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ETHICAL EVALUATION AND OPTIMIZATION OF ARTIFICIAL INTELLIGENCE ALGORITHMS BASED ON SELF SUPERVISED LEARNING

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Abstract. Active learning solves the problem of requiring a large amount of manpower and resources due to the large size of training samples. The core problem is how to select valuable samples to reduce annotation costs. Using neural networks as classifiers, most methods choose samples with large amounts of information without considering the issue of information redundancy between the selected samples. Through the study of redundancy issues, the author proposes a sample selection optimization method to reduce information redundancy. Using uncertainty methods to select samples with high information content to form a candidate sample set, and using latent variable vectors calculated in the network to represent sample information, the cosine distance between candidate samples is calculated using this vector to select subsets with large interval distance and low information redundancy. Compared with several uncertainty methods in the Mnist, Fashion mnist, and Cifar-10 datasets, this method reduces labeled samples by a minimum of 11% with the same sample accuracy. The higher the dimensionality of the feature vector calculated by CNN, the more candidate samples it contains, and the more information it contains. After being improved by self supervised learning algorithms, the effect becomes more significant. The more candidate samples are selected, the stronger the information redundancy. The better the performance of self supervised learning algorithms.

Key words: Artificial intelligence algorithms, Information redundancy, Cosine distance, Uncertainty method

1. Introduction. With the rapid development of artificial intelligence (AI), intelligent algorithms are being applied more and more widely in various fields, such as autonomous driving, medical diagnosis, financial analysis, etc [1]. The introduction of these algorithms has brought great convenience and benefits, but at the same time, it has also raised concerns about ethical issues related to these algorithms. In the decision-making and behavior of AI algorithms, there may be significant impacts on individuals, society, and the environment [2]. For example, in the field of autonomous driving, intelligent algorithms are responsible for determining the trajectory and behavior of vehicles, which is directly related to driving safety and road traffic order. In medical diagnosis, AI algorithms can assist doctors in disease diagnosis and treatment decisions, but their accuracy and safety are also factors that need to be considered. In financial analysis, intelligent algorithms can assist in investment decision-making and risk assessment, but the fairness and transparency of their decisions are also controversial [3].

Therefore, in order to ensure the security, fairness, and trustworthiness of AI algorithms, ethical evaluation and optimization have become crucial. The purpose of ethical evaluation is to examine whether the decisions and behaviors of algorithms comply with ethical and ethical standards, and to predict their potential impacts. This requires consideration of ethical considerations in algorithm design and training, as well as the potential risks and impacts that may arise during algorithm application. Firstly, in the process of algorithm design and training, it is necessary to consider whether the collection and use of data are legal and compliant [4]. For the processing of sensitive information, such as personal identity information, medical records, etc., relevant laws and regulations should be strictly followed to protect the privacy rights of users. At the same time, it is necessary to ensure the quality and reliability of the data, and avoid erroneous decisions made by algorithms due to data bias or incompleteness. In addition, the training process of the algorithm should also follow the principles of fairness and equality to avoid discriminatory results. Secondly, in the process of algorithm application, it is necessary to consider the transparency and interpretability of the algorithm. Intelligent algorithms are usually built based on machine learning and deep learning techniques, and their decision-making process is often black

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box like, difficult to explain and understand. This is a challenge for users and relevant stakeholders as they are unable to understand how algorithms make decisions [5]. Therefore, the interpretability of algorithms has become an important ethical issue. In order to address this issue, researchers are working hard to develop interpretable AI algorithms and promoting the development of relevant standards and specifications. In addition, the fairness of algorithms is also an ethical issue that needs to be considered. The decision-making of intelligent algorithms may be affected by data bias and unfairness, such as discriminatory outcomes for certain specific groups. Therefore, it is necessary to review and calibrate the training data of the algorithm to avoid bias and discrimination. At the same time, it is necessary to establish supervision and feedback mechanisms to promptly correct unfair decisions made by algorithms and protect the rights and interests of users [6]. Finally, risk assessment and management of algorithms are also important aspects of ethical assessment. Intelligent algorithms may bring some potential risks, such as privacy breaches, security vulnerabilities, ethical conflicts, etc. Therefore, it is necessary to conduct a comprehensive assessment and management of these risks, take corresponding measures to reduce risks, and establish supervision and monitoring mechanisms to timely identify and solve problems [7].

The sample selection strategy is a core issue in the process of artificial intelligence algorithms. In the pool sample mode, different classifiers have different selection strategies. Under the condition of using SVM as a classifier, the information content of samples is clearly measured by the distance between samples and support vectors, such as SVM's batch pattern artificial intelligence algorithm method. However, considering the distribution problem between samples, Maximum Mean Discrepancy (MMD) is used to measure the distribution difference between sample sets, thereby ensuring the consistency of distribution between unlabeled and labeled sets, for example, the Batch Mode Active Learning (BMAL) method and the Discriminative and Representative Model Active Learning (DRMALs) method [8]. Furthermore, the Similarity based Sparse Modeling Representative Selection (DSMRS) and mutual information method were used to measure the similarity between sample sets, thereby reducing the redundancy between sample sets. For example, adaptive active learning methods, Convex Programming Active Learning (CPAL) methods, etc.

Under the condition of using neural networks as classifiers, similar to SVM, the closer the sample information is to the classification boundary, the greater the amount of information. Currently, most uncertainty methods are used for measurement. Due to the lack of clear explanation from neural networks, some scholars believe that the current method does not select samples close enough to the classification boundary and needs to reselect samples near the classification boundary, such as: The Bayesian Active Learning (DBAL) algorithm calculates the mean of the results after multiple dropouts as the final classification result; Attack the Unmarked Sample (DFAL) algorithm using the Deeppool algorithm that generates adversarial samples; Considering the sample distribution relationship, in order to ensure the consistency of distribution between labeled and unlabeled sample sets, a Cost Effective Active Learning (CEAL) method with classifier self labeling is used to transform the sample selection problem into a K-center problem using Euclidean distance, these methods ensure distribution consistency and allow for the selection of samples with large amounts of information, but they do not solve the problem of information redundancy. The author proposes a self supervised learning algorithm to reduce redundancy and achieve better results.

2. Problem Description. This section defines the active learning problem, which indirectly measures the amount of sample information and the redundancy of sample information through latent variables in CNN with MLP. Combining the process of artificial intelligence algorithms, the problem of minimizing redundancy is defined. Assuming there are n samples of m classes [9]. The problem of artificial intelligence algorithm based on pool sample selection sample pattern is as follows:

Question 1. Assuming the number of labeled samples is n_L and $L = \{x_i | i = 1, 2, ..., n_L\}$; The number of unlabeled samples is n_U, $U = \{x_i | i = 1, 2, ..., n_U\}$, $x_i \in R^k$ and $n_L + n_U = n$; Sample label set: $Y = \{y_i | i = 1, 2, ..., n_L\}$ and $y_i \in R^m$. The loss function of the CNN model is $l(L, Y; f(\theta))$, which is mapped to $R^{n_L \times k} \times R^{n_L \times m} \to R^{n_L}$.

Each time k samples are selected from U to form a S_i set and placed in L. The active learning problem is:

$$min_L E[l(L, Y; f(\theta))] - E[;(L, Y; f(\theta))] s.t. |S_i| = k \quad and \quad L = \overset{U}{_{i=1:T}} S_i \tag{2.1}$$

The loss function is the information cross entropy function, which is:

$$l(L,Y,\theta) = -\frac{1}{n_L}\sum_{i=1}^{n_L}\sum_{j=1}^{m}\{y_i = j\} logp(y_i = j|x_i;\theta) \tag{2.2}$$

In the formula, T is the number of iterations; 1 $\{\cdot\}$ is the indicator function, which is 1 when CNN predicts correctly, otherwise $p(y_i = j|x_i;\theta)$ is the output result of class j after the Softmax process.

Due to the lack of clear interpretability of CNN, it is difficult to determine what specific information the sample has about CNN. Given this issue, it is assumed that the CNN is connected to an MLP fully connected layer after passing through a convolutional layer, and the output vector of the hidden layer in MLP is specified as a latent variable, abstracting sample information through latent variables. The modulus of latent variable vectors represents the amount of information, and information redundancy is represented by calculating the distance between samples. The commonly used distance measures include Euclidean distance and cosine distance. The cosine distance is more effective in calculating and yields the same conclusion, so cosine distance is chosen[10]. Furthermore, the inner product measures the redundancy of information between samples, meaning that a larger inner product indicates a higher similarity of latent variables and a higher redundancy of information between the two samples being compared.

Definition 1. For samples x_i and x_j, the latent variables calculated by CNN are x_i' and x_j', and $x_i', x_j' \in R^n \in R$", the information redundancy matrix R and information quantity I between n samples are:

$$R = \begin{pmatrix} r_{11} & r_{12} & ... & r_{1k} \\ r_{21} & r_{22} & ... & r_{2k} \\ . & . & & . \\ . & . & ... & . \\ . & . & & . \\ r_{k1} & r_{k2} & ... & r_{kk} \end{pmatrix} \tag{2.3}$$

$$I = (I_1, I_2, ..., I_n) \tag{2.4}$$

In order to solve problem 1, the goal is achieved by reducing redundancy by selecting a sample set with high information content and low redundancy. Question 1 becomes how to select the sample set S_i to minimize the redundancy between samples[11].

Question 2. Assuming that there is already a redundancy matrix R, select the sample set S_i from U to minimize the mean of R, that is:

$$min_L average(R) s.t. |S_i| = k \quad and \quad L = \overset{U}{_{i=1:T}} S_i \tag{2.5}$$

3. Redundancy methods. The redundancy problem mainly occurs between multiple selections of S_i, between sample sets, or between samples in a single selection of S_i. Assuming that after each selection of S_i, the CNN converges on the set L after labeling, there is less information redundancy between the S_i sample sets selected in each iteration, and the redundancy problem mainly lies between the samples in the Si set [12].

The analysis of the redundancy problem of Si set is shown in Figure 3.1, where: circle and triangle represent two types of samples m_1 and m_2; The dashed line represents the initial classification boundary; The solid line is the classification boundary after selecting samples; Grid points are candidate sample sets; The real point is the selected sample set. The samples are divided into two categories: m_1 and m_2, where $m_j^{(i)}$ represents the i-th subset of samples belonging to the j-th category. Assuming that some samples have been selected and labeled based on uncertainty methods. As shown in Figure 3.1 (a), several samples were selected from the $m_1^{(1)}$,$m_2^{(2)}$ sample set near the CNN classification boundary. After iterative training, the original dashed boundary became a solid boundary, and the result did not completely separate the two types of samples. It can be seen that the sample set selected based on uncertainty methods has information redundancy. In response to this issue, the author proposes a self supervised learning algorithm [13].

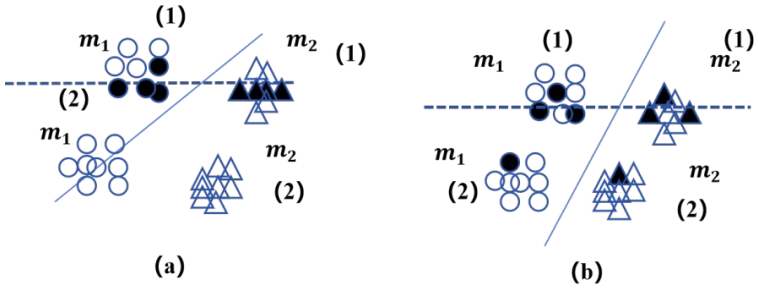


Fig. 3.1: Analysis of Redundancy Issues in S_i Sets

3.1. Uncertainty methods. The principle of sample selection based on the pooling sample pattern is mainly to select samples with high information content in the unlabeled pool to enable CNN to quickly fit the samples. High information content means that after CNN calculation, the probability of unlabeled samples in each classification is close to $\frac{1}{m}$, or they are uncertain in the most likely classification. Such samples close to the classifier boundary are the selected samples in Figure 3.1 (a). The current methods of uncertainty are as follows:

(1) Low credibility:

$$x^* = argmax_x[1 - p(y_{max}|x_i;\theta)] \tag{3.1}$$

In the formula: $y_{max} = max(y_i = j|x_i;\theta)$. Sort the maximum values of samples in various classification probabilities from small to large, and select the top K samples.

(2) Information entropy:

$$x^* = argmax_x - \sum_i p(y_i = j|x_i;\theta)log(y_i = j|x_i;\theta) \tag{3.2}$$

Sort the top K samples in descending order of information entropy.

(3) Bayesian estimation:

$$p = \frac{1}{T}\sum_{t=1}^{T} p(y_i = j|x_i;\theta, dropout_t) \tag{3.3}$$

Average the classification results under multiple dropout values, and then select samples based on Equations 3.1 and 3.2.

3.2. Redundancy algorithm. As shown in Figure 3.1(a), the above uncertainty method only selects some samples as Si sets based on the given calculation indicators, without considering sample redundancy, thus selecting meaningless samples. A self supervised learning algorithm is proposed based on this problem, as shown in Figure 3.1(b), which constructs a candidate sample set consisting of samples located near the CNN classification boundary, which includes all categories. Finally, select a subset of samples with low redundancy from the candidate sample set.

Select samples located near the CNN classification boundary based on uncertainty methods to form a candidate sample set. Calculate the cosine distance matrix between latent variables for all candidate samples:

$$D = \begin{pmatrix} d_{11} & d_{12} & ... & d_{1k} \\ d_{21} & d_{22} & ... & d_{2k} \\ . & . & & . \\ . & . & ... & . \\ . & . & & . \\ d_{k1} & d_{k2} & ... & d_{kk} \end{pmatrix} = \frac{R}{{}^2\sqrt{I^T \times I}} \tag{3.4}$$

Using the distance matrix to obtain a sample set with low redundancy, that is, selecting the sample from the candidate set that is least similar to the labeled set each time. If L is an empty set, selecting the sample that is most similar to the candidate set[14].

3.3. Self supervised learning algorithms. From the above algorithms, it can be seen that the purpose of using cosine distance and redundancy algorithms is to select sample sets with category diversity and low redundancy from the candidate sample set.

Assuming that K samples are selected in an unlabeled sample pool in one round, and the LeNet5 network is used as a classifier with S convolutional kernels, with a single convolutional kernel computation time of ts, the time complexity analysis of self supervised learning algorithms and uncertainty methods is as follows:

Uncertainty methods:

$$T_U = T_s + T_k \tag{3.5}$$

Self supervised learning algorithms:

$$T_D = T_s + T_k + T_R \tag{3.6}$$

In the formula, T_s is the time taken for network training; T_k is the sorting selection sample time; T_R is the redundancy calculation time.

$$T_s = t_s KS = O(t_s S) \tag{3.7}$$

$$T_k = K = O(1) \quad T_R = NK = O(N) \tag{3.8}$$

Obviously, $t_s >> N > 1$, then $T_s >> T_R > T_k$, the time is mainly spent on training the neural network. Therefore, Equations 3.1 and 3.2 have the following relationship:

$$T_U \approx T_D \approx O(t_s S) \tag{3.9}$$

From Equation 3.5, it can be concluded that the running time of the two methods is roughly the same[15].

4. Experiments and Result Analysis.

4.1. Datasets and Network Structures. Multiple experiments were conducted on Mnist, Fashion mnist, and Cifar-10 on the Lenet and NIN models. The neural network structure is shown in Tables 4.1 and 4.2, and the description of the dataset is as follows:

(1) Mnist: 28 × 28 grayscale images, totaling 10 categories. Used for recognizing handwritten digit datasets, including 50000 for training, 5000 for validation, and 10000 for testing. 10000 samples were used as unlabeled sample pools in the experiment.

(2) Fashion latest: 28 × 28 grayscale images, totaling 10 categories. Used to identify fashion clothing datasets, including 50000 training sets and 10000 testing sets. Due to its higher complexity than Mnist, the experiment used 20000 samples as an unlabeled sample pool.

(3) Cifar-10: 32 × thirty-two × 3 color images, totaling 10 categories. A small dataset for identifying universal objects, including 50000 training sets and 10000 testing sets. 20000 samples were used as unlabeled sample pools in the experiment[16].

4.2. Experimental parameters. In order to reduce the impact of experimental randomness, each dataset experiment had an average of 5 results. In each experiment, in order to avoid the model being biased during the training process, the validation set selected for each iteration is to randomly and uniformly extract 2% of samples from each class in the existing labeled set, and the CNN initialization network parameters are the same in each dataset experiment[17]. The experiment used the Keras toolkit on the Python platform to compare self supervised learning algorithms with low credibility, information entropy, and Bayesian methods in uncertainty methods multiple times. For the Mnist dataset, n_0=100, T=15, N=3, K=100, feature vector length 128, and network structure are shown in Table 4.1. For the Fashion mnist dataset, n_0=200, T=20, N=10, K=150, the feature vector length is 256, the network structure is shown in Table 4.1, and the output length of the Fc layer is changed to 256[18]. Considering the complexity of the Cifar-10 dataset and network training issues, in order to reduce overfitting and result stability, the dropout value is reduced, n_0=1 000 T = 20 N = 30 K = 150 dropout = 0.25 the length of the feature vector is 512.

Table 4.1: Mnist and Fashion mnist experimental network structures

type	Core size/step size	Output Size
convolution	3 × 3 /1	28 × 28 × 32
Pooling	2 × 2 /2	13 × 13 × 64
convolution	3 × 3 /1	13 × 13 × 64
Pooling	2 × 2 /2	6 × 6 × 64
Fc(dropout50%)	—	1 × 1 × 128
Fc	—	1 × 1 × 10
Softmax	—	1 × 1 × 10

Table 4.2: Cifar-10 Experimental Network Structure

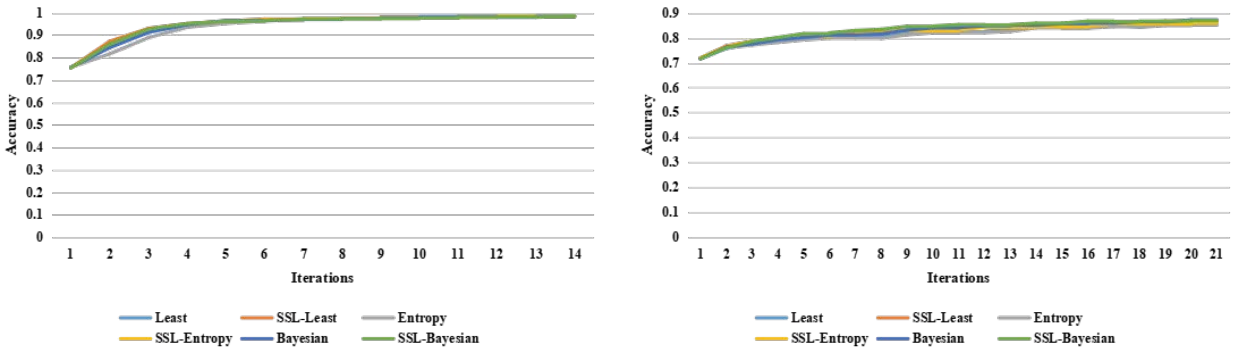
type	Core size/step size	Output Size
convolution	5 × 5 /1	32 × 32 × 192
Batch normalization	—	32 × 32 × 192
convolution	1 × 1 /1	32 × 32 × 160
convolution	1 × 1 /1	32 × 32 × 96
Pooling	3 × 3 /2	15 × 15 × 96
convolution	5 × 5 /1	15 × 15 × 192
Batch normalization	—	15 × 15 × 192
convolution	1 × 1 /1	15 × 15 × 192
convolution	1 × 1 /1	15 × 15 × 192
Pooling	3 × 3 /2	7 × 7 × 192
convolution	3 × 3 /1	7 × 7 × 192
BN	—	7 × 7 × 192
convolution	1 × 1 /1	7 × 7 × 192
convolution	1 × 1 /1	7 × 7 × 64
Fc(dropout25%)	—	1 × 1 × 512
Fc	—	1 × 1 × 10
Softmax	—	1 × 1 × 10

4.3. Analysis of experimental results. In order to verify the effectiveness of self supervised learning algorithms, different datasets use different network structures due to their varying complexity. The results are shown in Figure 4.1.

It can be clearly seen that self supervised learning algorithms have significant improvements in the existing uncertainty methods. Compared to the samples required for the highest accuracy of the uncertainty method, in Mnist, when the uncertainty method reaches 98%, the entropy method reduces the maximum number of samples by 28%, while the Bayesian method reduces the minimum number of samples by 16%; In Fashion mnist, when the uncertainty method reaches 85%, the maximum decrease in lead is 30%, and the minimum decrease in entropy is 14%; In Cifar-10, the three methods achieved a maximum lead reduction of 22% and a minimum sample reduction of 11% for Bayesian when achieving an accuracy of 52%. From the above results analysis, it can be seen that the Self supervised learning algorithm (SSL) reduces samples by up to 30% and the lowest by 11% in the three methods.

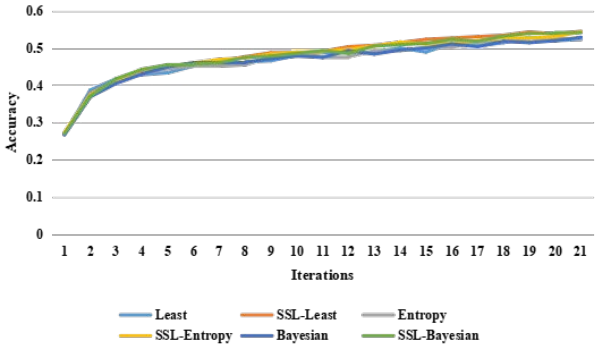
From these results, it can be found that the information of the samples selected by the original three uncertainty methods is redundant for the classifier. Because self supervised learning algorithms mainly select sample sets with low redundancy through redundancy algorithms. The accuracy in Figure 4.1 increases, and under the same number of samples, the amount of information increases, resulting in a decrease in redundancy. Self supervised learning algorithms can effectively enhance uncertainty methods at the cost of time [19].

In order to reduce the impact of latent variable feature vector length and candidate sample number on sample redundancy research, experiments were conducted on latent variable feature vector length and candidate



(a) Mnist

(b) Fashion-mnist



(c) Cifar-10

Fig. 4.1: Experimental results of SSL algorithm on different datasets

sample number. Under the conditions of 128 and 256 feature vectors, as well as 300 and 1000 candidate samples, in Fashion minimum, two sets of experiments were conducted using the self supervised learning algorithm - fast method. The experimental results on the relationship between information redundancy and the length of feature vectors and the number of candidate samples are shown in Figures 4.2 and 4.3.

The experiment in Figure 4.2 is conducted on the Fashion mnist dataset, with a candidate sample size of 1000 and feature vector lengths of 128 and 256, respectively. Due to the different widths of CNN in the last layer, the initialization network parameters are inconsistent. To address this issue, this experiment aims to ensure that the initialization network performs equally on the test set as much as possible. It can be seen that when the model accuracy reaches 80%, the former has 100 more labeled samples than the latter. So, the longer the feature vector, the more information it carries. The experiment in Figure 4.3 is conducted on the same dataset, with n_0=200, T=20, K=100, and a feature vector length of 256. The sample size of the candidate set is 300 and 1000, respectively, and the initialization network parameters are the same. Similarly, when the model accuracy reaches 80%, the former uses 100 more labeled samples than the latter. Through this experiment, it can be compared that if the number of candidate samples is small, the information contained in the candidate sample set is insufficient, but the redundancy is small, which will be affected by the number of samples[20]. Through the above experiments, it can be seen that the higher the dimensionality of the feature vectors calculated by CNN, the more candidate samples contain more information, and the more obvious the effect is after being improved by self supervised learning algorithms. The more candidate samples are selected, the stronger the information redundancy. The better the performance of self supervised learning algorithms.

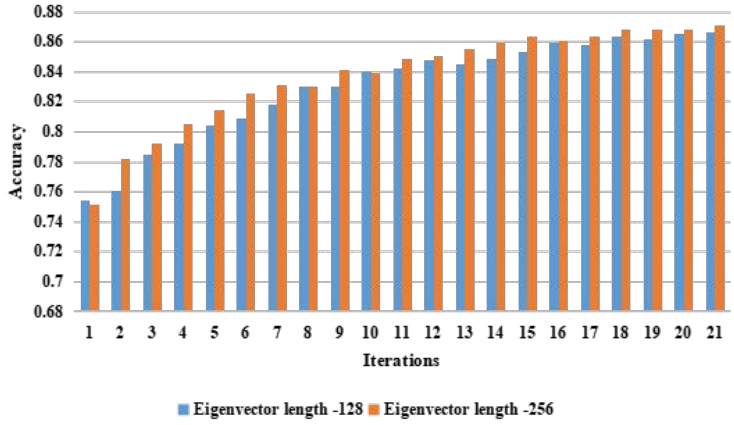


Fig. 4.2: The length of feature vectors in self supervised learning algorithms

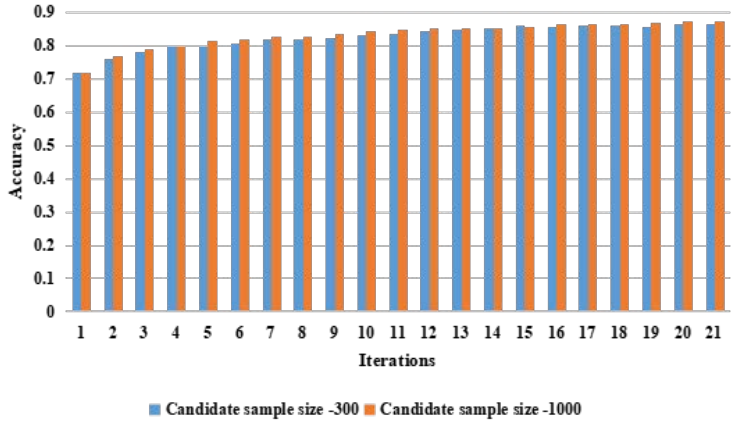


Fig. 4.3: Number of candidate samples in self supervised learning algorithms

5. Conclusion. In the sample selection mode of artificial intelligence algorithm pool, the author proposes a self supervised learning algorithm to reduce sample information redundancy. Using uncertainty methods, a large number of candidate samples are selected by CNN to form a candidate set. In the candidate set, the cosine distance relationship of the samples is used for a second screening, resulting in a sample set with large information content and low redundancy. This method can effectively reduce sample data redundancy and further reduce the number of labeled samples required by the model. In the future, uncertainty methods can be further optimized.

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REFERENCES

[1] Zeng, Y., & Xu, X. (2022). The construction and optimization of an ai education evaluation indicator based on intelligent algorithms. International journal of cognitive informatics and natural intelligence, 187(7), 7-11.
[2] Wang, Y., & Na, K. S. (2022). Innovative research on english teaching model based on artificial intelligence and wireless communication. International journal of reliability, quality and safety engineering, 26(1), 63-87.
[3] Song, J. Y., Li, Z. X., Li, Y. X., & Han, D. S. (2022). The optimization method of mechanical fault diagnosis based on artificial intelligence technology. Journal of Physics: Conference Series, 2158(1), 012033.
[4] Wang, Y., Guo, J., Wang, J., Wu, C., Song, S., & Huang, G. (2023). Erratum to meta-semi: a meta-learning approach for semi-supervised learning. CAAI Artificial Intelligence Research, 2, null-null, 15(4), 308-314.
[5] Loukas, C. (2022). Surgical gesture recognition in laparoscopic tasks based on the transformer network and self-supervised learning. Bioengineering, 9(7),52-56.
[6] Ezugwu, A. E., Ikotun, A. M., Oyelade, O. O., Abualigah, L., Agushaka, J. O., & Eke, C. I., et al. (2022). A comprehensive survey of clustering algorithms: state-of-the-art machine learning applications, taxonomy, challenges, and future research prospects. Engineering Applications of Artificial Intelligence, 110(47), 104743.
[7] Alwi, S., Salleh, M., Abu, M. F., Ismail, A. F., Abbas, M. S., & Fadzilah, A. H. H. (2023). Concept of integration of blockchain and artificial intelligence. 2023 3rd International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE), 15(7),1160-1163.
[8] Jangmin, O. H. (2022). Short-term stock price prediction by supervised learning of rapid volume decrease patterns. IEICE Transactions on Information and Systems, E105.D(8), 1431-1442.
[9] Xueqin Lü, Deng, R., Li, X., & Wu, Y. (2022). Comprehensive performance evaluation and optimization of hybrid power robot based on proton exchange membrane fuel cell. International Journal of Energy Research, 46(2), 1934-1950.
[10] ZhaoHongyu, LyuFang, & LuoYalan. (2022). Research on the effect of online marketing based on multimodel fusion and artificial intelligence in the context of big data. Security and Communication Networks, 40(3), 422-440.
[11] Mubarak, M. A. (2023). Sustainably developing in a digital world: harnessing artificial intelligence to meet the imperatives of work-based learning in industry 5.0. Development and Learning in Organizations: An International Journal, 37(3), 18-20.
[12] Mei, Z. (2023). 3d image analysis of sports technical features and sports training methods based on artificial intelligence. Journal of Testing and Evaluation: A Multidisciplinary Forum for Applied Sciences and Engineering, 34(20), 18125-18141.
[13] Zhu, W., Zhang, T., Wu, Y., Li, S., & Li, Z. (2022). Research on optimization of an enterprise financial risk early warning method based on the ds-rf model. International review of financial analysis(May), 16(1), 79-93.
[14] Li, H., Xu, Q., Wang, Q., & Tang, B. (2023). A review of intelligent verification system for distribution automation terminal based on artificial intelligence algorithms. Journal of Cloud Computing, 12(1),85-89.
[15] Nguyen, N., & Chang, J. M. (2022). Csnas: contrastive self-supervised learning neural architecture search via sequential model-based optimization. IEEE Transactions on Artificial Intelligence,65(4), 3.
[16] Rekawek, P., Herbst, E. A., Suri, A., Ford, B. P., Rajapakse, C. S., & Panchal, N. (2023). Machine learning and artificial intelligence: a web-based implant failure and peri-implantitis prediction model for clinicians. The International journal of oral & maxillofacial implants,11(03), 176-191.
[17] Yang, W., Cheng, X., Zhao, Y., Qian, R., & Li, J. (2023). Depth edge and structure optimization-based end-to-end self-supervised stereo matching. International Journal of Pattern Recognition and Artificial Intelligence, 37(13),63-65.
[18] Villar, A., & Andrade, C. R. V. D. (2024). Supervised machine learning algorithms for predicting student dropout and academic success: a comparative study. Discover Artificial Intelligence, 4(1),78-79.
[19] Leng, J., Wang, D., Ma, X., Yu, P., Wei, L., & Chen, W. (2022). Bi-level artificial intelligence model for risk classification of acute respiratory diseases based on chinese clinical data. Applied intelligence (Dordrecht, Netherlands), 52(11), 13114-13131.
[20] Yin, J., Qiu, J. J., Liu, J. Y., Li, Y. Y., Lao, Q. C., & Zhong, X. R., et al. (2023). Differential diagnosis of dcis and fibroadenoma based on ultrasound images: a difference-based self-supervised approach. Interdisciplinary Sciences: Computational Life Sciences, 15(2), 262-272.

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