Vision Transformers in Medical Imaging: A Review

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**KEY WORD**

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**ABSTRACT**

Transformer, a model comprising attention-based encoder-decoder architecture, have gained prevalence in the field of natural language processing (NLP) and recently influenced the computer vision (CV) space. The similarities between computer vision and medical imaging, reviewed the question among researchers if the impact of transformers on computer vision be translated to medical imaging? In this paper, we attempt to provide a comprehensive and recent review on the application of transformers in medical imaging by; describing the transformer model comparing it with a diversity of convolutional neural networks (CNNs), detailing the transformer based approaches for medical image classification, segmentation, registration and reconstruction with a focus on the image modality, comparing the performance of state-of-the-art transformer architectures to best performing CNNs on standard medical datasets.

1 Introduction

The transformer (Vaswani et al., 2017), identified by its attention mechanism, has become the dominant deep learning architecture in the field of natural language processing (NLP) due to its success in text to speech translation (Li et al., 2019), natural language generation (Topal et al., 2021), text synthesis (Li et al., 2019) and speech recognition (Feng et al., 2022). The success of transformers in the field of natural language processing owes primarily to their ability to capture long range dependencies that aids in the retention of contextual information (Vaswani et al., 2017) as opposed to recurrent neural networks (RNNs) (Graves et al., 2013; Sak et al., 2014) that utilizes a sequential inference process and cannot efficiently capture long range dependencies. A plethora of transformer architectures for natural language processing have been proposed since 2017, a few of the popular architectures are; Bidirectional Encoder Representation from Transformer (BERT) and its variants (Devlin et al., 2019; Lan et al., 2019; Liu et al., 2019), Generative Pre-Trained Transformer (GPT) and its variants (Hoppe & Toussaint, 2020; Radford et al., 2018; Winata et al., 2021).

In the computer vision field, convolutional neural networks (CNNs) have achieved efficient performance mainly due to the structure of their architectures (He et al., 2016; Louis, 2013; Peng et al., 2021; Yang et al., 2022; Y. Zhang et al., 2020). Recent evidence show CNNs exploits the locality of pixels aiding capture of vision semantics and yield acceptable performance even on small datasets (d’Ascoli et al., 2021), CNNs are also known to possess progressively enlarge receptive field that aids in the representation of image hierarchical structure in form of semantics. However, the advent of transformers apprised researchers of CNNs’ major drawback, the inability to capture long range dependencies such as the extraction of contextual information and the non-local correlation of objects (Zhang et al., 2020). This has led to attempts to incorporate self-attention either spatially (Cao et al., 2019; Huang et al., 2019; Xiaolong Wang et al., 2018) or channel-wise (Hu et al., 2020; Q. Wang et

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al., 2020; Woo et al., 2018), into the conventional CNN architecture. Eventually, the first pure transformer for computer vision application named Vision Transformer (ViT) was proposed by (Dosovitskiy et al., 2020), in which they demonstrated the equivalence between multi-head self-attention attached to a multi-layer perceptron and CNNs by considering image classification as a sequence prediction task hence utilizing patch down-sampling and quadratic positional encoding in order to capture long-range dependencies between image tokens (patches). In recent literatures, these pure or hybrid vision transformers (ViTs) have achieved state-of-the-art performance over the CNN benchmarks. This has been consistent across a variety of computer vision tasks, such as image classification (Dosovitskiy et al., 2020), image reconstruction (Jiang et al., 2021), pixel segmentation (Zheng et al., 2021), image captioning (Cheng et al., 2021), three-dimensional imaging (Zhou et al., 2021) and video applications (Zhou et al., 2018).

CNNs have substantially influenced the field of medical imaging because of the pertinent need for classification, segmentation and detection, required of the variety of imaging modalities including ultrasound, X-ray radiography, magnetic resonance imaging (MRI), computed tomography (CT), whole-slide-images (WSIs) etc. (Darby et al., 2012). Surprisingly, about 90% of all healthcare data are compiled instances of the various medical imaging modalities. This implies that there is an outlay of data available to foster efficient modelling for clinical diagnosis and decision-making. CNNs (He et al., 2016; Hu et al., 2020; Weng & Zhu, 2021) have excelled because of the ability to learn spatio-temporal dependencies within an image and utilize this in the extraction of distinguishable representation (Li et al., 2020; Susanti et al., 2017; Yu & Helwig, 2022). However, convolutional layers have stationary weights that do not adapt for a specific input image, offer their models a limited effective receptive field that limits the ability to capture long-range dependencies between pixels.

The successes of transformers on natural images, have encouraged researchers to query further the application of self-attention in medical imaging in order to effect long-range dependencies between pixels. Additionally, transformers have achieved comparable performance to state-of-the-art CNNs on medical image classification (Xie, Zhang, Xia, et al., 2021), detection (Ghaderzadeh & Asadi, 2021), segmentation (Tragakis et al., 2022) and reconstruction (Zhou et al., 2022). Literatures have recorded transformers of better performance than state-of-the-art CNNs however the performance of transformers over CNNs is still debatable and newer modifications to the transformer architecture emerge every day in an attempt to mitigate transformer related problems.

This paper attempts to provide a detailed review on the application of transformers in medical imaging and to compare their performance with state-of-the-art CNNs.

The paper provides detailed and recent review on of transformer state-of-the-art in medical imaging and detailed comparison between CNN and transformer benchmarks. To aid in visual identification and comprehension we have included a taxonomy articulating the disparate application of transformers in medical imaging with references.

Our paper is outlined as follows: the preliminaries of the original transformer, and CNNs by detailing the various combinations with transformers as can be found in the literature. The current progress of the transformer state-of-the-art in medical image classification, segmentation, registration, and reconstruction. In addition, the paper, identifies all known positives and negatives of the transformer, and provide a detailed comparison between present state-of-the-art transformer approaches and that of CNNs.

2 TRANSFORMERS

2.1 Attention in Transformers

The fundamental transformer architecture as proposed by Vaswani et al. (2017) is a sequence-to-sequence model that is composed of self-attention and point-wise feed-forward network (FFN) block that extracts global dependencies between tokens.
Attention mechanism is the primary way humans sort relevant from irrelevant data by unintentionally paying attention to some part of data set, while discarding other parts. Few scientists have attempted to build neural networks that model this behavior, initially for use in language processing tasks (Bahdanau et al., 2015; Dai et al., 2017; Xu et al., 2015). A typical attention, regarded as the “Bahdanau attention” computes a weighted sum of each feature while highlighting the most relevant features from a feature matrix.

Self-attention was designed to emphasize relationships between data regardless of their position in the sequence. It is mathematically expressed by a map function of queries, keys and values such that for each input \( X \in \mathbb{R}^c \), \( i = 1, ..., n \) there exist a query \( Q \in \mathbb{R}^{n \times d} \), a key \( K \in \mathbb{R}^{n \times d} \), and a value \( V \in \mathbb{R}^{n \times d} \), which are utilized in generating learning parameters \( W^q, W^k, W^v \) respectively.

\[
Q = X \times W^q, \quad W^q \in \mathbb{R}^{c \times d},
K = X \times W^k, \quad W^k \in \mathbb{R}^{c \times d}, \quad (1)
V = X \times W^v, \quad W^v \in \mathbb{R}^{c \times d},
\]

The output is a probability that requires normalization, usually achieved by a softmax function to attain an output distribution represented by the equation (2).

\[
Attention(Q, K, V) = \text{softmax} \left( \frac{Q K^T}{\sqrt{D_k}} \right) V = AV \quad (2)
\]

The output of a self-attention block is the sum of element \( V \) and the matrix \( A \) equipping this attention block with the ability to capture global dependencies within a data.

Multi-head self-attention can be applied to better capture hierarchical features. These are computed in parallel after the final output is obtained by concatenating each individual attention block. This operation is similar to the use of multiple kernels within convolution operations, mathematically expressed by:

\[
Z_i = Attention(Q \times W_i^q, K \times W_i^q, V \times W_i^v),
\]

\[
MSA(Q, K, V) = \text{concat}[Z_1, ..., Z_h] \times W^o \quad (3)
\]

Here \( h \) represents the total number of heads and \( W^o \) represents an output matrix of the concatenated projection of all self-attention \( W_i^q, W_i^q, W_i^v \) of the \( i^{th} \) attention.
2.2 **Point-Wise Feed-Forward Network**

The output from the multi-head self-attention block is fed into a feed-forward network comprising two linear activation function and a rectified linear unit (ReLU) activation, as expressed in equation (4).

\[
FFN(X) = \text{ReLU}(XW_a + B_a)W_b + B_b \tag{4}
\]

Here \(X\) represents the output from the previous layer and \(W_a, W_b, B_a, B_b\) are trainable parameters of dimensions \(D^c\) and \(D^n\), represented as \(W_i \in \mathbb{R}^{D^c \times D^n}\) and \(B_i \in \mathbb{R}^{D^c \times D^n}\) where \(i = a, b\). It is to be noted that \(n\) should always be larger than \(c\).

2.3 **Positional Encoding**

Learnable parameters are typically employed to aid the network retain positional information, this could be achieved by recurrence or convolutions however, in the transformer architecture this is achieved by inputting information about the position of tokens (words or patches) into the sequence. Vaswani *et al.* (2017) experimentally utilized sine and cosine functions of varying frequencies

\[
PE_{(pos,i)} = \begin{cases} 
\sin(pos \times w_n) & \text{if } i = 2n \\
\cos(pos \times w_n) & \text{if } i = 2n + 1 
\end{cases} \tag{5}
\]

\[
w_n = \frac{1}{10000^{2n/k}}, \quad n = 1, ..., k/2
\]

Here \(pos\) represents the initial position of the vector while \(n\) represents the length of the vector, \(i\) represents the particular instance. In the first pure vision transformer by (Dosovitskiy *et al.*, 2020) the learned position is outputted as a vector and serves as input into the encoder. This vector is a sequence of \(n\)-dimension patches where \(n = 1, ..., k\). While a lower \(n\)-value will store better positional information; it will also be computationally expensive.

![Vision Transformer model overview: Based on original transformer architecture (Dosovitskiy *et al.*, 2020).](image)

2.4 **Vision Transformers**

A variety of transformer based vision models exists, a few of the prominent ones are; Vision Transformer (ViT) (Dosovitskiy *et al.*, 2020), Detection Transformer (DETR) (Carion *et al.*, 2020), data-efficient image transformer (DeiT) (Touvron *et al.*, 2020) and Swin-Transformer (Ze Liu *et al.*, 2021). The ViT was the first pure adaptation of the vanilla transformer in the field of computer vision. It entails an encoder and a task specific decoder structure where input images are broken into a sequence of non-overlapping patches of size \((C \times P \times P)\). Here \(C\) represents the number of channel of the image and \(P\) represents its length and width. The information about the position of patches in the image is converted into a vector. This positional information, along with the sequence of non-
overlapping patches are fed into the encoder block of the transformer containing multi-head self-attention, layer normalization and a multi-layer perceptron (FFN), this is depicted in Figure (2).

DETR is a hybrid that attaches a transformer encoder to a CNN architecture; it was the first attempt at partially conveying attention from the vanilla transformer to a vision task of object detection. The swin-transformer was designed to reduce the computational cost of the ViT and was tested majorly on segmentation tasks. Liu et al., (2021) attempted varying patch sizes so as to reduce the requirement of full attention due to the input sequence of non-overlapping patches; they introduced the shifted window attention that creates patches of various sizes in a hierarchical order, and further assists in preserving spatial information.

The efficiency of the ViT could only be observed during large scale training as it performs poorly on small datasets, and Touvron et al., (2020) proposed the DeiT in an attempt at solving this problem. DeiT adopts a CNNs teacher and a transformer student structure in a knowledge distillation framework in which a distillation token is added for the purpose of learning from the teacher model. This knowledge is then inherited by the student model while imparting inductive bias.

2.5 Hybrids

Hybrids including DETR and DeiT can be grouped into three categories, according to the work of Jun Li et al., (2022). These categories are; ConvNet-like-Transformer, Transformer-like-ConvNets and Transformer-ConvNet hybrids.

ConvNet-like-Transformers are vision transformers that inherit the properties of conventional CNNs with the aim of improving the efficiency of the transformer. The DeiT (Touvron et al., 2020) is an example of this type of transformer, it attempts to develop transformers that inherit the inductive bias present in convolutional neural networks. Other examples include; Swin Transformer (Ze Liu et al., 2021), HaloNets (Vaswani et al., 2021), DAT (Xia et al., 2022) and PVT (Wang et al., 2021). Transformer-like-ConvNets are convolutional neural networks that inherit some of the properties of transformers by sparing or partial integration of transformers into the architecture. The most prominent properties researchers try to integrate to CNNs is self-attention from transformers. Few example include; CoT (Yehao Li et al., 2022), BoTNet (Srinivas et al., 2021) and ConvNext (Zhuang Liu et al., 2022). Transformer-ConvNet hybrids try to form architectures that consist of convolutions, multi-layer perceptrons and multi-head self-attention blocks in an attempt to fully leverage the strength of both architectures and form models that are more efficient. A few examples include CvT (Wu et al., 2021), Mobile-former (Chen et al., 2021), Conformer (Peng et al., 2021), CoAtNet (Dai et al., 2021) and ConViT (d’Ascoli et al., 2021).

3 TRANSFORMER IN MEDICAL IMAGING

3.1 Datasets

Transformers are generally known to perform better in large training than small sized training due to the absence of inductive bias that bolsters few shot learning. In an attempt to solve this problem, researchers have proposed several hybrid architectures that seeks to incorporate strengths of the convolutional neural network into the transformer. The availability of public medical datasets of diverse modalities have been a major deterrent to the training and re-training of state-of-the-art CNN architectures like ResNet (K. He et al., 2016) and EfficientNet (Tan & Le, 2019) for the development of domain specific weights to serve as a feature extractor layer in transfer learning for both CNNs and Transformers. A few researchers have proven that transformers benefit more from transfer learning than CNNs (Caron et al., 2021; Raghu et al., 2019, 2021). However, standard weights like ImageNet do not serve as efficient feature extractors for medical imaging tasks across architectures (Hosseinzadeh Taher et al., 2021) hence the need for a detailed outline of publicly available medical datasets. The detailed compilation

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of most of the publicly available datasets of various medical image modalities with their description; their download link is provided in within their publication in Table 1 (Parvaiz et al., 2022).

| Table 1: Compilation of published available dataset of medical image modalities |
|------------------------------------------------------------|
| **DETECTION**                                             | **CLASSIFICATION**                                           |
| **Modality**                                              | **Modality**                                                 | **Dataset**                                           | **Description**                                                                 |
| Histopathology Images                                     | CT-scan                                                      | COVID-19 CT-2A (Gunraj et al., 2022)                  | A benchmark dataset containing 3 classes, COVID pneumonia, non-COVID pneumonia and normal. Comprises data collated from 15 countries and contains about 4,500 samples. |
|                                                          |                                                              | COVID-19 CT-DB (Kollias et al., 2021)                  | Contains annotated data that indicates the existence of COVID-19                  |
|                                                          |                                                              | COVIDx (Gunraj et al., 2022)                           | A dataset of 3 classes: COVID positive, viral pneumonia and normal images.      |
|                                                          |                                                              | COVIDGR-E (Tabik et al., 2020)                         | Contains about 430 images of COVID-19 pneumonia                                  |
|                                                          |                                                              | IDRID (Saeed et al., 2021)                             | A dataset comprising 81 images for Micro-anneurysm detection.                   |
| Fundus Images                                             |                                                              |                                                      |                                                                               |
|                                                          |                                                              |                                                      |                                                                               |
|                                                          |                                                              |                                                      |                                                                               |

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**X-ray**

| Dataset | Description |
|---------|-------------|
| Shenzen dataset *(Jaeger et al., 2014)* | A dataset collated in Shenzen China on tuberculosis. |
| COV19 chest x-ray *(Maguolo & Nanni, 2019)* | A dataset contain chest x-rays for classifying covid-19 from bacterial pneumonia. |
| Montgomery chest x-ray *(Jaeger et al., 2014)* | A dataset collated in the Montgomery county. |
| CXR Images *(Kermany, Daniel; Zhang, Kang; Goldbaum, n.d.)* | A dataset containing OCT and chest X-rays. |
| COVIDx *(Linda Wang et al., 2020)* | A 3-class dataset for normal, viral pneumonia and covid-19. |
| BIMCV-COV19+ *(Vayá et al., 2020)* | This is a database of chest x-rays and CT images. |
| Extensive-XR-CT *(X. Yang et al., 2020)* | A dataset of CT and X-rays for patients with and without covid. |
| Posterior-Anterior Chest Radiography COV19 *(Haghanifar et al., 2022)* | This is a combination dataset of about 15 smaller chest X-ray datasets. |

**Fundus Images**

| Dataset | Description |
|---------|-------------|
| Color Fundus *(Hajeb Mohammad Alipour et al., 2012)* | This Dataset contains fundus images in DR-grading. |

**SEGMENTATION**

| Modality | Dataset | Description |
|----------|---------|-------------|
| CT-scans | IMDTD-18 *(Kermany et al., 2018)* | A dataset containing about 9000 OCT scans. |
| MRI-scans | Kits19 *(Heller et al., 2022)* | A dataset annotated for the segmentation of renal tumor. |
| MRI-scans | M&MS-21 *(Campello et al., 2021)* | A dataset containing 375 annotated cardiac magnetic resonance images. |
| MRI-scans | MR-Brain-S *(Mendrik et al., 2015)* | A dataset containing 20 annotated multi sequence brain MRI. |
| MRI-scans | ERI *(Stirrat et al., 2017)* | A dataset containing 375 cardiac MRIs. |
| MRI-scans | CHAOS *(Kavur et al., 2021)* | An MRI annotated dataset for abdominal organ segmentation: kidney and liver. |
| MRI-scans | UKBB *(Sudlow et al., 2015)* | A dataset for identifying the causes of a wide range of complex diseases. |
| MRI-scans | BrATS-20 *(Bakas et al., 2017)* | A dataset for brain tissue segmentation, with about 2000 images. |
| MRI-scans | Iseg-17 *(Li Wang et al., 2019)* | A dataset for brain tissue segmentation consisting of 20 images. |
| X-ray | OAC *(Peterfy et al., 2008)* | A dataset containing annotated knee images. |
DICRLN (Shiraishi et al., 2000)  A database of annotated chest images for detecting lung nodule.
IN-breast (Moreira et al., 2012)  A database containing annotated breast mammograms.

3.2 Classification and Segmentation

Classification of medical images is a vital task in healthcare because of the increasing need for diagnosis, identification and distinction of healthcare images and relevance in intended applications. Varieties of transformer architectures have been employed in modelling with the aim of achieving higher efficiency than previously obtained. Researchers have employed pure vision transformers an
3.2.1 Histopathological Images

Various staining substances and methods have aided the diagnosis, detection and classification of tumors and carcinomas in pathology. These slide images, in digital form, serve as a resource bank for the development of computational models to perform automatic diagnosis, to facilitate efficient and faster diagnosis. The earliest known ViT utilized for histopathological image classification, in literature is TransMIL (Shao et al., 2021), which integrate transformers to a multiple instance learning (MIL) framework, in order to introduce correlation between various instances. In this work, MIL is achieved by pooling operations performed on learning instances extracted by a pre-trained CNN (He et al., 2016). These instances, after squaring, are passed into a block containing multi-head self-attention (MSA), positional encoding and an MLP for weakly supervised classification.
Figure 4: (1) Hierarchical Image Pyramid Transformer designed to exploit the hierarchical nature of WSIs while utilizing DINO self-supervised pre-training (Chen et al., 2022): HIPT architecture (a1), a colorectal cancer attention map from HIPT (a2). (2) xVITCOS utilizing the pure ViT architecture for chest X-ray classification (Mondal et al., 2022): (b1) is the ViT architecture, (b2) is the detection output and score.
The resultant models achieved AUC scores of 93.09% and 96.03% in classifying binary tumors and cancer subtypes respectively. Wang et al. (2022) introduced a contrastive learning strategy based on self-supervised learning (SSL). In general, SSL is known to ameliorate the annotation of large-scale data by utilizing an unlabeled dataset in the extraction of useful representations that generalize well to multiple downstream tasks. Semantically relevant contrastive learning (SRCL), unlike traditional contrastive learning, seeks to acquire more representations that are informative by aligning closely related positive pairs. This is achieved by pre-training CTransPath (an integration of CNNs and multiple swin transformers) with a plethora of unlabeled data, to serve as a feature extractor for the downstream task performed by SRCL. GasHis-Transformer (Chen et al., 2022) introduces an approach for gastric histopathological image classification based on global and local information capture. Local information capture is realized by a CNN architecture while global information capture is accomplished by attention blocks coupled to CNNs. Advocates of self-supervised ViTs in histopathology (Chen & Krishnan, 2022) proposed a novel vision transformer based on the Hierarchical nature of WSIs. Hierarchical image pyramid transformer (HIPT) (Chen et al., 2022), employs a two-level self-supervised learning framework to exploit both the hierarchical nature of WSIs and the large sequence length of WSI tokens as a result of their pixel nature. This is performed by aggregating visual tokens at three levels (cell, patch and region) in order to form the slide representation and utilizing self-attention as a permutation-equivariant aggregation layer; the HIPT with hierarchical pre-training yielded better performance than SOTA methods for survival prediction and cancer subtyping.

3.2.2 Computed Tomography Scans

CT-scans can create detailed cross-sections of bones, soft tissues, organs and blood vessels, these sections can also be formatted to multiple frames that aid in the generation of three-dimensional images. The application of ViTs in computational tomography has largely been focused on thoracic diseases because of the contrast between gas and tissue. These ViTs are designed for two-dimensional, as well as three-dimensional CT images. CTNet as proposed by Liang et al. (Liang et al., 2021) is a hybrid model comprising a CNN feature extractor and ViT for the detection of COVID-19 from three-dimensional chest scans. After training on the COV19-CT dataset, it achieved 88% in F1 evaluation. Barhoumi et al. (2021) proposed scopeformer, a hybrid model for the classification of intracranial hemorrhage from CT images. Their work demonstrates that by stacking several Xception CNN blocks and aggregating their feature maps, a feature-rich map can be developed to serve as the input to a ViT and improve the model performance. Consequently, the model achieved a test accuracy of 98.04% on the corresponding classification task.

The effective diagnosis of pancreatic cancer from two-dimensional CT images was demonstrated by Xia et al (2021). In this work, a region-of-interest (ROI) feature map is developed from annotated training data based on the U-net segmentation algorithm. This pancreas ROI feature map is fed as input to a transformer that is built upon the U-net algorithm for segmentation. The model is trained on a 3-class labeled data for classification, and achieved specificity and sensitivity of 95.2% and 95.8% respectively after training on a dataset of 1321 patents. SwinUNETR (Tang et al., 2021) is a prominent model for the classification of 3 dimensional CT images. It implements a hierarchical encoder for self-supervised pre-training, it was fine-tuned for classification and segmentation tasks at the Beyond the Cranial Vault (BTCV) challenge. Their model outperformed all other models submitted for the challenge.
Table 2: A summary of the reviewed transformer-based approach for medical image classification.

| Archi  | Modality | Organ     | Type | Evaluation | Highlights                                                                 | Reference                      |
|--------|----------|-----------|------|------------|----------------------------------------------------------------------------|--------------------------------|
| Hybrid | Pathology | Prostate  | 2D   | Accuracy   | The classification task is performed according a grading system regarded as 'Gleason' | Ikromjanov (Al., 2022)          |
| Hybrid | Pathology | Stomach   | 2D   | Precision, F1 | Classification based on the parallel structure of LIM and GIM modules. | Chen et al. (H. Chen et al., 2022) |
| Hybrid | Pathology | Cell      | 2D   | SP, H-mean, F1 | Utilizes transfer learning and an attention based decoder in classifying cervical cells. | Zhao et al. (C. Zhao et al., 2022) |
| Hybrid | Pathology | Multiple  | 2D   | Accuracy, AUC, F1 | Introduces a TAE module that aid the ViT in aggregating tokens, which are passed into an FFN. | TransPath (Xiyue Wang et al., 2022) |
| Hybrid | Pathology | Multiple  | 2D   | Accuracy AUC | A CNN encoder attached to a ViT decoder for the extraction of spatial information from WSIs. | TransML (Shao et al., 2021)       |
| Hybrid | Pathology | Multiple  | 2D   | Accuracy, Precision, recall | A CNN, transformer encoder to capture high level features for classification. | i-VIT (Z. Gao et al., 2021)       |
| Hybrid | Pathology | Multiple  | 2D   | MSE        | Combining self-supervised learning and transfer learning in extracting morphological features from WSIs. | R. J. Chen et al. (R. J. Chen & Krishnan, 2022) |
| Pure ViT | Pathology | Multiple  | 2D   | AUC        | Developed a novel Hierarchical transformer that leverages self-supervised learning for classifying cancer and survival prediction. | R. J. Chen et al. (R. J. Chen et al., 2022) |
| Hybrid | Pathology | Lung      | 2D   | ACC, PRE, SE, SP, RE. | Consisting of a CNN feature extractor and a feed forward network for classifying WSIs. | GTN (Y. Zheng et al., 2022)       |
| Pure ViT | CT      | Chest     | 3D   | Accuracy, F1 | Defined a new ViT architecture that was implemented for covid-19 classification. | COVID-VIT (X. Gao., 2021)         |
| Hybrid | CT       | Chest     | 3D   | F1         | Proposed two-stage process of segmentation using U-net then classification using swin-transformer. | Zhang et al. (L. Zhang & Wen, 2021) |
| Hybrid | CT       | Chest     | 3D   | Accuracy, Precision, Recall, F1 | The implementation of Wilcoxon signed-rank test for preserving CT slices after which spatial features are extracted by a transformer that contains convolutions. | Hsu et al (Hsu et al., 2021)      |
| Hybrid | CT       | Pancreas  | 3D   | Sensitivity, Specificity, AUC | Localization is achieved by U-net and then passed to a transformer. | Xia et al. (Y. Xia et al., 2021)   |
| Pure ViT | CT      | Lung      | 2D   | F1         | Utilized a teacher student framework to aid knowledge distillation. | Li et al. (Jingxing Li et al., 2021) |
| Hybrid | CT       | Brain     | 2D   | -          | The stacked several feature maps produced by a CNN into a ViT to improve classification accuracy. | Scopeformer (Barhoumi & Ghulam, 2021) |
| Hybrid | CT       | Lung      | 3D   | F1         | Combines convolution and attention in the classification of 3D chest images. | CNet (Liang et al., 2021)         |
| Pure ViT | CT      | Chest     | 2D   | Precision, Recall, F1, Specificity | Introduces a transfer learning approach of multiple stages where ViT performs the upstream task. | xVITCOS (Mondal et al., 2022)     |
| Pure ViT | CT      | Multiple  | 3D   | Specificity | Introduced a new 3D transformer that has a hierarchical encoder for SSL. | Tang et al. (Tang et al., 2021)    |
| Pure ViT | MRI     | Ear       | 3D   | Accuracy, Precision | This work contains the first transformer model for multi-modal image classification performed on ear MRI. | Matsokus et al. (Y. Dai et al., 2021) |
| Hybrid | MRI | Tissue | Dim | Metric | Description |
|--------|-----|--------|------|--------|-------------|
| Hybrid | MRI | Hepatic | 2D   | MAE    | This work utilizes 3 parallel CNN encoders for feature extraction and a transformer decoder for classification of hepatocellular carcinoma. |
| Hybrid | MRI | Knee   | 3D   | -      | They introduced 3D convolutional block encoding to reduce cost of computation and utilized a teacher student approach to train ViT. |
| Hybrid | MRI | Brain  | 2D   | MAE, PC | Utilizes two parallel CNNs; one extracts features from the whole image, the other from patches. A transformer acts as the decoder. |
| Hybrid | MRI | Alzheimer | 3D   | Accuracy, AUC | This work proposes an architecture that combines a 2D and 3D CNN for classification, with a transformer encoder. |
| Pure ViT | MRI | Brain | 2D   | Accuracy | The work pre-trains a ViT on ImageNet and fine-tunes it for brain tumor classification. |
| Pure ViT | MRI | Brain | 3D   | AUC, PC | Proposes an attention based encoder requiring patch meshes, for classification tasks. |
| Hybrid | MRI | Brain | 3D   | AUC, MAE | Pre-trains a hybrid model in a self-supervised manner for 3D brain disease diagnostic etc. |
| Hybrid | MRI | Brain | 2D | R2, MAE, CC | This work presents an end-to-end attention guided deep learning approach for gestational age prediction utilizing an attention based intermission. |
| Hybrid | X-ray | Lung | 2D | Accuracy | Develops a hybrid model consisting of CNNs for image processing and a multiple swin-transformers in sequence for classification. |
| Hybrid | X-ray | Lung | 2D | - | Utilizes a CNN encoder and incorporates average pooling to the attention block MLP. |
| Pure ViT | X-ray | Lung | 2D | AUC | Introduces a ViT with random patch distribution for multi-task learning. |
| Pure ViT | X-ray | Lung | 2D | AUC | This work introduces a self-ensemble ViT architecture to improve ViT robustness. |
| Pure ViT | X-ray | Lung | 2D | AUC | Demonstrated split performance without adulterations to performance. |
| Hybrid | X-ray | Lung | 2D | AUC | Proposes an approach of diagnosis through knowledge distillation. |
| Pure ViT | Fundus | Eye | 2D | Accuracy, F1, Recall, Precision | Investigates lesions as a localization problem of a weakly supervised nature, for classifying diabetic retinopathy grades and diagnosing lesions. |
| Hybrid | Fundus | Eye | 2D | AUC, Kappa | This work utilizes 3 parallel CNN encoders for feature extraction and a transformer decoder for classification of hepatocellular carcinoma. |
| Pure ViT | Fundus | Eye | 2D | AUC | Investigates the performance of DEIT compared to SOTA CNN for classification tasks. |

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The segmentation of CT-scans is important in the diagnosis, evaluation and monitoring of various phenomena in healthcare. Swin UNETR (Tang et al., 2021) also performs 3D segmentation primarily for computed tomography images. It attaches self-supervised heads, aggregated by contrastive learning strategy to a swin transformer encoder. It also achieved state-of-the-art performance in segmentation. Similarly Xia et al (2021) hybrid model train by classification supervision can be utilized for CT segmentation tasks as well, and for CT classification task as discussed above. Because of the computational cost involved in modelling global representation on full resolution images Zhang (2021) proposed PMTrans, a hybrid model that incorporates multi-scale attention to a CNN feature extractor with the aim of capturing diverse range relationships from multi-resolution images. This method is recorded to have outperformed other CNN and Transformer based models at the time of publication. UNETR (Tang, et al., 2022) was designed for semantic segmentation of 3D brain MRI and spleen CT scans. It attaches a transformer encoder to a Unet-like CNN decoder for semantic segmentation.

3.2.3 Magnetic Resonance Imaging

MRI provide very detailed anatomical images due to its powerful and effective non-invasive imaging technology: it also produces two-dimensional as well as three-dimensional images. It is therefore of importance to consider the dimensionality of the image instance that the modelling method is suited. M3T (Jang & Hwang, 2022) is a three-dimensional image processing technique for the classification of Alzheimer’s disease. It proposes two- and three-dimensional representation with pre-trained 2D CNN and 3D CNN respectively. These CNNs are designed to append inductive bias to the modelling technique while global sequential information from multiple planes are captured by the ViT attached sequentially to the 2D-3D CNNs structure. Their model was trained on the Alzheimer’s Disease Neuroimaging Initiative (ADNI) dataset and was validated on the Australian Imaging, Biomarker and Lifestyle Flagship Study of Ageing (AIBL) dataset. The model outperforms all other models in Area under Curve (AUC) evaluation. Tummala (2022) employs an ensemble of ViT models pre-trained and fine-tuned on ImageNet for brain tumor classification, demonstrating the efficiency of disparate domain information transfer. They achieved a test accuracy of 98%. Works on age prediction based on MRI were performed by He et al. (2022) and Shen et al. (2022). On the one hand, the former attempts at estimating brain age by a global-pathway-local-pathway transformer network that aids the simultaneous capture of global and local representations from images. The particular model was trained on a collective of six publicly available dataset. After evaluation on two additional datasets, it exhibited state-of-the-art performance in age prediction. On the other hand, the latter attempted at extracting age-specific morphological information from Fetal MRI to promote age-based classification. They also demonstrate the inferiority of traditional CNN approaches to that of attention-guided CNN methods: achieved by incorporating attention-guided mask inference to a traditional ResNet-50 architecture. Their method resulted in R² score of 0.945 and MAE of 6.7 days.

The fully convolutional transformer (Tragakis et al., 2022) leverages the success of U-net algorithm in development of a fully-convolutional, depth-wise transformer that replaces the convolution blocks in U-net architecture with fully convolutional transformers. This method aids efficient segmentation that considers the fine-grained nature of medical images. Their model extracts global information as well as capturing hierarchical attributes from features. UNetFormer (Xu, et al., 2022) attempts to adapt the dubbed UNetFormer architecture by redefining each encoder block with swin transformers and each decoder block with CNNs; they also included skip connections at different data resolutions. For encoder pre-training, they incorporated self-supervised learning with the aim of letting the model randomly predict masked volumetric tokens.

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Segmentation

(1) TransAttUnet (Chen et al., 2021) is an attention guided u-net with transformers for segmentation: its architecture (a1) utilizes TSA and GSA mechanism, (a2) is a comparative gland segmentation result. (2) medical transformer (Jun et al., 2021) is utilized for 3D MRI analysis: (b1) is its architecture that shows that slices are processed in 2D before being combined to form the output, (b2) is a comparative between medical transformer and other approaches.

Figure 5: (1) TransAttUnet (Chen et al., 2021) is an attention guided u-net with transformers for segmentation: its architecture (a1) utilizes TSA and GSA mechanism, (a2) is a comparative gland segmentation result. (2) medical transformer (Jun et al., 2021) is utilized for 3D MRI analysis: (b1) is its architecture that shows that slices are processed in 2D before being combined to form the output, (b2) is a comparative between medical transformer and other approaches.

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An alternative modelling method that proposes a deformable bottleneck transformer module to aid the capture of shape; TransBTSV2 (Jiangyun Li et al., 2022) retains a CNN encoder decoder structure with only major changes to the bottleneck region, it requires no pre-training and stores local information through its CNN encoder while also capturing global sequential representations. This architecture was tested on four publicly available datasets and generated results that are comparable with state-of-the-art classification techniques. Another variation of this approach is the nnFormer Zhou (2021), attempts to aid the capture of volumetric information by defining a local and volume based bottleneck on a conventional CNN encoder-decoder structure. It achieved significant reduction of both the dice score and Hausdorff distance metric.

Not a lot of researchers apply major changes to their transformer structure. However, in an attempt to reduce the dimensional and computational complexity of the vanilla transformer Xie et al. (2021) developed CoTr. This deformable transformer unlike the vanilla transformer that pays unequal attention to all image positions. Utilizing the deformable transformer coupled to a CNN encoder-decoder, they effectively processed multi-scale and high-resolution feature maps while capturing local image representations.

Another modelling approach is to convert three-dimensional images to two-dimensional slices (Jun et al., 2021), utilizing only two-dimensional convolutions. This network is pre-trained using DINO self-supervision, after which the two-dimensional slices are re-combined for the purpose of prediction. This method has been successfully applied for regression and classification, as well as segmentation tasks.

3.2.4 X-ray

The passage of X-rays through a body can aid the generation of informative images of tissues and the internal structure of the body. X-rays are inexpensive and convenient and have a wide range of application in medical imaging such as cancers, fractures and various pneumonia (including COVID-19) etc. Thus, they are an important source of medical data capture to clinicians and researchers alike. SEViT (Almalik et al., 2022) attempts to model self-ensemble transformers based on experiment that proved that the feature representations learned by the initial ViT blocks are generally unaffected by adversarial perturbations. In order to model resilience to adversarial attacks, they proposed learning multiple classifiers that aggregates feature representations learned from initial ViT blocks to those learned from final ViT blocks. This method leverage the details presented from the final ViT representation as well as the robustness of intermediate ViTs. Mondal et al (2022) employed a pure transformer for the detection and classification of COVID-19 from X-ray images. In their work, a multi-stage transfer learning strategy based on ViT is adopted where a ViT is pre-trained on domain specific data for the extraction of domain relevant information. This feature extractor is attached to a conventional transformer that performs classifications based on its fully connected multi-layer perceptron (MLP). Chest X-ray data and other X-ray forms required for adequate modelling are scarce. However, availability of such data is on the rise. With an increase in the available data comes increasing demand for annotation. Park (2022) tried to provide solutions to these issues in his works p-FESTA (Park & Ye, 2022) and DISL (Park et al., 2022). For scarcity of training samples, they proposed p-FESTA that employs multi-task distributed learning that is based on federation and shared learning. They achieved this by exchanging the CNN in the original Federated Split Task Agnostic (FESTA) with random patch permutation with an aim of improving performance of the multi-task learning while maintaining privacy. For the problem of annotating newer datasets, they proposed DISL that incorporates self-supervision and self-training to ViTs with the aim of developing a model that can learn useful representations from un-annotated data. DISTL was evaluated on data from three hospitals and improved in performance with increase in the size of unlabeled training data.
Table 3: A summary of the reviewed transformer-based approach for medical image segmentation.

| Archi | Modality | Organ | ViT Enco|inter|deco | Type | Evaluation | Highlights | Reference |
|-------|----------|-------|---------|--------|-------|--------|------------|------------|-----------|
| Hybrid | CT       | Multiple | 1|0|0 | 3D | Dice, HD | Introduced a new 3D transformer that has a hierarchical encoder for SSL. | Swin UNETR (Tang et al., 2021) |
| Hybrid | CT       | Pancreas | 0|0|1 | 3D | Sensitivity, Specificity, AUC | A model comprising u-net and transformer is trained based on classification and segmentation supervision. | Y. Xia et al. (Y. Xia et al., 2021) |
| Hybrid | CT       | Multiple | 0|0|1 | 2D | Dice | Aimed at reducing the computational cost of current ViTs by limiting learning to the capture of multi-range relationship between varying resolutions. | PMTrans (Zhuangzhuan Zhang, 2021) |
| Hybrid | CT, MRI  | Brain, Spleen | 1|0|0 | 3D | Dice, HD | A hybrid transformer comprising a transformer encoder and a CNN decoder for brain and spleen classification. | UNETR (Hatamizadeh, Tang, et al., 2022) |
| Hybrid | MRI, CT, | Multiple | 1|1|1 | 3D | sensitivity | A U-net shaped, depth wise, fully convolutional transformer designed for medical image segmentation. | HiFormer (Heidari et al., 2022) |
| Hybrid | MRI, CT  | Liver | 1|1|1 | 3D | Dice, HD | Comprising convolution and transformer in each block of the depth-wise architecture. | UNetFormer (Hatamizadeh, Xu, et al., 2022) |
| Hybrid | MRI, CT  | Multiple | 1|0|1 | 3D | Dice | Incorporates bidirectional multi-head attention to a depth-wise U-net structure. | MedFormer (Y. Gao et al., 2022) |
| Hybrid | MRI, CT  | Multiple | 0|1|0 | 3D | Dice, HD | Utilizes a CNN encoder-decoder structure with a transformer bottleneck. | TransBTSV2 (Jiangyun Li et al., 2022) |
| Hybrid | MRI, CT  | Multiple | 0|1|0 | 3D | Dice, HD | Introduces a local and volume type of attention mechanism that aids in learning global representations. | nnFormer (H.-Y. Zhou et al., 2021) |
| Hybrid | CT, MRI  | Multiple | 0|1|0 | 3D | Dice | Introduces deformable self-attention to aid in processing multi-scale, high-resolution images. | CoTr (Xie, Zhang, Shen, et al., 2021) |
| Hybrid | MRI      | Brain | 0|0|1 | 3D | Dice | Converts a 3D image into two-dimensional slices, processes image in 2D then recombines as output. | Medical Transformer (Jun et al., 2021) |
| Pure ViT | X-ray, CT | Lung | 1|1|1 | 2D | IoU, Accuracy | Utilizes several swin-transformers with patch and positional encoding to achieve classification and segmentation training. | Sun et al. (Sun & Pang, n.d.) |
| Hybrid | X-ray    | Lung | 0|0|1 | 2D | Dice | Introduces a ViT with random patch distribution for multi-task learning. | Park et al. (S. Park & Ye, 2022) |
| Hybrid | X-ray    | teeth | 1|0|0 | 2D | Dice | Utilizes a Fourier descriptor based loss function to aid in integrating the shape after which it is passed to grouped transformer blocks. | GTUNet (Yunxiang Li et al., 2021) |
| Hybrid | CT, X-ray | Multiple | - | 2D | Dice | Aims at solving the information recession issue by attempting multi-level attention. | TransAttUNet (B. Chen et al., 2021) |
| Hybrid | Fundus   | Eye | 0|1|0 | 2D | Precision, Recall, AUC | Defined two kinds of transformer blocks: global and relation transformers in order to aid the detection of minute sizes and blurred borders. | RT-Net (S. Huang et al., 2021) |
| Hybrid | Fundus   | Multiple | - | 2D, 3D | Dice | Utilizes squeeze and expansion blocks that serves to regularize the self-attention module as well as learn diversified representations. | Segtran (S. Li et al., 2021) |
A lot of the research on the X-ray modality is performed for classification however, there are a few works that attempts the segmentation of chest X-rays. Sun et al. (Sun & Pang, n.d.) developed a model for the classification and segmentation of chest X-rays based solely on the swin transformer. So far, very few models employ just the transformer architecture in performing segmentation tasks. Yet they achieved a segmentation accuracy of 95% from three variations of their swin-transformer model. The p-FESTA method discussed earlier also tested for segmentation of X-rays; inducing federation and shared learning towards the performance of segmentation tasks after self-supervised pre-training. TransAttUnet (Chen et al., 2021) was developed for the accurate segmentation of organs and lesions from X-ray and CT imaging by defining an encoder-decoder network with multi-scale skip connection for processing higher resolution images and multi-level guided attention for mapping global relationships between multiple resolutions. These skip connections were also applied to the decoder part of the architecture to aggregate semantic-scale up-sampling features, alleviating information recession and developing a more detailed pixel map. To aid in root canal therapy assessment Li et al. (2021) developed GT U-Net that retains the depth-wise nature of U-net but replaces the convolutions with group transformer-hybrids. The idea behind implementing group transformers rather than individual vanilla-type transformer is to reduce computational cost. They also defined a shape-sensitive Fourier Descriptor loss function in order to aid model optimization.

3.2.5 Fundus

Fundus photography aids in the diagnosis of a variety of medical conditions. Due to its complex nature; comprising retina, macula, optic disc, fovea and blood vessels, it is expedient that computation be employed in more efficient and reproducible diagnostics. Rui et al. (2021) developed an encoder-decoder decoder structure with a pixel relation based encoder and a filter based decoder. This model employs weakly supervised training via filter based transformer decoder, as well as lesion region importance and lesion region diversity to enable the model learn filters well. The model was tested for DR grading and lesion discovery, and recorded state-of-the-art performance.

With the aim of aiding ophthalmologist in the automatic segmentation of diabetic retinopathy lesions Huang et al (2022) developed RT-Net following a clinical approach: They investigated the pathogenic causes of diabetic retinopathy lesions and found that certain lesions present relative patterns with each other and appear close to specific vessels. This finding aided the proposition of a relation transformer block composed of self-attention for global relationship and cross-attention that enables interactions between lesion and vessel features. They also proposed a global transformer block to aid the capture of finer details of small lesion patterns. Their dual-transformer approach was capable of segmenting four kinds of DR lesions and attains state-of-the-art performance. Segtran (Li et al., 2021) was developed with the aim of capturing fine details as well as global features simultaneously. They successfully developed a transformer-based approach that has unlimited effective receptive field at high and low resolutions by utilizing squeeze and expansion transformer networks, with each transformer block performing a unique function: the squeeze block attempts regularization of the attention block to aid global information capture, the expansion block learns a diverse array of representations. Tested on the BraTS dataset (Bakas et al., 2017) the model achieved the most segmentation accuracy.
3.3 Registration and Reconstruction

Medical image registration becomes relevant when we intend to analyze the same image captured with different modalities or at different times. Registration aims at establishing relationships between static and moving images by finding dense per-voxel displacement. In recent times, transformers are seen as the architecture of choice for extracting relating features from multimodal images required in registration tasks because of the offering of better understanding of spatial representations. SVoRT (Junshen Xu et al., 2022) attempts volume registration from slides based on an attention mechanism. Features extracted by a ResNet architecture, as well as the position of slices in 2D and 3D are fed into the transformer to encode spatial and global representations. SVoRT was tested on real world data and achieved state-of-the-art performance. Dahan et al (2022) developed a transformer-based technique for the projection of surface features to a curved surface by leveraging multi-head self-attention and spatial encodings.

The transformation of signals into an interpretable image that can serve as data for diagnosis is a task that is performed efficiently by transformers.

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**Table 1: A summary of the reviewed transformer-based approaches for medical image registration and reconstruction.**

| Archi | Modality | Organ | Type | Evaluation | Reference |
|-------|----------|-------|------|------------|-----------|
| Hybrid | MRI | Brain | 3D | Proposed slice-to-volume registration that predicts the transformation of a slide based on information from other slides. | SVoRT (Junshen Xu et al., 2022) |
| ViT | MRI | Brain | 3D | Utilizes a pure transformer for the projection of surface data on a curved manifold | SiT (Dahan et al., 2022) |
| Hybrid | MRI, CT | Multiple | 3D | Presents a hybrid transformer for image registration along with 2 model variants. | TransMorph (J. Chen et al., 2021) |
| Hybrid | CT | Multiple | 3D | An encoder-decoder architecture composed of transformer blocks for denoising medical images. | Eformer (Luthra et al., 2021) |
| ViT | CT | Multiple | 3D | Comprises a symmetrical encoder-decoder architecture solely based on transformers for denoising. | TED-net (D. Wang et al., 2021) |
| ViT | MRI | Multiple | 3D | Cascading swin transformers forming a reconstruction network with a self-supervised learning strategy | DSFormer (B. Zhou et al., 2022) |
| Hybrid | MRI | Multiple | 2D | Proposed a CNN-Transformer for both super-resolution and MRI reconstruction | T²Net (C. M. Feng et al., 2021) |
| ViT | MRI | Multiple | 2D | A multi-modal transformer capable of transmitting features from the target modality to the auxiliary modality. | MTrans (C.-M. Feng et al., 2022) |
| Hybrid | CT | Multiple | 2D | Introduces a flexible architecture for residual data and image capture, introduces enhancement filters for preserving edges, then a swin transformer to aid reconstruction. | MIST-net (Pan et al., 2022) |
Figure 6: (1) TransMorph (Chen et al., 2021) is a model developed for unsupervised medical image registration, its architecture (a1) takes in two inputs and generates a nonlinear warping function. (a2) depicts the ERF of other methods compared to it. (2) SVoRT (Junshen Xu et al., 2022) is an iterative transformer for fetal MRI reconstruction: (b1) depicts its architecture, (b2) shows reconstructed volumes by the model.
Figure 7: (1) MINST-net (Pan et al., 2022) is a model based on the swin transformer for sparse-view CT reconstruction; consists of an architecture with 3 stages (a1), (a2) is a comparative of the result of other methods alongside MINST-net. (2) MTrans (Feng et al., 2022) is a multimodal transformer for MRI reconstruction. (b1) depicts its architecture while (b2) shows comparison between different multi-coil reconstruction methods.
This progress has led to; the reduction of the number of MRI measurements required to establish a scan, aid in reducing the radiation dose required in CT scans, ease of rebuilding surgical scenes. DSFormer (Zhou et al., 2022) presents a self-supervised learning approach based on the transformer and aids the acceleration of multi-contrast MRI reconstruction. It achieves this by developing deep conditional cascade transformer from swin transformers with two unique strategies to encourage information sharing. During evaluation, DSFormer achieved almost equivalence performance when train on full supervision and self-supervision. T² Net (Feng et al., 2021) developed a hybrid model of convolutions and transformer architecture for MRI reconstruction and super-resolution by situating task transformer networks after two parallel CNNs. Feng et al. (2022) presents (MTrans) that utilizes a transformer architecture for multi-modal MR imaging for the purpose of global information capture. They additionally defined a cross-attention module to extract multi-scale information from the different modalities and recorded state-of-the-art performance upon evaluation. MIST-net (Pan et al., 2022) was developed for sparse-view tomographic reconstruction. It entails a robust architecture of three modules; initial recovery based on a flexible network architecture comprising convolution and pooling layers arranged in an encoder-decoder structure; data consistency aimed at preserving edge information by utilizing an enhancement filter defined by convolution and concatenation operations, high-definition reconstruction via swin transformers. This model performed efficiently on evaluation.

4 DISCUSSION

Transformer architecture and its application cut across various imaging modalities in medical imaging. However, there hasn’t been a clear and detailed comparison between transformers and their CNN counterpart. Comparatively, we consider the performance of both architectures; with the exploration of the strengths and weaknesses as well as on their performance under various scenarios.

4.1 Key Properties of Transformers

A few distinctive properties govern the behaviors of transformers. A good understanding of its strengths and drawbacks have informed researchers on ways to deploy transformers for the creation of problem-specific and more efficient models that are relevant in the real world. These properties are discussed below.

4.1.1 Long-Range Dependency

In natural language processing (NLP) long-range dependency can be viewed as the preservation of contextual information in a sequence of word tokens, this can be transmitted to computer vision as the relationship between patches of an image (Devlin et al., 2019). This feature can be attributed to the multi-head, self-attention module that maps all token together with a constant distance thereby capturing token-to-token relationships. CNNs lacks such feature hence have limited receptive fields (Kim et al., 2021).

4.1.2 Model Capacity

Transformers aggregate projections progressively at a constant scale whereas CNNs aggregate projections through a series of convolution and pooling operations that continuously rescales the image. Constant scale multi-processing aids in better preservation of global information than rescaling operations (Yanghao Li et al., 2022). Similarly, transformers have a better loss landscape than CNNs due to self-attention, and it leads to better generalizability (Park & Kim, 2022).

4.1.3 Integration and Manipulation

Due to the dynamic nature of transformers, a variety of architectures, hybrid or pure, can be created. This property is necessary for reducing the limitations of the method. Additionally, their performance improves with training size and model capacity, a property that also induces increase computation cost and time.
4.1.4 Adversarial Noises

One disadvantage of CNNs is their vulnerability to adversarial noises, these limit the model’s ability to output an ideal representation of the input data (Choi et al., 2022). Transformers are generally more robust to perturbations and corruptions (Bhojanapalli et al., 2021).

4.1.5 Inductive Bias

The scale-adjustment processing employed in convolutional neural networks accords them the ability to extract more local information from individual pixels, leading to faster convergence and better performance when trained on smaller datasets (Cordonnier et al., 2019). This is not the case with transformers because same-scale processing in transformers capture more global, than local, information (Ramachandran et al., 2019).

4.2 Transformer and CNNs

Considering the properties of both architectures and optimizations performed to mitigate their limitations, a comparative analysis on how both model types perform on different domains, considering; training from initialized weights, transfer learning, self-supervision and inference.

4.2.1 Training From Randomly Initialized Weights

Random weight initialization requires the model to learn representations from scratch and; only from that which was fed into the model for training. The performance of transformers trained from scratch and CNNs (He et al., 2015) are compared in a variety of literature (Fauw, 2022; Park & Kim, 2022; Shuang Yu, 2021). On smaller datasets, CNNs seem to have performed better because of the inductive bias inherent within their architecture. However, as the data size increases, transformers are seen to gradually out-perform their CNN counterpart. Training from scratch is seldom practiced in medical imaging due to the small size of most medical data.

4.2.2 ImageNet and Same Domain Pre-training

To augment for the size of most domain specific data in computer vision and medical imaging, ImageNet pre-trained weights are often employed for model initialization: this usually results in improved performance (Morid et al., 2021). Researchers have investigated the benefits and extent of transfer learning to ViTs. They discovered that both CNN and ViTs seem to benefit from ImageNet pre-trained weight and same domain pre-training as well, it is also recorded that transformers benefit the most from transfer learning (Hosseinrzaadeh Taher et al., 2021; Raghu et al., 2019).

4.2.3 Self-Supervision

Self-supervision is the most effective solution to the problem of lack of large sized, well-annotated data for modeling in computer vision and medical imaging. The most utilized self-supervised learning schemes; BYOL and DINO, have been found to achieve performance that are comparable to supervised learning schemes. This has prompted their utilization, alongside supervised fine-tuning, in computer vision; achieving state-of-the-art performance (Afouras et al., 2020; Hendrycks et al., 2019; Kolesnikov et al., 2019; Jiaolong Xu et al., 2019). This concept have been attempted on a variety of medical image modalities (R. J. Chen et al., 2022; Jun et al., 2021; Xiyue Wang et al., 2022; B. Zhou et al., 2022) also recording state-of-the-art performances. Additionally, ViTs are found to benefit slightly more from self-supervised pre-training than CNNs.

4.2.4 Inference without Fine-Tuning

In cases of extremely scarce data, features extracted from a pre-trained network can be utilized directly for classification and clustering operations. This is most optimal when the pre-trained features are closely related to the target features. One research assessed whether ViTs performed better that CNNs in inference without fine-tuning by applying $k$-NN evaluation on the penultimate layer of a CNN and the CLS token of a ViT. They evaluated for both in-domain and out-domain pre-trained weights and recorded that ViTs performed better in both scenarios (Fauw, 2022).
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