

## **Healthcare Data Quality Assessment for Cybersecurity Intelligence**

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This is a Author's accepted manuscript (AAM) version of a publication  
published by IEEE  
in IEEE Transactions on Industrial Informatics

**DOI:** 10.1109/TII.2022.3190405

**Copyright of the original publication:**

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**Please cite the publication as follows:**

Li Y., Yang J., Zhang Z., Wen J., Kumar P. (2022). Healthcare Data Quality Assessment for Cybersecurity Intelligence. IEEE Transactions on Industrial Informatics. DOI: 10.1109/TII.2022.3190405

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# Healthcare Data Quality Assessment for Cybersecurity Intelligence

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**Abstract**—Considering the efficiency and security of healthcare data processing, indiscriminate data collection, annotation, and transmission are unwise. In this work, we propose the normalized double entropy (NDE) method to assess image data quality in the form of meta-task. In specific, the probability entropy and distance entropy are both adopted and normalized to evaluate the data quality. The experimental results show the stable ability of the NDE to distinguish good and bad data in terms of information contribution. Further, the model's diagnostic performances driven by selected good and bad data are compared, and a clear gap exists between them under the premise of the same amount of data. Screening 70% of the dataset can achieve almost the same accuracy as that based on all data. This work focuses on healthcare data quality and data redundancy and provides a practical evaluation tool to facilitate the identification and collection of valuable data, which is beneficial to improve efficiency and protect cybersecurity in healthcare systems.

**Index Terms**—Data mining, Few-shot, Feature distribution, Information entropy, Meta-task.

This work was supported by the National Natural Science Foundation of China under Grant No.32101612 and No.61871283. (Corresponding author: Jiachen Yang)

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## I. Introduction

WIRELESS intelligent healthcare system uses modern communication technology to provide long-distance medical services, allowing access to a large amount of medical data [1]. The healthcare data plays an essential role in patient treatment, diagnosis, and decision purpose, including current treatments, health history, medication allergies, and insurance information. Due to the explosion of healthcare data, the cybersecurity of patient privacy in a communication network cannot be ignored. In terms of medical images, the healthcare image quality assessment is helpful to support cybersecurity intelligence in healthcare systems. Given many medical images from different patients with the same disease, these images are very similar in appearance and feature, and they are redundant for training an intelligent diagnostic network. Since each data contains private patient information, it is better not to annotate and transmit medical data with less information contribution in the wireless network, protecting the data privacy in healthcare systems.

Healthcare image recognition and intelligent diagnosis can alleviate the expert doctors' burden of massive medical data processing [2], [3]. In the past decade, deep learning and intelligent computing have developed rapidly and made remarkable achievements in the image-based recognition areas. For example, timely and early skin lesion image detection is essential for suitable treatment, but manual detection is time-consuming and heavily relied on experience. So, the massive skin images are collected with the patient information, which is used to train the deep classification models to assist doctors to seek automatic and accurate diagnoses [4].

To address the data cybersecurity problem in healthcare systems and protect patient privacy, there are two branches. One is the security protocol related, such as intrusion detection, firewalls, digital forensics, anti-virus software, access control, and encryption [5]. The other is the few-shot learning method, which aims to train the neural network based on limited labeled data [6]-[8]. Inspired by the idea of few-shot learning, we focus on the healthcare data quality assessment to reduce the use of unnecessary data with low information contribution, aiming at protecting privacy and security in healthcare systems. In general, we summarize our core contributions in this work as follows.

1) A healthcare privacy protection approach based on data quality assessment is proposed. Different from the perceptual and subjective image quality assessment, this work focuses on the data information contribution. If some data has high information contribution to improve the model performance of intelligent healthcare systems, it should be collected and labeled; otherwise, it is better not to annotate and transmit online to protect patient privacy.

2) A normalized double entropy (NDE) method is proposed to assess healthcare image quality, which considers the information entropy based on predicted probabilities and the distance entropy based on feature distribution, further normalizing the double entropy value to a standard scope to facilitate comparative analysis.

3) Meta-task experiments are carried out to verify the applicability and stability of the proposed NDE method under different test sets. Further, the feature distribution of data with different information contributions is visualized. The NDE method is compared with the single entropy method, and the data redundancy and performance comparison based on good and bad data are conducted.

The rest parts are arranged as follows. The related works are described in Section II. Section III presents the framework and proposed method, which consists of the probability entropy and distance entropy. Further, the analysis and discussions of the results are presented in Section IV. Finally, the conclusions are put in Section V.

## II. Related Works

### A. Medical image recognition and diagnosis

Medical image recognition and diagnosis rely on deep learning and computer vision technologies, which extract the image feature using convolutional neural networks (CNN) and classify benign or malignant. Zhang et al. [9] proposed a model to obtain the multimodal feature mapping between medical images and reports and then trained an end-to-end network for interpretable medical diagnosis. Tournier et al. [10] designed a software package named MRtrix3, which is commonly used for medical image processing and visualization. Balakrishnan et al. [11] presented a deformable and pairwise image registration framework for

medical images. The used network was trained based on auxiliary data to improve testing registration accuracy. Ghalejoogh et al. [12] used a meta-learning method to conduct the classification of skin melanoma, which included two basic classifiers and their fused version. Gu et al. [13] designed a network model based on an encoder, extractor, and decoder to extract better high-level features for medical images in terms of image segmentation tasks. Karimi et al. [14] used three kinds of label noise to analyze the commonly used medical image datasets and designed many approaches to reduce the negative influence of label noise on medical image recognition.

In this work, the focus is not to design model algorithms to improve recognition accuracy but to analyze data differences and collection necessity from the viewpoint of data information contribution.

## B. Few-shot Learning

Few-shot learning, also called low-shot learning, aims to use limited labeled data to conduct the computer vision tasks, such as recognition, detection, and segmentation. Hu et al. [15] used the data augmentation method to generate more images based on the generative adversarial network, and the augmented images were further adopted to train the diseases classification model. Feng et al. [16] proposed the MPrNet to conduct the few-shot segmentation based on only a few labeled samples, which were called support data. The support data was directly used to guide the segmentation of query images. Argüeso et al. [17] set the PlantVillage dataset as a source and target domains with different classes. Then the few-shot classification task was conducted using transfer learning. Li et al. [18] used the triplet loss to train the few-shot classification model, the triplet samples were combined from the few original data, and the designed model was finally optimized and deployed on FPGA. Li et al. [19] established the few-shot classification dataset, considered the domain effect, provided meta-learning methods, and analyzed many impact factors on the performance. Li et al. [20] used semi-supervised learning to overcome the shortage of few data, many pseudo labels are obtained by the adaptive threshold to supplement the deficiency of initial labeled data. Tang et al. [21] proposed a few-shot segmentation framework for healthcare images based on the prototypical network.

Singh et al. [22] designed the MetaMed model based on the meta-learning method to solve the few-shot medical diseases recognition, and was tested on several medical image datasets.

However, the current few-shot learning community mainly focuses on the few data augmentation and algorithm design, ignoring the data differences in information contribution. Many studies adopt random sampling to analyze few-shot problems. In this work, we tend to focus on how to identify good data with high information contribution in the few-shot scenarios.

### C. Image Quality Assessment

Perceptual image quality assessment (IQA) mainly focuses on the subject feelings of human beings about pixel distortion and visual comfort, which can be adopted in many specific applications. Zhu et al. [23] used the meta-learning method to carry out the no-reference IQA. Many different tasks with various image distortions were collected. Then, these images were evaluated by some human volunteers to provide the meta knowledge. Yang et al. [24] designed a no-reference evaluation metric for the screen content images, which consisted of two networks. The method obtained good consistency with the human visual system in several datasets. Hosu et al. [25] created a large-scale dataset, named KonIQ-10k, including over ten thousand images, considering different image distortions and various indicators. Sim et al. [26] used deep similarity and local similarity to conduct the full reference IQA for 2D images and compared the similarity between original and distorted deep feature maps from trained CNN. Yang et al. [27] used the stacked autoencoders to design a blind IQA method for screen content images, where the scores of two autoencoders were weighted and summed as the perceptual quality score. Li et al. [28], [29] focused on the high-level AI task-oriented IQA and proposed several assessment methods based on information entropy and feature embedding to improve model performance.

This study is not focused on subjective visual perception but explores the high-level task-oriented data quality evaluation from the perspective of information contribution based on our previous work.

## III. PROPOSED METHODOLOGY

The overall framework of this study is shown in Fig .1, which consists of two fundamental steps. First, the ResNet18 model was used and finetuned based on the base data, which refers to those existing labeled healthcare data in storage. The reason not to select a deeper model is that the shallow network has been shown with a good ability to extract image features [30]. The skin medical images in the base data set are fed to the model, and the Global Average Pool (GAP) layer is used to obtain the high dimensional feature vector to represent the input image. Then, a classifier is trained based on the feature vectors to conduct the diagnosis. Second, to protect patient privacy, the unlabeled patient data with patient privacy are evaluated by the proposed normalized double entropy (NDE) metric, only the necessary data with high information contribution is collected, annotated, and transmitted in wireless communication network. In this way, through the healthcare image quality assessment, the amount of medical image data transmission is reduced, the privacy security is protected, and the learning is more efficient.

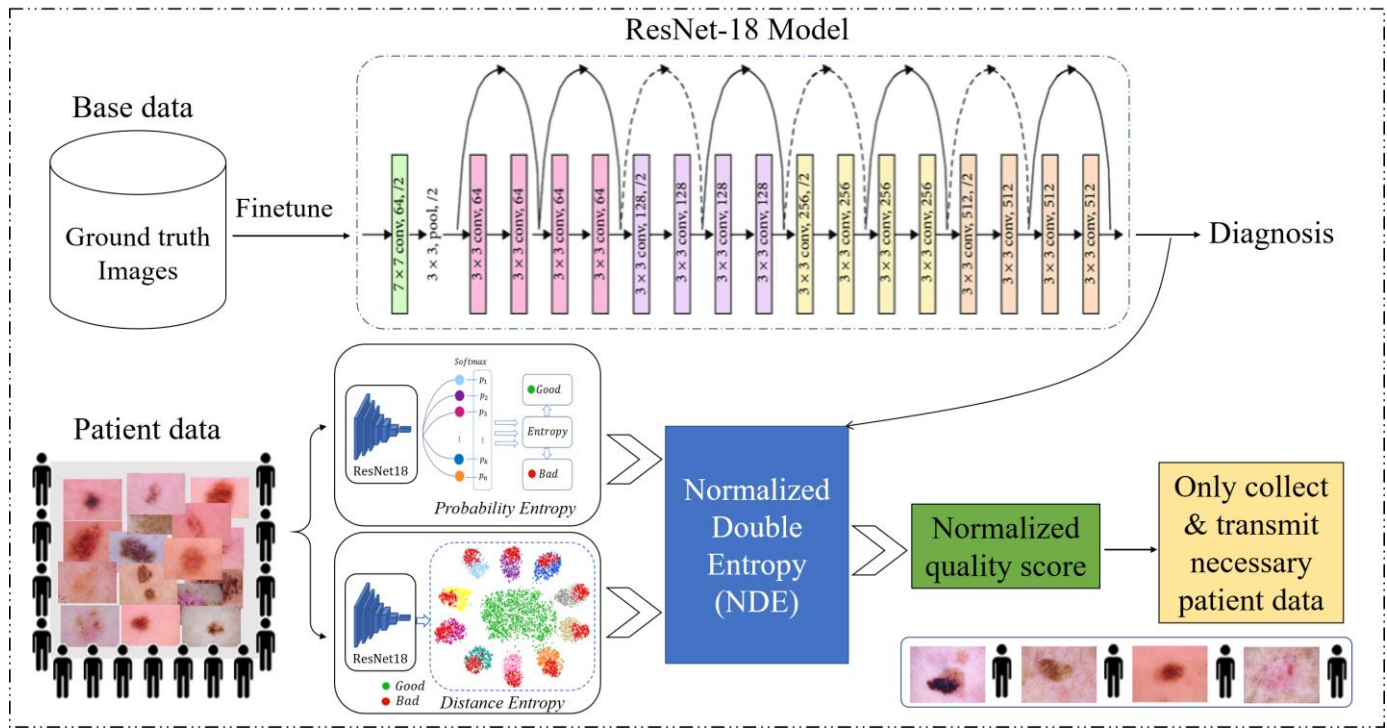


Fig. 1. The overall framework.

#### A. Probability entropy

The probability entropy refers to the information entropy calculated based on the model's predicted probabilities [28]. For skin images, the input image is fed to a trained model to get the predicted probability to

belong to each class, denoted as  $p_i$ . And  $K$  corresponds to the number of categories. In this case, the probability entropy  $E_p$  is expressed in (1).

$$E_p = -\sum_{i=1}^K p_i \cdot \log_2 p_i \quad (1)$$

Equation (1) represents the whole confidence of the trained model on the image to judge its category. As known, when each predicted probability is equal, the entropy is the largest value. In this condition, the current model is completely not familiar with it, thus this kind of data is the informative data with high information contribution to improving the model performance. Since the total number of target classes varies, the scope of the calculated value of entropy in (1) is not fixed, which is not a convenient to evaluate. In this paper, we proposed the normalized probability entropy  $E_p^*$ , expressed in (2).

$$E_p^* = -\sum_{i=1}^K p_i \cdot \log_K p_i \quad (2)$$

According to the Maximum Entropy Theory, the maximum value in (2) appears when the prediction probability to belong to each class  $p_i$  is the same, refer to as  $1/K$ , and the maximum value of the normalized probability entropy will be 1. So, the full range of normalized probability entropy values is 0 to 1.

### B. Distance entropy

Distance entropy refers to the information entropy calculated based on the distance similarity between new data and each center of categories, used to assess the information contribution [29]. The schematic diagram is shown in Fig. 2.

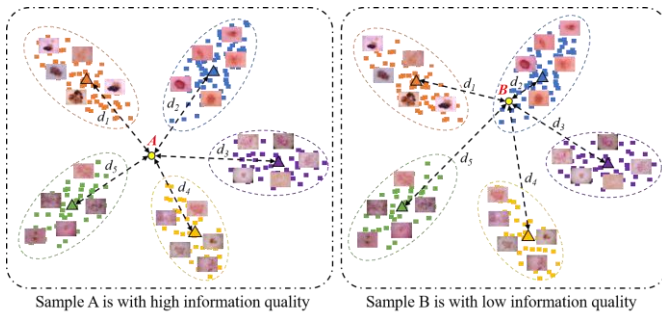


Fig. 2. The schematic diagram of data information contribution.



The colored square dots represent labeled samples in base data and the colored triangles are the prototypes of the classes. Here,  $S_c$  denotes the samples in the class  $c$ , and  $x_s$  denotes a sample in the class  $c$ . The prototype of each category, denoted as  $w_c$ , is computed via taking the mean vector, as (3). Where  $f_\theta$  stands for the feature extractor and converts input samples into feature vectors. Here, the ResNet-18 is used as the feature extractor.

$$w_c = \frac{1}{|S_c|} \sum_{x_s \in S_c} f_\theta(x_s) \quad (3)$$

Then, the distance function is used to measure the similarity between the feature vectors of new data and per class prototype, which is denoted as  $d_i$ . The commonly used distance metrics are Euclidean distance and Cosine distance. Given two feature vectors  $A$  ( $a_1, a_2, \dots, a_n$ ) and  $B$  ( $b_1, b_2, \dots, b_n$ ), the Euclidean and Cosine distances are calculated as (4) and (5), respectively.

$$d(A, B) = \sqrt{(a_1 - b_1)^2 + (a_2 - b_2)^2 + \dots + (a_n - b_n)^2} \quad (4)$$

$$\cos(A, B) = \frac{A \cdot B}{\|A\| \times \|B\|} = \frac{\sum_{i=1}^n A_i B_i}{\sqrt{\sum_{i=1}^n A_i^2} \sqrt{\sum_{i=1}^n B_i^2}} \quad (5)$$

As known, the Cosine similarity metric is used to measure the direction similarity. According to Fig. 2, the spatial feature distribution cannot well be explained by vector direction. Thus, in this work, we use the Euclidean distance to conduct the distance entropy. In specific, the similarity distance  $d_i$  is converted to the proportional distribution  $S(d_i)$  according to the exponential transformation, written as (6). So, the original distance entropy  $E_d$  is shown as (7).

$$S(d_i) = \frac{\exp(d_i)}{\sum_{j=1}^K \exp(d_j)} \quad (6)$$

$$E_d = -\sum_{i=1}^K S(d_i) \cdot \log_2 S(d_i) \quad (7)$$

According to the Maximum Entropy Theory, the maximum value in (7) appears when the distance to each class is the same. To normalize the distance entropy, the formula is revised as (8).

$$E_d^* = -\sum_{i=1}^K S(d_i) \cdot \log_K S(d_i) \quad (8)$$

In the case of normalized distance entropy, the value range is from 0 to 1.

### C. Proposed NDE

The proposed normalized double entropy (NDE) includes two entropy modules, i.e., the normalized probability entropy and normalized distance entropy, expressed in (2) and (8). The combination of double entropy is helpful to the quality evaluation of data information, the data uncertainty and space feature distribution can be simultaneously considered.

To obtain a standard data quality score from 0 to 1, the NDE formula is shown as (9). In this study, we set  $\alpha = \beta = 0.5$ .

$$\text{NDE} = \alpha \cdot E_p^* + \beta \cdot E_d^*, (\alpha + \beta = 1) \quad (9)$$

The large NDE score means that the data is more informative to the current model, with high data information contribution. Otherwise, if the quality score is low, the corresponding data is redundant and not necessary to collect, annotate, and transmit via a network. Although such data is less helpful to improve model performance, it still faces the risk of privacy disclosure of patient data during transmission.

## IV. Results and Analysis

### A. Experimental Setup

To verify the effectiveness and stability of the proposed NDE method, the meta-task experimental approach is adopted in this work. In specific, we use the skin lesion images to conduct the experiment. As unbalanced training data has a non-negligible impact on the training results of deep learning model, to fairly compare the effect of data information contribution without any specially designed loss function, the images from the ISIC 2019 are augmented to establish a balanced dataset. Some image samples are shown in Fig. 3, including

image rotation, scaling, mirroring, and other means. Moreover, the balanced dataset well supports the analysis of performance differences under the same data size in each class.

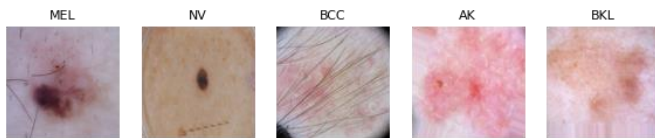


Fig. 3. Some image samples in the ISIC dataset.

The meta-task experimental approach means that several different tasks are prepared, where each task has different test data. The reason to adopt the meta-task setup is that the index of the deep learning model is based on the performance of test sets, but there is a contingency in a single test set. If the proposed method has stable performance in different test sets, it indicates that the proposed method can have better generalization. In this work, the number of meta tasks is ten, the used ISIC dataset consists of 5 classes. Each category has 3000 images, with a uniform image size of  $224 \times 224 \times 3$ . The random split of the dataset is 2500 samples as the train set and the rest 500 samples as the test set. Note that, according to the meta-task setting, there are ten different test sets. The labels in the dataset include melanoma (MEL), melanocytic nevus (NV), basal cell carcinoma (BCC), actinic keratosis (AK), and benign keratosis (BKL). The experiments are performed based on a Linux computer with a GPU of NVIDIA TITAN Xp, whose memory is 12GB. The software tool is Jupyter Notebook, using Python language with packages of Keras (2.2.4), TensorFlow (1.12.0), Numpy (1.19.2), and OpenCV (4.1).

Here, we briefly describe the experimental steps as follows. First, establish ten tasks and randomly split the dataset as train set and test set in each task. Second, randomly choose the base data from the labeled train set, and the ratio is 10%. Then, finetune the ResNet-18 model based on the base data, and the rest data in the train set is regarded as a pool set. Further, the samples in the pool set are evaluated by the proposed NDE, utilizing the model's predicted probabilities and feature distribution. Finally, the data information contribution is distinguished by the value of NDE, and the comparison experiments are carried out based on good data with high information contribution and bad data with low information contribution.

## B. Performance Analysis

The results of meta-task testing accuracy are analyzed in this section, based on training data with different information contribution assessed by the proposed NDE metric. Table I presents the average testing accuracy of ten different tasks. Each row in Table I represents an iterative update of the model under data addition. The model parameters in the latter iteration are initialed as the trained parameters in the previous iteration and each iteration has 100 epochs. The cross-entropy loss function and the stochastic gradient descent method are used to train the model, and the test set is evaluated after the model converges. The data with large NDE score stands for good data with high information contribution, which would be helpful to improve the model performance. Otherwise, the small NDE score means bad data with low information contribution. Through the performance comparison between the second and last columns, the contrast gap between good and bad data from the perspective of information contribution is obvious. For instance, when using half of the train set, there exists a 6% difference in the average testing accuracy between selected good and bad data, according to the proposed NDE.

TABLE I

Meta-task average testing accuracy based on selected data

Percentage of selected training data	Select according to large NDE score	Select according to small NDE score
10%	0.754	0.754
20%	0.787	0.762
30%	0.816	0.77
40%	0.843	0.785
50%	0.861	0.795
60%	0.871	0.811
70%	0.876	0.833
80%	0.877	0.848

90%	0.878	0.864
100%	0.879	0.879

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The comparison of the above experimental results is plotted in Fig. 4, where the beginning and end points of the two curves overlap, not by accident. The reason is that in these two cases, the used training data are the same, i.e., one is the initial base data, and the other is all data in the train set.

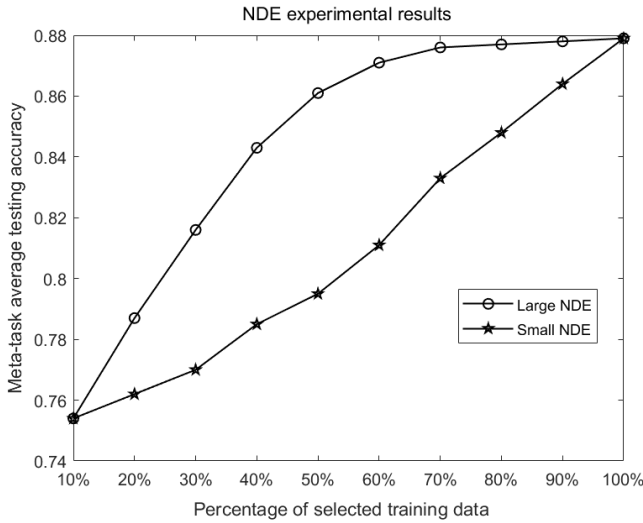


Fig. 4. The comparison of experimental results according to NDE.

The experimental results show that the proposed NDE is a suitable metric to assess data quality in terms of information contribution, targeted at the model performance improvement. A large NDE score means that the data has more uncertainty and difference in high-dimensional space feature distribution. Otherwise, a small NDE score means that the data brings less new information and the model has been already familiar with it. In this case, the collection and annotation of the data are of little significance and increase the cybersecurity risk during wireless transmission.

Besides, the above experimental results also shed light on data redundancy, which is worth seriously thinking about to achieve a trade-off between medical data quantity and quality. In Fig. 4, the good data with high information contribution help to improve model performance quickly, and tend to be flat after 70%, indicating the existence of large redundancy. However, low-information samples have a poor effect and weak

contribution in the initial stage but improve quickly in the later stage. But note that, this is because the remaining data are relatively high information, due to the experimental setting.

As known, the stability of designed algorithms is very important for practical applications. In this work, the NDE method is proposed and meta-task experiments are carried out. We analyze ten different experiments with different test sets and plot the accuracy distribution in terms of the box diagram, shown in Fig. 5 and Fig. 6, corresponding to the large and small NDE score respectively.

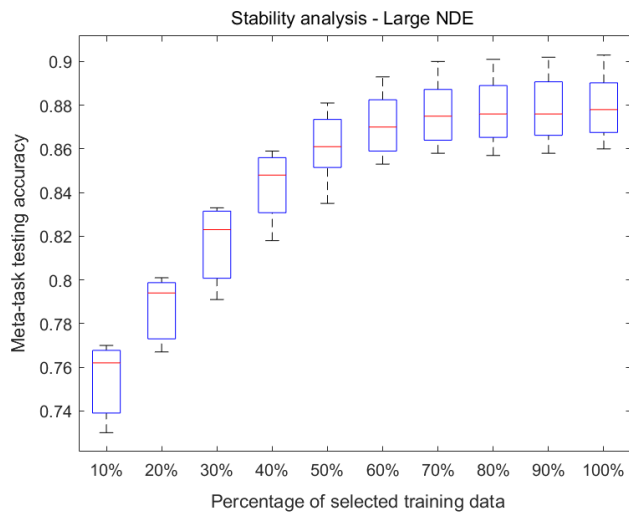


Fig. 5. The box plot of meta-task testing accuracy under large NDE.

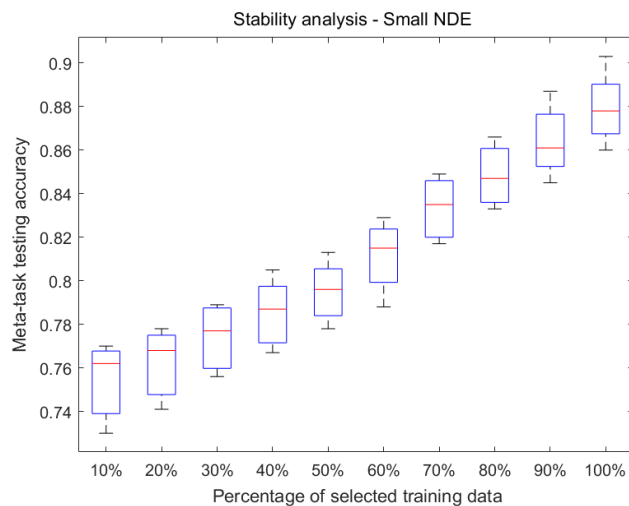


Fig. 6. The box plot of meta-task testing accuracy under small NDE.

The box plots indicate that the proposed NDE metric is stable and effective when faced with different test samples. All the trends in meta tasks are consistent with those in Fig. 4, and the difference is some specific

values, which is due to the differences in the composition of experimental data each time. Further, the middle red line of the boxes is the median of the data and represents the average level of the meta-task performance. This finding can guide the scheme of the limited amount of high-quality data collection rather than roughly pursuing a large size dataset.

### C. Discussion

In this section, the ablation experiments, visualizations, and limitations are carried out to give an in-depth discussion of this work.

**Ablation:** In this work, the proposed NDE metric consists of two entropy modules and shows the good ability of quality assessment. To explore the influence of different parts in the proposed method, a comparative experiment with single entropy is carried out. According to the same experimental setting, the average testing accuracies of ten tasks are shown in TABLE II. In particular, the single probability entropy (SPE) and single distance entropy (SDE) are used and compared with normalized double entropy (NDE) to select good data in terms of high information contribution.

TABLE II

Ablation results based on good selected data

Percentage of selected training data	NDE	SPE	SDE
10%	0.754	0.754	0.754
20%	0.787	0.774	0.776
30%	0.816	0.809	0.813
40%	0.843	0.836	0.839
50%	0.861	0.855	0.857
60%	0.871	0.866	0.868
70%	0.876	0.875	0.874

80%	0.877	0.877	0.877
90%	0.878	0.878	0.878
100%	0.879	0.879	0.879

The results indicate that the single module is also effective to distinguish the data information contribution. Because the proposed NDE metric considers both the uncertainty of prediction and the diversity of feature distribution, it has better performance than the single module. However, all the three methods illustrate the objectivity of data redundancy.

**Visualizations:** To explain the effect of NDE more intuitively and explore the metric’s working basis, we conduct the visualization of the feature distribution of selected good and bad samples in terms of data information contribution. In specific, the feature embeddings obtained from the trained model are some 512-dimensional vectors. The t-distributed stochastic neighbor embedding (t-SNE) method is further used to reduce the dimension of feature embeddings to 2 dimensions for easy visualization.

Since the experiments are conducted by iterative addition, the intermediate step is selected as an example, i.e., some existing samples in all classes are represented by colored dots, and supplementary data are assessed and screened based on the NDE, denoted by black stars. The good and bad samples in terms of data information contribution selected by the NDE are shown in Fig. 7 and Fig. 8, respectively.

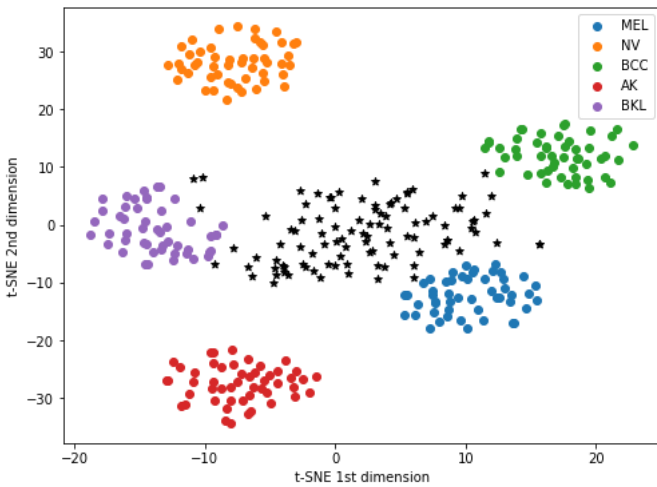


Fig. 7. The distribution visualization of screened good samples.



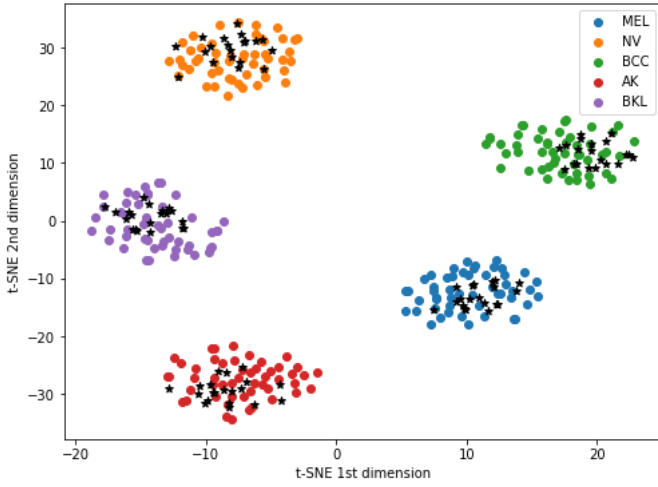


Fig. 8. The distribution visualization of screened bad samples.

Through the above visual comparison, it can be found that when NDE screens high informative samples, it tends to look for data with different distributions, which have little overlap with the existing distribution. In other words, the model is not familiar with these high informative samples and needs to re-learn and map them to a new distribution. However, the screened low informative data by NDE fall in the existing distribution, bringing relatively little information contribution. There will be many application scenarios of this phenomenon in the actual medical data processing, such as screening limited high informative medical data to reduce large-scale information leakage and improve model learning efficiency.

**Limitations:** In order to implement healthcare data quality assessment to reduce the collection and transmission of low informative and unnecessary data, this work adopts the balanced dataset setting to evaluate information contribution under the premise of the same data size. But in practical applications, the data corresponding to those rare or malignant diseases is certainly unbalanced, and this case will be further analyzed in our future work. In addition, the same coefficient is adopted in the NDE equation, that is, the weight of the probability entropy and the distance entropy is the same. In the future, this issue should be further optimized to discuss the influence of different weighted coefficients.

## V. Conclusion

The digital and intelligent healthcare systems have been generating lots of healthcare data and bringing many challenges to cybersecurity and privacy. In this study, we focus on healthcare data quality assessment in

terms of information contribution to reduce the annotation and wireless transmission of low informative and unnecessary data. The normalized double entropy (NDE) method is proposed and many experiments are conducted in the form of meta-task to verify the generalization and validity of the NDE method to screen good and bad data from the perspective of information contribution. The results show that the NDE method is stable and effective, and exceeds that of the single entropy module. Furthermore, the feature distribution visualization of screened results is also carried out to intuitively analyze the principle of NDE. The performance comparison between screened high and low informative data has a clear gap, which illustrates the serious redundancy of the dataset. Finally, this work makes a positive attempt to call for the community to pay more attention to the issues of data quality in different aspects.

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