Medical image analysis based on transformer: A Review

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Abstract

The transformer has dominated the natural language processing (NLP) field for a long time. Recently, the transformer-based method has been adopted into the computer vision (CV) field and shows promising results. As an important branch of the CV field, medical image analysis joins the wave of the transformer-based method rightfully. In this review, we illustrate the principle of the attention mechanism, and the detailed structures of the transformer, and depict how the transformer is adopted into medical image analysis. We organize the transformer-based medical image analysis applications in a sequence of different tasks, including classification, segmentation, synthesis, registration, localization, detection, captioning, and denoising. For the mainstream classification and segmentation tasks, we further divided the corresponding works based on different medical imaging modalities. The datasets corresponding to the related works are also organized. We include thirteen modalities and more than twenty objects in our work.

Keywords Deep Learning · Transformer · Attention Mechanism · Convolutional Neural Network · Medical Image Analysis

1 Introduction

Transformer [1] is one of the most widely used models in the natural language processing (NLP) field and has achieved great success in many tasks, such as paraphrase generation [2], text-to-speech synthesis [3], and speech recognition [4]. It is designed for transduction and sequence modeling within the remarkable capability of modeling long-range dependencies with the data.

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Figure 1: Different medical image analysis applications discussed in this review. Including classification, segmentation, synthesis, registration, localization, detection, captioning, and denoising. The illustrative image for registration is accessed from [24]. The illustrative images for other tasks are accessed from the BUSI dataset [25] and pre-processed to the resolution of $256 \times 256$.

The transformer is composed of an encoder and a decoder where both the encoder and the decoder are the tandem of consecutive identical blocks. It is convolutional-free and solely based on the self-attention mechanism or attention mechanism in short. The attention mechanism is a process to relate different positions of a single sequence to compute the sequence’s representation [1] and it has achieved much success in many NLP tasks, such as sentence embedding [5], natural language inference [6], abstractive summarization [7], and machine reading [8, 9]. Unlike the NLP field, the computer vision (CV) field has been dominated by the convolutional neural network (CNN) for a long, no matter of classification [11], segmentation [12, 13], detection [14, 15], or other tasks since the AlexNet [16] was proposed. CNN is a type of deep learning (DL) model to process data with a grid pattern and is designed to capture features’ spatial hierarchies [17]. It has the remarkable capability of induction and is composed of many kinds of blocks, such as convolution layers, fully connected layers, and so on. Inspired by the success that the transformer achieved in the NLP field, many trials have been done to combine CNN and attention [18, 19] while none of them influence CNN’s leadership in the CV field. In 2020, Dosovitskiy and colleagues [20] proposed a revolution model to combine CNN and transformer directly. They patch and embed the images used in the CV field and feed the embedded images to the modified transformer encoder used in the NLP field. Their proposed work achieve unprecedented success and starts a milestone in solving CV tasks with transformer-based methods. Till now, the transformer-based method has been implemented in many CV tasks and achieved superior results [21, 22, 23].

Medical image analysis, an important branch in the CV field, is involved in this revolution, as it should be. Medical imaging utilizes various modalities to create a visual representation of the inside body [26] and is capable of helping doctors in medical diagnoses. There are many kinds of medical imaging modalities, including magnetic resonance imaging (MRI), computed tomography (CT), ultrasound (US), wireless capsule endoscopy (WCE), optical coherence tomography (OCT),
The “Others” part shares a large proportion due to the large number of objects that exist. One of the main reasons is that some of the objects contain other objects or are a part of other objects, such as the liver and the abdomen, and these objects are counted separately.

In practice, image analysis is usually performed qualitatively by medical personnel. This may result in varying interpretations and degrees of accuracy, usually because of varying degrees of reader experience or varying image quality. Moreover, such image analysis may be time- and labor-intensive. Due to these, the DL method has been widely applied in the field of medical image analysis to reduce inter-reader variation as well as reduce time and manpower costs. The transformer-based method has been widely used in medical image analysis either using the transformer solely \[27, 28, 29\] or hybridizing CNN and transformer to capture both local and global information \[30, 31, 32\]. However, an insightful and critical review of transformer-based medical image analysis is absent.

In this review, we state the structure of the transformer in detail and summarize its applications in the sequence of different medical image analysis tasks, including classification, segmentation, synthesis, registration, localization, detection, captioning, and denoising. The structure of this review is shown in Figure 1. For the mainstream classification and segmentation, we further divided the corresponding works based on different medical imaging modalities. There are a total of thirteen modalities and more than twenty objects included in our review and we list the proportion that each modality and object share in Figure 2. Note that some infrequently evaluated modalities and objects are classified into “Others”. For the modality, CT and MRI are two of the most dominant imaging modality, occupying more than a quarter of all modalities respectively. X-ray is also widely researched with around 15\% share, followed by the scanner with around 8\%. The other modalities are much less frequently evaluated. As for the object, most of the works focus on the brain, occupying a share of over 15\%, followed by the chest with around 13\%. The other organs are much less frequently assessed.

The rest of this paper is organized as follows: In Chapter 2, we illustrate the principle of the attention mechanism, the detailed structures of the transformer, and depict how the transformer is adopted into the medical image analysis field. A short introduction to different medical image analysis...
tasks is also included. In Chapter 3, we organize the transformer-based medical image analysis applications from the perspective of different tasks, including classification, segmentation, synthesis, registration, localization, detection, captioning, and denoising. The related datasets used are also listed. For mainstream classification and segmentation, we further divide the works according to the modalities. There are thirteen modalities and more than twenty objects included in this work. In Chapter 4, we summarize the current challenges that this field faces and points out the future potential research directions. A short conclusion is illustrated in Chapter 5.

2 Background

2.1 Attention mechanism

Given three vectors, query, keys, and values, the attention mechanism maps a query and a set of key-value pairs to output. The output is computed by summarizing all the values according to the weight and the weight is calculated using a compatibility function of the query with the related key. The attention mechanism can be divided into scaled dot-product attention and multi-head attention.

**Scaled dot-product attention.** Several queries, keys, and values compose the input of the scaled dot-product attention. The queries and keys have a dimensionality of $d_k$ and the values have the dimensionality of $d_v$. The dot product of all keys and the query are calculated. The resulting values are divided by a scale factor, $\sqrt{d_k}$, and pass a softmax function. Through the dot product with the values, attention can be calculated. Practically, a set of queries, keys, and values are packed into corresponding matrices, $Q, K, V$, and the outputs matrix can be calculated using the below formula:

$$Attention(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$

**Multi-head attention.** The queries, keys, and values are projected for $h$ times, where $h$ is the number of heads, and the attention function is performed on each of the projected results parallelly. The output values are concatenated and projected again to obtain the final values. A concise illustration of the multi-head attention is shown in Figure 3. With multi-head attention, information from different representation subspaces at different positions, which is inhibited in a single attention head due to averaging, is jointly attended. The multi-head attention can be described using the below equation:

$$\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \ldots, \text{head}_h) W^O$$

where

$$\text{head}_i = Attention\left(Q W_i^Q, K W_i^K, V W_i^V\right)$$

Where $W_i^Q \in \mathbb{R}^{d_{model} \times d_k}$, $W_i^K \in \mathbb{R}^{d_{model} \times d_k}$, $W_i^V \in \mathbb{R}^{d_{model} \times d_v}$, and $W^O \in \mathbb{R}^{h d_v \times d_{model}}$ illustrate the projections.

2.2 Transformer

The transformer, merely composed of the attention mechanism, has an encoder-decoder structure and both the encoder and the decoder are tandem by several identical blocks. The blocks are composed
Figure 3: An intuitive illustration of multi-head attention mechanism. The result of each head is calculated separately and the values are then concatenated.

of several parts including masked multi-self attention, multi-self attention, layer normalization, and position-wise feed-forward network. The detailed structure of the transformer can be found in Figure 4.

Encoder. The transformer encoder consists of $N$ identical blocks. For each block, there are two main parts and both parts employ the residual connection proposed by He et al. [33]. The bottom part is composed of a multi-head attention part and layer normalization. The top part consists of a fully connected feed-forward network and layer normalization. The fully connected feed-forward network consists of two linear layers and the ReLU is selected as the activate function for both. The procedure can be expressed using the below equation:

$$\text{FFN}(x) = \max(0, xW_1 + b_1)W_2 + b_2$$

Decoder. The transformer decoder is composed of $N$ identical blocks like the encoder and consists of three main parts in each block. The bottom part is similar to that of the encoder, while the multi-head attention is masked to ensure the positions not be affected by the subsequent positions. The middle part is similar to the bottom part in the encoder while it also takes the encoder’s output as the input. The top part is the same as the top part in the encoder. The residual connection is implemented for all three parts.

2.3 Transformer in medical image analysis

To adopt the transformer in medical image analysis [20], images needed to be preprocessed. The pre-processing can be divided into two main procedures, patch generation, and embedding. The patch generation part splits the input image into several patches. The embedding part flattens the patches and generates patch embeddings. Positional embeddings and class embedding are also added. The processed images are fed into the transformer encoder, which is slightly modified, to extract useful information. The detailed structure of the transformer used in the medical image process field is illustrated in Figure 5.
Figure 4: Structure of the transformer [1]. MHA refers to multi-head attention and Norm represents layer normalization. The output of the encoder is fed into the MHA block in the decoder. **Left**: encoder, and **Right**: decoder.

Figure 5: The detailed structure of the transformer in the field of medical image analysis. MHA refers to multi-head attention, Norm represents layer normalization and MLP illustrates the multi-layer perceptron. The illustrative image is accessed from the BUSI dataset [25] and pre-processed to the resolution of $256 \times 256$.

**Patch generation.** The patch generation part receives image $x \in \mathbb{R}^{H \times W \times C}$ as the input, where $H$ and $W$ are the height and the weight of the image, respectively. The input image is reshaped into a patch sequence $x_p \in \mathbb{R}^{N \times (P^2 \cdot C)}$, where $P$ is the dimension of each image patch, and $N$ shows the number of patches [20]. The relationship between $N$, $H$, $W$, and $P$ is expressed as:

$$N = \frac{HW}{P^2}$$

**Embedding.** The embedding part obtains patches as the input, flattening and mapping them to $D$ dimensions using a linear projection $E$, where $D$ is the latent vector size of the layers of the transformer. This process results in patch embeddings. The class embedding [34] is concatenated with the path embeddings. To retain positional information, the position embeddings are summed with the concatenation of the patch embeddings and class embedding. The overall procedure can be
described through the below equation [20]:

\[ y = [x_{\text{class}}; x_1^p E; x_2^p E; \cdots; x_N^p E] + E_{\text{pos}} \quad \text{where} \quad E \in \mathbb{R}^{(P^2 \cdot C) \times D}, \ E_{\text{pos}} \in \mathbb{R}^{(N+1) \times D} \]

**Transformer encoder.** The transformer encoder takes the resulting embeddings as the input. The overall encoder structure is similar to that in Figure 3 while the sequence of the layer normalization is changed. The multi-layer perceptron block is composed of two linear layers and both of the layers use GELU as the activation function.

Training the transformer is not an easy task. It is reported that training the transformer with less than 100 million images usually obtains a suboptimal solution compared to that of using CNN, and the larger the dataset used for training, the better the overall performance of the transformer [20]. However, producing a medical image dataset is not like making a nature image dataset due to several reasons. For instance, To make a medical image dataset, we usually need different kinds of expensive types of equipment to capture the images and the captured images need to be annotated by human experts. This process not only costs many funds but also lasts a long time. Besides, the collected dataset cannot be directly provided publicly even for the researchers as the privacy of the patients need to be taken into consideration. So in the medical image analysis field, it is not possible to collect a dataset with more than 100 million images, and sometimes there are only thousands of images or even hundreds of images in a medical image dataset. To relieve the common data shortage, most of the researchers combine the transformer with CNN to let their model capture both local and global information thus improving the performance.

### 2.4 Medical image analysis tasks

There are many tasks consisted in the field of medical image analysis and we include classification, segmentation, synthesis, registration, localization, detection, captioning, and denoising in this review. Classification is a process aimed at classifying given images into different classes, which are essentially labels, to assist in disease diagnosis. Segmentation is a procedure to partition the image into various subgroups or objects. It can be regarded as a process of classifying all the pixels in the image. Image synthesis is defined as a process of synthesizing desired images with certain content artificially and can be considered as an opposite process of image classification. Image registration is defined as a procedure to transform several sets of data obtained from different sensors, viewpoints, times, etc. [35] into a unified coordinate system. Image localization is defined as a process of finding the desired object, which is usually the main one or most visible one, and drawing a surrounding box around the object. Object detection is a similar process to image localization while it aims at finding all the objects together with their boundaries. Image captioning illustrates a process of generating language descriptions using images’ visual information. Image denoising is a process to remove the noise existing in the images. A concise graphical illustration for each task can be found in Figure 1.

### 3 Applications

We illustrate the transformer-based medical image analysis applications in the sequence of different tasks, including classification, segmentation, synthesis, registration, localization, detection, captioning, and denoising. For mainstream classification and segmentation, we further divide them
by modalities such as X-ray, US, MRI, and so on due to a large number of works contained. The datasets corresponding to the related works are also organized. There are thirteen modalities, as shown in Figure 6 and more than twenty objects included in this review.

3.1 Classification

Classification works are organized in the sequence of the number of works included in different modalities. Most of the classification research concentrates on the X-ray and scanner, followed by the MRI, fundus camera, and dermoscopic. The microscope, camera, CT, and OCT are less well evaluated. Works containing more than one modality are listed separately. Table 1 concludes the classification applications based on the transformer. Some of the authors utilize the transformer only while most of the remaining combine the transformer with CNN.

**X-ray.** Dinh et al. [27] used the swin transformer [48] to classify COVID-19 chest X-ray images on a customized datasets [49, 50, 51, 52]. Krishnan and colleagues [28] fine-tuned the transformer to classify X-rays images [53, 54]. Gu et al. designed a model called Chest L-Transformer [30] to classify chest X-ray images using the SIIM-ACR pneumothorax dataset [55]. The proposed model is composed of a backbone block based on the ResNeXt [56], a position attention block, and a classifier. Duong and colleagues [32] constructed a novel framework and evaluated it on several X-ray datasets [57, 58, 59, 19]. The proposed method consists of a CNN backbone based on EfficientNet [60], a transformer encoder, a transformer decoder, and a classifier layer. Jiang et al. [61] designed an MXT architecture to classify chest X-ray images with multi-label using the ChestX-ray14 dataset [62] and the Catheter dataset [63]. The MXT consists of five stages, where the first four stages are composed of several downsample spatial reduction transformer blocks and
a multi-layer overlap patch embedding block and the last stage is composed of two class token transformer blocks and a multi-label attention block. Sheng and colleagues [31] developed a method to classify chest X-ray images [64]. The method is composed of a Gamma transformer block and a combined model block and the latter block hybrids the CNN and transformer.

**Scanner.** Ikromjanov et al. [65] proposed a method to classify images extracted from scanned prostate WSI images [66]. The proposed method is based on the Gleason grading system and has three parts. An extraction part to extract patches, a transformer part to execute classification, and a graded part to perform scoring and grading. Zeid and colleagues [67] utilize the transformer and the compact convolutional transformer [68] to classify scanned colorectal cancer images [43].

The compact convolutional transformer is a transformer that uses a convolutional-based patching approach. Gul et al. [69] implemented a Self-ViT-MIL method to classify breast WSI images [70]. There are two phases in the developed method. First, the transformer is trained in a self-supervised manner using the DINO training approach [71]. Second, the weights of the transformer are frozen and a multiple instance learning aggregator is trained. Wang and colleagues [72] developed a model named TransPath to classify scanned WSI images using multiple datasets [73, 70, 74]. The proposed method consists of a CNN encoder, a transformer encoder, and a token-aggregating and excitation module and is trained in a self-supervised manner using the BYOL architecture [75]. Two datasets are used for pre-training [76, 77].

**MRI.** Dai et al. [78] developed a method named TransMed to classify head, neck, and knee MRI images [79]. The proposed TransMed is composed of an image serialization part, a CNN branch based on the ResNet [33], and a transformer branch. Hu and colleagues [37] proposed a double-scale DL method to classify medical MRI images [80]. The developed method is composed of a generator and two discriminators: a local discriminator based on the CNN, and a global discriminator based on the transformer.

**Fundus camera.** Yu et al. [81] developed a transformed-based model named MIL-VT to classify retinal images captured by fundus camera using the APTOS2019 dataset [82] and RFMiD2020 dataset [83]. The transformer was pre-trained using a large dataset and its output is fed to the multiple instance learning head. The cross-entropy loss between the multi-layer perceptron head and the label and between the multiple instance learning head and label are computed. Kamran and colleagues [84] proposed a VTGAN model to classify retinal fundus camera images [85]. The proposed method is composed of a coarse and a fine generator based on the generative adversarial network (GAN) [86] and two transformers as discriminators. Each transformer discriminator takes one of the generator’s outputs as the input.

**Dermoscopic.** Aladhadh et al. [45] developed an MVT-based framework based on transformer to classify skin dermoscopic images using the HAM10000 dataset [87]. Different data augmentation methods are introduced to extend the dataset, including image flip, scaling, rotation, and contrast. Wang and colleagues [88] designed a novel model named O-Net to classify dermoscopic images using the ISIC2017 dataset [89]. The proposed O-Net has a circle shape and is composed of four core blocks: EfficientNet encoder block, swin transformer encoder block, CNN decoder block, and swin transformer decoder block. To illustrate the O-Net clearly, we show its structure in Figure 7.

**Microscope.** Islam et al. [44] developed an explainable transformer-based model to classify malaria parasites images on two microscope datasets [90, 91]. The compact convolutional transformer is utilized and a gradient-weighted class activation map technique is employed to show which parts of an image are paid how much attention by generating a heatmap.
Camera. Qayyum et al. [42] developed a multi-model architecture to classify toe images using the DFUC-21 dataset [92]. The proposed architecture consists of two separate pre-trained transformers and the outputs of both transformers are concatenated using pair-wise feature concatenation.

CT. Wu et al. [29] used the transformer model to classify lung CT images using computed tomography emphysema database [93, 94]. Large patches are cropped from original images and then resized. Obtained results are divided into small patches and fed for embedding.

OCT. Wang et al. [95] developed an architecture named ViT-P to classify OCT images using the GSM dataset and UCSD dataset [40]. The developed method is composed of a proposed slim model and several transformer encoders. The slim model is composed of four stages, a convolution layer, and a flatten layer. The channel attention mechanism [96] is employed in all four stages. Besides, DCGAN [97] and proposed B-DCGAN were used to perform data augmentation.

Multiple. Gong et al. [98] developed a model called SSBTN to classify both X-ray and WCE medical images using the INbreast dataset [99] and CrohnIPI dataset [100]. The proposed model is composed of three modules, which are a pretext channel module, a transformer-based transfer module, and a downstream channel module. Rahhal and colleagues [101] proposed a customized framework to classify X-ray and CT images [102, 103]. The developed framework is symmetric and consists of two transformers. The outputs of the transformers are passed through a weighted fusion layer.
Table 1: Medical image classification based on transformer.

| Method                                      | Year | Modality | Object                  | Dataset                                      |
|---------------------------------------------|------|----------|-------------------------|----------------------------------------------|
| swin transformer [27]                       | 2022 | X-ray    | chest                  | COVID-19 [49, 50, 51, 52]                   |
| transformer [28]                            | 2021 | X-ray    | chest                  | COVID-19 [53, 54]                           |
| Chest L-Transformer [30]                    | 2022 | X-ray    | chest                  | pneumothorax [55], tuberculosis [57]        |
| hybrid framework [32]                       | 2021 | X-ray    | chest                  | COVID-19 [58], thorax diseases [59], pneumonia [19] |
| MXT architecture [61]                       | 2022 | X-ray    | lung                   | prostate cancer [66]                        |
| enhanced transformer [31]                  | 2022 | X-ray    | prostate               | colorectal cancer [43]                      |
| Gleason grading system based [65]           | 2022 | scanner  | prostate               | colorectal cancer [43]                      |
| transformer, compact convolutional transformer [67] | 2021 | scanner  | colorectal polyps [74]  | colorectal polyps [74]                      |
| Self-ViT-MIL [69]                           | 2022 | scanner  | breast                 | breast cancer [70]                          |
| TransPath [72]                              | 2021 | scanner  | breast, colorectal     | anterior cruciate ligament, meniscal tears [79] |
| TransMed [78]                               | 2021 | MRI      | head, neck, knee       | blindness [80], ocular diseases [83]        |
| double-scale DL [37]                        | 2021 | MRI      | brain                  | diabetic retinopathy [85]                   |
| MIL-VT [81]                                 | 2021 | fundus camera | retinal               | pigmented skin lesion [87], malaria parasite [89] |
| VTGAN [84]                                  | 2021 | fundus camera | retinal               | diabetic foot ulcer [92]                    |
| MVT-based framework [45]                    | 2022 | dermoscopic | skin                  | pulmonary emphysema [93, 94]                |
| O-Net [88]                                  | 2022 | dermoscopic | cell                   | genitourinary syndrome [93, 94]             |
| explainable transformer-based [44]          | 2022 | microscope | cell                   | breast cancer [99], crohn’s disease lesions [100] |
| multi-model architecture [42]               | 2021 | camera   | toe                    | COVID-19 [102, 103]                         |
| transformer [29]                            | 2021 | CT       | lung                   |                                              |
| ViT-P [95]                                  | 2021 | OCT      | genitourinary syndrome |                                              |
| SSBTN [98]                                  | 2022 | X-ray, WCE | breast, small intestine |                                              |
| symmetric dual transformer [101]            | 2022 | X-ray, CT | chest                  |                                              |
3.2 Segmentation

The same as that classification-related works, the segmentation-related works are also organized in the sequence of the number of works included in different modalities. A large amount of segmentation works focus on the MRI and CT, followed by the X-ray, US, fundus camera, scanner, laryngoscopy, and colonoscopy. Works with more than one modality are summarized separately. The summary of the transformer-based segmentation works is shown in Table 2. Most of the segmentation works combine the transformer with one of the most famous and widely used segmentation models or its variants, the U-Net \[104\]. The U-Net is composed of a contracting path, or the encoder, which follows the structure of CNN, and an expansive path, which is the decoder. The encoder is composed of several CNN blocks with the ReLU activation function. The output of each CNN block passes the max pooling for downsampling. With the downsampling, the number of feature channels is doubled. As for the decoder, it is composed of several upsampling, which halves the passed features’ channels and several CNN blocks with the ReLU activation function. The features in the CNN blocks are concatenated with the feature obtained from the encoder at different scales.

**MRI.** Karimi et al. \[105\] developed a 3D transformer to segment MRI images using the brain cortical plate dataset and hippocampus dataset \[106\]. Their proposed transformer network removes the residual connections and two CT datasets \[107, 108\] and one MRI dataset \[109\] were utilized for pre-training to tackle the common problem of data shortage. Gao and colleagues \[110\] proposed an architecture named UTNet to segment cardiac MRI images \[111\]. The proposed transformer encoder block with both attention mechanism and convolution layer is implanted in the U-Net. Chen et al. \[112\] designed a U-shape model named MRA-TUNet to segment MRI images \[113, 114\]. The encoder is composed of a convolution block and four multiresolution aggregation modules and the decoder consists of a proposed CvT block and four convolution blocks. The CvT block is composed of a convolutional token embedding and a convolutional transformer block. Sun and colleagues \[115\] implemented an architecture named HybridCTrm to segment MRI images using MRBrainS dataset \[116\] and iSEG-2017 dataset \[117\]. The proposed HybridCTrm has two versions depending on the connection methods between the convolution block and transformer block. Gao et al. \[118\] developed a consistency-based co-segmentation model to segment MRI images using a public dataset \[119\]. The proposed model is composed of two U-Net with transformer encoders and decoders, and each of them takes short-axis images and long-axis images as the input, respectively. The segmentation loss is computed using the label and the consistency loss is obtained between two predictions. Liang and colleagues \[120\] developed a network named TransConver to segment MRI images using multiple datasets \[121, 122, 123\]. The encoder is composed of a convolution block, three TC-inception blocks, and three downsampling operations. Cross-attention fusion mechanisms were implemented in the decoder. Similar work contains UTransNet proposed by Feng et al. \[124\]. Wang and colleagues \[125\] developed a network named TransBTS to segment MRI images using BraTS challenges’ datasets \[121, 122, 123\]. The proposed work inserts a transformer encoder between the encoder and the decoder and the skip connection is implemented between the encoder and decoder at different scales. Similar works including METrans proposed by Wang et al. \[126\], SwinBTS developed by Jiang and colleagues \[127\], and BTSwin-Unet implemented by Liang et al. \[128\].

**CT.** Pan et al. \[135\] developed a CVT-Vnet to segment head and neck CT images \[136\]. The proposed model is composed of a down-sample part, an up-sample part, and a connection part. The
Table 2: Medical image segmentation based on transformer. The mark "-" shows the corresponding information is not publicly available.

| Method               | Year | Modality | Object                                                                 | Dataset                     |
|----------------------|------|----------|------------------------------------------------------------------------|-----------------------------|
| 3D transformer       | 2022 | MRI      | brain, left ventricle, right ventricle, left ventricular myocardium, left atrium | Alzheimer’s [106]           |
| UTNet                | 2021 | MRI      | brain                                                                  | brain tumor [127], [122], [123] |
| MRA-TUNet            | 2022 | MRI      | brain                                                                  | stroke [129]                |
| HybridCTr            | 2021 | MRI      | brain                                                                  | brain tumor [121], [122], [123] |
| consistency-based co-segmentation | 2021 | MRI      | right ventricle                                                       | stroke [130], ischemic stroke lesion [129] |
| TransConver          | 2022 | MRI      | brain                                                                  | brain tumor [121], [122], [123] |
| UTransNet            | 2021 | MRI      | brain                                                                  | stroke [130], ischemic stroke lesion [129] |
| TransBTS             | 2022 | MRI      | brain                                                                  | brain tumor [121], [122], [123] |
| METrans              | 2022 | MRI      | brain                                                                  | stroke [130], ischemic stroke lesion [129] |
| SwinBTS              | 2022 | MRI      | brain                                                                  | brain tumor [121], [122], [123] |
| BTSWNet              | 2021 | CT       | head, neck                                                            | organs at risk [136]        |
| CoTr                 | 2021 | CT       | abdomen                                                               | colorectal cancer, ventral hernia [138] |
| transformer-UNet     | 2021 | CT       | lung                                                                  | [140], organs at risk [143], organs at risk [144] |
| After-UNet           | 2022 | CT       | abdomen, thorax                                                       | kidney tumor [108], lung lesion [146], bladder cancer [147] |
| HT-Net               | 2022 | CT       | lung, kidney, bladder                                                | -                           |
| UCATR                | 2021 | CT       | brain                                                                 | COVID-19 [58]              |
| CCAT-net             | 2022 | CT       | chest                                                                 | -                           |
| CAC-EMVT             | 2021 | CT       | chest                                                                 | -                           |
| MSHT                 | 2021 | CT       | liver, kidney                                                         | kidney tumor [108], lung tumor [152] |
| temporary transformer | 2022 | X-ray    | catheter                                                              | -                           |
| Chest L-Transformer  | 2022 | X-ray    | chest                                                                 | -                           |
| TransBridge          | 2021 | US       | left ventricle                                                        | cardiovascular disease [56] |
| dilated transformer  | 2022 | US       | breast                                                                | breast tumor [156]         |
| PCAT-UNet            | 2022 | fundus camera | vessel                                           | diabetic retinopathy [157], [158], cardiovascular risk [159] |
| Swin-PANet          | 2022 | scanner | colon, nuclei                                                        | colon cancer [161], [162]   |
| RANT                 | 2022 | laryngoscopy | throat                                           | colorectal polyp            |
| SwinE-Net            | 2022 | colonoscopy | colorectal                                           | intraventricular hemorrhage [160], [166], [169], [170] |
| MedT                 | 2021 | US, scanner | brain, colon, nuclei                                               | colon cancer [161], [162], [171] |
| USegTransformer-P    | 2022 | dermoscopic, MRI, CT, microscope | brain, lung, nuclei, skin, chest | melanoma [175], COVID-19 [176] |
| USegTransformer-S    | 2022 | dermoscopic, MRI, CT, microscope | brain, lung, nuclei, skin, chest | colorectal cancer [171], colon cancer [161], colorectal polyp |
| DS-TransUnet         | 2022 | colonoscopy, dermoscopic, scanner, microscope, WCE | colon, skin, colorectal, nuclei | 164, 165, [169], [170] |
| MS-TransUnet++       | 2022 | MRI, CT  | abdominal, left ventricle, right ventricle, myocardium               | liver tumor [107], prostate cancer [179] |
| DSTUNet              | 2022 | MRI, CT  | abdominal, left ventricle, right ventricle, myocardium               | cardiac disease [113], colorectal cancer, ventral hernia [138], cardiac disease [185] |
| SegTransVAE          | 2022 | CT, MRI  | kidney, brain                                                        | kidney tumor [108], brain tumor [133], colorectal cancer, ventral hernia [138] |
| MT-UNet              | 2022 | CT, MRI  | abdomen, left ventricle, right ventricle, left ventricular myocardium | previous myocardial infarction, dilated cardiomyopathy, hypertrophic cardiomyopathy, abnormal right ventricle [181] |
| ECT-NAS              | 2021 | CT, MRI  | abdominal, left ventricle, right ventricle, left ventricular myocardium | cardiac disease [113], [185], [186] |
| ViTBIS               | 2021 | CT, MRI  | abdomen, brain                                                       | brain tumor [123], colorectal cancer, ventral hernia [138] |
| O-Net                | 2022 | dermoscopic, CT | skin, abdomen               | melanoma [59], colorectal cancer, ventral hernia [138] |
connection part is a CNN-transformer-based encoder consisting of several convolutional multi-head attention blocks and multi-head attention blocks. The connection part takes the output of the encoder at different levels and its outputs are fed to the decoder. Xie and colleagues [137] designed a novel framework called CoTr to segment CT images using the BCV dataset [138]. The proposed CoTr has three parts: A CNN encoder, a DeTrans encoder, and a Decoder. The DeTrans encoder connects the CNN encoder and the decoder at different scales. Guo et al. [139] designed a transformer-based model to segment CT images using a lung cancer dataset [140]. The transformer is embedded into the U-Net, followed by the upsampling operation. Yan and colleagues [141] developed a model named AFTer-UNet to segment CT images using three public datasets [142, 143, 144]. CNN encoder is used to encode the neighboring slice group and an axial fusion transformer is applied to the resulted feature map group. Afterward, the fusion feature group is fed to the CNN decoder. Ma et al. [145] proposed a model named HT-Net to segment CT images [146, 108, 147]. The skip connection in the developed U-shape model is composed of a residual atrous pyramid pooling module, a position-sensitive axial attention module, and a hierarchical context-attention module. Luo and colleagues [148] designed a model named UCATR to segment acute ischemic stroke lesions using the NCCT CT dataset. The proposed model is composed of a CNN-transformer encoder and a cross-attention decoder. Skip connection is implemented at different scales. Liu et al. [149] developed a CCAT-net to segment CT images [38]. Both encoder and decoder in the proposed network are composed of three CNN blocks and three swin transformer blocks. Ning and colleagues [150] proposed a CAC-EMVT architecture to segment CT images using a privacy dataset. The proposed model is composed of a local branch and a global branch. The local branch is composed of CNN layers followed by dilated CNN layers and transposed CNN layers. The global branch consists of a non-local sparse context fusion module and two non-local multi-scale context aggregation modules. Wang et al. [151] developed a model called MSHT to segment liver and kidney CT images [152, 108]. Their method implements parallel CNN and transformer as the encoder and a 3D image position embedding method was developed to generate position encoding.

**X-ray.** Zhang et al. [153] proposed a temporary transformer network to segment X-ray images using an unpublished dataset. The proposed model takes both the current and previous frames as the input to obtain temporary information. The current frame is fed into the CNN and transformer while the previous frame is fed into the CNN only. The Chest L-Transformer [30] introduced in Table [ ] for image classification are also designed for segmentation.

**US.** Deng et al. [154] proposed a model named TransBridge to segment left ventricle images [36]. Both the proposed encoder and decoder are based on CNN and the transformer encoder is used to skip connect them. Within the transformer encoder, an embedding layer is implemented by using shuffled group convolution and dense patch division. Shen and colleagues [155] developed a dilated transformer model to segment US images [156]. The proposed method utilizes a dilation convolution block to connect the encoder and decoder. The encoder contains the multi-head attention mechanism and the decoder is mainly composed of deconvolution. Their developed method performs better compared with other state-of-the-art methods and we show the performance comparison in Figure [8]. The dilated transformer and the SAUnet [189] perform better across all methods due to low false positives, which means the boundaries can be distinguished precisely. Within the two methods, the dilated transformer can capture information in more detail, for instance, the results shown in the fifth row.

**Fundus camera.** Chen et al. [41] designed a model called PCAT-UNet to classify fundus vessel images [157, 158, 159]. The proposed U-shape network contains two main components named
Figure 8: Segmentation results using different segmentation methods on the US dataset [156]. From left to right, each column represents the selected images, the ground truth, and the segmentation results obtained by the MedT [168], dilated transformer [155], U-Net [104], U-Net++ [188], and SAUnet [189].
patches convolution attention transformer and feature grouping attention module. Both encoder and decoder are composed of several patches convolution attention transformer blocks and the outputs of the feature grouping attention modules are fed into the patches convolution attention transformer blocks. The predicted segmentation maps at different decoder scales are predicted.

**Scanner.** Liao et al. [160] proposed a model called Swin-PANet to segment medical images using the gland dataset [161] and MoNuSeg dataset [162]. The skip connection is employed to connect the encoder to the decoder and the enhanced attention block. The attention and the ground truth constitute intermediate supervision while the prediction and the ground truth constitute direct supervision.

**Laryngoscopy.** Pan et al. [163] proposed a framework named RANT to segment laryngoscopy images [47]. Features are processed using reverse attention and RRM block, which is composed of reverse attention and receptive field block, and features at different scales are cascaded. The segmentation results are optimized using convolutional conditional random fields.

**Colonoscopy.** Park et al. [46] proposed a model named SwinE-Net to segment colonoscopy images using five public datasets [164, 165, 166, 39, 167]. The proposed SwinE-Net is mainly composed of an EfficientNet, a swin transformer, and an attentive deconvolution network. The intermediate outputs produced by the EfficientNet and swin transformer are created by the multi-feature aggregation block, and the attentive deconvolutional network-based decoder is utilized to upsample feature maps.

**Multiple.** Valanarasu et al. [168] designed a MedT model to segment US and scanned images using public datasets [169, 170, 161, 171, 162]. The proposed method contains a global branch and a local branch, which takes the images and the patches as the input respectively. The output of the local branch is resampled and added to the output of the global branch. Dhamija and colleagues [172] proposed two DL models named USegTransformer-P and USegTransformer-S to segment medical MRI, CT, microscope, and dermoscopic images using five public [173, 146, 174, 175, 87, 176].
The USegTransformer-P has two branches. One is composed of a transformer encoder and a convolution-based decoder, another is a U-Net-based encoder. The outputs of both branches are fed into a fully convolutional ensemble encoder. The USegTransformer-S is composed of a transformer encoder, a convolution-based decoder, and a U-Net-based encoder. Lin et al. [177] proposed a DS-TransUNet model to segment colonoscopy, dermoscopic, scanner, microscope, and WCE images [164, 165, 166, 167, 39, 175, 161, 174]. There are two encoder branches in their proposed network and the outputs of the branches are fused using the transformer interactive fusion module. Wang and colleagues [178] designed an architecture called MS-TransUNet++ to segment MRI and CT images [179, 107]. Its encoder is composed of both CNN and transformer and the decoder is composed of CNN. The encoder and the decoder at different scales are connected. We illustrate the structure of the MS-TransUNet++ in Figure 9 for further explanation. Cai et al. [180] developed a DSTUNet to segment CT [138] and MRI [181, 113] images. Their proposed U-shape model is symmetric and skip-connected using proposed dense swin transformer blocks at different scales. The transformer blocks in the transformer block are densely connected. Pham and colleagues [182] proposed a SegTransVAE network to segment MRI [133] and CT images [108]. The proposed network has an encoder-decoder architecture and the transformer layers were implemented between the encoder and decoder. Wang et al. [183] proposed a model named MT-UNet to segment CT [138] and MRI images [181]. Both the encoder and decoder are composed of several CNN blocks and developed mixed transformer modules. The mixed transformer module is also used to connect the encoder and decoder and is mainly composed of a Local-Global Gaussian-Weighted Self-Attention block and an external attention block. Xu and colleagues [184] proposed an ECT-NAS structure to segment CT and MRI images using three public datasets [185, 186, 113]. The proposed method is composed of several searching blocks consisting of CNN and a developed LiteTrans with two
parallel branches of convolution and local-global self-attention. Sagar [187] developed a ViTBIS network to segment CT [138] and MRI images [123, 122]. The proposed network is symmetric and both encoder and decoder consist of three transformer blocks at different scales. Skip connection is implemented between the encoder and decoder. Besides solving image classification problems, the O-Net [88] introduced in Table 1 is also capable of image segmentation using a separate output port shown in Figure 7. The difference is that both dermoscopic and CT datasets [89, 138] are chosen.

### 3.3 Miscellaneous

Miscellaneous works are organized in the sequence of different tasks and are not further divided according to the modality as the number of works is limited. The tasks follow the sequence of synthesis, registration, localization, detection, captioning, and denoising. The summary of this part can be found in Table 3.

#### Synthesis

Dalmaz et al. [192] developed a model named ResViT to synthesize brain MRI images [80, 123] and pelvis CT-MRI images [193]. The proposed method consists of an encoder, an information bottleneck, and a decoder. The information bottleneck is composed of several aggregated residual transformer blocks.

#### Registration

Song et al. [24] proposed a network named TD-Net to perform MRI image registration [194]. The proposed U-shape network is composed of both CNN where CNN is used to obtain the feature maps and the transformer is utilized to capture global information. The resulted outputs are fed for upsampling using CNN.

#### Localization

Chen et al. [195] developed a model called UTRAD to localize retinal OCT [196], brain MRI [197], and head CT [198] images. The proposed method contains three transformer encoders and decoders at different scales are skip connected. Both relative positional encoding and global positional encoding were utilized.

#### Detection

The localization model UTRAD proposed by Chen et al. [195], as shown in Table 3 is designed for both localization and detection using the same datasets [196, 197, 198]. The classification framework proposed by Rahhal and colleagues [101], as illustrated in Table 1 is also designed for image detection and the datasets used for model evaluation remain unchanged [102, 103].
Captioning. Lee et al. [199] developed a method named CEDT to generate image captioning using two public X-ray datasets [200, 59]. The proposed method is composed of three transformer encoders and a decoder and each encoder is connected to all of the three decoders. Encoders at different scales connect the encoders using different ways. Hou and colleagues [190] proposed a network called RATCHET to generate captions using X-ray images [191]. The image is fed into a DenseNet [203] based encoder and its output passes the masked multi-head attention block. The text tokens are fed for embedding and then pass the transformer decoder. Their method performs well and is capable of generating correct keywords for the given selected images, as shown in Figure 10.

Denoising. Wang et al. [201] proposed a network named TED-Net to denoising low-dose liver CT images [202]. The symmetric model has an encoder-decoder structure and both the encoder and decoder contain several transformer blocks. The input to the encoder is tokenized and the decoder outputs the detokenized result. A transformer block is employed to link the encoder and decoder and the input is removed from the output to calculate the final result. They compare their developed method with four baselines, as shown in Figure 11 and the results show that their method obtains a state-of-the-art result. The proposed TED-Net is capable of keeping high-level smoothness and details when removing the artifact or noise, while other methods left more blotchy noise.

4 Challenges and Perspectives

Though the transformer-based method has shown promising results in the field of medical image analysis, there are areas that could be further explored. The areas can be summarised from three aspects: data augmentation, model modification, and research distribution.

Data augmentation. Attention to data augmentation is insufficient. In the field of medical image analysis, data shortage is always influencing the model performance and the data augmentation technique is an important research field to relieve this problem. However, in transformer-based medical image analysis research, many of the works have not gone deep into it. A large proportion
of the works only use traditional data augmentation, such as rotation, crop, and flip, and only seldom works implement advanced data augmentation methods, such as the GAN-based method. Even this, the GAN implemented is relatively basic and is not considered state-of-the-art. In this case, more sophisticated and advanced data augmentation methods should be taken into consideration.

**Model modification.** Model modifications are relatively superficial. Some of the works utilize the existing transformer directly and the only novelty point of their works is that they use their own chosen datasets. A large part of the work only made minor modifications to the existing models. For instance, add a simple CNN before the transformer’s input. Seldom methods modify them dramatically, for example, with precise mathematical derivation. To improve this situation, further research can pay more attention to modifying the structure of the model.

**Research distribution.** Research across different parts is unbalanced. All kinds of modalities and objects count while most of the research only works on several mainstream ones and the remainings are not fully investigated. For the modality, current works mainly focus on the CT, MRI, X-ray, and scanner and one of the most important medical image modalities, the US, has only attracted little attention. For the object, most existing works focus on the brain and chest, and the importance of many other objects is ignored, such as the head and lung. From this perspective, more attention should be paid to the modalities and objects which are not mainstream currently.

5 Conclusion

The transformers-based method has shown great potential and achieved great success in the field of medical image analysis. In this review, we illustrate the detailed structure of the transformer and summarize its applications in the sequence of different medical image analysis tasks, such as classification, segmentation, and so on. We summarize the collected works that evaluated a total of thirteen modalities and more than twenty objects as well as identify areas that further research can focus on. With a detailed summary, critical review, and insightful perspective, we believe our review may contribute to the development of transformer-based medical image analysis.

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