GasHisSDB: A New Gastric Histopathology Image Dataset for Computer Aided Diagnosis of Gastric Cancer

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ABSTRACT

Background and Objective: Gastric cancer has turned out to be the fifth most common cancer globally, and early detection of gastric cancer is essential to save lives. Histopathological examination of gastric cancer is the gold standard for the diagnosis of gastric cancer. However, computer-aided diagnostic techniques are challenging to evaluate due to the scarcity of publicly available gastric histopathology image datasets.

Methods: In this paper, a noble publicly available Gastric Histopathology Sub-size Image Database (GasHisSDB) is published to identify classifiers’ performance. Specifically, two types of data are included: normal and abnormal, with a total of 245,196 tissue case images. In order to prove that the methods of different periods in the field of image classification have discrepancies on GasHisSDB, we select a variety of classifiers for evaluation. Seven classical machine learning classifiers, three Convolutional Neural Network classifiers, and a novel transformer-based classifier are selected for testing on image classification tasks.

Results: This study performed extensive experiments using traditional machine learning and deep learning methods to prove that the methods of different periods have discrepancies on GasHisSDB. Traditional machine learning achieved the best accuracy rate of 86.08% and a minimum of just 41.12%. The best accuracy of deep learning reached 96.47% and the lowest was 86.21%. Accuracy rates vary significantly across classifiers.

Conclusions: To the best of our knowledge, it is the first publicly available gastric cancer histopathology dataset containing a large number of images for weakly supervised learning. We believe that GasHisSDB can attract researchers to explore new algorithms for the automated diagnosis of gastric cancer, which can help physicians and patients in the clinical setting.

1. Introduction

1.1. Research Background and Motivation

Gastric cancer is a common type of malignant tumor with a relatively poor prognosis and presents a severe threat to global health [1]. According to the recent Global Cancer Statistics, gastric cancer is the fifth most commonly diagnosed cancer [2], and accountable for 18.0% of the total cancer deaths [2]. Histopathological examination of gastric cancer is a microscopic examination of paraffin sections made from tissues taken from suspected cancerous sections by experienced pathologists [3]. It is the gold standard for gastric cancer diagnosis and an essential requirement before treatment initiation [1].

Hematoxylin and Eosin (H&E) staining is a commonly used staining method in paraffin section technology to demonstrate nucleus and cytoplasmic inclusions in clinical specimens and highlight the delicate structures of cells and tissues [4, 5, 6]. Firstly, the pathological segment is observed with naked eyes to observe whether the section is qualified or not to find the lesion roughly. Then, the use of a low magnification microscope to observe and diagnose. Finally, if doctors want to observe the fine structure of the lesion more clearly, they can move it to the center of the visual fields, switch to a high-power microscope for the analysis [7]. It can be seen that there are the following problems in the process of observing H&E staining sections of gastric cancer: the diagnosis results of medical doctors are subjective and hard to be quantitative described, their workload is heavy, and working hours are long, it is easy for doctors to omit section information, and it is inconvenient to use big data technology. Therefore, there is an urgent need for more efficient solutions to related problems.

With the rapid development of computer vision technology, especially the emergence of medical image classification, it is possible to examine every electron microscopic photo quickly and efficiently [8, 9]. Thus, it brings an opportunity to solve the problems related to the diagnosis of gastric cancer [10, 11]. Especially, image classification plays an important role in computer-aided diagnosis. In the field of distinguishing benign or malignant tumors, distinguishing the differentiation stage of tumors and distinguishing the subtype of cancer [12], the results of image classification methods can be used as an important reference for clinicians in...
diagnostic practice. Furthermore, with the development of medical image classification technology, the main purpose of this technology is to achieve high accuracy and have the high anti-interference ability [13, 14]. Although the mainstream trend is to scan the whole-slide images for analysis, the actual work often encounters the actual situation of computer performance shortage, where the whole-slide images are usually cropped into many sub-size images for analysis. To this end, we need a Sub-size Image Database to test the anti-interference ability of various medical image classification techniques [15]. This paper introduces a noble publicly available Gastric Histopathology Sub-size Image Database (GasHisSDB), consisting of 245196 sub-size pathological images of gastric cancer and contains three sub-size labels. Furthermore, each image in this database calculates three different features. Moreover, the evaluation results of different classification schemes based on features and images, using machine learning and deep learning methods, are presented to show each classifier’s discrimination ability. GasHisSDB is available at the URL: https://gitee.com/neuhwm/GasHisSDB.git. The main contributions of this paper are as follows:

- Development of a Gastric Histopathology Subsize Image Database based on open-source databases, in which several experts participated in the production of the database.
- Demonstrate that GasHisSDB can be used to differentiate the performance of classifiers including traditional machine learning classifiers and deep learning classifiers.
- This Gastric Histopathology Subsize Image Database is published as open source for non-commercial purposes.

1.2. Related work

In the field of classical machine learning methods for gastric cancer image classification, a commonly used open-source database is introduced in [16]. This dataset consists of 11 Human Epidermal Growth Factor Receptor 2 (HER2) and H&E stained Whole-Slide Images (WSI) at a magnification of 40x, annotated by ten pathologists, taken from surgical sections of patients with different gastric cancers [17]. In classical machine learning classification studies, this dataset is often pre-processed, including operations such as semi-automatic registration and conversion of HER2 WSI to H&E stained WSI [18]. Another commonly used open source database is the public database used in this paper [19], which contains 560 abnormal images and 140 normal images. Studies often pre-process this database, including random cuts, geometric transformations [20].

Meanwhile, some gastric cancer image classification studies use proprietary databases, such as the study using stomach molecular images taken from Pathology Department of the Medicine Faculty in the Firat University [21]. In the study, the size of these images is 2592x1944. 180 images are taken, of which 60 are normal, 60 are benign, and 60 are malignant.

The dataset in [16] is also public in the field of deep learning classification of gastric cancer images. In [22], this dataset is pre-processed with overlapping by a factor of 0.3, and affine transformations such as rotations with 10-degree intervals, reflection, rotation after reflection and shear by a factor of 0.1. After a further 512x512 cropping, this study yielded a total of 231000 initial data. In the field of deep learning classification, studies are using the same base database as [23]. In this study, the image pre-processing operation is to crop the whole image into 224x224 patches, obtaining 8992 abnormal patches and 14000 normal patches.

There are also deep learning studies of gastric cancer image classification using proprietary databases, as follows. A new large Whole Slide Gastric Image dataset (WSGI) is constructed by collaborating with The Sixth Affiliated Hospital of Sun Yat-sen University in [24]. The WSGI dataset consists of 608 complete slide images with a magnification of 40x. The labels of WSGI include three categories: normal, dysplasia, and cancer. The dataset used in [25] contains 410 pathological images of gastric cancer of size 2048x2048 and 210 images of normal tissue of the same size. This study rearrange and crop this dataset to 256x256 yielding 5905 training images and 655 test images. The deep learning model in the study of [26] is trained with 2123 pixel-level annotated H&E stained digital slides from 1500 patients, which include 958 surgical specimens (908 malignancies) and 542 biopsies (102 malignancies) with diverse tumor subtypes. Testing is then performed on a multicenter dataset, which included 355 cases (595 slides) from Peking Union Medical College Hospital and 541 cases (987 slides) from Cancer Hospital of Chinese Academy of Medical Sciences. In [27], a histopathological image dataset is obtained from gastroscopic biopsy specimens of 94 cases at Gyeongsang National University Changwon Hospital (Changwon, Korea). Then all 94 WSIIs are manually categorized into four groups: 13 well-differentiated, 11 moderately-differentiated, 20 poorly-differentiated adenocarcinoma and 50 poorly cohesive carcinoma. And poorly cohesive carcinoma include 20 signet-ring cell features and 30 normal gastric mucosa.

Table 1 summarizes existing studies and their use dataset for gastric histopathological image classification methods. The databases proposed in the above papers include large size images and are in small quantities. Data augmentation operations are often performed on the databases to expect better classification performance of the classifiers. The source database utilized in this paper also has the aforementioned problems. Therefore, this study makes full use of the already existing resources and complements the shortcomings of the original database functionality to make it more comprehensive.

1.3. Structure of this paper

This section describes the background and motivation for the database preparation and does related work on the database of related research papers. Next, the methods of preparing the database and evaluating the database are described in detail, which includes the details of each item of...
Table 1
Data usage in image classification of gastric cancer.

| Aim          | Year | Reference | Team                                      | Categorization                     | Amount |
|--------------|------|-----------|-------------------------------------------|------------------------------------|--------|
| Machine      | 2015 | [16]      | Sharma et al.                             | HER2+ tumor/HER2- tumor/Non-tumor   | 11     |
| Deep         | 2015 | [18]      | Sharma et al.                             | HER2+ tumor/HER2- tumor/Non-tumor   | 11     |
| learning     | 2017 | [20]      | Liu et al.                                | Abnormal/Normal                     | 560/140|
|              | 2018 | [21]      | Korkmaz et al.                            | Normal/Benign/Malignant             | 60/60/60|
|              | 2017 | [22]      | Sharma et al.                             | HER2+ tumor/HER2- tumor/Non-tumor   | 11     |
|              | 2018 | [23]      | Li et al.                                 | Abnormal/Normal                     | 560/140|
|              | 2019 | [24]      | Wang et al.                               | Normal/Dysplasia/Cancer             | 117/172/319|
|              | 2020 | [25]      | Zhu et al.                                | Cancer/Normal                       | 410/210|
|              | 2020 | [26]      | Song et al.                               | Malignancy/Normal                   | 1010/490|
|              | 2020 | [27]      | Kosaraju et al.                           | Well-differentiated/Moderately-differeniated adenocarcinoma/ poorly cohesive carcinoma | 13/11/20/50|

the database. The third chapter shows the results of the evaluation database. Section 4 discusses the results of section 3. Finally a summary and future work is given.

2. Method

2.1. Database preparation
GasHisSDB contains 245,196 sub-size images in two categories, including 97,076 abnormal images and 148,120 normal images. The details of the applied datasets are introduced as follows.

**Gastric Histopathology Sub-size Image Database:**

1. **Data source:**
   - **Stage 1:** Four pathologists from Longhua Hospital Shanghai University of Traditional Chinese Medicine provide 600 images of gastric cancer pathology images of size 2048×2048 and give tissue-level labels for a strongly supervised learning process [19, 23, 28].
   - **Stage 2:** Based on stage 1, five biomedical researchers from Northeastern University prepare 245196 sub-sized gastric cancer pathology images for weakly supervised learning [29], and two experienced pathologists from Liaoiong Cancer Hospital and Institute perform the calibration.

2. **Preparation rules:** According to the existing method of making the database [30, 31, 32], the preparation rules of this database is as follows:
   - **Rule 1:** Three sizes (160 × 160, 120 × 120, 80 × 80 pixels) of normal pathological sections are cropped directly. And, it is necessary to select the cancerous region as the region of interest when dealing with abnormal pathological sections.
   - **Rule 2:** The region of interest of the pathological section and the ground truth is cropped simultaneously. This work can be used to filter out images with very few cancerous areas.
   - **Rule 3:** In order to reduce the correlation among sub-size images from the same original images, each one is rotated randomly, and the image order of the whole database is scrambled.

The data preparation workflow of GasHisSDB is shown in Figure. 1.

3. **Staining:** H&E staining (See section 2.2.3 for details).
4. **Magnification:** 20×.
5. **Microscope:** Nikon (Japan) and Olympus (Japan).
6. **Acquisition software:** NewUsbCamera.
7. **Sub-database and image sizes:**
   - Sub-database A: 160×160 pixels,
   - Sub-database B: 120×120 pixels,
   - Sub-database C: 80×80 pixels.
8. **Scale:** See Table. 2.

Table 2
Dataset scale of GasHisSDB.

| Sub-database name | Cropping size       | Abnormal | Normal |
|-------------------|---------------------|----------|--------|
| Sub-database A    | 160×160 pixels      | 13,124   | 20,160 |
| Sub-database B    | 120×120 pixels      | 24,801   | 40,460 |
| Sub-database C    | 80×80 pixels        | 59,151   | 87,500 |
| Total             |                     | 97,076   | 148,120|

9. **Image format:** "*.png".
10. **Image types:**
    - Normal: No cancerous cells appeared in the section (See section 2.2.1 for details);
    - Abnormal: Cancerous cells appear in this section (See section 2.2.2 for details).
11. The research and preparation of GasHisSDB is approved by the Ethical Committee at Northeastern University.

2.2. Database description

2.2.1. Normal image
Every normal image does not contain cancerous region. Each cell has no or very small atypia (Figure. 2 (a)). Moreover, the nuclei of the cells in the image have almost no mitosis and are regularly arranged in one layer (Figure. 2 (b)). Therefore, when observed under the optic microscope, if no cancelation of any cells and tissues is observed, and the characteristics of the normal image are satisfied, it can be judged that this is a normal image [33]. In making normal image data set, we directly crop the whole image because of the characteristics of normal images. The resulting images are shown in (a) (b) (c) in Figure. 3.
Figure 1: Data preparation workflow of GasHisSDB.

### 2.2.2. Abnormal image

Each abnormal image contains gastric cancer. The general shape of gastric cancer is mostly ulcer type. As the disease progresses, cancer nests grow infiltrating from the mucosal layer to the muscle layer and serosal layer. It has a hard texture, and the section is often gray-white. When observing under a microscope, the cancer cells can be arranged in a nest, acinar, tubular, or cord shape, and the boundary with the stroma is generally clear (Figure 2 (c)). However, when the cancer cells infiltrate into the stroma, the boundary between them is not clear (Figure 2 (d)). Based on the above facts, when the cells are observed to form gland or adenoid structures with uneven size, different shapes, and irregular arrangement, it can be judged that the pathological image is abnormal. In the abnormal images, the cancerous cells are often irregularly arranged in many layers, and the nuclei have different sizes and division phenomena [1, 34, 35].

In the process of making the abnormal image dataset, we crop every cancerous region selected according to the original ground truth (GT) images. Then, the cropped images are filtered based on the cancerous area (usually 50%) in the images. The resulted images are shown in Figure. 3 - (d)(e)(f).

### 2.2.3. Staining method

H&E staining method is one of the commonly used staining methods in paraffin section technology and is often the gold standard. The hematoxylin is alkaline and stains cell nuclei a purplish blue, and eosin is acidic and stains the extracellular matrix and cytoplasm pink, with other structures taking on different shades, hues, and combinations of these colors [5, 36]. Therefore, pathologists can easily distinguish the nuclear and cytoplasmic parts of cells. In addition, the overall staining pattern of staining shows the overall layout and distribution of the cells and provides a general overview of the structure of the tissue sample [37]. H&E staining method is the most basic and most widely used technical method in histology, embryology, pathology teaching and scientific research.

The pathological image after he staining has more pink and white areas in the normal image. Compared with the normal image, in the abnormal image, the purplish blue area is more distributed and messy.
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Figure 2: Example of Pathological images: (a)(b) Normal pathological images, (c) Non-invasive abnormal pathological image, (d) Invasive abnormal pathological image.

Figure 3: Example of GasHisSDB.

2.3. Methods of feature extraction

Extracting various virtual features of a database is the preparation for classification using a machine learning classifier. In this paper, we use three methods to extract the visual features of the database, including color histogram, local binary pattern (LBP), and gray level co-occurrence matrix (GLCM) features.

2.3.1. Color histogram

Color histogram is the most commonly used method to describe the color characteristics of images. It can simply represent the global distribution of colors in an image, i.e., the proportion of different colors in the whole image. It is especially suitable for describing images that are difficult to segment automatically and images that do not need to consider the spatial location of objects [38, 39]. Its advantage is that it is not affected by image rotation, shift changes, and further normalization by image scale changes. The disadvantage is that it cannot describe the local distribution of colors in the image, each color’s spatial location, and specific objects.

2.3.2. Texture features

The texture is a visual feature that reflects homogeneity in an image. It reflects the organization and arrangement of surface structures with slow or periodic changes on the surface of an object. It is not based on the characteristics of pixels but needs to carry out the statistical calculation on the region containing multiple pixels [40]. The texture is represented by the gray distribution of pixels and their surrounding spatial neighbor, local texture information. Besides, global texture information is the degree of repetition of local texture information. This paper uses two methods to describe texture features of GasHisSDB, which are Local Binary Patterns (LBP) and Gray-level Co-occurrence Matrix (GLCM).

LBP is an effective texture description operator that measures and extracts textural information local to an image with significant advantages such as grey level invariance and rotational invariance, and the feature is easy to compute. The value of LBP for each pixel is eight values within its eight-neighbor compared to its pixel. If the pixel value in the eight-neighbor is greater than or equal to the central pixel value, the position is labeled by 1, and 0 for otherwise, aligning them clockwise after eight comparisons yield a binary number of eight lengths, yielding LBP values [41].

The GLCM is defined by the joint probability density of the pixels at two locations. It not only reflects the distribution of brightness but also reflects the distribution of location between pixels with the same or near brightness. It is a second-order statistical feature about the change of image brightness. GLCM is the basis for defining a set of texture features [42, 43, 44]. To more intuitively describe the texture state with a symbiotic matrix, some parameters reflecting the state of the matrix are derived from the symbiotic matrix, typically the following:

1. Contrast: Reflects the sharpness of the image and the depth of texture grooves.
2. Correlation: It measures the degree of similarity of spatial grayscale symbiosis matrix elements in a row or column directions.
3. Energy: It is the sum of squares of gray symbiosis matrix elements, so it is also called energy, which reflects the uniformity of gray distribution and texture thickness of the image.
4. Homogeneity: Returns a measure of the compactness of the diagonal distribution of elements in GLCM.

2.4. Methods of classification

After the steps of feature extraction, two classical machine learning methods are used to classify GasHisSDB, including Random Forest (RF) and linear Support Vector Machine (linear SVM). Furthermore, three classical or novel
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2.4.1. Classical machine learning methods

The machine learning method for classification interpreters whether the image is normal or not by its visual features. RF is a parallel ensemble learning method and an extended variant of Bagging. RF is based on a decision tree learner, which adds random attribute selection to the training process of the decision tree [45]. SVMs are classified into linear and non-linear according to the kernel functions. Linear SVM maps training examples to points in space to maximize the gap between the two categories. Then, the new examples are mapped to the same space and predicted to belong to a category based on which side of the gap they fall on.

2.4.2. Deep learning methods

The concept of deep learning originates from the research of Artificial Neural Network [46], where a multi-layer perceptron with multiple hidden layers is a deep learning structure. Deep learning forms a more abstract high-level representation attribute category or feature by combining low-level features to discover distributed feature representations of data [47].

In 2014, the Visual Geometry Group and Google DeepMind developed a new deep convolutional neural network: VGG [48]. VGG is a Convolutional Neural Network (CNN) improved by AlexNet. Several forms of VGG models are released, and the most commonly used in the field of image classification is VGG16 one. In VGG16, three 3×3 convolution kernels are used instead of 7×7 convolution kernels, and two 3×3 convolution kernels are used instead of 5×5 convolution kernels. The main purpose of this structure is to ensure the same perceptual field conditions, enhance the depth of the network, and to a certain extent enhance the effect of the neural network.

In 2016, to solve the difficulty of training deep networks due to the disappearance of gradients, Kaiming He et al. proposed various forms of ResNet [49]. The most commonly used in the field of image classification is ResNet50. The ResNet50 team separately constructed a ResNet50 building block with "Shortcut Connection" and a down-sampling ResNet50 building block. A 1×1 convolution operation is added to the main branch of the regional down-sampling building block.

In 2020, Alexey Dosovitskiy et al. proposed the ViT model [50] by using the transformer, which is very effective in the field of natural language processing. It also provides good results in the image classification domain and reduces the dependence on CNNs. ViT crops an image into small chunks and provides a sequence of linear embeddings of these chunks as input to the Transformer and trains the model in a supervised manner for image classification.

3. Result

3.1. Results of classical machine learning methods

In this paper, various classification experiments are conducted on the GasHisSDB database (160×160 pixels, 120×120 pixels and 80×80 pixels) to demonstrate that GasHisSDB can be used to discriminate the performance of classifiers. Table. 3 show the comparison results of the classical machine learning methods. All the classification comparison experiments use the same parameters. The number of trees in the RF is set to 10. The SVM kernel function uses a linear kernel.

3.2. Results of deep learning methods

In this part, classical and novel deep learning methods are used to classify the Sub-database A, Sub-database B and Sub-database C of GasHisSDB. In a series of comparative experiments, the ratio of the training, validation and test sets to the three Sub-databases is split 4:4:2. Each model uses a learning rate of 0.00002, the batch size is set to 32, and the experiment is performed for 100 epochs, to observe the classification results of this database on different models. The results of the comparative experiment are shown in Table. 4.

3.3. Additional experiment

Since it is observed that the ViT did not fully converge in 100 epochs, a series of additional experiments are performed in this section. The experimental results are shown in the last item of each Sub-database in Table. 4. In the follow-up additional experiment of Sub-database A, under the same parameter conditions, the training time is controlled to be similar to that of ResNet with running 100 epochs, so ViT needed to run 400 epochs.

4. Discussion

4.1. Classical machine learning results discussion

Sub-database A has the largest sample size and the smallest number of samples. The color histogram is the extracted feature with the most feature items. According to Table. 3, the color histogram obtains the best classification accuracy in the classification results of different classifiers using three different features on Sub-database A in the RF, which is 85.99%. However, the linear SVM classifier performs poorly on color histogram features, less than 50%. As a comparison, the classification effect on LBP does not perform as well as the color histogram, and the highest classification effect on RF is only 70.27%. And the classification effect of linear support vector machine on LBP is also less than 50%. GLCM contains the least amount of data among all features, with only four items per image. The classification results of RF on GLCM are similar to those on LBP, but the linear SVM has a significant improvement in classification accuracy reaching 66.50% on GLCM.

Sub-database B has more balanced sample size and sample number. Overall, there was only a slight change in the classification accuracy of Sub-database B compared to the classification results of Sub-database A. On Sub-database B, the best classification accuracy remained on the color histogram using RF classification, with a result of 86.08%. The RF is greater than 70% on all three features and performs consistently. Another classical machine learning classifier,
Table 3
Classification results of three image features using different classifiers in three sub-databases of GasHisSDB (In [%]). The bold text in the table indicates the highest value of the classification result for the same sub-database.

| Sub-database | Features  | Methods | Acc  | Precision | Recall | Specificity | F1-score | Abnormal | Precision | Recall | Specificity | F1-score | Normal | Precision | Recall | Specificity | F1-score |
|--------------|-----------|---------|------|-----------|--------|------------|----------|----------|-----------|--------|------------|----------|--------|-----------|--------|------------|----------|
| Sub-database A | Color histogram | RF | 85.99 | 81.65 | 87.83 | 84.55 | 84.63 | 89.88 | 84.55 | 87.83 | 87.13 | 84.63 | 84.55 | 87.83 | 87.13 |
| | | linear SVM | 41.12 | 33.92 | 35.96 | 45.16 | 34.91 | 47.40 | 45.16 | 35.96 | 46.25 | 45.16 | 35.96 | 47.40 | 45.16 |
| | LBP | RF | 70.27 | 62.16 | 62.84 | 75.10 | 62.50 | 75.64 | 75.10 | 62.84 | 75.37 | 62.50 | 75.10 | 75.64 | 75.37 |
| | | linear SVM | 48.17 | 36.83 | 44.02 | 50.87 | 40.10 | 58.27 | 50.87 | 44.02 | 54.32 | 40.10 | 58.27 | 50.87 | 54.32 |
| | GLCM | RF | 71.39 | 63.16 | 65.85 | 75.00 | 64.48 | 77.14 | 75.00 | 65.85 | 76.06 | 64.48 | 77.14 | 75.00 | 76.06 |
| | | linear SVM | 66.50 | 55.89 | 71.27 | 63.39 | 62.65 | 77.22 | 63.39 | 71.27 | 69.63 | 62.65 | 77.22 | 63.39 | 71.27 |
| Sub-database B | Color histogram | RF | 86.08 | 80.36 | 83.87 | 87.43 | 82.08 | 89.84 | 87.43 | 83.87 | 88.62 | 82.08 | 89.84 | 87.43 | 88.62 |
| | | linear SVM | 46.28 | 39.48 | 77.62 | 27.06 | 52.34 | 66.36 | 27.06 | 77.62 | 38.45 | 27.06 | 52.34 | 66.36 | 38.45 |
| | LBP | RF | 70.13 | 60.88 | 59.90 | 76.41 | 60.39 | 75.66 | 76.41 | 59.90 | 76.03 | 60.39 | 75.66 | 76.41 | 76.03 |
| | | linear SVM | 46.21 | 29.70 | 30.40 | 55.89 | 30.05 | 56.71 | 55.89 | 30.40 | 56.30 | 30.05 | 56.71 | 55.89 | 56.30 |
| | GLCM | RF | 71.15 | 61.42 | 64.72 | 75.09 | 63.03 | 77.64 | 75.09 | 64.72 | 76.34 | 63.03 | 77.64 | 75.09 | 76.34 |
| | | linear SVM | 66.66 | 55.02 | 67.30 | 66.28 | 60.54 | 76.78 | 66.28 | 67.30 | 71.14 | 60.54 | 76.78 | 66.28 | 71.14 |
| Sub-database C | Color histogram | RF | 83.27 | 77.14 | 83.15 | 83.34 | 80.03 | 87.98 | 83.34 | 83.15 | 85.60 | 80.03 | 87.98 | 83.34 | 85.60 |
| | | linear SVM | 60.81 | 50.86 | 83.15 | 45.41 | 63.24 | 80.36 | 45.41 | 83.58 | 58.03 | 45.41 | 63.24 | 80.36 | 58.03 |
| | LBP | RF | 68.16 | 60.13 | 62.49 | 71.98 | 61.29 | 73.95 | 71.98 | 62.49 | 72.95 | 61.29 | 73.95 | 71.98 | 72.95 |
| | | linear SVM | 43.10 | 27.68 | 25.48 | 55.01 | 26.53 | 52.20 | 55.01 | 25.48 | 53.56 | 26.53 | 52.20 | 55.01 | 53.56 |
| | GLCM | RF | 68.39 | 60.13 | 64.23 | 71.21 | 62.11 | 74.65 | 71.21 | 64.23 | 72.89 | 62.11 | 74.65 | 71.21 | 72.89 |
| | | linear SVM | 66.82 | 57.14 | 71.04 | 63.97 | 63.33 | 76.57 | 63.97 | 71.04 | 69.71 | 63.33 | 76.57 | 63.97 | 69.71 |

Table 4
Classification results of four deep learning classifiers on GasHisSDB (In [%]). The bold text in the table indicates the maximum value or the best index of the classification results of different categories.

| Sub-database | Model | Quantity of epoch | Model size | best epoch | training time | Acc  | Category | Precision | Recall | Specificity | F1-score |
|--------------|-------|-------------------|------------|------------|---------------|------|----------|-----------|--------|------------|----------|
| Sub-database A | VGG16 | 100 | 268.16 | 100 | 13873 | 95.90 | Abnormal | 93.8 | 96.0 | 95.9 | 94.9 |
| | ResNet50 | 100 | 83.12 | 84 | 10023 | 96.09 | Abnormal | 94.6 | 95.6 | 96.4 | 95.1 |
| | | 100 | 31.17 | 97 | 2587 | 86.21 | Abnormal | 83.8 | 86.9 | 89.9 | 88.2 |
| | | 400 | 31.17 | 399 | 10014 | 92.23 | Abnormal | 92.1 | 89.1 | 95.6 | 93.2 |
| Sub-database B | VGG16 | 100 | 268.16 | 100 | 26105 | 96.47 | Abnormal | 96.7 | 94.0 | 98.0 | 95.3 |
| | ResNet50 | 100 | 83.12 | 94 | 19087 | 96.09 | Abnormal | 96.4 | 93.0 | 97.8 | 94.6 |
| | | 100 | 31.17 | 100 | 41992 | 89.44 | Abnormal | 96.2 | 92.2 | 93.0 | 94.6 |
| | | 500 | 31.17 | 496 | 41135 | 94.59 | Abnormal | 95.4 | 93.4 | 95.3 | 93.2 |
| Sub-database C | VGG16 | 100 | 268.16 | 90 | 62152 | 96.12 | Abnormal | 94.2 | 94.0 | 96.0 | 95.2 |
| | ResNet50 | 100 | 83.12 | 97 | 41992 | 96.09 | Abnormal | 97.4 | 96.0 | 96.3 | 96.7 |
| | | 100 | 31.17 | 89 | 41992 | 96.09 | Abnormal | 96.2 | 94.0 | 97.5 | 95.1 |
| | | 500 | 31.17 | 496 | 41135 | 94.57 | Abnormal | 95.6 | 95.5 | 93.4 | 95.4 |

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4.2. Deep learning results discussion

In general, deep learning models are far superior to classical machine learning methods, and even the lowest ViT accuracy is still higher than the highest accuracy of classical machine learning methods. In Sub-database A, The accuracy of the VGG model is more than 95%, but it has the longest training time and the model size is much larger than other deep learning models. The accuracy of ResNet50 is slightly higher than that of VGG16, which is the highest value among all methods reaching 96.09%. Both the model size and training time of ResNet50 are better than VGG16. ViT is the latest model based on transformer structure. Its accuracy is at least 86.21%, but it is still higher than the classification accuracy of RF on the color histogram. Importantly, compared to ResNet, ViT achieves such accuracy in only 1/4 of the training time and 1/3 of the model size. Moreover, the accuracy curve still has an increasing trend and the loss function still has not fully converged.

Because there are more training samples, VGG16 is the classifier with the highest accuracy in the classification results of the deep learning method of Sub-database B, which is 96.47%. The corresponding training time has also become twice that of Sub-database A. The accuracy of ResNet50 almost caught up with that of VGG16 with 95.94% accuracy. The accuracy of ViT also improved somewhat with the increase in the amount of training data, reaching 89.44%.

Sub-database C is the Sub-database with the largest number of samples. The accuracy of the four classifiers has only slightly changed. The classification model with the highest accuracy rate is still 96.12% for VGG16. The lowest accuracy rate is still the ViT model with the least training time, which is 90.23%. However, the training time of ViT in the Sub-database C has almost become 13.26% of the training time of VGG16 with the highest accuracy.

4.3. Additional experimental results discussion

This experiment achieved an accuracy of 92.23%. Moreover, as the amount of data increases, when the control training time is the same as ResNet50, the accuracy of the ViT model with Sub-database B and Sub-database C is increased to 94.59% and 94.57%. These image classification results have reached the general level of medical image classification, and the ViT model is excellent in terms of model size.

4.4. Overall performance evaluation

This chapter compares the different classifier’s classification results from the Linear Regression to Visual Transformer on the Sub-database A, Sub-database B and Sub-databases C of the GasHisSDB. Each method has a completely different classification performance on GasHisSDB. Classical machine learning methods have strict theoretical foundations, simple ideas, and excellent performance in some specific features and algorithms. However, deep learning methods are still far ahead of classical machine learning methods in terms of image classification accuracy and experimental workload. As a sub-size image database, GasHisSDB can be proved to have distinguishing in a variety of methods.

5. Conclusion and futures works

In this paper, a sub-size gastric histopathological image database is developed, namely GasHisSDB. GasHisSDB have three Sub-databases, 160 × 160 pixels Sub-database, 120 × 120 pixels Sub-database and 80 × 80 pixels Sub-database. Each Sub-database contains two folders of normal images and abnormal images. Each folder contains cropped images that have been renamed and shuffled. GasHisSDB has the function of discriminating the performance of classifiers. This paper is divided into the following two parts for testing. For classical machine learning methods, this paper extracts five different features. Then test the classification performance of seven different classification methods on three sub-databases, and analyze the differences in the accuracy of each classifier. For deep learning methods, this paper tests three repeatedly proven CNN methods and ViT, which have only recently been used in the field of image classification. This paper focuses on the analysis of the four models from the accuracy rate, model size, training time and other indicators. In addition, this paper conducts additional experiments for training time to find the best classification performance of ViT on GasHisSDB. GasHisSDB demonstrates that the performance in the image classification experiments in this paper is competent to test existing image classification methods.

The creation of the dataset means that more image classification methods can be used for this dataset. We will try newer image classification methods on the GasHisSDB to compare and analyze image classification methods and obtain better practical methods to contribute to medical progress.

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