# Research Progress and Trend of the Machine Learning based on Fusion

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***Abstract*—Machine learning is widely used in the data processing including data classification, data regression, data mining and so on, and based on a single type of machine learning technology, it is often difficult to meet the requirements of data processing; in recent years, the machine learning based on fusion has become an important approach to improve data processing effect, and at the same time, corresponding summary study is relatively limited. In this study, we summarize and compare different types of fusion machine learning such as ensemble learning, federated learning and transfer learning from the perspectives of classification, principle and characteristics, and try to explore the research development trend, in order to provide effective reference for subsequent related research and application; furthermore, as an application of fusion machine learning，we also conduct a study on the modeling optimization for car service complaint text classification.**

***Keywords*—Machine learning; fusion; ensemble learning; federated learning; transfer learning**

## I. Introduction

In recent years, machine learning research has developed rapidly and achieved widespread attention; with the expanding and deepening of the development, it is found that traditional machine learning methods often fail to meet the needs of data modeling for certain scenarios; therefore, fusion-based machine learning has become a research hotspot, and relevant research has involved the fields of agriculture, geology, environment, machinery, communication, medicine and so on. This study summarizes and compares the fusion-based machine learning methods from multiple perspectives, it is expected that this study could provide support for effectively obtaining a general understanding for the research progress of the machine learning based on fusion, and explore the research development trend based on summary and analysis.

## II. Machine Learning based on Fusion

Fig. 1 summarizes the main fusion-based machine learning methods from the perspectives of classification, principles, and characteristics.

Fusion-based machine learning involves technology fusion and data fusion.

The technology fusion includes horizontal fusion and vertical fusion. The horizontal fusion mainly refers to ensemble learning, the ensemble strategies include bagging, blending, stacking and so on. The vertical fusion mainly refers to different types of neural networks stacking to form multiple neural networks, and also includes other multi-layer information processing methods based on the stacking of different types of basic technologies.

The Data fusion mainly refers to federated learning which is based on distributed model training; and the method of transfer learning shares model training results through parameters between the models trained based on different parts of data, which could be understood as another kind of machine learning based on data fusion.

### A. Ensemble Learning

Ensemble learning commonly uses multiple algorithms to train individual models independently of each other, and then combines the training results through certain strategy to form a comprehensive model based on model horizontal combination to improve the modeling effect.

Different types of machine learning technologies commonly have different characteristics, applicability and limitation, and ensemble learning could effectively combine the advantages of multiple machine learning technologies to optimize the effects of machine learning modeling. In recent years, ensemble learning has received extensive attention, related research had involved agriculture, geology and so on [1-2].

The basic technologies used in the individual model training mainly include the classic technologies such as random forest, support vector machine, ridge regression, and the technologies based on neural network such as bidirectional long short term memory neural network, error back propagation neural network and so on; the ensemble strategies mainly include bagging, blending and stacking.

The bagging ensemble strategy is mainly based on the idea of voting, for classification issue, the calculation results from the individual models could be regarded as votes, and the prediction category with the most votes could be took as the classification prediction output of the overall ensemble model, for regression issue, the weighted average of the outputs from multiple individual models could be computed as the output of the overall ensemble model.

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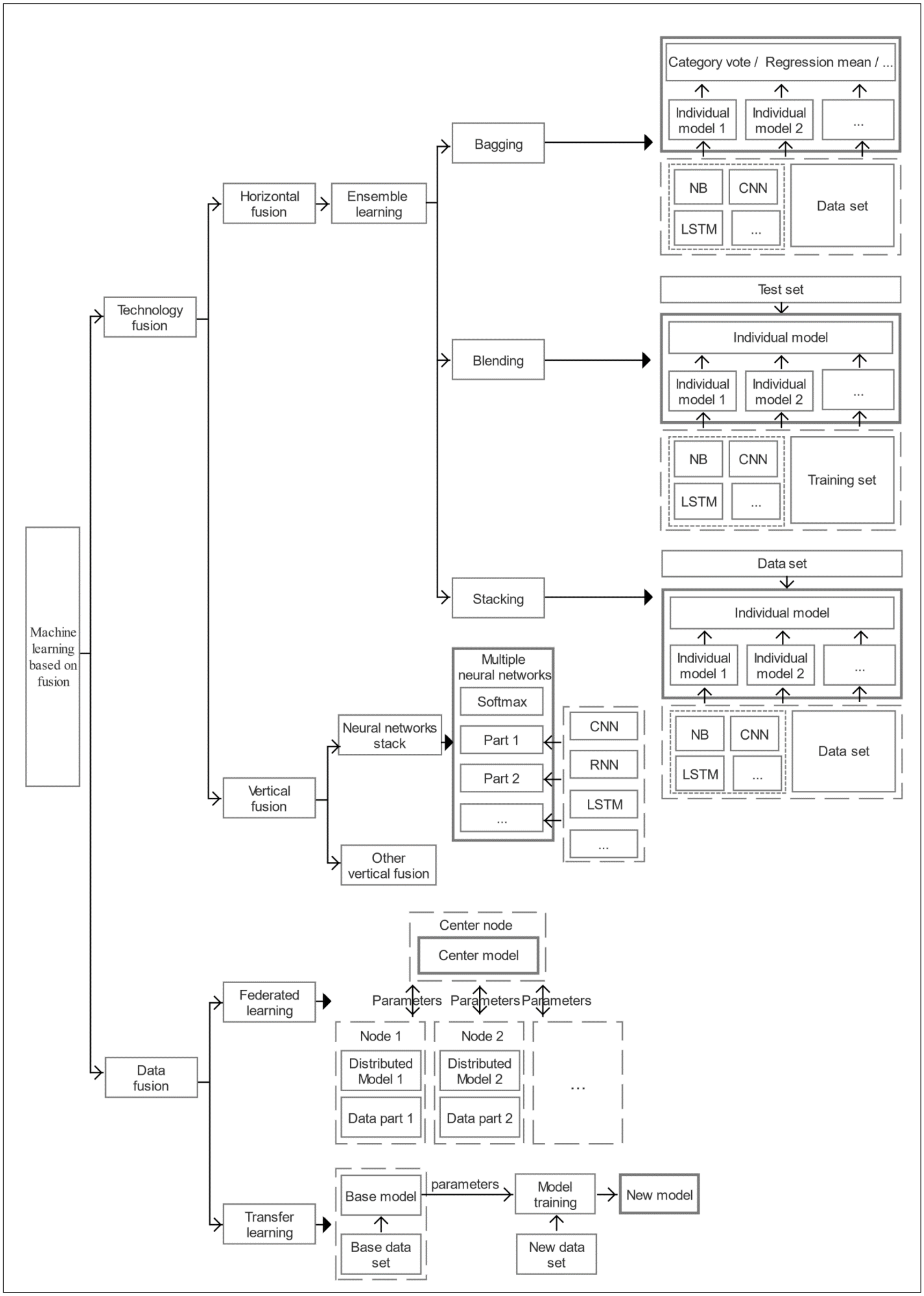


Fig. 1. Machine Learning based on Fusion.

The blending ensemble model usually consists of two layers, the first layer is commonly a plurality of individual models trained independently, the second layer is another individual model, which operate prediction based on the outputs of the first layer, and the predicted result from the second layer would be used as the final output of the ensemble model; to build a blending ensemble model, the dataset is commonly divided into a test set and a training set firstly, and then the model training of first layer is performed based on the training set, and the model training of second layer is performed based on the test set.

The stacking ensemble model commonly includes two layers too, the first layer consists of multiple individual models; and the second layer is another individual model, which conducts prediction based on the outputs of the multiple individual models of the first layer; the stacking ensemble strategy is similar to the blending ensemble strategy, the main difference lies in the data segmentation in the model training, in stacking model training, the data used for the first-layer model training and the second-layer model training is consistent, and in the training of blending model, the training data of the second-layer does not intersect with the training data of the first-layer.

Table I generally summarizes and compares the research examples for the ensemble learning from the aspects of ensemble strategy, basic technology, etc.

### B. Transfer Learning

Transfer learning commonly initializes new model training based on pre-trained model parameters, and through little applicability adjustment, achieves quickly and effective data modeling [3-6]. The transfer learning methods used in related research are mainly based on neural network, which commonly redesigns the fully connected layer and freeze the other layers of the pre-trained model, or freeze part layers and adjust the other layers.

Transfer learning provides an effective alternative approach mainly for two kinds of scenarios, one is the data modeling based on a limited amount of data, by transfer learning, effective modeling could commonly be achieved through fine-tuning based on a pre-trained model trained based on enough data; the second is the scenario where the machine learning model training takes too much time, through transfer learning, the pre-trained model could be used as basis to quickly realize the modeling for a new dataset, which could effectively reduce the training time and reduce the timeliness constraint of the model use.

Transfer learning is commonly based on convolutional neural networks, and related methods mainly include four categories, including the methods based on AlexNet, the methods based on VGGNet, the methods based on ResNet and the methods based on DenseNet. Table II generally summarizes and compares the research examples for different kinds of transfer learning from the aspects of research method, benchmark method and so on.

TABLE I. FUSION STRATEGIES OF ENSEMBLE LEARNING AND THE RESEARCH EXAMPLES

| No. | Integration strategy | Research method | Research object | References |
|---|---|---|---|---|
| 1 | Bagging | Individual learning: KNN (k-nearest neighbor), BP (error back propagation neural network), GBDT (gradient boosting decision tree), RF (random forest); using improved weighted voting strategy | Electricity theft detection | [7] |
| | | Individual learning: DT (decision tree) | Personal credit evaluation | [8] |
| | | Individual learning: DT | Character recognition | [9] |
| | | Obtaining different datasets based on the bootstrap sampling method and training multiple BP models separately | Water bloom prediction | [10] |
| 2 | Blending | Individual learning: GBDT, linear-SVM (linear support vector machine), RBF-SVM (radial basis function-support vector machine),<br>Fusing: linear-SVM | Infrared spectroscopy data analysis | [11] |
| 3 | Stacking | Individual learning: LR (logistic regression), KNN, RF, GBDT<br>Fusing: GBDT | Strains classification of Anoectochilus roxburghii | [12] |
| | | Individual learning: RF, XGBoost, LightGBM<br>Fusing: LR (linear regression) | Gaseous nitrous prediction (in air) | [13] |
| | | Individual learning: RF, GBDT, SVM (support vector machine), RR (ridge regression)<br>Fusing: RR | Estimation of summer corn fractional vegetation coverage (based on drone multispectral image) | [14] |
| | | Basic method: KNN, SVM, RF, GBDT | Classification of rice phenomics entitie | [15] |
| | | Basic method: KNN, RF, adaptive boosting | Estimation of nitrogen contents in citrus leaves | [16] |
| | | Basic method: RF, LDA (latent dirichlet allocation), LIBSVM | Classification of black Goji berry | [17] |

TABLE II. CATEGORIES OF TRANSFER LEARNING AND THE RESEARCH EXAMPLES

| No. | Category | Research method | Contrast method | Research object | References |
|---|---|---|---|---|---|
| 1 | AlexNet | AlexNet | SVM (support vector machine, BP (error back propagation neural network), VGG-19, GoogLeNet Inception v2 | Image recognition of cotton leaf diseases and pests | [18] |
| | | AlexNet | CNN (convolutional neural network) | Flotation performance recognition | [19] |
| 2 | ResNet | ResNet-101 | ResNet-50 | Intelligent lithology identification | [20] |
| | | TL-SE-ResNeXt-101 (based on improved deep residual network SE-ResNeXt-101) | ResNet-50, VGG-16, DenseNet-121, GoogLeNet | Crop disease classification | [21] |
| | | CDCNNv2 (based on residual network ResNet-50) | ResNet 50, VGG16, VGG19, DenseNet 121, Xception | Crop diseases detection | [22] |
| | | MPDE-VMD+DTL (multiple population differential evolution-variational mode decomposition, deep transfer learning) | BP, ResNet, migration component analysis | Mechanical fault diagnosis | [23] |
| 3 | VGGNet | VGG-16 | AlexNet, ResNet 50, Inception v3 | Grape leaf disease detection | [24] |
| | | Grape-VGG-16 (a kind of grape leaf disease identification model) | New learning | Grape leaf disease recognition | [25] |
| 4 | DenseNet | DL–T (based on DenseNet and LSTM) | RNN–T | Speech recognition | [26] |
| | | DenseNet-GCForest (based on DenseNet and deep forest ) | CNN | Wafer map defect recognition | [27] |

## C. Federated Learning

Federated learning commonly does not centralize training data, but is based on distributed model training, independent partial model training is performed on multiple terminals based on different parts of the data, and the partial training result parameters would be centralized, based on which the central model parameters could be updated through certain strategy, so as to achieve the purpose of integrating multi-source data to improve the machine training effect.

The characteristics and advantages of federated learning mainly include three aspects, firstly, it is not necessary for federated learning to centralize raw data from different sources or terminals, which could effectively protect the data security and user privacy; secondly, federated learning could be combined with the idea of edge computing, and a large amount of data processing workload would be distributed to terminals, which could effectively relieve the computational pressure of the central node and improve the performance of the overall machine learning system; finally, under the condition of multi-node computing, since the data transmission between the terminal nodes and the central node does not involve the transmission of original data but only a small amount of data such as training parameters, the data transmission pressure could be significantly reduced and the performance of the machine learning system could be further optimized.

With the rapid development and wide application of information technology, as the disadvantage side of the double-edged sword of the technology, data security and privacy security risk are gradually being highlighted; at the same time, the application of the internet of things is becoming more and more extensive, and there are always more and more big data processing scenarios; therefor, federated learning has become a hot topic. Related researches have involved the fields of communication, medicine, multimedia and so on. In the field of communications, Wang Jia Rui et al. (2021) proposed a clustered wireless federated learning algorithm for the scenario of high-speed internet of vehicle, the test based on handwriting recognition model show that under the condition in which the channel state is poor and the user transmit power is greatly limited, the convergence value of the loss function could be effectively reduced based on this method, compared with traditional centralized algorithm [28]. Jing Xing Hong et al. (2021) proposed a LTE-V2X (long term evolution-vehicle to everything) channel estimation algorithm based on federated learning, which estimates the time-varying channel based on CNN-LSTM-DNN (convolutional neural network-long short term memory-deep neural network), and allocates the required computation to vehicle users, research result show that the method could effectively track the time-varying channel in the high-speed mobile scene of vehicle user, which only lose a small amount of performance compared with the centralized learning algorithm [29]. In medical field, Wang Sheng Sheng et al. (2021) proposed a kind of federated learning method based on improved RetinaNet and attention mechanism for the privacy protection requirements in the model training for medical image target detection, and research result show that compared with centralized learning method, the model performance is slightly lower and the training speed is accelerated to a large extent [30]; moreover, Wang Sheng Sheng et al. (2021) proposed a kind of machine learning method based on federated learning and blockchain for the data protection requirements in the model training for the segmentation of new coronary pneumonia chest CT image [31]. In multimedia field, Zhao Yu et al. (2020) proposed a kind of federated learning method based on lightweight neural network and sub-scenario model training for the problem of high latency in video surveillance, and research result show that the method could improve the accuracy and training speed compared with the benchmark method [32].

## III. Application of Fusion Machine Learning

As an application of fusion machine learning in natural language text classification, this section studies the modeling of car service complaint text classification based on ensemble learning.

The research data of this section is from the Beijing Car Quality Net Information Technology Limited Company, and the dataset used includes 7 classes of car service complaint text data，the total data amount is 2100，and the data amount of every class is 300.

The technology route is shown in Fig. 2

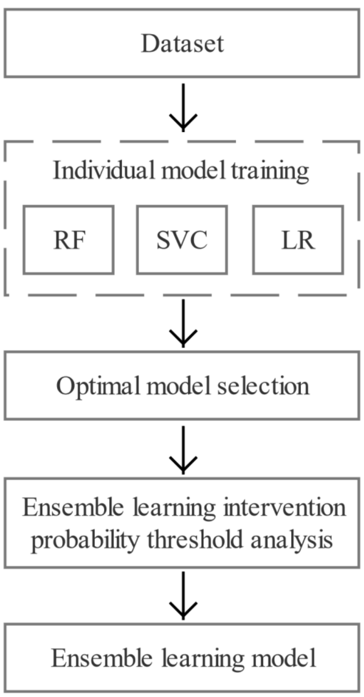


Fig. 2. The Technical Route of Ensemble Learning.

In previous research foundation, we have conducted research on the classification modeling of car service complaint texts based on RF method and formed corresponding academic paper; this section mainly focuses on the modeling optimization based on ensemble learning. We take the RF model as a basic, and when the highest predicted probability of the RF model for different classes is less than the threshold, select the class corresponding to the highest predicted probability of the RF model, SVC model, and LR model as the output of the integrated learning model; the comparison of the model prediction effects under different threshold conditions is shown in Table III.

TABLE III. Prediction Comparison under Different Intervention Threshold Conditions

| No. | Threshold | Accuracy | Recall | F1-score |
|---|---|---|---|---|
| 1 | 0.1 | 0.8476 | 0.8476 | 0.8495 |
| 2 | 0.2 | 0.8476 | 0.8476 | 0.8495 |
| 3 | 0.3 | 0.8524 | 0.8524 | 0.8539 |
| 4 | 0.4 | 0.8571 | 0.8571 | 0.8597 |
| 5 | 0.5 | 0.8476 | 0.8476 | 0.8498 |
| 6 | 0.6 | 0.8429 | 0.8429 | 0.8447 |
| 7 | 0.7 | 0.8429 | 0.8429 | 0.8447 |
| 8 | 0.8 | 0.8381 | 0.8381 | 0.8397 |
| 9 | 0.9 | 0.8381 | 0.8381 | 0.8397 |
| 10 | 1.0 | 0.8381 | 0.8381 | 0.8397 |

Comparison of the prediction effects from different models is shown in Table IV. The research results show that the ensemble learning model has the optimal effect, which could effectively classify the car service complaint texts.

TABLE IV. Comparison of the Prediction Effects from different Models

| No. | Method | Accuracy | Recall | F1-score |
|---|---|---|---|---|
| 1 | RF | 0.8476 | 0.8476 | 0.8495 |
| 2 | SVC | 0.8000 | 0.8000 | 0.8022 |
| 3 | LR | 0.8381 | 0.8381 | 0.8408 |
| 4 | Ensemble learning (Threshold: 0.4) | 0.8571 | 0.8571 | 0.8597 |

In general, the threshold-based ensemble learning is an effective approach to improve the modeling effect of natural language text classification, and the methods based on fusion enrich the machine learning to a great extent.

## IV. Conclusion and Outlook

Generally, different kinds of fusion methods have corresponding advantages, applicability and limitation, the rapid development of fusion machine learning has built a better foundation for further data science research. For the technological development trend, in terms of basic research, the innovation in the model integration strategies for ensemble learning and the innovation in the parameter fusion strategies for federated learning would be of great significance; in terms of application, the development of fusion machine learning has enriched the data modeling methods greatly, and follow-up related research could take the characteristics of specific scenario as basis to comprehensively consider the applicability of traditional machine learning methods and different types of fusion machine learning methods to achieve high-quality data modeling. In particular, the effective combination of federated learning and edge computing would make important social value in the fields of big data processing and privacy protection.

In order to provide convenient reference for relevant researchers, we have sorted up the research reports cited in this paper according to the research field, research object and fusion strategy, as shown in Table V, it is expected that subsequent researchers could make quick reference based on the reference table or take it as the basis for further improvement.

TABLE V. APPLICATION FIELDS OF THE MACHINE LEARNING BASED ON FUSION AND THE FUSION METHODS

| Field | Research object | Fusion | Reference |
|---|---|---|---|
| Agriculture | Rice seed vigor detection | Transfer learning | [3] |
| | Strains classification of anoectochilus roxburghii | Ensemble learning | [12] |
| | Estimation of summer corn fractional vegetation coverage | Ensemble learning | [14] |
| | Classification of rice phenomics entitie | Ensemble learning | [15] |
| | Estimation of nitrogen contents in citrus leaves | Ensemble learning | [16] |
| | Classification of black Goji berry | Ensemble learning | [17] |
| | Image recognition of cotton leaf diseases and pests | Transfer learning | [18] |
| | Crop disease classification | Transfer learning | [21] |
| | Crop diseases detection | Transfer learning | [22] |
| | Grape leaf disease detection | Transfer learning | [24] |
| | Grape leaf disease recognition | Transfer learning | [25] |
| Energy | Power tower detection in remote sensing imagery | Transfer learning | [5] |
| | Electricity theft detection | Ensemble learning | [7] |
| Environment | Water bloom prediction | Ensemble learning | [10] |
| | Gaseous nitrous prediction | Ensemble learning | [13] |
| Medicine | Medical image object detection | Federated learning | [30] |
| | Chest CT image segmentation | Federated learning | [31] |
| Transportation | Federated learning in high-speed internet of vehicles | Federated learning | [28] |
| | Channel estimation | Federated learning | [29] |
| | Vehicular abnormal behaviors detection | Ensemble learning | [1] |
| Mechanical | Bearing remaining useful life prediction | Transfer learning | [4] |
| | Abnormal condition identification for the electro-fused magnesia | Transfer learning | [6] |
| | Mechanical failure warning | Ensemble learning | [2] |
| | Mechanical fault diagnosis | Transfer learning | [23] |
| Multimedia | Speech recognition | Transfer learning | [26] |
| | Video surveillance | Federated learning | [32] |
| Finance | Personal credit evaluation | Ensemble learning | [8] |
| Others | Character recognition | Ensemble learning | [9] |
| | Infrared spectroscopy data analysis | Ensemble learning | [11] |
| | Flotation performance recognition | Transfer learning | [19] |
| | Intelligent lithology identification | Transfer learning | [20] |
| | Wafer map defect recognition | Transfer learning | [27] |

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