

# A Survey of Deep Active Learning

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Active learning (AL) attempts to maximize a model’s performance gain while annotating the fewest samples possible. Deep learning (DL) is greedy for data and requires a large amount of data supply to optimize a massive number of parameters if the model is to learn how to extract high-quality features. In recent years, due to the rapid development of internet technology, we have entered an era of information abundance characterized by massive amounts of available data. As a result, DL has attracted significant attention from researchers and has been rapidly developed. Compared with DL, however, researchers have relatively low interest in AL. This is mainly because before the rise of DL, traditional machine learning requires relatively few labeled samples, meaning that early AL is rarely accorded the value it deserves. Although DL has made breakthroughs in various fields, most of this success is due to the large number of publicly available annotated datasets. However, the acquisition of a large number of high-quality annotated datasets consumes a lot of manpower, making it unfeasible in fields that require high levels of expertise (such as speech recognition, information extraction, medical images, etc.) Therefore, AL is gradually coming to receive the attention it is due.

It is therefore natural to investigate whether AL can be used to reduce the cost of sample annotations, while retaining the powerful learning capabilities of DL. As a result of such investigations, deep active learning (DAL) has emerged. Although research on this topic is quite abundant, there has not yet been a comprehensive survey of DAL-related works; accordingly, this article aims to fill this gap. We provide a formal classification method for the existing work, along with a comprehensive and systematic overview. In addition, we also analyze and summarize the development of DAL from an application perspective. Finally, we discuss the confusion and problems associated with DAL and provide some possible development directions.

CCS Concepts: • **Computing methodologies** → **Machine learning algorithms**.

Additional Key Words and Phrases: Deep Learning, Active Learning, Deep Active Learning.

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## 1 INTRODUCTION

Both deep learning (DL) and active learning (AL) have important applications in the machine learning community. Due to their excellent characteristics, they have attracted widespread research interest in recent years. More specifically, DL has achieved unprecedented breakthroughs in various challenging tasks; however, this is largely due to the publication of massive labeling datasets [16, 87]. Therefore, DL is limited by the high cost of sample labeling in some professional fields that require rich knowledge. In comparison, an effective AL algorithm can theoretically achieve exponential acceleration in labeling efficiency [12]. This huge potential saving in labeling costs

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is a fascinating development. However, the classic AL algorithm also finds it difficult to handle high-dimensional data [160]. Therefore, the combination of DL and AL, referred to as DAL, is expected to achieve superior results. DAL has been widely utilized in various fields, including image recognition [35, 47, 53, 68], text classification [145, 180, 185], visual question answering [98] and object detection [3, 39, 121], etc. Although a rich variety of related work has been published, DAL still lacks a unified classification framework. In order to fill this gap, in this article, we will provide a comprehensive overview of the existing DAL related work, along with a formal classification method. We will next briefly review the development status of DL and AL in their respective fields. Subsequently, in Section 2, the necessity and challenges of combining DL and AL are further explicated.

### 1.1 Deep Learning

DL attempts to build appropriate models by simulating the structure of the human brain. The McCulloch-Pitts (MCP) model proposed in 1943 by [40] is regarded as the beginning of modern DL. Subsequently, in 1986, [129] introduced backpropagation into the optimization of neural networks, which laid the foundation for the subsequent rapid development of DL. In the same year, Recurrent Neural Networks (RNNs) [75] were first proposed. In 1998, the LeNet [92] network made its first appearance, representing one of the earliest uses of deep neural networks (DNN). However, these pioneering early works were limited by the computing resources available at the time and did not receive as much attention and investigation as they should have [90]. In 2006, Deep Belief Networks (DBNs) [62] were proposed and used to explore a deeper range of networks, which prompted the name of neural networks as DL. In 2012, in the ImageNet competition, the DL model AlexNet [87] won the championship in one fell swoop. AlexNet uses the ReLU activation function to effectively suppress the gradient disappearance problem, while the use of multiple GPUs greatly improves the training speed of the model. Subsequently, DL began to win championships in various competitions and constantly beat records in various tasks. From the perspective of automation, the emergence of DL has transformed the manual design of features [30, 102] in machine learning to facilitate automatic extraction [58, 149]. It is precisely because of this powerful automatic feature extraction ability that DL has demonstrated such unprecedented advantages in many fields. After decades of development, the field of DL-related research work quite rich. In Fig.1a, we present a standard deep learning model example: convolutional neural network (CNN) [91, 130]. Based on this approach, similar CNNs are applied to various image processing tasks. In addition, RNNs and Generative Adversarial Networks (GANs) [132] are also widely utilized. Beginning in 2017, DL gradually shifted from the initial feature extraction automation to the automation of model architecture design [11, 124, 189]; however, this still has a long way to go.

Thanks to the publication of a large number of existing annotation datasets [16, 87], in recent years, DL has made breakthroughs in various fields including machine translation [4, 13, 159, 168], speech recognition [110, 116, 120, 136], and image classification [60, 106, 115, 174]. However, this comes at the cost of a large number of manually labeled datasets, and DL has a strong greedy attribute to the data. While, in the real world, obtaining a large number of unlabeled datasets is relatively simple, the manual labeling of datasets comes at a high cost; this is particularly true for those fields where labeling requires a high degree of professional knowledge [64, 153]. For example, the labeling and description of lung lesion images of COVID-19 patients requires experienced clinicians to complete, and it is clearly impractical to demand that such professionals complete a large amount of medical image labeling. Similar fields also include speech recognition [1, 188], medical imaging [64, 93, 109, 176], recommender systems [2, 26], information extraction [17], satellite remote sensing [99] and robotics [7, 22, 158, 186], etc. Therefore, a way of maximizing the performance gain of the model when annotating a small number of samples is urgently required.

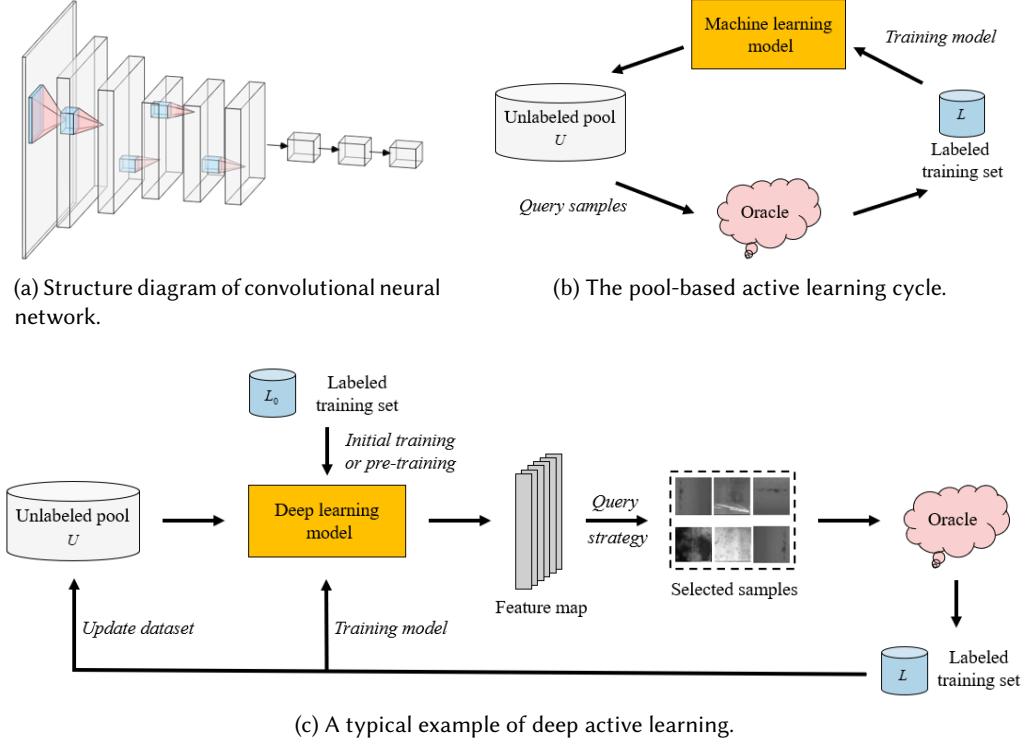


Fig. 1. Comparison of typical architectures of DL, AL and DAL. (a) A common DL model: Convolutional Neural Network. (b) The pool-based AL cycle: Use the query strategy to query the sample in the unlabeled pool  $U$  and hand it over to the oracle for labeling, then add the queried sample to the labeled training dataset  $L$  and train, and then use the newly learned knowledge for the next round of querying. Repeat this process until the label budget is exhausted or the pre-defined termination conditions are reached. (c) A typical example of DAL: The parameters  $\theta$  of the DL model are initialized or pre-trained on the label training set  $L_0$ , and the samples of the unlabeled pool  $U$  are used to extract features through the DL model. Then select samples based on the corresponding query strategy, and query the label in querying to form a new label training set  $L$ , then train the DL model on  $L$ , and update  $U$  at the same time. Repeat this process until the label budget is exhausted or the pre-defined termination conditions are reached.

## 1.2 Active Learning

AL is such a method. It aims to select the most useful samples from the unlabeled dataset and hand it over to the oracle (e.g., human annotator) for labeling, so as to reduce the cost of labeling as much as possible while still maintaining performance. AL approaches can be divided into membership query synthesis [8, 82], stream-based selective sampling [29, 85] and pool-based [95] AL from application scenarios [139]. Membership query synthesis means that the learner can request to query the label of any unlabeled sample in the input space, including the sample generated by the learner. Moreover, the key difference between stream-based selective sampling and pool-based sampling is that the former makes an independent judgment on whether each sample in the data stream needs to query the labels of unlabeled samples, while the latter chooses the best query sample based on the evaluation and ranking of the entire dataset. Although the pool-based scenario

seems to be more common in the application of the paper, it is clear that the application scenario of stream-based selective sampling is more suitable for scenarios involving small mobile devices where timeliness is required. In Fig.1b, we illustrates the framework diagram of the pool-based active learning cycle. In the initial state, we can randomly select one or more samples from the unlabeled pool  $U$ , give this sample to the oracle query label to get the labeled dataset  $L$ , and then train the model on  $L$  using supervised learning. Next, we use this new knowledge to select the next sample to be queried, add the newly queried sample to  $L$  and then conduct training. This process is repeated until the label budget is exhausted or the pre-defined termination conditions are reached.

It is different from DL by using manual or automatic methods to design models with high-performance feature extraction capabilities. AL starts with datasets, primarily through the design of elaborate query rules to select the best samples from unlabeled datasets and query their labels, in an attempt to reduce the labeling cost to the greatest extent possible. Therefore, the design of query rules is crucial to the performance of AL methods. The related research is also quite rich. For example, in a given set of unlabeled datasets, the main query strategies include the uncertainty-based approach [14, 76, 95, 123, 142, 161], diversity-based approach [18, 47, 55, 111] and expected model change [43, 127, 141]. In addition, many works have also studied hybrid query strategies [10, 146, 177, 183], taking into account the uncertainty and diversity of query samples, and attempting to find a balance between these two strategies. Because separate sampling based on uncertainty often results in sampling bias [31], the currently selected sample is not representative of the distribution of unlabeled datasets. On the other hand, considering only strategies that promote diversity in sampling may lead to increased labeling costs, as may be a considerable number of samples with low information content will consequently be selected. More classic query strategies are examined in [140]. Although there is a substantial body of existing AL-related research, AL still faces the problem of expanding to high-dimensional data (e.g., images, text and video, etc.) [160]; thus, most AL works tend to concentrate on low-dimensional problems [61, 160]. In addition, AL often queries high-value samples based on features extracted in advance, and does not have the ability to extract features.

## 2 THE NECESSITY AND CHALLENGE OF COMBINING DL AND AL

DL has a strong learning ability in the context of high-dimensional data processing and automatic feature extraction, while AL has significant potential to effectively reduce labeling costs. Therefore, an obvious approach is to combine DL and AL, as this will greatly expand their application potential. This combined approach, referred to as DAL, was proposed by considering the complementary advantages of the two methods, and researchers have high expectations for the results of studies in this field. However, although AL-related research into query strategy is quite rich, it is still quite difficult to apply this strategy directly to DL. This is mainly due to:

- Insufficient data for label samples. AL often relies on a small amount of labeled sample data to learn and update the model, while DL is often very greedy for data [63]. The labeled training samples provided by the classic AL method thus insufficient to support the training of traditional DL. In addition, the one-by-one sample query method commonly used in AL is also not applicable in the DL context [183].
- Model uncertainty. The query strategy based on uncertainty is an important direction of AL research. In classification tasks, although DL can use the softmax layer to obtain the probability distribution on the label, the facts show that they are too confident. The softmax response (SR) [166] of the final output is unreliable as a measure of confidence, and the performance of this method will thus be even worse than that of random sampling [165].

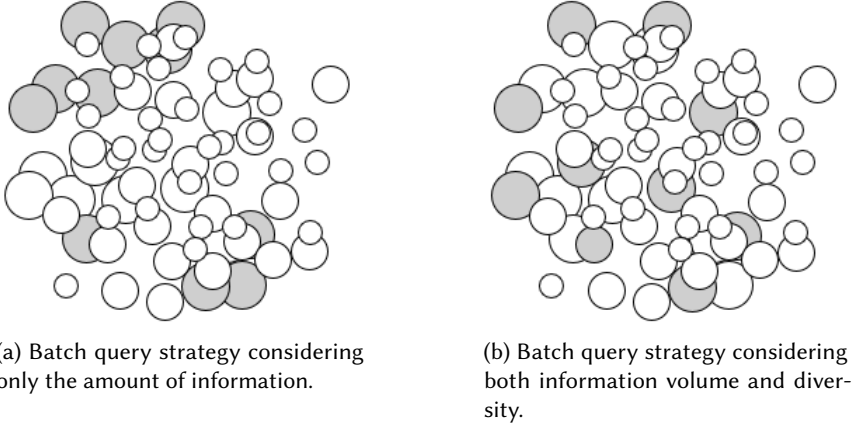


Fig. 2. A comparison diagram of two batch query strategies, one that only considers the amount of information and one that considers both the amount and diversity of information. The size of the dots indicates the amount of information in the samples, while the distance between the dots represents the similarity between the samples. The points shaded in gray indicate the sample points to be queried in a batch.

- Processing pipeline inconsistency. The processing pipelines of AL and DL are inconsistent. Most AL algorithms focus primarily on the training of classifiers, and the various query strategies utilized are largely based on fixed feature representations. In DL, however, feature learning and classifier training are jointly optimized. Only fine-tuning the DL models in the AL framework, or treating them as two separate problems, may thus cause divergent issues [166].

To address the first problem, researchers have considered using generative networks for data augmentation [162] or assigning pseudo-labels to high-confidence samples in order to expand the labeled training set [166]. Some researchers have also used labeled and unlabeled datasets to combine supervised and semisupervised training across AL cycles [65, 148]. In addition, previous heuristic-based AL [139] query strategies have proven to be ineffective when applied to DL [138]; therefore, for the one-by-one query strategy in classic AL, many researchers focus on the improvement of the batch sample query strategy [10, 51, 84, 183], taking both the amount of information and the diversity of batch samples into account. In order to solve the neglect of model uncertainty in DL, some researchers have applied Bayesian deep learning [45] to deal with the high-dimensional mini-batch samples with fewer queries in the AL context [47, 84, 118, 162], thereby effectively alleviating the problem of the DL model being too confident about the output results. Furthermore, to deal with the pipeline inconsistency problem, researchers have considered modifying the combined framework of AL and DL to make the proposed DAL model as general as possible, an approach that can be extended to various application fields. This is of great significance to the promotion of DAL. For example, [178] embeds the idea of AL into DL and consequently proposes a task-independent architecture design.

We will focus on the detailed discussion and summary of the various strategies used in DAL in Section 3.

### 3 DEEP ACTIVE LEARNING

In this section, we will provide a comprehensive and systematic overview of DAL-related works. Fig.1c illustrates a typical example of DAL model architecture. The parameters  $\theta$  of the deep learning model are initialized or pre-trained on the label training set  $L_0$ , while the samples of the unlabeled pool  $U$  are used to extract features through the deep learning model. The next steps are to select samples based on the corresponding query strategy, and query the label in the oracle to form a new label training set  $L$ , then train the deep learning model on  $L$  and update  $U$  at the same time. This process is repeated until the label budget is exhausted or the pre-defined termination conditions are reached. From the DAL framework example in Fig.1c, we can roughly divide the DAL framework into two parts: namely, the AL query strategy on the unlabeled dataset and the DL model training method. These will be discussed and summarized in the following Section 3.1 and 3.2 respectively. Finally, we will discuss the efforts made by DAL on the generalization of the model in Section 3.3.

#### 3.1 Query Strategy Optimization in DAL

In the pool-based method, we define  $U^n = \{X, \mathcal{Y}\}$  as an unlabeled dataset with  $n$  samples; here,  $X$  is the sample space,  $\mathcal{Y}$  is the label space, and  $P(x, y)$  is a potential distribution, where  $x \in X, y \in \mathcal{Y}$ .  $L^m = \{X, Y\}$  is the current labeled training set with  $m$  samples, where  $x \in X, y \in Y$ . Under the standard supervision environment of DAL, our main goal is to design a query strategy  $Q$ ,  $U^n \xrightarrow{Q} L^m$ , using the deep model  $f \in \mathcal{F}, f : X \rightarrow \mathcal{Y}$ . The optimization problem of DAL in a supervised environment can be expressed as follows:

$$\arg \min_{L \subseteq U, (x, y) \in L} \mathbb{E}_{(x, y)}[\ell(f(x), y)], \quad (1)$$

where  $\ell(\cdot) \in \mathcal{R}^+$  is the given loss equation, and we expect that  $m \ll n$ . Our goal is to make  $m$  as small as possible while ensuring a predetermined level of accuracy. Therefore, the query strategy  $Q$  in DAL is crucial to reduce the labeling cost.

**3.1.1 Batch Mode DAL (BMDAL).** The main difference between DAL and classic AL is that DAL uses batch-based sample querying. In traditional AL, most algorithms use a one-by-one query method, which leads to frequent training of the learning model but little change in the training data. The training set obtained by this query method is not only inefficient in the training of the DL model, but can also easily lead to overfitting. Therefore, it is necessary to investigate BMDAL in more depth. In the context of BMDAL, at each acquisition step, we score the batch of candidate unlabeled data samples  $\mathcal{B} = \{x_1, x_2, \dots, x_b\} \subseteq U$  based on the acquisition function used  $a$  and the deep model  $f_\theta(L)$  trained on  $L$ , to select a new batch of data samples  $\mathcal{B}^* = \{x_1^*, x_2^*, \dots, x_b^*\}$ . This problem can be formulated as follows:

$$\mathcal{B}^* = \arg \max_{\mathcal{B} \subseteq U} a_{batch}(\mathcal{B}, f_\theta(L)). \quad (2)$$

A naive approach would be to continuously query a batch of samples based on the one-by-one strategy. For example, [46, 73] adopts the method of batch acquisition, and chooses to query Bayesian Active Learning by Disagreement (BALD) [67] to obtain the top  $b$  samples with the highest scores. Obviously, however, this method is not feasible, as it is very likely to choose a set of information-rich but similar samples. The information provided to the model by such similar samples is essentially the same, which not only wastes labeling resources, but also makes it difficult for the model to learn genuinely useful information. Therefore, the core of BMDAL is to query a set of samples that are both information-rich and diverse. Fig.2 illustrates a schematic diagram of this idea.

The batch-based query strategy forms the basis of the combination of AL and DL, and related research on this topic is also very rich. We will provide a detailed overview and discussion of BMDAL query strategies in the following sections.

**3.1.2 Uncertainty-based and hybrid query strategies.** Because the the uncertainty-based approach is simple in form and has low computational complexity, it is a very popular query strategy in AL. This query strategy is mainly used in certain shallow models (eg, SVM [161] or KNN [72]). This is mainly because the uncertainty of these models can be accurately obtained by traditional uncertainty sampling methods (e.g., Margin Sampling, Least Confidence and Entropy [140]).

There are many DAL [9, 59, 114, 123] methods that directly utilize an uncertainty-based sampling strategy. However, as analyzed in Section 3.1.1, this can easily lead to insufficient diversity of batch query samples (such that relevant knowledge regarding the data distribution is not fully utilized), which in turn leads to low or even invalid DL model training performance. A feasible strategy would thus be to use a hybrid query strategy in a batch query, taking into account both the information volume and diversity of samples in either an explicit or implicit manner.

Early Batch Mode Active Learning (BMAL) [20, 77, 111, 171, 173] algorithm performance is often excessively reliant on the measurement of similarity between samples. In addition, these algorithms are often only good at exploitation (learners tend to focus only on samples near the current decision boundary, corresponding to high-information query strategies), meaning that the samples in the query batch sample set cannot represent the true data distribution of the feature space (due to the insufficient diversity of batch sample sets). To address this issue, Exploration-P [177] uses a deep neural network to learn the feature representation of the samples, then explicitly calculates the similarity between the samples. At the same time, the processes of exploitation and exploration (in the early days of model training, learners used random sampling strategies for exploration purposes) are balanced to enable more accurate measurement of the similarity between samples. Moreover, DBAL [183] adds informativeness to the optimization goal of K-means by weight, and further presents an in-depth study of a hybrid query strategy that considers the sample information volume and diversity under the mini-batch sample query setting. DBAL [183] can easily achieve expansion from the generalized linear model to DL; this not only increases the scalability of DBAL [183] but also increases the diversity of active query samples in the mini-batch. This hybrid query strategy is quite popular. For example, WI-DL [99] mainly considers the two stages of DBN. In the unsupervised feature learning stage, the key consideration is the representativeness of the data, while in the supervised fine-tuning stage, the uncertainty of the data is considered; these two indicators are then integrated, and finally optimized using the proposed weighted incremental dictionary learning (WI-DL) algorithm.

Although the above improvements have resulted in good performance, there is still a hidden danger that must be addressed: namely, that, diversity-based strategies are not appropriate for all datasets. More specifically, the richer the category content of the dataset, the larger the batch size, and the better the effect of diversity-based methods; by contrast, an uncertainty-based query strategy will perform better with smaller batch sizes and less rich conten. These characteristics depend on the statistical characteristics of the dataset. the BMAL context, the data are unfamiliar and potentially unstructured, making it impossible to determine which AL query strategy is more appropriate. In light of this, Batch Active learning by Diverse Gradient Embeddings (BADGE) [10] samples point groups that are disparate and high magnitude when represented in a hallucinated gradient space, meaning that both the prediction uncertainty of the model and the diversity of the samples in a batch are considered simultaneously. Most importantly, BADGE can achieve an automatic balance between forecast uncertainty and sample diversity without the need for manual hyperparameter adjustments. Moreover, while BADGE [10] considers this hybrid query strategy in

an implicit way, Wasserstein Adversarial Active Learning (WAAL) [146] proposes a hybrid query strategy that explicitly balances uncertainty and diversity. In addition, WAAL [146] uses Wasserstein distance to model the interactive procedure in AL as a distribution matching problem, derives losses from it, and then decomposes WAAL [146] into two stages: DNN parameter optimization and query batch selection. Task-Aware Variational Adversarial Active Learning (TA-VAAL) [81] also explores the balance of this hybrid query strategy. The assumption underpinning TA-VAAL is that the uncertainty-based method does not make good use of the overall data distribution, while the data distribution-based method often ignores the structure of the task. Consequently, TA-VAAL proposes to integrate the loss prediction module [178] and the concept of RankCGAN [133] into Variational Adversarial Active Learning (VAAL) [150], enabling both the data distribution and the model uncertainty to be considered. TA-VAAL has achieved good performance on various balanced and unbalanced benchmark datasets. The structure diagram of TA-VAAL and VAAL is presented in Fig.6a.

Notably, although the hybrid query strategy achieves superior performance, the uncertainty-based AL query strategy is more convenient to combine with the output of the softmax layer of DL. Thus, the query strategy based on uncertainty is still widely used.

**3.1.3 Deep Bayesian Active Learning (DBAL).** As noted in Section 2, which analyzed the challenge of combining DL and AL, the acquisition function based on uncertainty is an important research direction of many classic AL algorithms. Moreover, traditional DL methods rarely represent such model uncertainty.

For this reason, Deep Bayesian Active Learning has been developed. In the given input set  $X$  and the output  $Y$  belonging to class, the probabilistic neural network model can be defined as  $f(x; \theta)$ ,  $p(\theta)$  is a prior on the parameter space  $\theta$  (usually Gaussian), and the likelihood  $p(y = c|x, \theta)$  is usually determined by  $\text{softmax}(f(x; \theta))$  given. Our goal is to obtain the posterior distribution over  $\theta$ , as follows:

$$p(\theta|X, Y) = \frac{p(Y|X, \theta)p(\theta)}{p(Y|X)}. \quad (3)$$

For a given new data point  $x^*$ ,  $\hat{y}$  is predicted by:

$$p(\hat{y}|x^*, X, Y) = \int p(\hat{y}|x, \theta) p(\theta|X, Y) d\theta = \mathbb{E}_{\theta \sim p(\theta|X, Y)}[f(x; \theta)]. \quad (4)$$

DBAL [47] combines Bayesian convolutional neural networks (BCNNs) [45] with AL methods to adapt BALD [67] to the deep learning environment, thereby developing a new AL framework for high-dimensional data. This approach adopts the above method to first perform Gaussian prior modeling on the weights of a CNN, and then uses variational inference to obtain the posterior distribution of network prediction. In addition, in practice, researchers often also use a powerful and low-cost Monte-Carlo dropout (MC-dropout) [156] stochastic regularization technique to obtain posterior samples, consequently attaining good performance on real-world datasets [80, 94]. Moreover, this regularization technique has been proven to be equivalent to variational inference [46]. However, a core-set approach [138] points out that DBAL [47] is unsuitable for large datasets due to the need for batch sampling. It should be noted here that while DBAL [47] allows the use of dropout in testing for better confidence estimation, the analysis presented in [51] contends that the performance of this method is similar to the performance of using neural network softmax response (SR) [166] as uncertainty sampling, which requires vigilance. In addition, DFAL [36] pointed out that the uncertainty-based DBAL [44, 46] method may be fooled by adversarial examples, such that even a slight disturbance may result in unacceptable performance loss. DEBAL [118] argues that the pattern collapse phenomenon [155] in the variational inference method leads to the overconfident prediction characteristic of the DBAL method. For this reason, DEBAL combines the expressive



power of ensemble methods with MC-dropout to obtain better uncertainty in the absence of trading representativeness. For its part, BatchBALD [84] opts to expand BALD [67] to the batch query context; this approach no longer calculates the mutual information between a single sample and model parameters, but rather recalculates the mutual information between the batch samples and the model parameters to jointly score the batch of samples. This enables, BatchBALD to more accurately evaluate the joint mutual information. Inspired by the latest research on Bayesian core sets [23, 69], ACS-FW [117] reconstructed the batch structure to optimize the sparse subset approximation of the log posterior induced by the entire dataset. Using this similarity, ACS-FW then employs the Frank-Wolfe [42] algorithm to enable effective Bayesian AL at scale, while its use of random projection has made it still more popular. Compared with other query strategies (e.g. maximizing the predictive entropy (MAXENT) [47, 138] and BALD [67]), ACS-FW achieves better coverage across the entire data manifold. DPEs [28] introduces an expandable Deep Probabilistic Ensembles (DPEs) technology, which uses a regularized ensemble to approximate deep BNN, then evaluates the classification effect of these DPEs in a series of large-scale visual AL experiments.

ActiveLink [114] is inspired by the latest advances in Bayesian deep learning [46, 172]. Adopting the Bayesian view of the existing neural link predictors, it expands the uncertainty sampling method by using the basic structure of the knowledge graph, thereby creating a novel DAL method. ActiveLink further noted that although AL can sample efficiently, the model needs to be retrained from scratch for each iteration in the AL process, which is unacceptable in the DL model training context. A simple solution would be to use newly selected data to train the model incrementally, or to combine it with existing training data [145]; however, this would cause the model to be biased either towards a small amount of newly selected data or towards data selected early in the process. In order to solve this bias problem, ActiveLink adopts a principled and unbiased incremental training method based on meta-learning. More specifically, in each AL iteration, ActiveLink uses the newly selected samples to update the model parameters, then approximates the meta-objective of the model's future prediction by generalizing the model based on the samples selected in the previous iteration. This enables ActiveLink to strike a balance between the importance of the newly and previously selected data, and thereby to achieve unbiased estimation of the model parameters.

In addition to the above-mentioned DBAL work, due to the lesser parameter of BNN and the uncertainty sampling strategy being similar to traditional AL, the research into DBAL is quite extensive, and there are many works related to this topic [54, 105, 126, 147, 175, 179].

**3.1.4 Density-based Methods.** The term, density-based method, mainly refers to the selection of samples from the perspective of the set (core set). The construction of the core set is a representative query strategy. This idea is mainly inspired by the compression idea of the coreset dataset, and attempts to use the core set to represent the distribution of the feature space of the entire original dataset, thereby reducing the labeling cost of AL.

Farthest First Active Learning (FF-Active) [49] is based on this idea and uses the farthest-first traversals in the space of neural activation over a representation layer to query consecutive points from the pool. It is worth noting here that FF-Active [49] and Exploration-P [177] resemble the way in which random queries are used in the early stages of AL to enhance AL's exploration ability, which prevents AL from falling into the trap of insufficient sample diversity. Similarly, in order to solve the sampling bias problem in batch querying, the diversity of batch query samples is increased. The Core-set approach [138] attempts to solve this problem by constructing a core subset. A further attempt was made to solve the k-Center problem [38] by building a core subset, so that the model learned on the selected core set will be more competitive than the rest of the data. However, the Core-set approach requires a large distance matrix to be built on the unlabeled data

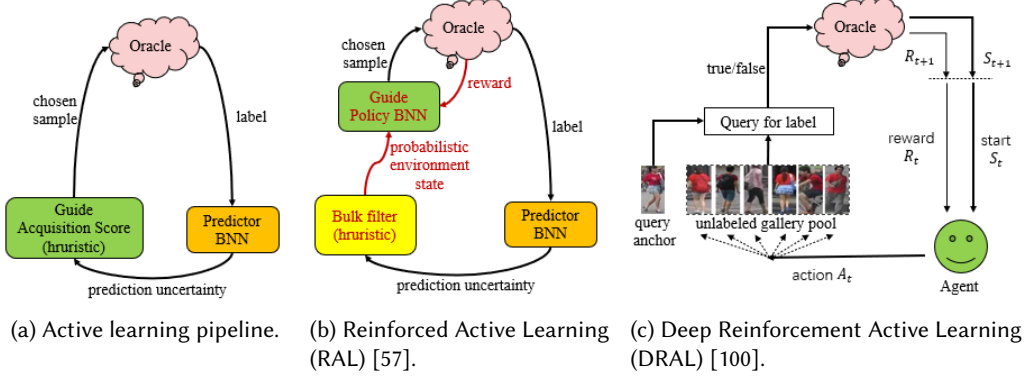


Fig. 3. Comparison of standard AL, RAL [57] and DRAL [100] pipelines. (a) The standard AL pipeline usually consists of three parts. The oracle provides a set of labeled data; the predictor (here, BNN) is used to learn these data, and provides predictable uncertainty for the guide. The guide is usually a fixed, hard-coded acquisition function that picks the next sample for the oracle to restart the cycle. (b) RAL replaces the fixed acquisition function with the policy BNN. The policy BNN learns in a probabilistic manner, obtains feedback from the oracle, and learns how to select the next optimal sample point (new parts in red) in a reinforcement learning-based manner. Therefore, RAL can adjust the acquisition function more flexibly to adapt to the existing dataset. (c) DRAL utilizes a deep reinforcement active learning framework for the person Re-ID task. For each query anchor (probe), the agent (reinforcement active learner) will select sequential instances from the gallery pool during the active learning process and hand it to the oracle to obtain manual annotation with binary feedback (positive/negative). The state evaluates the similarity relationships between all instances and calculates rewards based on oracle feedback to adjust agent queries.

set, meaning that this search process is computationally expensive; this disadvantage will become more apparent on large-scale unlabeled datasets [10].

Active Palmprint Recognition [35] applies DAL to high-dimensional and complex palmprint recognition data. Similar to the core set concept, Active Palmprint Recognition [35] regards AL as a binary classification task. It is expected that the labeled and unlabeled sample sets will have the same data distribution, making the two difficult to distinguish; that is, the goal is to find a labeled core subset with the same distribution as the original dataset. More specifically, due to the heuristic generative model simulation data distribution being difficult to train and unsuitable for high-dimensional and complex data such as palm prints, the author considers whether the sample can be positively distinguished from the unlabeled or the labeled dataset with a high degree of confidence. Those samples that can be clearly distinguished are obviously different from the data distribution of the core annotation subset. These samples will then be added to the annotation dataset for the next round of training. Previous core-set-based methods [49, 138] often simply try to query data points as far as possible to cover all points of the data manifold without considering the density, which results in the queried data points overly representing sample points from manifold sparse areas. Similar to [35], Discriminative Active Learning (DAL) [51] also regards AL as a binary classification task, and further aims to make the queried labeled dataset indistinguishable from the unlabeled dataset. The key advantage of DAL [51] is that it can sample from unlabeled dataset in proportion to the data density, without biasing the sample points in the sparse popular domain. Moreover, the method proposed by DAL [51] is not limited to classification tasks, which are conceptually easy to transfer to other new tasks.

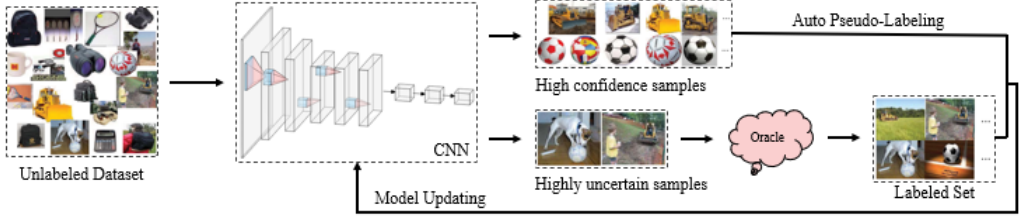


Fig. 4. In CEAL [166], the overall framework of DAL is utilized. CEAL [166] gradually feeds the samples from the unlabeled dataset to the initialized CNN, after which the CNN classifier outputs two types of samples: a small number of uncertain samples and a large number of samples with high prediction confidence. A small number of uncertain samples are labeled through the oracle, and the CNN classifier is used to automatically assign pseudo-labels to a large number of high-prediction confidence samples. These two types of samples are then used to fine-tune the CNN, and the updated process is repeated.

In addition to the corresponding query strategy, some researchers have also considered the impact of batch query size on query performance. For example, [10, 84, 117, 183] focus primarily on the optimization of query strategies in smaller batches, while [27] recommended expanding the query scale of AL for large-scale sampling (10k or 500k samples at a time). Moreover, by integrating hundreds of models and reusing intermediate checkpoints, the distributed searching of training data on large-scale labeled datasets can be efficiently realized with a small computational cost. [27] also proved that the performance of using the entire dataset for training is not the upper limit of performance, as well as that AL based on subsets specifically may yield better performance.

Density-based methods primarily consider the selection of core subsets from the perspective of data distribution. There are relatively few related research methods, which suggests a new possible direction for sample querying.

**3.1.5 Other methods.** There are also some existing studies that are not as focused as the above query methods; we will summarize them below.

For example, [37] redefines the heuristic AL algorithm as a reinforcement learning problem and introduces a new description through a clear selection strategy. Unlike most previous uncertainty-based methods, DFAL [36] contends that these methods are easily fooled by adversarial examples; thus, it focuses on the study of examples near the decision boundary, and actively uses the information provided by these adversarial examples on the input spatial distribution in order to approximate their distance to the decision boundary. This adversarial query strategy can effectively improve the convergence speed of CNN training. On the other hand, AL aims to utilize the relative importance of the data to engage in as little data labeling as possible while still efficiently training a model with satisfactory performance. Therefore, the attributes of the dataset itself also have an important impact on the performance of DAL. With this in mind, GA [164] assessed the relative importance of image data in common datasets and proposed a general data analysis tool designed to facilitate a better understanding of the diversity of training examples in the dataset. GA found that not all datasets can be trained on a small sub-sample set, because the relative difference of sample importance in some datasets is almost negligible; therefore, it is not advisable to blindly use smaller sub-datasets in the AL context. [14] found that compared with the Bayesian deep learning approach (Monte-Carlo dropout [47]) and density-based [137] methods, ensemble-based AL can effectively offset the imbalance of categories in the dataset during the acquisition process, resulting in more calibration prediction uncertainty, and thus better performance.

Some researchers have also noted that, in traditional AL workflows, the acquisition function is often regarded as a fixed known prior, and that it will not be known whether this acquisition function is appropriate until the label budget is exhausted. This makes it impossible to flexibly and quickly tune the acquisition function. Accordingly, one good option may be to use reinforcement learning to dynamically tune the acquisition function. RAL [57] proposes to use BNN as a learning predictor for acquisition functions. As such, all probability information provided by the BNN predictor will be combined to obtain a comprehensive probability distribution; subsequently, the probability distribution is sent to a BNN probabilistic policy network, which performs reinforcement learning in each labeling round based on the oracle feedback. This feedback will fine-tune the acquisition function, thereby continuously improving its quality. DRAL [100] adopted a similar idea and designed a deep reinforcement active learning framework for the person Re-ID task. This approach uses the idea of reinforcement learning to dynamically adjust the acquisition function so as to obtain high-quality query samples. Fig.3 presents a comparison between traditional AL, RAL and DRAL pipelines.

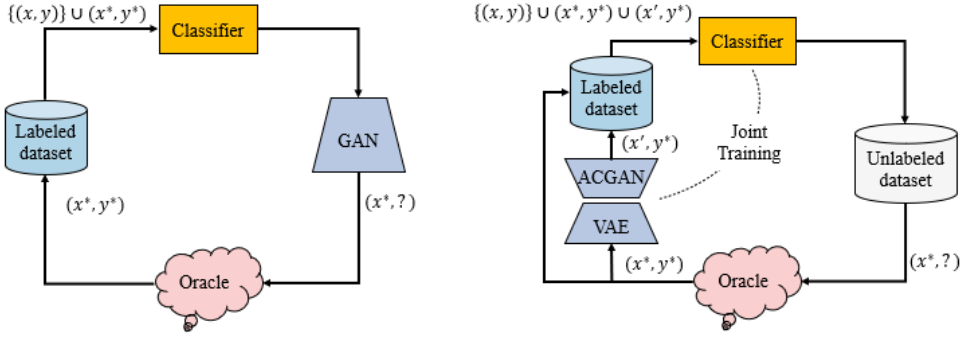
On the other hand, Active-iNAS [50] notices that most previous DAL methods [3, 5, 89] assume that a suitable DL model has been designed for the current task, meaning that their primary focus is on how to design an effective query mechanism; however, the existing DL model is not necessarily optimal for the current DAL task. Active-iNAS [50] accordingly challenges this assumption and uses neural architecture search (NAS) [124] technology to dynamically search for the most effective model architectures while conducting active learning. There is also some work devoted to providing a convenient performance comparison platform for DAL; for example, [108] discusses and studies the robustness and reproducibility of the DAL method in detail, and presents many useful suggestions.

In general, these query strategies are not independent of each other, but are rather interrelated. Batch-based BMDAL provides the basis for the update training of AL query samples on the DL model. Although the query strategies in DAL are rich and complex, they are largely designed to take the diversity and uncertainty of query batches in BMDAL into account. Previous uncertainty-based methods often ignore the diversity in the batch, and can thus be roughly divided into two categories: those that design a mechanism that explicitly encourages batch diversity in the input or learning representation space, and those that directly measure the mutual information (MI) of the entire batch.

### 3.2 Insufficient Data in DAL

AL often requires only a small amount of labeled sample data to realize learning and model updating, while DL requires a large amount of labeled data for effective training. Therefore, the combination of AL and DL requires as much as possible to use the data strategy without consuming too much human resources to achieve DAL model training. Most previous DAL methods [181] often only train on the labeled sample set sampled by the query strategy. However, this ignores the existence of existing unlabeled datasets, meaning that the corresponding data expansion and training strategies are not fully utilized. These strategies help to improve the problem of insufficient labeled data in DAL training without adding to the manual labeling costs. Therefore, the study of these strategies is also quite meaningful.

For example, CEAL [166] enriches the training set by assigning pseudo-labels to samples with high confidence in model prediction in addition to the labeled data set sampled by the query strategy. This expanded training set is then also used in the training of the DL model. This strategy is shown in Fig.4. Another very popular strategy involves performing unsupervised training on labeled and unlabeled datasets and incorporating other strategies to train the entire network structure. For example, WI-DL [99] notes that full DBN training requires a large number of training samples,



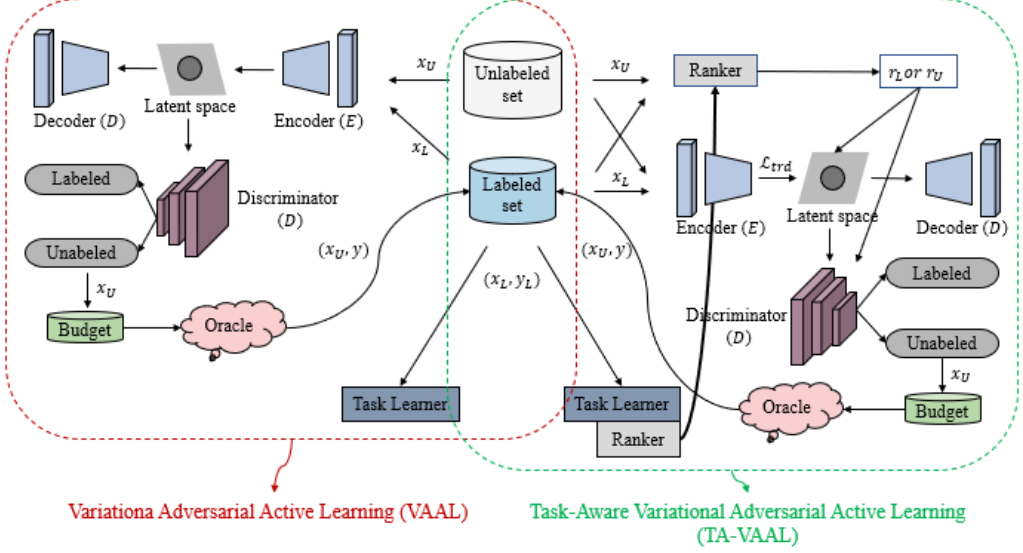
(a) Generative adversarial active learning (GAAL). (b) Bayesian generative active deep learning (BGADL).

Fig. 5. Structure comparison chart of GAAL [187] and BGADL [162]. For more details, please see [162].

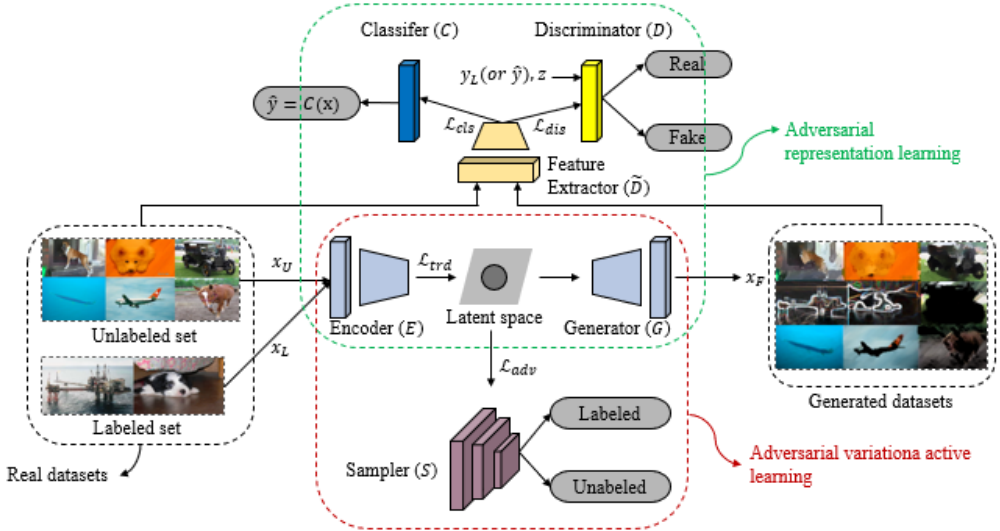
and it is impractical to apply DBN to a limited training set in an AL context. Therefore, in order to improve the training efficiency of DBN, WI-DL employs a combination of unsupervised feature learning on all datasets and supervised fine-tuning on labeled datasets.

At the same time, some researchers have considered using Generative Adversarial Networks (GAN) for data augmentation. For example, GAAL [187] introduced the Generative Adversarial Network (GAN) to the AL query method for the first time. GAAL aims to use generative learning to generate samples with more information than the original dataset. However, random data augmentation does not guarantee that the generated samples will have more information than those contained in the original data, and could thus represent a waste of computing resources. Accordingly, BGADL [162] expands the idea of GAAL [187] and proposes a Bayesian generative active deep learning method. More specifically, BGADL combines the generative adversarial active learning (GAAL) [187], Bayesian data augmentation [163], auxiliary-classifier generative adversarial networks (ACGAN) [113] and variational autoencoder (VAE) [83] methods, with the aim of generating samples of disengagement regions [140] belonging to different categories. A structure comparison between GAAL and BGADL is presented in Fig.5.

Subsequently, VAAL [150] and ARAL [107] borrowed from several previous methods [99, 162, 187] not only to train the network using labeled and unlabeled datasets, but also to introduce generative adversarial learning into the network architecture for data augmentation purposes, thereby further improving the learning ability of the network. In more detail, VAAL [150] noticed that the batch-based query strategy based on uncertainty not only readily leads to insufficient sample diversity, but is also highly susceptible to interference from outliers. In addition, density-based methods [138] are susceptible to  $p$ -norm limitations when applied to high-dimensional data, resulting in calculation distances that are too concentrated [6]. To this end, VAAL [150] proposes to use the adversarial learning representation method to distinguish between the potential spatial coding features of labeled and unlabeled data, thus reducing interference from outliers. VAAL [150] also uses labeled and unlabeled data to jointly train a variational autoencoder (VAE) [83, 154] in a semi-supervised manner; the goal here is to deceive the adversarial network [52] into predicting that all data points come from the labeled pool, in order to solve the problem of distance concentration. VAAL [150] can learn an effective low-dimensional latent representation on a large-scale dataset, and further provides an effective sampling method by jointly learning the representation form and uncertainty.



(a) Structure comparison chart of VAAL [150] and TA-VAAL [81]. 1) VAAL uses labeled data and unlabeled data in a semi-supervised way to learn the latent representation space of the data, then selects the unlabeled data with the largest amount of information according to the latent space for labeling. 2) TA-VAAL expands VAAL and integrates the loss prediction module [178] and RankCGAN [133] into VAAL in order to consider data distribution and model uncertainty simultaneously.



(b) The overall structure of ARAL [107]. ARAL also represents an expansion of VAAL. ARAL uses not only real datasets (both labeled and unlabeled), but also generated datasets to jointly train the network. The whole network consists of an encoder (E), generator (G), discriminator (D), classifier (C) and sampler (S), and all parts of the model are trained together.

Fig. 6. The structure comparison of VAAL [150], ARAL [107] and TA-VAAL [81].

Subsequently, ARAL [107] expanded VAAL [150], aiming to use as few manual annotation samples as possible while still making full use of the existing or generated data information in order to improve the model's learning ability. In addition to using labeled and unlabeled datasets, ARAL [107] also uses samples produced by deep production networks to jointly train the entire model. ARAL [107] comprises both VAAL [150] and adversarial representation learning [33]. By using VAAL [150] to learn the potential feature representation space of the labeled and unlabeled data, the unlabeled samples with the largest amount of information can be selected accordingly. At the same time, both real and generated data are used to enhance the model's learning ability through confrontational representation learning [33]. Similarly, TA-VAAL [81] also extends VAAL by using the global data structure from VAAL and local task-related information from the learning loss for sample querying purposes. We present the frameworks of VAAL [150], ARAL [107] and TA-VAAL [81] in Fig.6.

Unlike ARAL [107] and VAAL [150], which use labeled and unlabeled datasets for adversarial representation learning, SSAL implements a new training method. More specifically, SSAL uses unsupervised, supervised and semi-supervised learning methods across AL cycles, and makes full use of existing information for training without increasing the cost of labeling as much as possible. In more detail, the process is as follows: before the AL starts, first use labeled and unlabeled data for unsupervised pre-training. In each AL learning cycle, first perform supervised training on the labeled dataset, then perform semi-supervised training on all datasets. This represents an attempt to devise a wholly new training method. The author found that, compared with the difference between the sampling strategies, this model training method yields a surprising performance improvement.

As analyzed above, this kind of exploration of training methods and data utilization skills is also highly important; in fact, the resultant performance gains may even exceed those generated by changing the query strategy. Applying these techniques enables the full use of existing data without any associated increase in labeling costs, which helps in resolving the issue of the number of AL query samples being insufficient to support the updating of the DL model.

### 3.3 Common Framework DAL

As mentioned in Section 2, a processing pipeline inconsistency exists between AL and DL; thus, only fine-tuning the DL model in the AL framework, or simply combining AL and DL to treat them as two separate problems, may cause divergence. For example, [9] first conducts offline supervised training of the DL model on two different types of session datasets to grant basic conversational capabilities to the backbone network, then enables the online AL stage to interact with human users, enabling the model to be improved in an open way based on user feedback. AL-DL [165] proposes an AL method for DL models with DBNs, while ADN [184] further proposes an active deep network architecture for sentiment classification. [157] proposed an AL algorithm using CNN for captcha recognition. However, generally speaking, the above methods first perform routine supervised training on this deep model on the labeled dataset, then actively sample based on the output of the deep model. There are many similar related works [39, 144] that adopt this split-and-splitting approach that treats the training of AL and deep models as two independent problems and consequently increases the possibility, which the two problems will diverge. Although this method achieved some success at the time, a general framework that closely combines the two tasks of DL and AL would play a vital role in the performance improvement and promotion of DAL.

CEAL [166] is one of the first works to combine AL and DL in order to solve the problem of depth image classification. CEAL [166] merges deep convolutional neural networks into AL, and consequently proposes a novel DAL framework. It sends samples from the unlabeled dataset to the CNN step by step, after which the CNN classifier outputs two types of samples: a small number of uncertain samples, and a large number of samples with high prediction confidence. A small number

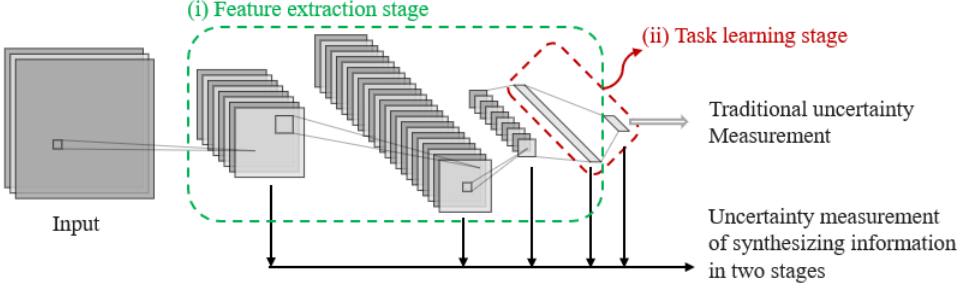


Fig. 7. Taking a common CNN as an example, this figure presents a comparison between the traditional uncertainty measurement method [35, 103, 176] and the uncertainty measurement method of synthesizing information in two stages [59, 178, 182] (i.e., the feature extraction stage and task learning stage).

of the uncertain samples are labeled by the oracle, and the CNN classifier is used to automatically assign pseudo-labels to a large number of high-prediction-confidence samples. Then, these two types of samples are used to fine-tune the CNN and the update process is repeated. In Fig.4, we present the overall framework of CEAL. Moreover, HDAL [96] uses a similar framework for face recognition tasks: it combines AL with a deep CNN model to integrate feature learning and AL query model training.

In addition, Fig.1c illustrates a very common general framework for DAL tasks. Related works include [35, 59, 103, 176, 182], among others. More specifically, [176] proposes a framework that uses a fully convolutional network (FCN) [101] and AL to solve the medical image segmentation problem using a small number of annotations. It first trains FCN on a small number of labeled datasets, then extracts the features of the unlabeled datasets through FCN, using these features to estimate the uncertainty and similarity of unlabeled samples. This strategy, which is similar to that described in Section 3.1.2, helps to select highly uncertain and diverse samples to be added to the labeled dataset in order to start the next stage of training. Active Palmprint Recognition [35] proposes a similar DAL framework as that for the palmprint recognition task. The difference is that, inspired by domain adaptation [15], Active Palmprint Recognition [35] regards AL as a binary classification task: it is expected that the labeled and unlabeled sample sets have the same data distribution, making the two difficult to distinguish. Supervision training can be performed directly on a small amount of labeled datasets, which reduces the burden associated with labeling. [103] proposes a DAL framework for defect detection. This approach involves performing uncertainty sampling based on the features output by the detection model in order to generate a list of candidate samples for annotation. In order to further take the diversity of defect categories in the samples into account, [103] designed an average margin method to control the sampling ratio of each defect category.

Different from the above methods, it is common for only the final output of the DL model to be used as the basis for determining the uncertainty or diversity of the sample (Active Palmprint Recognition [35] uses the output of the first fully connected layer). [59, 178, 182] also used the output of the DL model's middle hidden layer. As analyzed in Section 3.1.2 and Section 2, due to the difference in learning paradigms between the deep and shallow models, the traditional uncertainty-based query strategy cannot be directly applied to the DL model. In addition, unlike the shallow model, the deep model can be regarded as composed of two stages, namely the feature extraction stage and the task learning stage. It is inaccurate to use only the output of the last layer of the DL model as the basis for evaluating the sample prediction uncertainty; this is because the



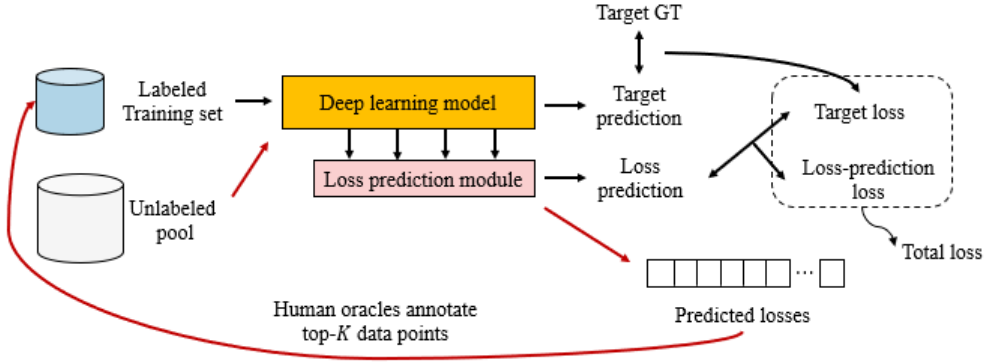


Fig. 8. The overall framework of LLAL [178]. The black line represents the stage of training model parameters, optimizing the overall loss composed of target loss and loss-prediction loss. The red line represents the sample query phase of AL. The output of the multiple hidden layers of the DL model is used as the input of the loss prediction module, while the top- $K$  unlabeled data points are selected according to the predicted losses and assigned labels by the oracle.

uncertainty of the DL model is in fact composed of the uncertainty of these two stages. A schematic diagram of this concept is presented in Fig.7. To this end, AL-MV [59] treats the features from different hidden layers in the middle of CNN as multi-view data, taking the uncertainty of both stages into account, and the AL-MV algorithm is designed to implement adaptive weighting of the uncertainty of each layer, so as to enable more accurate measurement of the sample uncertainty. LLAL [178] also used a similar idea. More specifically, LLAL designed a small parameter module of the loss prediction module to attach to the target network, using the output of multiple hidden layers of the target network as the input of the loss prediction module. The loss prediction module is learned to predict the target loss of the unlabeled dataset, while the top- $K$  strategy is used to select the query samples. LLAL achieves task-agnostic AL framework design at a small parameter cost, and further achieves competitive performance on a variety of mainstream visual tasks (namely, image classification, target detection, and human pose estimation). Similarly, [182] uses a similar strategy to implement a DAL framework for finger bone segmentation tasks. [182] uses Deeply Supervised U-Net [125] as the segmentation network, then subsequently uses the output of the multi-level segmentation hidden layer and the output of the last layer as the input of AL; this input information is then integrated to form the basis for the evaluation of the sample information size. We take LLAL [178] as an example to explicate the overall network structure of this idea in Fig.8.

The research on the general framework is highly beneficial to the development and promotion of DAL, as this task-independent framework can be conveniently transplanted to other fields. In the current fusion of DL and AL, DL is primarily responsible for feature extraction, while AL is mainly responsible for sample querying; thus, a deeper and tighter fusion will help DAL achieve better performance. Of course, this will require additional exploration and effort on the part of researchers.

#### 4 VARIOUS APPLICATIONS OF DAL

Today, DAL has been applied to areas including but not limited to visual data processing (such as object detection, semantic segmentation, etc.), NLP (such as sentiment analysis, question and answer, etc.), speech and audio processing, social network analysis, medical image processing, wildlife protection, industrial robotics and disaster analysis, among other fields. In this section,

we provide a systematic and detailed overview of existing DAL-related work from an application perspective.

#### 4.1 Visual Data Processing

Just as DL is widely used in the computer vision field, the first field in which DAL is expected to reach its potential is that of computer vision. In this section, we mainly discuss DAL-related research in the field of visual data processing.

*4.1.1 Image classification and recognition.* As with DL, the classification and recognition of images in DAL forms the basis for research into other vision tasks. One of the most important problems that DAL faces in the field of image vision tasks is that of how to efficiently query samples of high-dimensional data (an area in which traditional AL performs poorly) and obtain satisfactory performance at the smallest possible labeling cost.

To solve this problem, CEAL [166] assigns pseudo-labels to samples with high confidence and adds them to the highly uncertain sample set queried using the uncertainty-based AL method, then uses the expanded training set to train the DAL model image classifier. [123] first integrated the criteria of AL into the deep belief network, and subsequently conducted extensive research on classification tasks on a variety of real uni-modal and multi-modal datasets. WI-DL [99] uses the DAL method to simultaneously consider the two selection criteria of maximizing representativeness and uncertainty on hyperspectral image (HSI) datasets for remote sensing classification tasks. Similarly, [32, 97] also studied the classification of HSI. [97] introduces AL to initialize HSI, and then performs transfer learning. This work also recommends constructing and connecting higher-level features to source and target HSI data in order to further overcome the cross-domain disparity. [32] proposed a unified deep network combined with active transfer learning, thereby training the HSI classification well while using less labeled training data.

In addition, medical image analysis is also an important application. For example, [41] explore the use of AL rather than random learning to train convolutional neural networks for tissue (e.g., stroma, lymphocytes, tumor, mucosa, keratin pearls, blood, and background/adipose) classification tasks. [21] conducted a comprehensive review of DAL-related methods in the field of medical image analysis. As discussed above, since the annotation of medical images requires strong professional knowledge, it is usually both very difficult and very expensive to find well-trained experts willing to perform annotation. In addition, DL has achieved impressive performance on various image feature tasks. Therefore, a large number of works continue to focus on combining DL and AL in order to apply DAL to the field of medical image analysis [25, 34, 89, 131, 134, 135, 151, 152]. The DAL method is also used to classify in situ plankton [19], and perform the automatic counting of cells [5].

In addition, DAL also has a wide range of applications in our daily life. For example, [157] proposed an AL algorithm that uses CNN for verification code recognition. It can use the ability to obtain labeled data for free to avoid human intervention and greatly improve the recognition accuracy when less labeled data is used. HDAL [96] combines the excellent feature extraction capabilities of deep convolutional neural networks (CNN) and the ability to save on AL labeling costs to design a heuristic deep active learning framework for face recognition tasks.

*4.1.2 Object detection and semantic segmentation.* Object detection and semantic segmentation have important applications in various fields, including autonomous driving, medical image processing, and wildlife protection. However, these fields are also limited by the higher sample labeling cost. Thus, the lower labeling cost of DAL is expected to accelerate the application of corresponding DL models in certain real-world areas where labeling is more difficult.

[128] designed a DAL framework for object detection, which uses the layered architecture where labeling is more difficult as an example of "query by committee" to select the image set to be queried, while at the same time introducing a similar exploration/exploitation trade-off strategy to [177]. DAL is also widely used in natural biological fields and industrial applications. For example, [112] uses deep neural networks to quickly, transferably and automatically extract information, and further combines transfer learning and AL to design a DAL framework for species identification and counting in camera trap images. [79] uses unmanned aerial vehicles (UAV) to obtain images for wildlife detection purposes; moreover, to enable this wildlife detector to be reused, [79] uses AL and introduces transfer sampling (TS) to find the corresponding area between the source and target datasets, thereby facilitating the transfer of data to the target domain. [39] proposes a DAL framework for deep object detection in autonomous driving to train LiDAR 3D object detectors. [103] proposes the adaptation of a very common DAL framework to defect detection in real industries, along with an uncertainty sampling method for use in generating candidate label categories. This work uses the average margin method to set the sampling scale of each defect category, and is thus able to obtain the required performance with less labeled data.

In addition, DAL also has important applications in the area of medical image segmentation. For example, [48] proposes an AL-based transfer learning mechanism for medical image segmentation, which can effectively improve the image segmentation performance on a limited labeled dataset. [176] combines fully convolutional networks (FCN) and AL to create a DAL framework for biological image segmentation. This work uses the uncertainty and similarity information provided by the FCN to extend the maximum set cover problem, significantly reducing the required labeling workload by pointing out the most effective labeling areas. DASL [170] proposes a deep region-based network, Nodules R-CNN, for pulmonary nodule segmentation tasks. This work generates segmentation masks for use as examples, and at the same time, combines AL and Self-Paced Learning (SPL) [88] to propose a new Deep Active Self-paced Learning (DASL) strategy that reduces the labeling workload. [169] proposes a Nodule-plus Region-based CNN for pulmonary nodule detection and segmentation in 3D thoracic Computed Tomography (CT). This work combines AL and self-paced learning (SPL) strategies to create a new deep self-paced active learning (DSAL) strategy, which reduces the annotation workload and makes effective use of unannotated data. [182] further proposes a new deep-supervised active learning method for finger bone segmentation tasks. This model can be fine-tuned in an iterative and incremental learning manner, and uses the output of the intermediate hidden layer as the basis for sample selection. Compared with the complete markup, [182] achieved comparable segmentation results using fewer samples.

**4.1.3 Video processing.** Compared with images, which require only the processing of spatial features, video tasks also need to process temporal features. This makes the work of annotating video tasks is more expensive, meaning that the need to introduce AL is therefore more urgent. DAL also has broader application scenarios in this field.

For example, [70] proposes to use imitation learning to perform navigation tasks. The visual environment and actions taken by the teacher viewed from a first-person perspective are used as the training set. Through training, it is hoped that students will become able to predict and execute corresponding actions in their own environment. When performing tasks, students use deep convolutional neural networks for feature extraction, learn imitation strategies, and further use the AL method to select samples with insufficient confidence, which are added to the training set to update the action strategy. [70] significantly improves the initial strategy using fewer samples. DeActive [66] proposed a DAL activity recognition model. Compared with the traditional DL activity recognition model, DeActive requires fewer labeled samples, consumes less resources, and achieves high recognition accuracy. [167] minimizes the annotation cost of the video-based

person Re-ID dataset by integrating AL into the DL framework. Similarly, [100] proposes a deep reinforcement active learning method for person Re-ID, using oracle feedback to guide the agent (i.e. the model in the reinforcement learning process) in selecting the next uncertainty sample. The agent selection mechanism is continuously optimized through alternately refined reinforcement learning strategies. [3] further proposes an active learning object detector method based on convolutional neural networks, for pedestrian target detection in video and static images.

## 4.2 Natural Language Processing (NLP)

NLP has always been a very challenging task. The goals of NLP are to make computers understand complex human language and to help humans deal with various natural language-related tasks. Insufficient data labeling is also a key challenge in the NLP context. Below, we introduce some of the most famous DAL methods in the NLP field.

**4.2.1 Sentiment Analysis.** In this typical NLP task, the aim is to make the computer understand a natural language description and extract and analyze the meaning information.

The relevant application scenarios are numerous and varied, including but not limited to sentiment classification, news identification, named entity recognition (NER), etc. More specifically, for example, [184] uses restricted Boltzmann machines (RBM) to construct an active deep network (ADN), then conduct unsupervised training on the labeled and unlabeled datasets. ADN uses a large number of unlabeled datasets to improve the model's generalization ability, and further employs AL in a semi-supervised learning framework, unifying the selection of labeled data and classifiers in a semi-supervised classification framework; this approach obtains competitive results on sentiment classification tasks. [17] proposes a human-computer collaborative learning system for news accuracy detection tasks (that is, identifying misleading and false information in news) that utilizes only a limited number of annotation samples. This system is a deep AL-based model that uses 1-2 orders of magnitude fewer annotation samples than fully supervised learning. Such a reduction in the number of samples greatly accelerates the convergence speed of the model and results in an astonishing 25% average performance gain in detection performance.

In addition, [24, 143, 145] uses the combination of DL and AL to determine how the technical level of NER can be improved in the case of a small training set. [119] uses relevant tweets from disaster-stricken areas to extract information that facilitates the identification of infrastructure damage during earthquakes. For this reason, [119] combines RNN and GRU-based models with AL, using AL-based methods to pre-train the model so that it will retrieve tweets featuring infrastructure damage in different regions, thereby significantly reducing the manual labeling workload. Moreover, entity resolution (ER) is the task of recognizing the same real entities with different representations across databases, and represents a key step in knowledge base creation and text mining. [78] developed a DL-based ER method that combines transfer learning and AL to design an architecture that allows for the learning of a model that is transferable from high-resource environments to low-resource environments.

**4.2.2 Question-answering and summarization.** Question-answering systems and automatic summarization are also common processing tasks in the NLP context, and DL has achieved impressive results in these areas. However, the performance of these applications still relies on the availability of massive labeled datasets; AL is expected to bring new hope to this challenge.

The automatic question-answering system has a very wide range of applications in the industry, and DAL is also highly valuable in this field. For example, [9] uses the online AL strategy combined with the DL model to achieve an open domain dialogue by interacting with real users and learning incrementally from user feedback in each round of dialogue. [74] found that AL strategies designed

for specific tasks (e.g., classification) often have only one correct answer, and that these uncertainty-based measurements are often calculated based on the output of the model. Many real-world vision tasks often have multiple correct answers, which leads to the overestimation of uncertainty measures and sometimes even worse performance than random sampling baselines. For this reason, [74] proposes to estimate the uncertainty in the hidden space within the model rather than the uncertainty in the output space of the model in the Visual Question Answer (VQA) generation, thus overcoming the paraphrastic nature of language.

Automatic summarization aims to extract the most useful and important information from large texts. [104] proposes a novel active learning policy neural network (ALPNN) designed to recognize the concepts and relationships in large electroencephalogram (EEG) reports; this approach can help humans extract available clinical knowledge from a large number of such reports.

### 4.3 Other Applications

The emergence of DAL is exciting, as it is expected to reduce the annotation costs by orders of magnitude while maintaining performance levels. For this reason, DAL is also widely used in other fields.

These applications include, but are not limited to, gene expression, robotics, wearable device data analysis, social networking, ECG signal analysis, etc. For some more specific examples, MLFS [71] combines DL and AL to select genes/miRNAs based on expression profiles and proposes a novel multi-level feature selection method. MLFS also considers the biological relationship between miRNAs and genes and applies this method to miRNA expansion tasks. Moreover, due to the fact that the failure risk of real-world robots is expensive, [7] proposed a risk-aware resampling technique; this approach uses AL together with existing solvers and DL to optimize the robot's trajectory, enabling it to effectively deal with the collision problem in scenes with moving obstacles, and verify the effectiveness of the DAL method on a real nano-quadcopter. [186] further proposes an active trajectory generation framework for the inverse dynamics model of the robot control algorithm, which enables the systematic design of the information trajectory used to train the DNN inverse dynamics module.

In addition, [54, 65] uses sensors installed in wearable devices or mobile terminals to collect user movement information for human activity recognition purposes. [65] proposes a DAL framework for activity recognition with context-aware annotator selection. ActiveHARNet [54] proposes a resource-efficient deep ensembled model that supports incremental learning and inference on the device, utilizes the approximation in the BNN to represent the uncertainty of the model, and further proves the feasibility of ActiveHARNet deployment and incremental learning on two public datasets. For its part, DALAUP [26] designs a DAL framework for anchor user prediction in social networks that reduces the cost of annotating anchor users and improves prediction accuracy. DAL is also used in the classification of electrocardiogram (ECG) signals. For example, [122] proposes an active DL-based ECG signal classification method. [56] proposed an AL-based ECG classification method using eigenvalues and DL. Use of the AL method enables the cost of marking ECG signals by medical experts to be effectively reduced. Furthermore, the cost of label annotation in the speech and audio fields is also relatively high. [1] found that a model trained on a corpus composed of thousands of recordings collected by a small number of speakers is unable to be generalized to new domains; therefore, [1] developed a practical scheme that involves using AL to train deep neural networks for speech emotion recognition tasks when label resources are limited.

In general, the current applications of DAL are mainly focused on visual image processing tasks, although there are also relatively scattered applications in NLP and other fields. Compared with DL and AL, DAL is still in the preliminary stage of research, meaning that the corresponding classic

works are relatively few; however, it still has the same broad application scenarios and practical value as DL.

## 5 DISCUSSION AND FUTURE DIRECTIONS

DAL combines the common advantages of DL and AL: it inherits not only DL's ability to process high-dimensional image data and conduct automatic feature extraction, but also AL's potential to effectively reduce annotation costs. DAL therefore has fascinating potential especially in areas where labels require high levels of expertise and are difficult to obtain.

Most recent work reveals that DAL has been successful in many common tasks. DAL has attracted the interest of a large number of researchers by reducing the cost of annotation and its ability to implement the powerful feature extraction capabilities of DL; consequently, the related research work is also extremely rich. However, there are still a large number of unanswered questions on this subject. As [108] discovered, the results reported on the random sampling baseline (RSB) differ significantly between different studies. For example, under the same settings, using 20% of the label data of CIFAR 10, the RSB performance reported by [178] is 13% higher than that in [162]. Secondly, the same DAL method may yield different results in different studies. For example, using 40% of the label data of CIFAR 100 [86] and VGG16 [149] as the extraction network, the reported results of [138] and [150] differ by 8%. Furthermore, the latest DAL research also exhibits some inconsistencies. For example, [138] and [36] point out that diversity-based methods have always been better than uncertainty-based methods, and that uncertainty-based methods perform worse than RSB; however, the latest research of [178] shows that this is not the case.

Compared with AL's strategic selection of high-value samples, RSB has been regarded as a strong baseline [138, 178]. However, the above problems reveal an urgent need to design a general performance evaluation platform for DAL work, as well as to determine a unified high-performance RSB. Secondly, the reproducibility of different DAL methods is also an important issue. The highly reproducible DAL method helps to evaluate the performance of different DALs. A common evaluation platform should be used for experiments under consistent settings, and snapshots of experimental settings should be shared. In addition, multiple repetitive experiments with different initializations under the same experimental conditions should be implemented, as this could effectively avoid misleading conclusions caused by experimental setup problems. Researchers should pay sufficient attention to these inconsistent studies to enable them to clarify the principles involved. On the other hand, adequate ablation experiments and transfer experiments are also necessary. The former will make it easier for us to determine which improvements bring about performance gains, while the latter can help to ensure that AL selection strategy does indeed enable the indiscriminate selection of high-value samples for the dataset.

The current research directions regarding DAL methods focus primarily on the improvement of AL selection strategies, the optimization of training methods and the improvement of task-independent models. As noted in Section 3.1, the improvement of AL selection strategy is currently centred around taking into account the query strategy based on uncertainty and diversity in an explicit or implicit manner. Moreover, hybrid selection strategies are increasingly favored by researchers. Moreover, the optimization of training methods mainly focuses on labeled datasets, unlabeled datasets, or the use of methods such as GAN to expand data, as well as the hybrid training method of unsupervised, semi-supervised, and supervised learning across the AL cycle. This training method promises to deliver even more performance improvements than are thought to be achievable through changes to the selection strategy. In fact, this makes up for the issues of the DL model requiring a large number of labeled training samples and the AL selecting a limited number of labeled samples. In addition, the use of unlabeled or generated datasets is also conducive to making full use of existing information without adding to the annotation costs. Furthermore, the

incremental training method is also an important research direction. From a computing resources perspective, it is unacceptable to train a deep model from scratch in each cycle. While simple incremental training will cause the deviation of model parameters, the huge potential savings on resources are quite attractive. Although, related research remains quite scarce, this is still a very promising research direction.

Task independence is also an important research direction, as it helps to make DAL models more directly and widely extensible to other tasks. However, the related research remains insufficient, and the corresponding DAL methods tend to focus only on the uncertainty-based selection method. Because DL itself is easier to integrate with the uncertainty-based AL selection strategy, we believe that uncertainty-based methods will continue to dominate research directions not related to these tasks in the future. On the other hand, it may also be advisable to explicitly take the diversity-based selection strategy into account; of course, this will also give rise to great challenges. In addition, it should be pointed out that blindly pursuing the idea of training models on smaller subsets would be unwise, as the relative difference in sample importance in some datasets with a large variety of content and a large number of samples can almost be ignored.

Obviously, there is no conflict between the above-mentioned improvement directions; thus, a mixed improvement strategy is an important development direction for the future. In general, DAL research has significant practical application value in terms of both labeling costs and application scenarios; however, DAL research remains in its infancy at present, and there is still a long way to go in the future.

## REFERENCES

- [1] Mohammed Abdelwahab and Carlos Busso. 2019. Active Learning for Speech Emotion Recognition Using Deep Neural Network. (2019), 1–7.
- [2] Gediminas Adomavicius and Alexander Tuzhilin. 2005. Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions. *IEEE Transactions on Knowledge and Data Engineering* 17, 6 (2005), 734–749.
- [3] Hamed H Aghdam, Abel Gonzalez-Garcia, Joost van de Weijer, and Antonio M López. 2019. Active learning for deep detection neural networks. In *Proceedings of the IEEE International Conference on Computer Vision*. 3672–3680.
- [4] Roei Aharoni, Melvin Johnson, and Orhan Firat. 2019. Massively multilingual neural machine translation. *arXiv preprint arXiv:1903.00089* (2019).
- [5] Saeed S Alahmari, Dmitry B Goldgof, Lawrence O Hall, and Peter R Mouton. 2019. Automatic Cell Counting using Active Deep Learning and Unbiased Stereology. (2019), 1708–1713.
- [6] u v amsterdam. 2014. High-dimensional Data Analysis. (2014).
- [7] Olov Andersson, Mariusz Wzorek, and Patrick Doherty. 2017. Deep Learning Quadcopter Control via Risk-Aware Active Learning. 5 (2017), 3812–3818.
- [8] Dana Angluin. 1988. Queries and Concept Learning. *Machine Learning* 2, 4 (1988), 319–342.
- [9] Nabih Asghar, Pascal Poupart, Xin Jiang, and Hang Li. 2016. Deep Active Learning for Dialogue Generation. *arXiv: Computation and Language* (2016).
- [10] Jordan T Ash, Chicheng Zhang, Akshay Krishnamurthy, John Langford, and Alekh Agarwal. 2019. Deep Batch Active Learning by Diverse, Uncertain Gradient Lower Bounds. *arXiv: Learning* (2019).
- [11] Bowen Baker, Otkrist Gupta, Nikhil Naik, and Ramesh Raskar. 2017. Designing Neural Network Architectures using Reinforcement Learning. In *5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24–26, 2017, Conference Track Proceedings*.
- [12] MariaFlorina Balcan, Alina Beygelzimer, and John Langford. 2009. Agnostic active learning. *J. Comput. System Sci.* 75, 1 (2009), 78–89.
- [13] Anthony Bau, Yonatan Belinkov, Hassan Sajjad, Nadir Durrani, Fahim Dalvi, and James R. Glass. 2019. Identifying and Controlling Important Neurons in Neural Machine Translation. *ArXiv abs/1811.01157* (2019).
- [14] William H Beluch, Tim Genewein, Andreas Nurnberger, and Jan M Kohler. 2018. The Power of Ensembles for Active Learning in Image Classification. (2018), 9368–9377.
- [15] Shai Bendavid, John Blitzer, Koby Crammer, Alex Kulesza, Fernando Pereira, and Jennifer Wortman Vaughan. 2010. A theory of learning from different domains. *Machine Learning* 79, 1 (2010), 151–175.

- [16] Yoshua Bengio, Pascal Lamblin, Dan Popovici, and Hugo Larochelle. 2006. Greedy Layer-Wise Training of Deep Networks. (2006), 153–160.
- [17] Sreyasee Das Bhattacharjee, Ashit Talukder, and Bala Venkatram Balantrapu. 2017. Active learning based news veracity detection with feature weighting and deep-shallow fusion. (2017), 556–565.
- [18] Mustafa Bilgic and Lise Getoor. 2009. Link-based Active Learning. (2009).
- [19] Erik Bochinski, Ghassen Bacha, Volker Eiselein, Tim J W Walles, Jens C Nejstgaard, and Thomas Sikora. 2018. Deep Active Learning for In Situ Plankton Classification. (2018), 5–15.
- [20] Klaus Brinker. 2003. Incorporating diversity in active learning with support vector machines. (2003), 59–66.
- [21] Samuel Budd, Emma C Robinson, and Bernhard Kainz. 2019. A Survey on Active Learning and Human-in-the-Loop Deep Learning for Medical Image Analysis. *arXiv: Learning* (2019).
- [22] Sylvain Calinon, F Guenter, and Aude Billard. 2007. On Learning, Representing, and Generalizing a Task in a Humanoid Robot. 37, 2 (2007), 286–298.
- [23] Trevor Campbell and Tamara Broderick. 2019. Automated Scalable Bayesian Inference via Hilbert Coresets. *Journal of Machine Learning Research* 20, 15 (2019), 1–38.
- [24] Hawshuan Chang, Shankar Vembu, Sunil Mohan, Rheeya Uppaal, and Andrew Mccallum. 2019. Overcoming Practical Issues of Deep Active Learning and its Applications on Named Entity Recognition. *arXiv: Computation and Language* (2019).
- [25] Xuhui Chen, Jinlong Ji, Tianxi Ji, and Pan Li. 2018. Cost-Sensitive Deep Active Learning for Epileptic Seizure Detection. (2018), 226–235.
- [26] Anfeng Cheng, Chuan Zhou, Hong Yang, Jia Wu, Lei Li, Jianlong Tan, and Li Guo. 2019. Deep Active Learning for Anchor User Prediction. (2019), 2151–2157.
- [27] Kashyap Chitta, Jose M Alvarez, Elmar Haussmann, and Clement Farabet. 2019. Training Data Distribution Search with Ensemble Active Learning. *arXiv: Learning* (2019).
- [28] Kashyap Chitta, Jose M Alvarez, and Adam Lesnikowski. 2018. Large-scale visual active learning with deep probabilistic ensembles. *arXiv preprint arXiv:1811.03575* (2018).
- [29] Ido Dagan and Sean P Engelson. 1995. Committee-based sampling for training probabilistic classifiers. (1995), 150–157.
- [30] Navneet Dalal and Bill Triggs. 2005. Histograms of Oriented Gradients for Human Detection. In *2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR 2005), 20–26 June 2005, San Diego, CA, USA*. 886–893.
- [31] Sanjoy Dasgupta. 2011. Two faces of active learning. *Theoretical Computer Science* 412, 19 (2011), 1767–1781.
- [32] Cheng Deng, Yumeng Xue, Xianglong Liu, Chao Li, and Dacheng Tao. 2019. Active Transfer Learning Network: A Unified Deep Joint Spectral&Spatial Feature Learning Model for Hyperspectral Image Classification. *IEEE Transactions on Geoscience and Remote Sensing* 57, 3 (2019), 1741–1754.
- [33] Jeff Donahue and Karen Simonyan. 2019. Large Scale Adversarial Representation Learning. *arXiv: Computer Vision and Pattern Recognition* (2019).
- [34] Baolin Du, Qi Qi, Han Zheng, Yue Huang, and Xinghao Ding. 2018. Breast cancer histopathological image classification via deep active learning and confidence boosting. In *International Conference on Artificial Neural Networks*. Springer, 109–116.
- [35] Xuefeng Du, Dexing Zhong, and Huikai Shao. 2019. Building an Active Palmprint Recognition System. In *2019 IEEE International Conference on Image Processing, ICIP 2019, Taipei, Taiwan, September 22–25, 2019*. 1685–1689.
- [36] Melanie Ducoffe and Frederic Precioso. 2018. Adversarial Active Learning for Deep Networks: a Margin Based Approach. *arXiv: Learning* (2018).
- [37] Meng Fang, Yuan Li, and Trevor Cohn. 2017. Learning how to Active Learn: A Deep Reinforcement Learning Approach. (2017), 595–605.
- [38] zanjirani reza farahani and masoud hekmatfar. 2009. Facility location: concepts, models, algorithms and case studies. (2009).
- [39] Di Feng, Xiao Wei, Lars Rosenbaum, Atsuto Maki, and Klaus Dietmayer. 2019. Deep Active Learning for Efficient Training of a LiDAR 3D Object Detector. (2019).
- [40] Frederic Brenton Fitch. 1944. McCulloch Warren S. and Pitts Walter. A logical calculus of the ideas immanent in nervous activity. *Bulletin of mathematical biophysics* , vol. 5 (1943), pp. 115&133. *Journal of Symbolic Logic* 9 (1944), 49–50.
- [41] Jonathan Folmsbee, Xulei Liu, Margaret Brandwein-Weber, and Scott Doyle. 2018. Active deep learning: Improved training efficiency of convolutional neural networks for tissue classification in oral cavity cancer. In *2018 IEEE 15th International Symposium on Biomedical Imaging (ISBI 2018)*. IEEE, 770–773.
- [42] Marguerite Frank and F. Wolfe. 1956. An algorithm for quadratic programming. *Naval Research Logistics Quarterly* (1956), 95–110.



- [43] Alexander Freytag, Erik Rodner, and Joachim Denzler. 2014. Selecting Influential Examples: Active Learning with Expected Model Output Changes. (2014), 562–577.
- [44] Yarin Gal. 2016. Uncertainty in deep learning. *University of Cambridge* 1, 3 (2016).
- [45] Yarin Gal and Zoubin Ghahramani. 2015. Bayesian Convolutional Neural Networks with Bernoulli Approximate Variational Inference. *arXiv: Machine Learning* (2015).
- [46] Yarin Gal and Zoubin Ghahramani. 2016. Dropout as a Bayesian approximation: representing model uncertainty in deep learning. (2016), 1050–1059.
- [47] Yarin Gal, Riashat Islam, and Zoubin Ghahramani. 2017. Deep Bayesian Active Learning with Image Data. *CoRR* (2017).
- [48] Utkarsh Gaur, Matthew J Kourakis, Erin Newmansmith, William C Smith, and B S Manjunath. 2016. Membrane segmentation via active learning with deep networks. (2016), 1943–1947.
- [49] Yonatan Geifman and Ran Elyaniv. 2017. Deep Active Learning over the Long Tail. *arXiv: Learning* (2017).
- [50] Yonatan Geifman and Ran Elyaniv. 2019. Deep Active Learning with a Neural Architecture Search. (2019), 5974–5984.
- [51] Daniel Gissin and Shai Shalevshwartz. 2018. Discriminative Active Learning. *arXiv: Learning* (2018).
- [52] J. Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, C. Aaron Courville, and Yoshua Bengio. 2014. Generative Adversarial Nets. *NIPS* (2014), 2672–2680.
- [53] Denis A. Gudovskiy, Alec Hodgkinson, Takuya Yamaguchi, and Sotaro Tsukizawa. 2020. Deep Active Learning for Biased Datasets via Fisher Kernel Self-Supervision. *CoRR* abs/2003.00393 (2020).
- [54] Gautham Krishna Gudur, Prahalathan Sundaramoorthy, and Venkatesh Umaashankar. 2019. Activeharnet: Towards on-device deep bayesian active learning for human activity recognition. In *The 3rd International Workshop on Deep Learning for Mobile Systems and Applications*. 7–12.
- [55] Yuhong Guo. 2010. Active Instance Sampling via Matrix Partition. (2010), 802–810.
- [56] Kazim Hanbay. 2019. Deep Neural Network Based Approach for ECG Classification Using Hybrid Differential Features and Active Learning. *Iet Signal Processing* 13, 2 (2019), 165–175.
- [57] Manuel Haussmann, Fred A Hamprecht, and Melih Kandemir. 2019. Deep Active Learning with Adaptive Acquisition. (2019), 2470–2476.
- [58] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. 2016. Deep Residual Learning for Image Recognition. In *2016 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2016, Las Vegas, NV, USA, June 27-30, 2016*. 770–778.
- [59] Tao He, Xiaoming Jin, Guiguang Ding, Lan Yi, and Chenggang Yan. 2019. Towards Better Uncertainty Sampling: Active Learning with Multiple Views for Deep Convolutional Neural Network. (2019), 1360–1365.
- [60] Tong He, Zhi Zhang, Hang Zhang, Zhongyue Zhang, Junyuan Xie, and Mu Li. 2019. Bag of Tricks for Image Classification with Convolutional Neural Networks. *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)* (2019), 558–567.
- [61] Miguel Jos   Hern  andez-Lobato and Ryan Adams. 2015. Probabilistic Backpropagation for Scalable Learning of Bayesian Neural Networks. *International Conference on Machine Learning* (2015).
- [62] E Geoffrey Hinton, Simon Osindero, and Yee-Whye Teh. 2006. A fast learning algorithm for deep belief nets. *Neural Computation* (2006), 1527–1554.
- [63] Geoffrey E Hinton, Nitish Srivastava, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. 2012. Improving neural networks by preventing co-adaptation of feature detectors. *arXiv: Neural and Evolutionary Computing* (2012).
- [64] Steven C H Hoi, Rong Jin, Jianke Zhu, and Michael R Lyu. 2006. Batch mode active learning and its application to medical image classification. (2006), 417–424.
- [65] H M Sajjad Hossain and Nirmalya Roy. 2019. Active Deep Learning for Activity Recognition with Context Aware Annotator Selection. (2019), 1862–1870.
- [66] HM Sajjad Hossain, MD Abdullah Al Haiz Khan, and Nirmalya Roy. 2018. DeActive: scaling activity recognition with active deep learning. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies* 2, 2 (2018), 1–23.
- [67] Neil Houlsby, Ferenc Huszar, Zoubin Ghahramani, and Mate Lengyel. 2011. Bayesian Active Learning for Classification and Preference Learning. *arXiv: Machine Learning* (2011).
- [68] Yue Huang, Zhenwei Liu, Minghui Jiang, Xian Yu, and Xinghao Ding. 2020. Cost-Effective Vehicle Type Recognition in Surveillance Images With Deep Active Learning and Web Data. *IEEE Transactions on Intelligent Transportation Systems* 21, 1 (2020), 79–86.
- [69] Jonathan H Huggins, Trevor Campbell, and Tamara Broderick. 2016. Coresets for Scalable Bayesian Logistic Regression. (2016), 4080–4088.
- [70] Ahmed Hussein, Mohamed Medhat Gaber, and Eyad Elyan. 2016. Deep Active Learning for Autonomous Navigation. (2016), 3–17.

- [71] Rania Ibrahim, Noha A Yousri, Mohamed A Ismail, and Nagwa M El-Makky. 2014. Multi-level gene/MiRNA feature selection using deep belief nets and active learning. In *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. IEEE, 3957–3960.
- [72] Prateek Jain and Ashish Kapoor. 2009. Active learning for large multi-class problems. (2009), 762–769.
- [73] David Janz, Jos Van Der Westhuizen, and Jose Miguel Hernandezlobato. 2017. Actively Learning what makes a Discrete Sequence Valid. *arXiv: Machine Learning* (2017).
- [74] Khaled Jedoui, Ranjay Krishna, Michael S Bernstein, and Feifei Li. 2019. Deep Bayesian Active Learning for Multiple Correct Outputs. *arXiv: Computer Vision and Pattern Recognition* (2019).
- [75] Michael I. Jordan. 1986. Serial Order: A Parallel Distributed Processing Approach. *Advances in psychology* 121 (1986), 471–495.
- [76] Ajay Joshi, Fatih Porikli, and Nikolaos Papanikolopoulos. 2009. Multi-class active learning for image classification. (2009), 2372–2379.
- [77] J. Ajay Joshi, Fatih Porikli, and Nikolaos Papanikolopoulos. 2010. Multi-class batch-mode active learning for image classification. *Robotics and Automation* (2010), 1873–1878.
- [78] Jungo Kasai, Kun Qian, Sairam Gurajada, Yunyao Li, and Lucian Popa. 2019. Low-resource Deep Entity Resolution with Transfer and Active Learning. (2019), 5851–5861.
- [79] Benjamin Kellenberger, Diego Marcos, Sylvain Lobry, and Devis Tuia. 2019. Half a Percent of Labels is Enough: Efficient Animal Detection in UAV Imagery Using Deep CNNs and Active Learning. *IEEE Transactions on Geoscience and Remote Sensing* 57, 12 (2019), 9524–9533.
- [80] Alex Kendall, Vijay Badrinarayanan, and Roberto Cipolla. 2015. Bayesian SegNet: Model Uncertainty in Deep Convolutional Encoder-Decoder Architectures for Scene Understanding. *arXiv: Computer Vision and Pattern Recognition* (2015).
- [81] Kwanyoung Kim, Dongwon Park, Kwang In Kim, and Se Young Chun. 2020. Task-Aware Variational Adversarial Active Learning. *arXiv: Learning* (2020).
- [82] Ross D King, Kenneth E Whelan, Ffion M Jones, Philip G K Reiser, Christopher H Bryant, Stephen Muggleton, Douglas B Kell, and Stephen G Oliver. 2004. Functional genomic hypothesis generation and experimentation by a robot scientist. *Nature* 427, 6971 (2004), 247–252.
- [83] Diederik P Kingma and Max Welling. 2013. Auto-Encoding Variational Bayes. *arXiv: Machine Learning* (2013).
- [84] Andreas Kirsch, Joost Van Amersfoort, and Yarin Gal. 2019. BatchBALD: Efficient and Diverse Batch Acquisition for Deep Bayesian Active Learning. *arXiv: Learning* (2019).
- [85] Vikram Krishnamurthy. 2002. Algorithms for optimal scheduling and management of hidden Markov model sensors. *IEEE Transactions on Signal Processing* 50, 6 (2002), 1382–1397.
- [86] Alex Krizhevsky. 2009. Learning Multiple Layers of Features from Tiny Images.
- [87] Alex Krizhevsky, Ilya Sutskever, and Geoffrey E Hinton. 2012. ImageNet Classification with Deep Convolutional Neural Networks. (2012), 1097–1105.
- [88] M P Kumar, Benjamin Packer, and Daphne Koller. 2010. Self-Paced Learning for Latent Variable Models. (2010), 1189–1197.
- [89] Bogdan Kwolek, Michal Koziarski, Andrzej Bukala, Zbigniew Antosz, Boguslaw Olborski, Pawel WÅsowicz, Jakub SwadÅzba, and Boguslaw Cyganek. 2019. Breast Cancer Classification on Histopathological Images Affected by Data Imbalance Using Active Learning and Deep Convolutional Neural Network. (2019), 299–312.
- [90] Yann Lecun, Yoshua Bengio, and Geoffrey E Hinton. 2015. Deep learning. *Nature* 521, 7553 (2015), 436–444.
- [91] Y. LeCun, B. Boser, S. J. Denker, D. Henderson, E. R. Howard, W. Hubbard, and D. L. Jackel. 1989. Backpropagation Applied to Handwritten Zip Code Recognition. *Neural Computation* (1989), 541–551.
- [92] Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner. 1998. Gradient-based learning applied to document recognition.
- [93] Byungjae Lee and Kyunghyun Paeng. 2018. A Robust and Effective Approach Towards Accurate Metastasis Detection and pN-stage Classification in Breast Cancer. (2018), 841–850.
- [94] Christian Leibig, Vaneeda Allken, Murat Seckin Ayhan, Philipp Berens, and Siegfried Wahl. 2017. Leveraging uncertainty information from deep neural networks for disease detection. *Scientific Reports* 7, 1 (2017), 17816–17816.
- [95] David D Lewis and William A Gale. 1994. A sequential algorithm for training text classifiers. (1994), 3–12.
- [96] Ya Li, Keze Wang, Lin Nie, and Qing Wang. 2017. Face Recognition via Heuristic Deep Active Learning. (2017), 97–107.
- [97] Jianzhe Lin, Liang Zhao, Shuying Li, Rabab K Ward, and Z Jane Wang. 2018. Active-Learning-Incorporated Deep Transfer Learning for Hyperspectral Image Classification. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 11, 11 (2018), 4048–4062.
- [98] Xiao Lin and Devi Parikh. 2017. Active Learning for Visual Question Answering: An Empirical Study. *arXiv: Computer Vision and Pattern Recognition* (2017).

- [99] Peng Liu, Hui Zhang, and Kie B Eom. 2017. Active Deep Learning for Classification of Hyperspectral Images. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing* 10, 2 (2017), 712–724.
- [100] Zimo Liu, Jingya Wang, Shaogang Gong, Huchuan Lu, and Dacheng Tao. 2019. Deep Reinforcement Active Learning for Human-in-the-Loop Person Re-Identification. (2019), 6122–6131.
- [101] Jonathan Long, Evan Shelhamer, and Trevor Darrell. 2015. Fully convolutional networks for semantic segmentation. (2015), 3431–3440.
- [102] David G. Lowe. 1999. Object Recognition from Local Scale-Invariant Features. In *Proceedings of the International Conference on Computer Vision, Kerkyra, Corfu, Greece, September 20-25, 1999*. 1150–1157.
- [103] Xiaoming Lv, Fajie Duan, Jiajia Jiang, Xiao Fu, and Lin Gan. 2020. Deep Active Learning for Surface Defect Detection. *Sensors* 20, 6 (2020), 1650.
- [104] Ramon Maldonado and Sanda M Harabagiu. 2019. Active deep learning for the identification of concepts and relations in electroencephalography reports. *Journal of Biomedical Informatics* 98 (2019), 103265.
- [105] Giovanna Martinez Arellano and Svetan Ratchev. 2019. Towards an active learning approach to tool condition monitoring with Bayesian deep learning. (2019).
- [106] Muhammad Mateen, Junhao Wen, Nasrullah, Sun Song, and Zhouping Huang. 2019. Fundus Image Classification Using VGG-19 Architecture with PCA and SVD. *Symmetry* 11 (2019), 1.
- [107] Ali Mottaghi and Serena Yeung. 2019. Adversarial Representation Active Learning. *arXiv: Computer Vision and Pattern Recognition* (2019).
- [108] Prateek Munjal, Nasir Hayat, Munawar Hayat, Jamshid Sourati, and Shadab Khan. 2020. Towards Robust and Reproducible Active Learning Using Neural Networks. *arXiv: Learning* (2020).
- [109] Ju Gang Nam, Sunggyun Park, Eui Jin Hwang, Jong Hyuk Lee, Kwang Nam Jin, Kun Young Lim, Thienkai Huy Vu, Jae Ho Sohn, Sangheum Hwang, Jin Mo Goo, et al. 2019. Development and Validation of Deep Learning-based Automatic Detection Algorithm for Malignant Pulmonary Nodules on Chest Radiographs. *Radiology* 290, 1 (2019), 218–228.
- [110] Ali Bou Nassif, Ismail Shahin, Imtinan B. Attili, Mohammad Azzeh, and Khaled Shaalan. 2019. Speech Recognition Using Deep Neural Networks: A Systematic Review. *IEEE Access* 7 (2019), 19143–19165.
- [111] T. Hieu Nguyen and Arnold Smeulders. 2004. Active learning using pre-clustering. *ICML* (2004), 79–79.
- [112] Mohammad Sadegh Norouzzadeh, Daniel D Morris, Sara Beery, Neel Joshi, Nebojsa Jojic, and Jeff Clune. 2019. A deep active learning system for species identification and counting in camera trap images. *arXiv: Learning* (2019).
- [113] Augustus Odena, Christopher Olah, and Jonathon Shlens. 2017. Conditional Image Synthesis With Auxiliary Classifier GANs. (2017), 2642–2651.
- [114] Natalia Ostapuk, Jie Yang, and Philippe Cudre-Mauroux. 2019. ActiveLink: Deep Active Learning for Link Prediction in Knowledge Graphs. *WWW '19: The Web Conference on The World Wide Web Conference WWW 2019* (2019), 1398–1408.
- [115] Mercedes Eugenia Paoletti, Juan Mario Haut, Rubén Fernández-Beltrán, Javier Plaza, Antonio J. Plaza, Jun Yu Li, and Filiberto Pla. 2019. Capsule Networks for Hyperspectral Image Classification. *IEEE Transactions on Geoscience and Remote Sensing* 57 (2019), 2145–2160.
- [116] Daniel S. Park, William Chan, Yu Zhang, Chung-Cheng Chiu, Barret Zoph, Ekin D. Cubuk, and Quoc V. Le. 2019. SpecAugment: A Simple Data Augmentation Method for Automatic Speech Recognition. In *INTERSPEECH*.
- [117] Robert Pinsler, Jonathan Gordon, Eric Nalisnick, and Jose Miguel Hernandezlobato. 2019. Bayesian Batch Active Learning as Sparse Subset Approximation. (2019), 6356–6367.
- [118] Remus Pop and Patric Fulop. 2018. Deep Ensemble Bayesian Active Learning : Addressing the Mode Collapse issue in Monte Carlo dropout via Ensembles. *arXiv: Learning* (2018).
- [119] Shalini Priya, Saharsh Singh, Sourav Kumar Dandapat, Kripabandhu Ghosh, and Joydeep Chandra. 2019. Identifying infrastructure damage during earthquake using deep active learning. (2019), 551–552.
- [120] Yao Qin, Nicholas Carlini, Ian J. Goodfellow, Garrison W. Cottrell, and Colin Raffel. 2019. Imperceptible, Robust, and Targeted Adversarial Examples for Automatic Speech Recognition. *ArXiv abs/1903.10346* (2019).
- [121] Zhenshen Qu, Jingda Du, Yong Cao, Qiuyu Guan, and Pengbo Zhao. 2020. Deep Active Learning for Remote Sensing Object Detection. *CoRR* (2020).
- [122] M M Al Rahhal, Yakoub Bazi, Haikel Alhichri, Naif Alajlan, Farid Melgani, and Ronald R Yager. 2016. Deep learning approach for active classification of electrocardiogram signals. *Information Sciences* 345, 345 (2016), 340–354.
- [123] Hiranmayi Ranganathan, Hemanth Venkateswara, Shayok Chakraborty, and Sethuraman Panchanathan. 2017. Deep active learning for image classification. (2017), 3934–3938.
- [124] Pengzhen Ren, Yun Xiao, Xiaojun Chang, Po-Yao Huang, Zhihui Li, Xiaojiang Chen, and Xin Wang. 2020. A Comprehensive Survey of Neural Architecture Search: Challenges and Solutions. *CoRR abs/2006.02903* (2020).
- [125] Olaf Ronneberger, Philipp Fischer, and Thomas Brox. 2015. U-Net: Convolutional Networks for Biomedical Image Segmentation. (2015), 234–241.

- [126] Matthias Rottmann, Karsten Kahl, and Hanno Gottschalk. 2018. Deep Bayesian Active Semi-Supervised Learning. *arXiv: Learning* (2018).
- [127] Nicholas Roy and Andrew McCallum. 2001. Toward Optimal Active Learning through Monte Carlo Estimation of Error Reduction. *International Conference on Machine Learning* (2001).
- [128] Soumya Roy, Asim Unmesh, and Vinay P Namboodiri. 2018. Deep active learning for object detection. (2018), 91.
- [129] David E. Rumelhart, Geoffrey E. Hinton, and Ronald J. Williams. 1986. Learning representations by back-propagating errors. *Nature* 323 (1986), 533–536.
- [130] e david rumelhart, e geoffrey hinton, and j ronald williams. 1986. Learning internal representations by error propagation. *Parallel distributed processing: explorations in the microstructure of cognition, vol. 1* (1986), 318–362.
- [131] Ario Sadafi, Niklas Koehler, Asya Makhro, Anna Bogdanova, Nassir Navab, Carsten Marr, and Tingying Peng. 2019. Multiclass Deep Active Learning for Detecting Red Blood Cell Subtypes in Brightfield Microscopy. (2019), 685–693.
- [132] Mathew Salvaris, Danielle Dean, and Wee Hyong Tok. 2018. Generative Adversarial Networks. *arXiv: Machine Learning* (2018), 187–208.
- [133] Yassir Saquil, Kwang In Kim, and Peter Hall. 2018. Ranking CGANs: Subjective Control over Semantic Image Attributes. (2018), 131.
- [134] G Sayantan, P T Kien, and K V Kadambari. 2018. Classification of ECG beats using deep belief network and active learning. *Medical & Biological Engineering & Computing* 56, 10 (2018), 1887–1898.
- [135] Melanie Lubrano Di Scandalea, Christian S Perone, Mathieu Boudreau, and Julien Cohenadad. 2019. Deep Active Learning for Axon-Myelin Segmentation on Histology Data. *arXiv: Computer Vision and Pattern Recognition* (2019).
- [136] Steffen Schneider, Alexei Baevski, Ronan Collobert, and Michael Auli. 2019. wav2vec: Unsupervised Pre-training for Speech Recognition. *ArXiv abs/1904.05862* (2019).
- [137] Ozan Sener and Silvio Savarese. 2017. A geometric approach to active learning for convolutional neural networks. *arXiv preprint arXiv:1708.00489* 7 (2017).
- [138] Ozan Sener and Silvio Savarese. 2018. Active Learning for Convolutional Neural Networks: A Core-Set Approach. *international conference on learning representations* (2018).
- [139] Burr Settles. 2009. Active Learning Literature Survey.
- [140] Burr Settles. 2012. Active Learning. *Active Learning* (2012).
- [141] Burr Settles, Mark Craven, and Soumya Ray. 2007. Multiple-Instance Active Learning. (2007), 1289–1296.
- [142] H S Seung, M Oppel, and H Sompolinsky. 1992. Query by committee. (1992), 287–294.
- [143] Matthew Shardlow, Meizhi Ju, Maolin Li, Christian OâŽReilly, Elisabetta Iavarone, John McNaught, and Sophia Ananiadou. 2019. A text mining pipeline using active and deep learning aimed at curating information in computational neuroscience. *Neuroinformatics* 17, 3 (2019), 391–406.
- [144] Artem Shelmanov, Vadim Liventsev, Danil Kireev, N A Khromov, Alexander Panchenko, Irina Fedulova, and Dmitry V Dylov. 2019. Active Learning with Deep Pre-trained Models for Sequence Tagging of Clinical and Biomedical Texts. (2019).
- [145] Yanyao Shen, Hyokun Yun, Zachary C Lipton, Yakov Kronrod, and Animashree Anandkumar. 2017. Deep Active Learning for Named Entity Recognition. *arXiv: Computation and Language* (2017).
- [146] Changjian Shui, Fan Zhou, Christian Gagne, and Boyu Wang. 2019. Deep Active Learning: Unified and Principled Method for Query and Training. *arXiv: Learning* (2019).
- [147] Aditya Siddhant and Zachary C Lipton. 2018. Deep Bayesian Active Learning for Natural Language Processing: Results of a Large-Scale Empirical Study. *arXiv: Computation and Language* (2018).
- [148] Oriane Simeoni, Mateusz Budnik, Yannis Avrithis, and Guillaume Gravier. 2019. Rethinking deep active learning: Using unlabeled data at model training. *arXiv: Computer Vision and Pattern Recognition* (2019).
- [149] Karen Simonyan and Andrew Zisserman. 2015. Very Deep Convolutional Networks for Large-Scale Image Recognition. In *3rd International Conference on Learning Representations, ICLR 2015, San Diego, CA, USA, May 7-9, 2015, Conference Track Proceedings*.
- [150] Samarth Sinha, Sayna Ebrahimi, and Trevor Darrell. 2019. Variational Adversarial Active Learning. *arXiv: Learning* (2019).
- [151] Asim Smailagic, Pedro Costa, Alex Gaudio, Kartik Khandelwal, Mostafa Mirshekari, Jonathon Fagert, Devesh Walawalkar, Susu Xu, Adrian Galdran, Pei Zhang, et al. 2019. O-MedAL: Online Active Deep Learning for Medical Image Analysis. *arXiv: Learning* (2019).
- [152] Asim Smailagic, Pedro Costa, Hae Young Noh, Devesh Walawalkar, Kartik Khandelwal, Adrian Galdran, Mostafa Mirshekari, Jonathon Fagert, Susu Xu, Pei Zhang, et al. 2018. MedAL: Accurate and Robust Deep Active Learning for Medical Image Analysis. (2018), 481–488.
- [153] Justin S Smith, Benjamin Nebgen, Nicholas Lubbers, Olexandr Isayev, and Adrian E Roitberg. 2018. Less is more: Sampling chemical space with active learning. *Journal of Chemical Physics* 148, 24 (2018), 241733.

- [154] Kihyuk Sohn, Xinchun Yan, and Honglak Lee. 2015. Learning structured output representation using deep conditional generative models. (2015), 3483–3491.
- [155] Akash Srivastava, Lazar Valkov, Chris Russell, U. Michael Gutmann, and A. Charles Sutton. 2017. VEEGAN: Reducing Mode Collapse in GANs using Implicit Variational Learning. *neural information processing systems* (2017), 3310–3320.
- [156] Nitish Srivastava, Geoffrey E Hinton, Alex Krizhevsky, Ilya Sutskever, and Ruslan Salakhutdinov. 2014. Dropout: a simple way to prevent neural networks from overfitting. *Journal of Machine Learning Research* 15, 1 (2014), 1929–1958.
- [157] Fabian Stark, Caner Hazırbaş, Rudolph Triebel, and Daniel Cremers. 2015. Captcha recognition with active deep learning. In *Workshop new challenges in neural computation*, Vol. 2015. Citeseer, 94.
- [158] Kuniyuki Takahashi, Tetsuya Ogata, Jun Nakanishi, Gordon Cheng, and Shigeki Sugano. 2017. Dynamic motion learning for multi-DOF flexible-joint robots using active-passive motor babbling through deep learning. *Advanced Robotics* 31, 18 (2017), 1002–1015.
- [159] Xu Tan, Yi Ren, Di He, Tao Qin, Zhou Zhao, and Tie-Yan Liu. 2019. Multilingual Neural Machine Translation with Knowledge Distillation. *ArXiv abs/1902.10461* (2019).
- [160] simon tong. 2001. Active learning: theory and applications. (2001).
- [161] Simon Tong and Daphne Koller. 2002. Support vector machine active learning with applications to text classification. *Journal of Machine Learning Research* 2, 1 (2002), 45–66.
- [162] Toan Tran, Thanhtoan Do, Ian Reid, and Gustavo Carneiro. 2019. Bayesian Generative Active Deep Learning. *arXiv: Learning* (2019).
- [163] Toan Tran, Trung Pham, Gustavo Carneiro, Lyle J Palmer, and Ian Reid. 2017. A Bayesian data augmentation approach for learning deep models. (2017), 2797–2806.
- [164] Kailas Vodrahalli, Ke Li, and Jitendra Malik. 2018. Are All Training Examples Created Equal? An Empirical Study. *arXiv: Learning* (2018).
- [165] Dan Wang and Yi Shang. 2014. A new active labeling method for deep learning. (2014), 112–119.
- [166] K. Wang, D. Zhang, Y. Li, R. Zhang, and L. Lin. 2017. Cost-Effective Active Learning for Deep Image Classification. *IEEE Transactions on Circuits and Systems for Video Technology* 27, 12 (2017), 2591–2600.
- [167] Menglin Wang, Baisheng Lai, Zhongming Jin, Xiaojin Gong, Jianqiang Huang, and Xiansheng Hua. 2018. Deep Active Learning for Video-based Person Re-identification. *arXiv: Computer Vision and Pattern Recognition* (2018).
- [168] Qiang Wang, Bei Li, Tong Xiao, Jingbo Zhu, Changliang Li, Derek F. Wong, and Lidia S. Chao. 2019. Learning Deep Transformer Models for Machine Translation. In *ACL*.
- [169] Wenzhe Wang, Ruiwei Feng, Jintai Chen, Yifei Lu, Tingting Chen, Hongyun Yu, Danny Z Chen, and Jian Wu. 2019. Nodule-Plus R-CNN and Deep Self-Paced Active Learning for 3D Instance Segmentation of Pulmonary Nodules. *IEEE Access* 7 (2019), 128796–128805.
- [170] Wenzhe Wang, Yifei Lu, Bian Wu, Tingting Chen, Danny Z Chen, and Jian Wu. 2018. Deep Active Self-paced Learning for Accurate Pulmonary Nodule Segmentation. (2018), 723–731.
- [171] Zengmao Wang, Bo Du, Lefei Zhang, and Liangpei Zhang. 2016. A batch-mode active learning framework by querying discriminative and representative samples for hyperspectral image classification. *Neurocomputing* 179 (2016), 88–100.
- [172] Max Welling and Whye Yee Teh. 2011. Bayesian Learning via Stochastic Gradient Langevin Dynamics. *ICML* (2011), 681–688.
- [173] Xide Xia, Pavlos Protopapas, and Finale Doshivelez. 2016. Cost-Sensitive Batch Mode Active Learning: Designing Astronomical Observation by Optimizing Telescope Time and Telescope Choice. (2016), 477–485.
- [174] Ismet Zeki Yalniz, Hervé Jégou, Kan Chen, Manohar Paluri, and Dhruv Kumar Mahajan. 2019. Billion-scale semi-supervised learning for image classification. *ArXiv abs/1905.00546* (2019).
- [175] Jie Yang, Thomas Drake, Andreas Damianou, and Yoelle Maarek. 2018. Leveraging Crowdsourcing Data For Deep Active Learning – An Application: Learning Intents in Alexa. (2018), 23–32.
- [176] Lin Yang, Yizhe Zhang, Jianxu Chen, Siyuan Zhang, and Danny Z Chen. 2017. Suggestive Annotation: A Deep Active Learning Framework for Biomedical Image Segmentation. (2017), 399–407.
- [177] C. Yin, B. Qian, S. Cao, X. Li, J. Wei, Q. Zheng, and I. Davidson. 2017. Deep Similarity-Based Batch Mode Active Learning with Exploration-Exploitation. In *2017 IEEE International Conference on Data Mining (ICDM)*. 575–584.
- [178] Donggeun Yoo and In So Kweon. 2019. Learning Loss for Active Learning. (2019), 93–102.
- [179] Jiaming Zeng, Adam Lesnikowski, and Jose M Alvarez. 2018. The Relevance of Bayesian Layer Positioning to Model Uncertainty in Deep Bayesian Active Learning. *arXiv: Learning* (2018).
- [180] Ye Zhang, Matthew Lease, and Byron C Wallace. 2016. Active Discriminative Text Representation Learning. *arXiv: Computation and Language* (2016).
- [181] Wencang Zhao, Yu Kong, Zhengming Ding, and Yun Fu. 2017. Deep Active Learning Through Cognitive Information Parcels. (2017), 952–960.
- [182] Ziyuan Zhao, Xiaoyan Yang, Bharadwaj Veeravalli, and Zeng Zeng. 2020. Deeply Supervised Active Learning for Finger Bones Segmentation. *arxiv* (2020).

- [183] Fedor Zhdanov. 2019. Diverse mini-batch Active Learning. *arXiv: Learning* (2019).
- [184] Shusen Zhou, Qingcai Chen, and Xiaolong Wang. 2010. Active Deep Networks for Semi-Supervised Sentiment Classification. (2010), 1515–1523.
- [185] Shusen Zhou, Qingcai Chen, and Xiaolong Wang. 2013. Active deep learning method for semi-supervised sentiment classification. *Neurocomputing* 120 (2013), 536–546.
- [186] Siqu Zhou and Angela P Schoellig. 2019. Active Training Trajectory Generation for Inverse Dynamics Model Learning with Deep Neural Networks. (2019).
- [187] Jiajie Zhu and Jose Bento. 2017. Generative Adversarial Active Learning. *arXiv: Learning* (2017).
- [188] Xiaojin Zhu, John D. Lafferty, and Ronald Rosenfeld. 2005. Semi-supervised learning with graphs.
- [189] Barret Zoph and Quoc V. Le. 2017. Neural Architecture Search with Reinforcement Learning. In *5th International Conference on Learning Representations, ICLR 2017, Toulon, France, April 24-26, 2017, Conference Track Proceedings*.