36	DLA5,7-9	Hetero. by LS4	W. by TEC2
DA14	TFE37	TLA7,17,21,22	Hetero. by LS4	M. by DEC3

Table. 15. The basic patterns of applying deep learning to TEL to evolve the UEDL approaches proposed in the reviewed works

App.1-5	Pattern	App.6-10	Pattern	App.11-14	Pattern
DA1	B	DA6	B	DA11	A
DA2	B	DA7	C		B
DA3	A	DA8	B	DA12	B
DA4	A	DA9	C	DA13	B
DA5	B	DA10	A	DA14	C

Based on these tables, we can summarize: Five of the reviewed works evolved UEDL approaches by employing pattern A, which utilized pretrained or unsupervised trained deep models to extract more expressive features from raw data; Eight of the reviewed works evolved UEDL approaches by employing pattern B, which replaced the traditional learning algorithms with deep learning algorithms to generate base deep learners with hand-crafted features or raw data; Three of the reviewed works evolved UEDL approaches by employing pattern C, which constructed meta-learning based ensembling criteria to form deep ensemble learner by deep learning algorithms; And one work of DA11 proposed an ensemble selection based ensembling criterion to reduce the costs of ensemble deep learner at testing, as it was more expensive than traditional ensemble learner. These summarizations reflect the primary underlying trends for the recent development of UEDL.

4.4 Unattainability

Based on the primary underlying trends of UEDL summarized in subsection 4.3.3, in this subsection, we discuss the unattainability of UEDL. Although a few learning strategies and ensemble criteria that are more appropriate for the methodology of UEDL have been proposed, the primary issue associated with the methodology of UEDL is that it still retains the paradigm of TEL by simply introducing DL to TEL. This nature of UEL considerably increases the time and space demands of training multiple base deep learners and testing the ensemble deep learner. To address this, the concept of knowledge distillation (Frosst and Hinton 2018) has become popular in many UEDL approaches. The key idea of knowledge distillation is using a student learner, which is often simpler, to distil knowledge of multiple teacher learners selected from a pool of pre-optimized teacher learners which are often more complex (Parisotto et al. 2016; Shen et al. 2019). Though knowledge distillation can reduce the costs at the testing

stage of ensemble deep learning, it still requires large extra expenses during the process of training which prevents adequate usage of UEDL in specific fields. Thus, new methodology for fast ensemble deep learning needs to be further studied.

5. Fast Ensemble Deep Learning

Retaining the paradigm of TEL, UEDL ignores the intrinsic characteristics of DL. To address this, taking the inherent characteristics of DL into consideration, fast ensemble deep learning (FEDL) emerges, which more intrinsically reduce the time and space overheads of EDL.

5.1 Existing FEDL approaches

To reduce the time overhead of EDL in training multiple base deep learners, Huang et al. (Huang et al. 2017a) proposed an FEDL approach named Snapshot, arguing that the local minima found on the optimizing path of stochastic gradient descent (SGD) (Duchi et al. 2010; Kingma and Ba 2015) can benefit ensembles of deep neural networks. Snapshot utilizes the non-convex nature of deep neural networks and the ability of SGD to converge and escape from local minima as needed. By allowing SGD to converge to local minima multiple times along the optimizing path via cyclic learning rates (Loshchilov and Hutter 2017; Smith 2017), instead of training multiple deep learners independently from scratch, they effectively reduced the time cost of obtaining multiple base deep learners. Garipov et al. (Garipov et al. 2018) found that paths with lower loss values existing between the local minima in the loss plane of deep neural networks, and proposed the fast geometric ensembling (FGE) algorithm to find local minima along these paths via cyclic learning rates. As a result, multiple base deep learners can be obtained with less time overhead. Although Snapshot and FGE can effectively reduce the time of training multiple base deep learners, in order to make full use of Snapshot and FGE to obtain better generalization performance, we need to store the obtained multiple base deep learners and average their predictions to form the final ensemble deep learner. This substantially increases the expenses for the testing stage of the final ensemble deep learner. Observing that the local minima found at the end of each learning rate cycle tend to accumulate at the boundary of the low-value area on the loss plane of deep neural networks, the stochastic weight averaging (SWA) algorithm (Izmailov et al. 2018; Maddox et al. 2019) was proposed to average the local minima at the boundary of low-value area to form the ensemble deep learner. It has been proved that SWA can produce ensemble deep learner with better generalization. At the end of each learning rate cycle, SWA saves the weights of the currently optimized deep neural network and averages them with the weights saved at the end of the last learning rate cycle to form the current ensemble deep learner. SWA can obtain multiple base deep learners under the time expense of training one deep learner and the space expense of additional one deep learner, and effectively reduces the time and space cost for the testing stage of the final ensemble deep learner.

5.2 Optional methodology of FEDL

Although several FEDL approaches have been proposed, there still lacks a clear definition for FEDL. Alleviating this situation, Yang et al. (Yang et al. 2021) presented an optional definition and inferred evaluations of FEDL based on observations of existing FEDL approaches. To present a clear definition, the problem of FEDL were divided into three procedures, including: A) training a base deep learner; B) starting from the pre-trained base deep learner to find local minima in the entire parameter space to obtain extra base deep learners; C) integrating the obtained multiple base deep learners to form the ensemble deep learner. The methodology of this definition for FEDL is shown in Fig. 7.
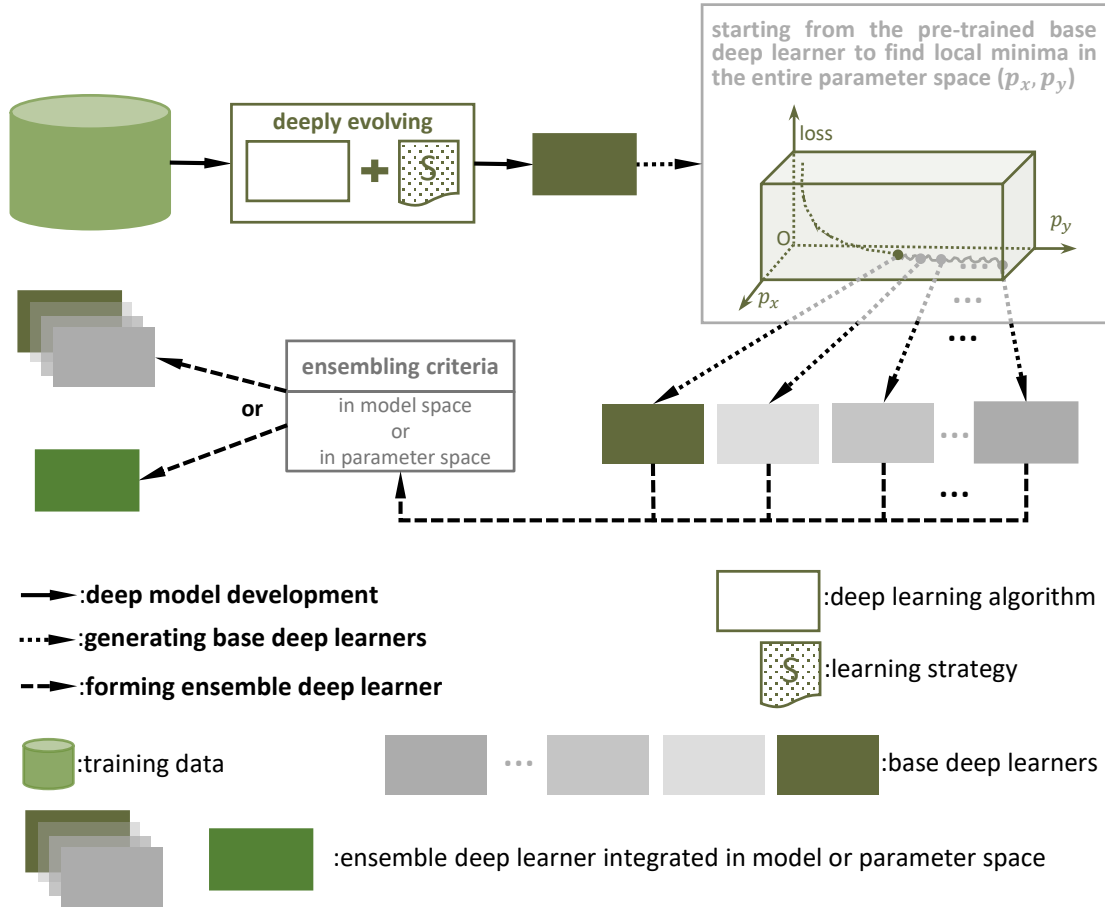
Figure. 7. The methodology of fast ensemble deep learning (FEDL). Deep model development: pre-training a base deep learner. B: starting from the pre-trained base deep learner to find local minima in the entire parameter space to generate extra base deep learners. C: integrating the obtained multiple base deep learners to form the final ensemble deep learner.

With a deep learning algorithm ($DLA = \{dl_0(*; \theta^{dl_0}), dopt_0(*,*; \theta^{dopt_0})\}$) and a learning strategy ($LS1 = \{ls_0(\theta^{ls_0})\}$), the procedure A) of FEDL can be formally expressed as

$$DL_0 = BaseDeepModelDevelopment(D, T, DLA, LS1) = \{dl_0(*; \theta_u^{dl_0})\},$$
$$\theta_u^{dl_0} = deeply\_evolving(D, T, dl_0(*; \theta^{dl_0}), dopt_0(*,*; \theta^{dopt_0}) \mid ls_0(\theta^{ls_0}))$$
$$= \arg\underset{\theta^{dl_0}}{dopt_0}\Big(dl_0(D; \theta^{dl_0}), T; \theta^{dopt_0} \mid ls_0(\theta^{ls_0})\Big).$$

With the pre-trained DL_0, DLA and additional learning strategies ($LS2 =$

$\{ls_1(\theta^{ls_1}), \cdots, ls_b(\theta^{ls_b})\})$, the procedure B) of FEDL can be formally expressed as

$$DL_b = ExtraBaseDeepLearnerGeneration(D, T, DL_0, DLA, LS2) =$$
$$\{dl_1(*; \theta_u^{dl_1}), \cdots, dl_b(*; \theta_u^{dl_b})\},$$
$$dl_b(*) = dl_0(*),$$
$$\theta_u^{dl_b} = deeply\_evolving\big(D, T, dl_0(*; \theta^{dl_0}|\theta_u^{dl_{b-1}}), dopt_0(*,*; \theta^{dopt_0}) \mid ls_b(\theta^{ls_b})\big)$$
$$= arg\, dopt_0 \Big(dl_0(D; \theta^{dl_0}|\theta_u^{dl_{b-1}}), T; \theta^{dopt_0} \mid ls_b(\theta^{ls_b})\Big).$$
$$\scriptstyle \theta^{dl_0}$$

Both ensemble criteria $EC = \{l_e(*; \theta^{l_e}), conf(*,*; \theta^{conf})\}$ for UEL and $DEC = \{dl_e(*; \theta^{dl_e}), dconf(*,*; \theta^{dconf})\}$ for UEDL can be leveraged for fast ensemble deep learner formation. In the context of FEDL, these two criteria are also named as ensemble in model space. Another ensemble criterion that is used by FEDL is ensemble in parameter space, which fuses multiple base deep learners into a single deep learner. Formally, let $ECPS = \{fusing(*, \theta^{fusing})\}$ denote the ensemble criterion in parameter space, the procedure C) of FEDL in parameter space can be formally expressed as follows

$$FDL_e = EnsembleDeepLearnerFormation(\{DL_0, DL_b\}, ECPS)$$
$$= \{fdl_e(*; \theta_u^{fdl_e})\},$$
$$fdl_e(*) = dl_0(*),$$
$$\theta_u^{fdl_e} = fusing(\{\theta_u^{dl_0}, \theta_u^{dl_1}, \cdots, \theta_u^{dl_b}\}; \theta^{fusing}).$$

At testing, given a test data point d_{test}, the inference procedures of the ensemble deep learner integrated in model space include computing the predictions of all base deep learners which can be expressed as

$$\tilde{t}_{test} = \{dl_0(d_{test}; \theta_u^{dl_0}), dl_1(d_{test}; \theta_u^{dl_1}), \cdots, dl_b(d_{test}; \theta_u^{dl_b})\},$$

and mapping $\tilde{t}_{test}$ to the final prediction t_{test} by the learner integrated in model space. Whereas, the inference procedure of the ensemble deep learner fused in parameter space can be simply expressed as

$$t_{test} = fdl_e(d_{test}; \theta_u^{fdl_e}).$$

5.3 Finding local minima in the sub-parameter space for FEDL

Existing FEDL approaches (like Snapshot, FGE and SWA) have promoted the deployment of ensemble deep learning in some artificial intelligence applications to some extent. However, due to the large expenses compared with TEL, FEDL still needs further advances in some specific fields, where the developing time and computing resources are usually restricted (f. e. the field of robotics vision (Yang et al. 2018, 2019)) or the data to be processed is of large dimensionality (f. e. the field of histopathology whole slide image analysis (Yang et al. 2020c, b)). In these specific fields, it is sometimes still difficult to deploy the TEL approaches, which makes the deployment of existing FEDL approaches still challenging.

To alleviate this, Yang et al (Yang et al. 2020a, 2021) argued that local minima found in the sub-parameter space (LoMiFoSS) can be effective for FEDL, and proposed the concept of LoMiFoSS-based fast ensemble deep learning (LoMiFoSS-FEDL). Referring to the optional methodology presented for FEDL, the problem of LoMiFoSS-FEDL were also divided into three procedures to present the methodology of LoMiFoSS-FEDL, including: A) pre-training a base deep learner; B) starting from the pre-trained base deep learner to find local minima in the sub-parameter space; C)

fusing the multiple base deep learners of the found local minima in the sub-parameter space to form the final ensemble deep learner. Different from current state-of-the-art FEDL approaches (Huang et al. 2017a; Garipov et al. 2018; Izmailov et al. 2018; Maddox et al. 2019) that optimize the entire parameters of a deep neural network architecture, LoMiFoSS-FEDL only optimizes partial parameters to further reduce the costs required for training multiple base deep learners. LoMiFoSS-FEDL provides an addition to current FEDL approaches. An optional methodology of LoMiFoSS-FEDL is shown in Fig. 8.
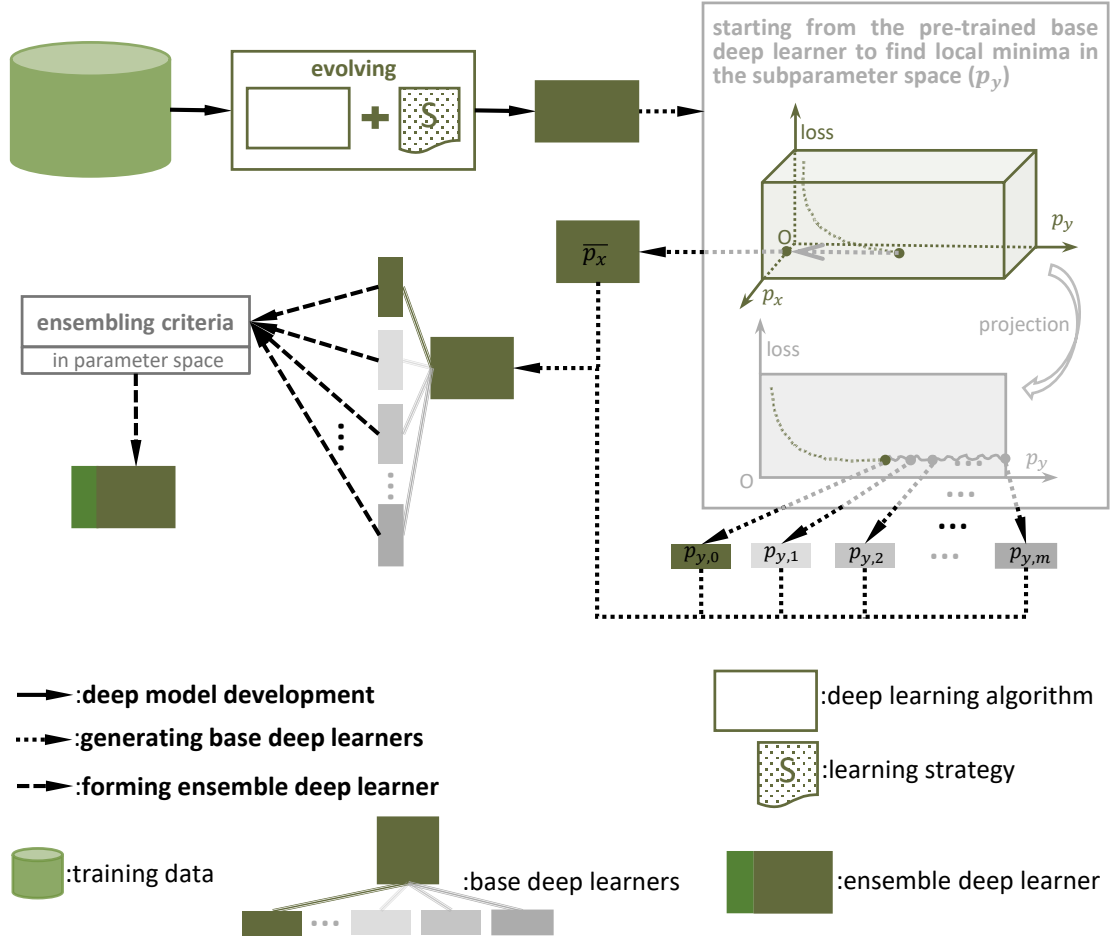
Figure. 8. The methodology of LoMiFoSS-FDEL for fast ensemble deep learning.

Formally, the procedure A) of LoMiFoSS-FEDL can be expressed exactly as the procedure A) of FEDL. With the pre-trained DL_0, DLA, a sub-parameter space $SPS = \{\theta^{dl_{0,s}} | \theta^{dl_{0,s}} \in \theta^{dl_0}; \theta^{dl_{0,f}} \in \theta^{dl_0}; (\theta^{dl_{0,s}} \cup \theta^{dl_{0,f}}) == \theta^{dl_0}\}$, and additional learning strategies ($LS2 = \{ls_1(\theta^{ls_1}), \cdots, ls_b(\theta^{ls_b})\}$), the procedure B) of LoMiFoSS-FEDL can be formally expressed as

$$DL_b = ExtraBaseDeepLearnerGeneration(D, T, DL_0, DLA, SPS, LS2) =$$
$$\{dl_1(*; \theta_u^{dl_1}), \cdots, dl_b(*; \theta_u^{dl_b})\},$$
$$dl_b(*) = dl_0(*),$$
$$\theta_u^{dl_b} = \theta_u^{dl_{0,f}} \cup \theta_u^{dl_{b,s}},$$

$$\theta_u^{dl_{b,s}} = partialy\_evolving\left(D, T, dl_0\left(*; \theta^{dl_{0,s}}|\theta_u^{dl_{b-1}}\right), dopt_0(*,\right.$$
$$\left.*; \theta^{dopt_0}\right) \mid ls_b(\theta^{ls_b})\big)$$
$$= \underset{\theta^{dl_{0,s}}}{arg\ dopt_0}\left(dl_0\left(D; \theta^{dl_{0,s}}|\theta_u^{dl_{b-1}}\right), T; \theta^{dopt_0} \mid ls_b(\theta^{ls_b})\right).$$

the ensemble criterion in parameter space $ECPS$, the procedure C) of LoMiFoSS-FEDL in parameter space can be formally expressed as

$$FDL_e = EnsembleDeepLearnerFormation(\{DL_0, DL_b\}, ECPS)$$
$$= \{fdl_e(*; \theta_u^{fdl_e})\},$$
$$fdl_e(*) = dl_0(*),$$
$$\theta_u^{fdl_e} = \theta_u^{dl_{0,f}} \cup \theta_u^{dl_{e,s}},$$
$$\theta_u^{dl_{e,s}} = fusing\left(\left\{\theta_u^{dl_{0,s}}, \theta_u^{dl_{1,s}}, \cdots, \theta_u^{dl_{b,s}}\right\}; \theta^{fusing}\right).$$

At testing, the inference procedure of the ensemble deep learner for LoMiFoSS-FDEL can be expressed the same as the inference procedure of the ensemble deep learner fused in parameter space for FDEL.

5.4 Remaining issues

The primary remaining issue associated with FEDL is the imperfection for its definition. From the existing methodologies (Fig. 7 and 8) presented for FEDL, we can notice that the found extra base deep learners are tightly related to the pre-trained base deep learner. However, we cannot be sure whether the found extra base deep learners and the pre-trained base deep learner can be united to produce the optimal ensemble solution. In addition, one may argue that finding multiple deep learners that are less tightly related to each other can achieve better ensemble performances. Thus, the two presented methodologies can only provide some optional perspectives for the definition of FEDL, and new methodologies from different angles for ensemble deep learning are still needed.

6 Discussion

This article is different from existing review articles (Sagi and Rokach 2018; Dong et al. 2020) that mostly discussed about traditional ensemble learning, reviews (Cao et al. 2020) that particularly discussed ensemble deep learning in bioinformatics, or specific technical innovations with ensemble learning introduced such as GAN-Ensembles (Durugkar et al. 2017; Ghosh et al. 2018; Han et al. 2020). With more fundamental discussions about the developing routes of both traditional ensemble learning and ensemble deep learning, in this article, we aim to reveal the intrinsic problems and technical challenges of deploying ensemble learning under the era of deep learning to a wider range of specific fields.

Data analyses of published works show that ensemble learning is still prosperously developing while the research of ensemble deep learning (EDL) compared with the research of traditional ensemble learning (TEL) is severely lagging behind. The primary reason for this phenomenon lies in that the time and space overheads for the training and testing stages of EDL are much larger than that of TEL.

Recent advances of TEL have achieved remarkable progresses in various applications.

However, most of these advances focused on proposing solutions for specific applications, based on combinatorial innovations by leveraging existing learning strategies for base learner generation and existing ensembling criteria for ensemble learner formation. Few proposed new learning strategies for base learner generation or new ensembling criteria for ensemble learner formation. This phenomenon reflects that the advances for the intrinsic problems of TEL seem to have reached to a bottleneck, although TEL is still prosperously developing in various applications. Besides, the primary issue associated with the methodology of TEL comes from the nature of usual machine learning (UML), which evolves a learner based on hand-crafted features which are usually difficult to design and not expressive enough.

Directly introducing deep learning (DL) to enhance the methodology of TEL by three basic patterns (introducing DL to feature extraction, introducing DL to base learner generation or introducing DL to ensemble learner formation), recent advances of usual EDL (UEDL) have promoted the solutions for various applications. However, the primary issue of the methodology of UEDL is that its nature still retains the paradigm of TEL, which considerably increases the costs of training multiple base deep learners and testing the ensemble deep learner. This can also be confirmed by the fact that knowledge distillation (Frosst and Hinton 2018) and ensemble selection based ensembling criterion (Ma and Chu 2019) for ensemble deep learner formation appeared in some recent advances of UEDL to reduce the testing overhead. A promising future direction is to more intrinsically reduce the expenses of EDL by taking into consideration the inherent characteristics of DL.

Fast ensemble deep learning (FEDL) emerges to more intrinsically reduce the costs of EDL, considering some inherent characteristics of DL. Finding local minima along the (global or local) optimization path of SGD for multiple base deep learners, existing advances of FEDL have provided preferrable solutions to promote the deployment of EDL in more artificial intelligence applications of specific fields. However, the primary remaining issue of FEDL is the imperfection for its definition, since currently existing alternative methodologies for FEDL can only provide uncomprehensive perspectives. A promising future direction is to comprehensively propose more appropriate definitions for FEDL.

Notably, many brilliant ideas have been proposed for TEL, another interesting direction is to introduce some ideas of TEL into DL for FEDL, with the reverse direction of the development of UEDL that introduces DL into TEL. For example, recently, Zhang et al (Zhang et al. 2021) introduced negative correlation learning (Liu and Yao 1999) to DL with a divide-and-conquer strategy and proposed a solution of deep negative correlation learning for FEDL.

Data Availability

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

Competing interests

The authors declare that they have no competing interests.

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