REPLICA: Enhanced Feature Pyramid Network by Local Image Translation and Conjunct Attention for High-Resolution Breast Tumor Detection

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Abstract
We introduce an improvement to the feature pyramid network of standard object detection models. We call our method enhanced feature Pyramid network by Local Image translation and Conjunct Attention, or REPLICA. REPLICA improves object detection performance by simultaneously (1) generating realistic but fake images with simulated objects to mitigate the data-hungry problem of the attention mechanism, and (2) advancing the detection model architecture through a novel modification of attention on image feature patches. Specifically, we use a convolutional autoencoder as a generator to create new images by injecting objects into images via local interpolation and reconstruction of their features extracted in hidden layers. Then due to the larger number of simulated images, we use a visual transformer to enhance outputs of each ResNet layer that serve as inputs to a feature pyramid network. We apply our methodology to the problem of detecting lesions in Digital Breast Tomosynthesis scans (DBT), a high-resolution medical imaging modality crucial in breast cancer screening. We demonstrate qualitatively and quantitatively that REPLICA can improve the accuracy of tumor detection using our enhanced standard object detection framework via experimental results.

1. Introduction
Object detection (OD) is one of the most important tasks in computer vision [37]. Its application is diverse, ranging from detecting dynamic objects in crowd-counting, self-driving cars and video surveillance, to static objects in face recognition and industrial anomaly detection.

Having a reliable model for object detection is essential. Attention mechanisms [47] have already shown great success when applied to computer vision, such as the use of pixel-wise, pair-wise and patch-wise self-attention for image recognition [21, 38]. Attention-based neural networks generally out-perform traditional convolutional neural networks (CNNs) on large-scale detection tasks, as the former allow for the scalable perception of an entire image, while the inefficiency of CNN receptive fields only allow for the perception of local image patches. The Visual Transformer (ViT) [16] and Swin Transformer [34] are two examples of such attention-based computer vision backbones. Such methods can logically also benefit the task of object detection, allowing for the creation of more reliable tumor detection frameworks.

Since the success of attention [47], this mechanism has been applied to OD, and has advanced the performance of OD, including OD with pyramid constrained self-attention [19], OD with dynamic attention [13] and OD with spatiotemporal attention [52]. More recently, given the success of transformers on images (ViT), Swin has been proposed as the state-of-the-art (SOTA) backbone for attention.

Despite the success of attention, we note that it is difficult to directly apply to medical images because most attention-based methods rely on the assumption that the task domain is of natural images, which usually have diverse object classes, are plentiful, and are of relatively moderate resolution. Specifically, we list the following distinct properties of medical images that prevent the success of attention: High-resolution of medical images. Applying spatial attention directly to medical images is impractical on modern hardware, as the size of medical images is generally considerably larger than natural images. Most medical images used for tumor detection have a resolution of more than $2560 \times 1920$ [5], while the resolution of natural images only contains $3 - 5\%$ pixels when compared to medical images [11, 14, 29, 35], making tumor detection using such models unrealistic in terms of computational complexity and resource availability.

Label & annotation scarcity. On the other side, there are usually not enough labelled data and annotated regions in medical scenarios to robustly train an attention mechanism. In a typical tumor detection dataset, healthy scans outnumber cancerous scans by a factor of about 200, due to the natural rarity of such cases in a randomly sampled screening population [36]. Furthermore, within scans that include...
Attention on Image Feature Patches

Figure 1. REPLICA's entire model architecture. It has two modules: on the left is the module for local image translation in 3.1, and on the right is the feature pyramid network with multi self-attention on image feature patches of ResNet outputs in 3.2.

tumors, the size of the tumor can often be less than 1/40 of the size of the entire image [5]. As a result, traditional machine learning methods can be very difficult to implement successfully for this domain.

To address the first problem, we adopt the attention method first proposed by ViT, instead of applying full-size images directly to the model. Specifically, we replace the FPN module, which naively sums the features from different layers, with an attention-based integration. To address the second problem, we train a local image translation model to augment existing tumor-labelled data and generate fake tumor images that are interpolated and reconstructed by their features extracted in hidden layers of the generator to expand the receptive field of visual transformer. The entire model structure is shown in Fig.1. To the best of our knowledge, REPLICA is the first work that addresses these major issues in tumor detection while also employing the attention mechanism on patches of hidden features of an image for enhancing the feature pyramid network (FPN) [28]. Compared to the baseline Faster-RCNN [40] model, our model achieves 50.4 in AP50, which outperforms the baseline by at least 13.1%. We also conduct ablation studies to prove the effectiveness of each proposed modification.

In summary, our contributions are as follows:

1. We generate realistic but fake images with tumors to mitigate the data-hungry problem in attention-based object detection model architecture for tumor detection.
2. We advance the detection model architecture through a novel backbone of attention on image feature patches on ResNet outputs that serve as inputs to FPN to improve the performance of tumor detection.

2. Related Works

Image-to-Image Translation. The objective of image-to-image translation is to discover a correspondence between an input and output image. Such models are divided into two primary classes: generative adversarial networks (GANs) based models [18], and inversion based ones. Pix2Pix [23] and CycleGAN [57] are two common paired and unpaired GAN-based translation models, respectively. Due to the scarcity of natural pairings of pictures for paired image translation, the majority of subsequent research focuses on unpaired data for image translation, such as the fields of multi-domain translation and image fidelity [9, 30, 31]. Recent research has also concentrated on representation disentanglement in terms of style, texture, and form [41, 53, 54], as well as multi-modal learning to keep cross-modal information or to produce diverse results during translation [2, 12, 22, 33, 58]. Finally, classifier-based inversion is a type of method where the objective is to construct a picture by modifying the hidden features of a trained classifier [42]. IMAGINE [48], one of the more recent of such models, incorporates a feature inversion technique that allows for the creation of a picture with a merged style from a single image.

For our scenario, the scarcity and complexity of tumor image data makes learning useful representations of tumors challenging and impracticable. Instead of generating new tumor pictures with trained GAN-styled models, we use an AutoEncoder [24] to reconstruct tumor images using heuristically selected and paired normal images in order to circumvent methods such as distribution learning and generalization that have higher dataset size requirements. To modify hidden features during reconstruction in order to realistically translate tumor objects into generated pictures,
we also use **progressive translation**, which is inspired by model inversion ideas.

**Attention and Visual Transformer.** Self-attention mechanisms, which first appeared as methods for dependency-modeling within sequences in natural language processing (NLP) tasks [47], have parameter-independent receptive field scaling and content-dependent interactions, making them effective for computer vision research. They have subsequently been integrated into a number of downstream vision tasks, including image classification, object detection, and segmentation [3, 43, 46]. Meanwhile, given the computationally cost of conducting spatial attention, researchers have turned to **attention on image patches** in vision tasks to enhance training efficiency [16]. Some recent works have focused on detecting saliency and context in visual recognition using ViT [26, 32].

**Object Detection.** Object detection is a central component of visual analysis and comprehension [55]. Besides general architectural innovations in multi-scale interaction, generalization and attention with CNNs [6, 7, 44], there are two mainstream research directions of object detection. These include two stage region proposal-based object detection frameworks [4, 40, 56] and one stage regression-based frameworks [17, 39]. Faster R-CNN [40] and YOLO [17] are the most common models for these two approaches, respectively. Object detection and segmentation frameworks include Detectron2 [50] and MMDetection [8], which possess capabilities of data augmentation, bounding boxes rotation and computational efficiency.

Inspired by various attention models in vision tasks and feature pyramid networks in object detection, we propose a method that allows us to connect the attention mechanism of ViT on image feature patches to the ResNet [20] backbone of a FPN and find a balance between computational complexity and model performance improvement through the attention mechanism on patches of hidden features of an image. The coupling of our object detection model and data augmentation allows us to mitigate the data-hungry problem of attention mechanism and attain higher performance in the task of tumor detection.

## 3. Proposed Method

In this section, we present the following sequentially. (1) Our local image translation module that uses a convolutional autoencoder to interpolate and reconstruct the features of normal and tumor images in hidden layers to get realistic but fake tumor images. (2) Our feature pyramid network with attention on the image feature patches of ResNet outputs. (3) The integrated REPLICA model that utilizes these generated tumor images to improve the performance of our attention-guided feature pyramid network.

### 3.1. Progressive Translation by Image Reconstruction

We consider a basic convolutional autoencoder model as our baseline model. We perform local translation by interpolating and reconstructing the features of both tumor and normal images in hidden layers of the autoencoder, and crop the region of tumors to the same positions in paired normal images. The spatial information within hidden layers of such a model can provide useful details of specific areas in the original input image [1], which is helpful for local translation. Additionally, by avoiding the usage of a generative model (e.g. a GAN) for distribution learning, this model is made effective by using overfitting to maintain the original information of the images as much as possible, and the generated images will preserve the high quality of the input images. The entire procedure is depicted in Fig. 2.

![Figure 2. The local image translation framework of our model. The lock icon represents an autoencoder image reconstruction model that has been pretrained and overfitted with a convolutional autoencoder. Data flow and intra-model computation are shown by dark gray arrows, whereas inter-model computation is denoted by red arrows.](image)

The basic idea behind autoencoders for image reconstruction is to train convolutional encoder and decoder neural networks to convert an image to a lower-dimensional feature representation, and then back to the same image, respectively [25]. The autoencoder training objective can be written as

\[
(e^*, d^*) = \arg \min_{e,d} L(x, d(e(x))),
\]

where \(e^*\) and \(d^*\) denote the optimal encoder and decoder, \(x\) and \(d(e(x))\) are the input image and the reconstructed image, and \(L(x, d(e(x)))\) defines the reconstruction error between them. We use an \(L_1\) reconstruction loss of

\[
L_{ae} = ||x - d(e(x))||_1.
\]

The first step for the image reconstruction model is to
obtain paired normal and tumor images through a novelty-designed heuristic image-matching rule, which ensures that a tumor is always within the outline or a normal image. Furthermore, to ensure the reconstruction quality, we select a balanced number of healthy and tumor scans, which serves as the input to the generation model.

We further propose to overfit the model with the input data, i.e., obtain $L_{ae} \simeq 0$. While this seems counter-productive to machine learning standards, we argue that such a method enables the model to capture most textures, shapes and color information that is crucial for the reconstruction process. After AE converges, we input a pair of normal and tumor images $(x, y)$ and interpolate between the two representations as follows:

$$g(x) = (1 - \lambda_k) \cdot g(x) + \lambda_k \cdot g(y),$$

where $g(x)$ and $g(y)$ denote the feature maps of the translated healthy image and cancerous image, respectively, obtained from the hidden layers of the convolutional autoencoder, $k$ denotes the $k_{th}$ hidden layer of the reconstruction model, $k$ should be related to $g(x)$ and $\lambda_k$ is the hidden feature ratio of the tumor image that will be interpolated with those of the normal image. To enable progressive content translation from the cancerous image to the healthy image, $\lambda_k$ should increase continuously with $k$, but should be less than 1, for both encoder and decoder layers.

In the final step of translation we merge the created mixed image with the paired normal image by cropping the content within the bounding box annotation of the tumor provided with the cancerous scan. Following this we use several pixel-level processing techniques, including marginal transition, boundary division, and cropping, to obtain a higher-quality image, which are attached in appendix.

3.2. Attention Guided Feature Pyramid

We propose a new ViT backbone for coupling with the feature pyramid network in order to improve detection performance. In our pipeline, raw images are fed into a ResNet50 to generate feature maps corresponding to the activation map of each hidden layer. Because spatial attention can significantly improve the connections between pixels, before feeding these outputs into the next Feature Pyramid Network (FPN) [28] that uses multi-scale pyramidal hierarchy to construct feature pyramids for Region Proposal Network (RPN) and Region of Interest (RoI) pooling [40], we use attention on image feature patches of the outputs of ResNet to improve the hidden representations of each inputs to FPN.

The entire procedure of our ViT-ResNet is shown in Fig. 3. It is divided into three parts: feature map transformation, attention on image feature patches, and feature map reconstruction. Each patch of feature map in the ResNet outputs will be subjected to the following transformation in the first section:

$$z = [x^1_p E; x^2_p E; \ldots; x^N_p E].$$

Since the output of ResNet follows a pyramid structure, with the increment in hidden dimension and stride over spatial dimension, we use divisible numbers of the spatial size of the last-layer representation as the patch size, which is $(5, 4)$. Then, all shallow layers are first resized along hidden dimension to match the depth information, i.e., $(256 \times 2, h \times w) \rightarrow (256, (2h \times w))$.

As with BERT [15] and ViT, we append a learnable positional embedding $E_{pos}$ to assist the network in remembering the locations of individual patches, as

$$z = z + E_{pos}.$$  (5)

Due to the fact that each ResNet feature map has a numbers of channels and patches, we utilize a positional embedding with a maximum length of $N \cdot \max(k)$ in our proposed model, where $\max(k) = 8$. Following that, the ViT-ResNet module’s final output is computed as
Figure 4. The integrated framework is shown in this diagram. The red boxes indicate patches containing real or translated tumor, while the blue boxes provide relevant background information. The original tumor patch can only have 4 reference patches in the background, whereas the number increases to 9 when a translated normal image is provided.

\[ z' = MSA(LN(z) + z), \]  

(6)

where \( MSA \) denotes multi self-attention, and \( LN \) is layer-wise normalization [47]. In contrast to ViT’s classification task design, we retain multi self-attention (MSA), but remove the multilayer perceptron (MLP) and classification token, and keep the final dimension fixed to the original dimension of the patch to generate the input of the subsequent FPN.

3.3. Integrated Model Details

By combining the local image translation and the attention-guided feature pyramid network, REPLICA mitigates the data-hungry problem in attention with a larger number of generated realistic but fake cancerous images, and fully exploits the hidden information contained in each tumor image by applying attention on image feature patches.

Because of the abundance of source images in common computer vision tasks, researchers can simply employ various advanced ViT architectures, such as DeiT [45] and PVT [49], that partition images into distillation embeddings or feature pyramids to boost model performance [10, 27]. However, because there are only a few tumor images in our case, it is almost impossible for the attention mechanism to learn sufficient background information for the object to be detected.

Given the constraint from fully attention-based model, we first replace only a component of the models with ViT. This is further improved by local image translation that introduces extra fake label images. We have found that local image translation is an effective method for introducing diversity in the background of tumors and improving attention perceptual ability. A pixel-level illustration of this concept is shown in Fig.4. Since the hidden features are in accordance with the positions of pixels, the pixel level illustration is comparable to the feature map of hidden layers.

The utility of performing local image translation can be considered as follows. Assume that a single tumor image has 12 patches, 1 of which include a piece of the tumor and 7 of which are blank. Without the additional translated normal images, the attention mechanism can only learn background information from up to 4 more patches. Doubling the number of useful patches around tumors helps the model to learn more variance from diverse yet informative backgrounds, enhancing generalization ability of attention.

Furthermore, the intrinsic property of medical images can help in the completion of the translation process. Since the backgrounds of most tumor images are identical to those of normal image, only the location of the tumor has a distinct distribution, so it’s important to introduce different backgrounds to assist in tumor detection.

4. Experiments

In this section, we will conduct thorough evaluations of our proposed REPLICA model on an open-source breast scan dataset, examining both image translation quality and object detection performance.

4.1. Experimental Settings

Digital Breast Tomosynthesis Dataset. We choose to use a publicly available dataset of breast cancer screening scans: the Digital Breast Tomosynthesis (BCS-DBT) dataset [5]. The BCS-DBT dataset comprises cancer cases that are normal, actionable, non biopsy-proven, and biopsy-proven. It contains 22032 breast tomosynthesis scans from 5060 individuals, with each scan containing up to 4 anatomical views and dozens of spatially-aligned slices in each view. Below are two examples of DBT images.

In our study, we randomly choose 5 slices from each view of a normal scan, therefore each normal scan will have up to 20 slices in our study. We preserve all 346 slices
Figure 5. The examples of normal and tumor images from BCS-DBT. Red box denotes the bounding box of the tumor image.

with bounding boxes in both the training and validation sets for tumor scans that include both biopsy-proven benign and cancer tumors.

Following the dataset split information, we use 224 tumor slices with 271 bounding boxes as the training set, 75 tumor slices with 75 bounding boxes as the validation set and 136 tumor slices with 136 bounding boxes as the test set. We chose 3519 normal patients and the corresponding 70380 slices as the pool for pairing with tumor images, as shown in Tab.1.

| Image Types | # of Image | # of Slices | # of Bboxes |
|-------------|------------|-------------|-------------|
| Normal      | 3519       | 70380       | N/A         |
| Tumor       | 299        | 299         | 346         |

Table 1. The number of data from the DBT dataset that we used in our research.

Evaluation Metrics. We use a range of metrics to evaluate the quality of local image translation and the performance of object detection with attention on image feature patches. In the image reconstruction training process, we use the training set $L_1$ reconstruction loss being less than 0.01 to indicate overfitting.

We also use the AP (Average Precision) metrics for object detection as a quantitative study of our model. There are metrics relying on IoU (Intersection over Union) that describes the intersection of ground-truth bounding boxes and predicted bounding boxes from models. The IoU formula is known as

$$IoU(A, B) = \frac{(A \cap B)}{(A \cup B)},$$

where $A$ and $B$ are ground-truth bounding boxes and predicted bounding boxes from models, respectively. $IoU(A, B) \in [0, 1]$.

In our study, we employ AP, AP50, AP75, APM, and API as analysis criteria, with AP50 serving as an indicator of model performance. Here, AP, AP50 and AP75 denote AP at IoU from 0.5 to 0.9 with step 0.05, IoU equals 0.5 and IoU equals 0.75, respectively. APM and API are for medium objects with areas $\in [32^2, 96^2]$ and large objects with areas more than $96^2$.

The original Detectron2 framework [50] has random data augmentation that resizes images to 8 various shapes, some of which may be incompatible to our preset patch size, as the widths and heights of hidden feature maps should be an integer multiple of the width and heights of the preset patch. As a result, we remove the random data augmentation in the experiments. The entire Detectron2 framework will be indicated as ResNet50 with random augmentation, which will be introduced in the quantitative studies of 4.2.

We included the details of model implementation in the appendix for brevity.

4.2. Experimental Results

We provide both qualitative and quantitative results of our experiments. We characterize the quality of local image translation by examining three different physiological types of tumors to be translated into normal images, and evaluate tumor detection performance with our model.

Quantitative Results. We compare images as reconstructed by our local image translation module in 3.1 with the original tumor and paired normal images as shown in Fig.6. In our translation task, there are three types of tumors: tumors on the boundary, tumors inside the boundary, and small tumors. They correspond to the first, second, and third rows of the figure, respectively.

In the translation from one tumor image to the paired normal images, the translated normal images are consistent in both style and content, indicating that the translation was successful. This can be seen in the first row of the figure, with three implanted tumors that are in accordance with the equivalent normal image. In the second row of the figure, the translated normal image can have a texture and tissues that are consistent with the original texture and tissues. In the final row, a tumor of smaller size is also properly translated into the final output.

We also evaluated CycleGAN’s performance in terms of output image quality for both global and local image translation in the appendix.

Quantitative Evaluations. In the quantitative evaluations, we separated the local image translation in 3.1 and attention guided feature pyramid network in 3.2 as two components to the ResNet50 backbones. For local image translation, we generate three extra locally translated datasets using real cancerous images of the BCS-DBT dataset in 4.1. For the 47 tumor images that include multiple tumor annotations, we keep the first annotation as the location for translation. The statistics of dataset after generation is shown in Tab.2. We denote the model with realistic but fake additional images is called ResNet50 with local image translation (LIT).

We incorporate the attention-guided feature pyramid net-
Figure 6. Examples of local image translation using convolutional autoencoder. The corresponding tumor for translation is shown by red boxes. The left side shows three tumor images as the source of translation, their paired normal images, and the normal images after translation. The right side shows three tumor images for translation and the translation results for three different paired normal images.

| Image Types  | # of Image | # of Slices | # of Bboxes |
|--------------|------------|-------------|-------------|
| Tumor        | 299        | 299         | 346         |
| Translated   | 665        | 665         | 665         |
| Total        | 964        | 964         | 1011        |

Table 2. Dataset statistics for quantitative experiments. The dataset is a combination of tumor images from DBT dataset and locally translated normal data in 3.1.

As indicated in Tab.3, two modules of REPLICA can compensate for each other. As shown in the best results, when adding the local image translation module without using patch-based attention, the ResNet50 (LIT) performs better than ResNet50 (RA), showing the effectiveness of using our translated images. When adding attention on image feature patches, the performance of ViT-ResNet50 improves significantly on the validation set, but remains lower than REPLICA. REPLICA outperforms other backbones in both the best and mean performance of the validation set.

When we switch to the mean results of the validation set, we notice some variations. While adding local image translation consistently improves performance of ResNet50 over ResNet50 (RA) on AP50, the performance of ViT-ResNet50 drops significantly, which is worse than ResNet50 (RA). This indicates to some extent that in the absence of sufficient data, attention mechanisms would show the instability of performance, partially demonstrated by the high variance of its AP50. Additionally, we found that adding locally translated photos can add variance to the detection of medium-sized tumors by ResNet50 (LIT). REPLICA mitigates this kind of variance while performing better than other backbones.

In terms of other criteria, we can see that ResNet50 (LIT) performs best in detecting large-sized tumors (AP1), demonstrating the efficiency of local image translation in assisting in the diagnosis of practically perceptible tumors. In addition, the ResNet50 (RA) performs best in AP, AP75 and APm, demonstrating the robustness of the whole convolutional structure under more strict detection criterion. REPLICA has the highest improvements in terms of AP50.
| Model Backbone          | AP at Validation Set (Best) | AP at Validation Set (Mean) | Variance |
|-------------------------|----------------------------|-----------------------------|----------|
|                         | AP | AP50 | AP75 | APm | API | AP | AP50 | AP75 | APm | API | AP50 | APm |
| ResNet50 (Baseline)     | 12.9 | 43.8 | 8.7 | 3.3 | 13.9 | 11.6 | 41.2 | 4.4 | 5.2 | 12.3 | 3.1 | 2.3 |
| ResNet50 (RA)           | 15.0 | 46.6 | 4.9 | 16.5 | 14.6 | 14.4 | 45.9 | 4.8 | 13.8 | 15.7 | 2.2 | 3.3 |
| ResNet50 (LIT)          | 14.9 | 47.8 | 6.4 | 20.3 | 13.8 | 12.4 | 43.2 | 3.7 | 6.7 | 13.0 | 16.5 | 14.6 |
| ViT-ResNet50            | 13.1 | 49.6 | 2.3 | 3.7 | 14.1 | 13.4 | 49.0 | 3.3 | 6.3 | 14.4 | 1.7 | 6.8 |
| REPLICA                 | 15.7 | 50.4 | 4.7 | 8.5 | 16.5 | 13.4 | 49.0 | 3.3 | 6.3 | 14.4 | 1.7 | 6.8 |

Table 3. The performance of REPLICA and the models it compares. RA and LIT stand for Random Augmentation and Local Image Translation in 3.1, respectively. Each simulation was performed 5 times for computing the means and variances of criteria.

| Aspect                      | Variant                          | AP (Best) | AP (Mean) | AP50 (Best) | AP50 (Mean) |
|-----------------------------|----------------------------------|-----------|-----------|-------------|-------------|
| REPLICA                     | N/A                              | **15.7**  | **13.4**  | **50.4**    | **49.0**    |
| Local Image Translation     | Generative Image Translation     | N/A       | N/A       | N/A         | N/A         |
| Local Image Translation     | Translated Images Only           | 9.0 (-6.7) | 8.2 (-5.2) | 34.3 (-16.1) | 31.2 (-17.8) |
| Attention Guided FPN        | Feedforward Layers in ViT        | 13.5 (-2.2) | 12.0 (-1.4) | 41.1 (-9.3) | 40.8 (-8.2) |
| Attention Guided FPN        | Depth of Attention Layers        | 15.1 (-0.6) | 12.1 (-1.3) | 41.3 (-9.1) | 39.5 (-9.5) |

Table 4. Ablation studies of REPLICA. Local Image Translation and Attention Guided FPN are in the section of 3.1 and 3.2, respectively. In the experiment, each simulation was performed 5 times for computing the mean of AP and AP50.

### 4.3. Ablation Studies

We conduct ablation studies on REPLICA to validate each proposed modification in our approach, including modifications of translation method and attention, and present the results in Tab.4.

**Generative Image Translation.** We remove the progressive translation and change the translation model to CycleGAN [57]. The results are analyzed in the appendix, showing that CycleGAN can only change the styles and textures of healthy images and it is not compatible with tumor translation. We omit the simulation stage because there are no visible tumors in the outputs.

**Translated Images Only** To evaluate the effectiveness of our translated images, we study the model performance of REPLICA with our realistic but fake tumor images only. The performance of REPLICA in this dataset drops 31.9% but still has 34.3 for the best AP50, showing the effectiveness of local image translation and the necessity of combing them with real cancerous images.

**Feedforward Layers in ViT** We further study the effect of removing feedforward layers in ViT [16] by training REPLICA with one feedforward layer after an attention layer. This leads to a 18.5% decrease in the best AP50, indicating that by introducing non-linearity to the output of attention layers, feedforward layers are incapable of improving the attention mechanism in our scenario.

**Depth of Attention Layers** To value the effectiveness of our attention mechanism on image feature patches, we study the performance of REPLICA by default depth of attention layers in ViT. Adding additional one layer of attention leads to a 18.1% decrease in best AP50. Both of the ablation studies of attention show the significance of the direct application of attention on image feature patches.

### 4.4. Limitations

A main limitation of our work is that our local image translation is specialized in translating medical images, which share similar textures, shapes and colors. It's almost impossible to generalize our model to natural images [23] because they are highly diverse and distinct in both their foregrounds and backgrounds.

Moreover, our work rely on multiple times of training for a larger fake dataset, because we need to ensure the quality of translation by keeping a balanced number of healthy and tumor scans and using overfitting of the autoencoder.

Last, our attention-guided feature pyramid network is based on the standard object detection framework. According to the recent benchmarks of object detection, most SOTA models are fully transformer-based, including Soft Teacher + Swin-L [51] and DyHead [13]. We analyzed the incompatibility of these methods for breast tumor detection in 3.3, but comparisons with fully transformer-based methods are missing in our work.

### 5. Conclusion

We proposed the REPLICA model in this work to improve the performance of the object detection model in the context of breast tumor detection. As a novel pipeline for improving performance and stability of high-resolution breast tumor detection and achieve higher performance on existing backbones, REPLICA provides a new idea for related problems.
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