

# LiT-4-RSVQA: LIGHTWEIGHT TRANSFORMER-BASED VISUAL QUESTION ANSWERING IN REMOTE SENSING

*Leonard Hackel<sup>\*1,3</sup>, Kai Norman Clasen<sup>\*1</sup>, Mahdyar Ravanbakhsh<sup>2</sup>, Begüm Demir<sup>1,3</sup>*

<sup>1</sup>Technische Universität Berlin, Germany <sup>2</sup>Zalando SE, Berlin, Germany

<sup>3</sup>BIFOLD – Berlin Institute for the Foundations of Learning and Data, Germany

## ABSTRACT

Visual question answering (VQA) methods in remote sensing (RS) aim to answer natural language questions with respect to an RS image. Most of the existing methods require a large amount of computational resources, which limits their application in operational scenarios in RS. To address this issue, in this paper we present an effective lightweight transformer-based VQA in RS (LiT-4-RSVQA) architecture for efficient and accurate VQA in RS. Our architecture consists of: i) a lightweight text encoder module; ii) a lightweight image encoder module; iii) a fusion module; and iv) a classification module. The experimental results obtained on a VQA benchmark dataset demonstrate that our proposed LiT-4-RSVQA architecture provides accurate VQA results while significantly reducing the computational requirements on the executing hardware. Our code is publicly available at <https://git.tu-berlin.de/rsim/lit4rsvqa>.

**Index Terms**— visual question answering, natural language processing, lightweight transformer, remote sensing.

## 1. INTRODUCTION

As a result of the increased volume of remote sensing (RS) image archives and the amount of information that can be extracted from them, the development of visual question answering (VQA) methods has recently become an important research topic in RS. In the task of VQA in RS, the user asks a question to a system in natural language concerning the content of RS images. During the last years, several VQA methods have been presented in RS. As an example, [1] defines the VQA task in RS as a classification problem. In this work, a ResNet-152 model is employed to extract features from RS images, while skip-thought vectors are used to extract features from the text data. Then, the multi-modal features obtained through point-wise multiplication are classified using a multi-layer perceptron (MLP) as classification head. In [1], the first large-scale VQA benchmark dataset for RS based on low- and high-resolution RS images and OpenStreetMap data is also introduced. In the VQA method presented in [2], the

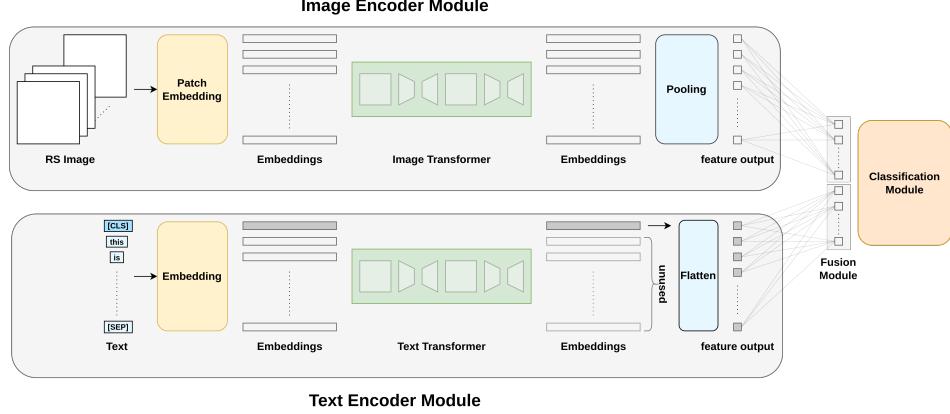
recurrent neural network (RNN) based skip-thought vectors model for text feature extraction used in [1] is replaced with the attention-based bidirectional encoder representations from transformers (BERT) [3]. For the feature fusion, [2] uses multi-modal tucker fusion for VQA (MUTAN), which enables a richer and more meaningful interaction between features compared to a simple point-wise operation. In [4], a multi-modal transformer-based VisualBERT fusion (VBFusion) architecture is proposed. VBFusion uses a ResNet-152 architecture as a region proposal system and a VisualBERT [5] model to learn the joint representation of image and text modalities instead of simply combining modality-specific representations. A similar approach is employed in [6], utilizing multi-modal BERT (MMBERT) [7]. This method also uses a ResNet-152 as a feature encoder. Instead of different regions of the input image, the backbone extracts five input representations at different resolutions and combines image and text features with a shallow MMBERT encoder. A comprehensive review of the current state-of-the-art of image-language models in RS is presented in [8].

All of the above-mentioned architectures provide good VQA accuracies. However, they are associated with high computational complexity and parameter count (PC), and thus have limited capability to be applied for operational VQA applications in RS. As an example, VBFusion has a PC of 277 million and requires about 184 billion floating point operations (FLOPs) per forward pass. To overcome these limitations, in this paper, we investigate the effectiveness of lightweight transformer-based models for VQA problems in RS that require few parameters and are thus associated with low computational requirements.

## 2. LIGHTWEIGHT TRANSFORMER-BASED MODELS FOR VQA

Given a triplet  $(\mathbf{I}, \mathbf{Q}, \mathbf{A})$  of an image, question, and answer, a VQA system provides the answer  $\mathbf{A}$  given the image  $\mathbf{I}$  and the question  $\mathbf{Q}$  as the input. In line with the RS literature, we consider VQA in RS as a classification problem, where  $\mathbf{A}$  is one of  $n_A$  predefined cases. In this paper, we study lightweight models for VQA in RS. To this end, we introduce the lightweight transformer-based VQA in RS (LiT-4-RSVQA) architecture

<sup>\*</sup>These authors contributed equally to this work



**Fig. 1.** Illustration of the LiT-4-RSVQA architecture.

that consists of four modules: i) a lightweight encoder module for the text modality; ii) a lightweight encoder module for the image modality; iii) a fusion module; and iv) a classification module (see Fig. 1). In detail, the text encoder module is realized as one lightweight transformer ( $\text{BERT}_{\text{TINY}}$ ), while the image encoder module is comprised of one of three lightweight image transformers: i) data-efficient vision transformer (Deit Tiny) [9]; ii) mobile vision transformer (MobileViT-S) [10]; or iii) cross-covariance image transformer (XCiT Nano) [11]. We select these models based on their proven success from the literature and investigate their effectiveness in VQA in RS. To the best of our knowledge, they are introduced for the first time in VQA problems in RS. We combine  $\text{BERT}_{\text{TINY}}$  with one of the above-mentioned image encoders, resulting in three VQA model configurations.

In general, text and image transformers are trained using multi-head self-attention (MSA), which is a mechanism that enables the model to focus on different parts (tokens) of an input sequence. Attention computes scores between each pair of input tokens through matrix multiplications and softmax operations, resulting in weights determining how much attention should be given to each token. The attention weights are utilized to prioritize relevant parts of the input, enabling the model to focus on the most essential tokens. The attention operation [12] can be defined as:

$$\text{Attention}(Q, K, V) = \text{Softmax} \left( \frac{QK^T}{\sqrt{d}} \right) V, \quad (1)$$

where  $Q$ ,  $K$ , and  $V$  are query, key, and value, respectively. For self-attention, they are defined as  $Q = XW_Q$ ,  $K = XW_K$  and  $V = XW_V$ , where  $W_Q$ ,  $W_K$  and  $W_V$  are linear projection matrices, and  $X$  is a sequence of  $d$ -dimensional embeddings of the input. For normalization, the attention weights  $QK^T$  are scaled by the square root of the embedding dimension  $d$ . To facilitate more diverse features, attention is computed in  $A$  parallel attention heads.  $L$  transformer block

layers are stacked to create a transformer network [12], [13].

To obtain representations for the text modality, we utilize  $\text{BERT}_{\text{TINY}}$  [14], which is a distilled version of  $\text{BERT}$  [3].  $\text{BERT}_{\text{TINY}}$  uses the same general architecture as  $\text{BERT}$  but with fewer layers  $L$ , attention heads  $A$ , and a smaller embedding dimension  $d$ . It uses MSA and a feed-forward network (FFN) to extract features from text tokens of the question input  $Q$ .  $\text{BERT}_{\text{TINY}}$  is pre-trained using a three-step method: 1) a large teacher model with more layers, attention heads, and larger embedding dimension is trained using masked language modeling (MLM) and next sentence objectives; 2)  $\text{BERT}_{\text{TINY}}$  is pre-trained with MLM; 3)  $\text{BERT}_{\text{TINY}}$  is additionally pre-trained using knowledge distillation of the large teacher model from the first step. During the last step, the student model  $\text{BERT}_{\text{TINY}}$  learns from the soft labels produced by the teacher model.

For the image feature extraction, Deit Tiny [9] uses MSA and a FFN. It extracts token embeddings from  $I$  by splitting the image into patches following [13]. Similar to  $\text{BERT}_{\text{TINY}}$ , it uses a reduced number of attention heads  $A$  and a smaller embedding dimension  $d$  to reduce the number of parameters and increase the throughput of the model.

MobileViT-S [10] uses  $n \times n$  and point-wise convolutions to encode local information about a pixel and project the information into a higher dimensional space. The resulting tensors are reshaped (unfolded) into non-overlapping patches (tokens) similar to [13], and attention is applied to the tokens to model long-range interactions. Afterwards, the tokens are reshaped into their original tensor dimensions (folding), which is possible as the previous unfolding operation keeps the pixel and patch order intact. This restores the original pixel location and allows for all pixels to encode information about all other pixels without the need for a large number of tokens in the attention operation. Combined with dimensionality-reducing MobileNet-blocks, the unfolding-attention-folding operations reduce the latency and the number of parameters.

XCiT Nano [11] changes the order of matrix operations in

MSA and thus greatly reduces the cost of the attention operation. This cross-covariance attention (XCA) between keys and queries is calculated between channels instead of tokens, significantly reducing the number of calculations required. XCA [11] can be defined as:

$$\text{Attention}_{\text{XC}}(Q, K, V) = V \text{ Softmax} \left( \frac{\hat{K}^T \hat{Q}}{\tau} \right), \quad (2)$$

where  $\hat{K}$  and  $\hat{Q}$  are the normalized  $K$  and  $Q$ , respectively, and  $\tau$  is a learnable temperature parameter. As this change removes explicit communication between patches, a block of convolutions, batch-norm, and non-linearity is added after each XCA block to re-introduce information exchange. For further detailed information on the considered models, we refer the reader to their respective papers mentioned above.

The feature fusion module consists of two linear projections and a modality combination. The projections map the two modalities with dimensions  $d_t$  and  $d_v$  into a common dimension  $d_f$ , where  $d_t$  and  $d_v$  denote the dimensions of the flattened output of the text and image encoder modules, respectively. The value of  $d_v$  differs depending on the used lightweight transformer. The projected features are then element-wise multiplied as in [1]. The classification module is defined as an MLP projection head. After training of the proposed architecture, the VQA system can be used to generate an answer  $\mathbf{A}$  for a given input image  $\mathbf{I}$  based on a natural language question  $\mathbf{Q}$ .

### 3. EXPERIMENTAL RESULTS

The experiments were conducted on the RSVQAxBEN benchmark dataset [15], which contains almost 15 million image/question/answer triplets extracted from the BigEarthNet-S2 dataset [16]. The questions provided in this dataset are about: i) the presence of one or more specific land use/land cover (LULC) classes, where the answers are associated to “Yes/No” (called *Yes/No*); and ii) the type of the LULC classes, where the answers are one or more LULC class names (called *LULC*). In this paper, we used all available Sentinel-2 bands with 10 m and 20 m spatial resolution included in the BigEarthNet-S2 dataset, as suggested in [4]. We restricted the model output to the  $n_A = 1,000$  most frequent answers. We use the train/validation/test split as proposed in [15].

In the experiments, we analyze our results between each other and compare them with those obtained from: i) VBFusion [4]; and ii) Deit3<sub>Base</sub> + BERT<sub>TINY</sub> (DBBT), which is a VQA model that exploits the large transformer Deit3<sub>Base</sub> [9] as image encoder and BERT<sub>TINY</sub> as a text encoder. Each model (except VBFusion, for which we used the same implementation proposed in [4]) is evaluated under two training regimes: i) the image encoder is pre-trained for 100 epochs on BigEarthNet-S2, and fine-tuned for additional ten epochs on the RSVQAxBEN dataset [15]; and ii) the full VQA network is trained in an end-to-end fashion for ten epochs. In

both cases, the text encoders use pre-trained weights from Huggingface [17]. Both training regimes use a linear-warmup-cosine-annuling learning rate schedule with a learning rate of  $5 \times 10^{-4}$  after 10,000 warm-up steps with batch size and dropout set to 512 and 0.25, respectively. All models are trained on a single A100 GPU with matrix multiplication precision set to “medium” in Pytorch 1.13.1. To evaluate the results, the models are compared in terms of their: i) accuracy on the two question types Yes/No and LULC; ii) overall accuracy (OA), which is the micro average of all answer classes; iii) average accuracy (AA), which is the macro average of the two aforementioned question types; iv) parameter count (PC); and v) floating point operations (FLOPs).

Table 1 shows the experimental results. From the table, one can see that all models within our LiT-4-RSVQA architecture provide competitive accuracies with significantly reduced computational complexity compared to both baseline models. Among the models in LiT-4-RSVQA, the configuration with pre-trained XCiT Nano achieves the highest accuracy with less than one-tenth of the number of parameters and one-seventh of the computational effort measured in FLOPs compared to DBBT. With an AA of 64.61%, it is almost 9% better than VBFusion [4] and more than 2.5% better than DBBT. However, it is worth noting that XCiT Nano performs worst of all compared configurations when trained end-to-end. In terms of FLOPs, the Deit Tiny-based configuration demands the fewest computational resources. It uses less than 10% of the FLOPs in comparison with the DBBT and more than 600 times fewer FLOPs when compared with VBFusion. However, the accuracy of this model is higher in all evaluated metrics than the respective DBBT model and VBFusion. In addition, one can observe that: i) models with pre-trained image encoders perform better than end-to-end trained networks; and ii) better-performing pre-trained models do not correspond to better-performing end-to-end trained models, highlighting the advantage of using a pre-trained image encoder.

### 4. CONCLUSION

In this paper, we have studied efficient transformer-based models in the framework of VQA in RS. In particular, we have introduced the LiT-4-RSVQA architecture. Our architecture is based on lightweight transformer encoder modules, a feature fusion module, and a classification module. Specifically, BERT<sub>TINY</sub> is used as a lightweight text encoder, and Deit Tiny, MobileViT-S, and XCiT Nano are considered as lightweight image encoders. Experimental results show that the investigated models can achieve high accuracy in the task of VQA for RS while having significantly fewer parameters and, therefore, lower computational requirements than larger models. We would like to note that our architecture is not limited to the considered lightweight models. As future works, we plan to: i) investigate different encoder models and on-board processing with field-programmable gate arrays (FPGAs) and application-

**Table 1.** Accuracy per question type as well as average accuracy (AA) and overall accuracy (OA) obtained on the RSVQAxBEN dataset. Parameter count (PC) and floating point operations (FLOPs) are given in millions and billions, respectively. The image encoders use all available Sentinel-2 bands with 10m and 20m spatial resolution. Results are averaged over three runs, with standard deviations provided in brackets. ✓▲ Pre-trained on ImageNet; ✓\* pre-trained on BigEarthNet [16].

Architecture	Encoder		Fusion	Question Type		AA	OA	PC	FLOPs	
	Image	pre-trained		Text	LULC					
VBFusion [4]	ResNet-152	✓▲	-	VisualBert	26.26	86.56	55.80	76.10	277.0	183.9
DBBT	Deit3 Base	✓*	Bert Tiny	Simple	36.26 (1.10)	87.83 (0.30)	62.04 (0.70)	79.15 (0.43)	92.6	4.4
	Deit3 Base	✗	Bert Tiny	Simple	29.53 (3.10)	85.21 (1.39)	57.36 (2.24)	75.84 (1.67)	92.6	4.4
LiT-4-RSVQA	Deit Tiny	✓*	Bert Tiny	Simple	38.37 (1.17)	88.65 (0.39)	63.51 (0.64)	80.19 (0.39)	11.0	0.3
	MobileViT S	✓*	Bert Tiny	Simple	34.43 (1.94)	89.02 (0.27)	61.37 (0.96)	79.95 (0.23)	10.4	0.5
	XCiT Nano	✓*	Bert Tiny	Simple	<b>39.50</b> (2.04)	<b>89.72</b> (0.65)	<b>64.61</b> (1.35)	<b>81.27</b> (0.88)	<b>8.1</b>	0.6
	Deit Tiny	✗	Bert Tiny	Simple	32.53 (1.93)	86.80 (0.43)	59.67 (1.16)	77.67 (0.66)	11.0	0.3
	MobileViT S	✗	Bert Tiny	Simple	27.18 (3.18)	85.51 (2.19)	56.34 (2.63)	75.70 (2.32)	10.4	0.5
	XCiT Nano	✗	Bert Tiny	Simple	21.45 (4.07)	81.97 (4.66)	51.71 (4.36)	71.79 (4.56)	<b>8.1</b>	0.6

specific integrated circuits (ASICs); and ii) develop a library to simplify the development of VQA models in RS.

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