BlazeNeo: Blazing fast polyp segmentation and neoplasm detection

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ABSTRACT In recent years, computer-aided automatic polyp segmentation and neoplasm detection have been an emerging topic in medical image analysis, providing valuable support to colonoscopy procedures. Attentions have been paid to improving the accuracy of polyp detection and segmentation. However, not much focus has been given to latency and throughput for performing these tasks on dedicated devices, which can be crucial for practical applications. This paper introduces a novel deep neural network architecture called BlazeNeo, for the task of polyp segmentation and neoplasm detection with an emphasis on compactness and speed while maintaining high accuracy. The model leverages the highly efficient HarDNet backbone alongside lightweight Receptive Field Blocks for computational efficiency, and an auxiliary training mechanism to take full advantage of the training data for the segmentation quality. Our experiments on a challenging dataset show that BlazeNeo achieves improvements in latency and model size while maintaining comparable accuracy against state-of-the-art methods. When deploying on the Jetson AGX Xavier edge device in INT8 precision, our BlazeNeo achieves over 155 fps while yielding the best accuracy among all compared methods.

I. INTRODUCTION

Colorectal polyps, especially adenomas with high-grade dysplasia, carry high risks of progressing into colorectal cancer (CRC) [10], which claims over 640,000 lives each year [3]. There are available procedures to screen and detect high-risk polyps in an early stage, increasing chances of successful treatment. Polyp detection and removal in colonoscopy are the most effective method to prevent colorectal cancer [14].

At the same time, practical factors such as overloading healthcare systems, low-quality endoscopy equipment, or personnel’s lack of experience [2], [21] can severely limit the effectiveness of colonoscopy. A review by Leufkens et al. [22] pointed out that 20 – 47% of polyps might have been missed during colonoscopies. Several types of image-enhanced endoscopies and accessories have been proposed to alleviate these, yet they can be prohibitively expensive for practical applications, especially in poor medical facilities. On the other hand, computer-aided systems for colonoscopy have shown a lot of promise and have attracted many researchers in recent years. Several works have achieved very good performance on benchmark datasets [9], [12], [39].

Polyp segmentation is a subset of medical image analysis that has gained much attention recently. Traditional machine learning methods for solving the problem are mostly based on hand-crafted features [15], [35] to extract image information such as color, shape, and textures. Since polyps have very high intra-class diversity and low inter-class variation, such approaches are often limited in representing and detecting polyps. Deep neural networks, and especially U-Net [32] have been the state-of-the-art methods for polyp segmentation in the last few years. These networks can learn highly abstract and complex features, allowing them to achieve good performances. At the same time, deep neural networks also come with a complexity trade-off, as models can be very large (up to several hundred million parameters) and cause high latency during inference.

Most of the existing research in endoscopy image analysis has focused on the polyp segmentation problem, in which lesion regions or polyps are segmented from the background pixels. Those works attempted to improve the learning models to provide accurate segmentation of polyps. However, the segmentation of polyps only does not provide...
information about the type of polyps, i.e., benign (non-
cancerous) or malignancy (presence of cancerous cells). In
our seminal work [20], we have defined the problem of Polyp
Segmentation and Neoplasm Detection (PSND), aiming at
fine-grained segmentation of polyps. This can be considered
as an extension of the polyp segmentation problem, providing
richer semantic information for the segmented regions.
Particularly, besides classifying image pixels as polyp or
background, the proposed formulation further identifies each
polyp pixel as non-neoplastic, neoplastic, or undefined. In
general, non-neoplastic polyps are typically benign, while
neoplastic polyps have a risk of developing cancer. Our
newly developed U-Net-based neural network architecture,
NeoUNet, has obtained state-of-the-art performance in solv-
ing this problem in terms of accuracy. However, attention
has not yet been paid to the model size and speed, which is
challenging for practical deployment.

In this paper, we further improve on our previous works on
Polyp Segmentation and Neoplasm Detection with the pro-
posal of BlazeNeo, a novel deep neural network architecture
with an efficient learning mechanism. Our main contributions
are:

- A new deep neural network architecture called
  BlazeNeo for polyp segmentation and neoplasm detec-
tion, aiming at reducing the model size and therefore
  improving inference speed;
- An auxiliary training strategy to fully exploit training-
data for maintaining high accuracy while reducing
  model size;
- Extensive experiments on the newly collected NeoPolyp
dataset and comparisons to existing models. Moreover,
we measure model latency and throughput on dedicated
hardware in a setting similar to real-life deployments of
polyp segmentation and neoplasm detection.

The rest of the paper is organized as follows. We provide a
brief review of related works in Section II. Section III briefly
describes the polyp segmentation and neoplasm detection
problem as formulated in [20]. The BlazeNeo architecture
is presented in Section IV. Section V showcases our experi-
mental studies. Finally, we conclude the paper and highlight
future works in Section VII.

II. RELATED WORK

In recent years, many computer vision tasks have seen
massive improvements through the advancements of convo-
lutional neural networks (CNNs). AlexNet [19] and VGG
[36] are among the first successful CNNs for the image
classification problem. However, these early models still suf-
er from degradation when increasing network depth. Many
works have attempted to modify the network architectures
to improve learning capability aiming at improving network
performance. Skip connections, first introduced in ResNet
[11] in 2016, helped alleviate the degradation and smoothed
out the loss landscape. ResNeXt [43] combined the idea of
skip connections with a multi-branch design first proposed by
the authors of GoogLeNet [37]. More recently, Tan et al. [38]
employed neural architecture search to produce EfficientNet,
a family of neural networks with varying levels of the trade-
off between accuracy and latency. Meanwhile, HarDNet [4]
is a model highly focused on optimizing inference latency
and memory traffic.

Many CNN architectures have been designed for the
semantic image segmentation task, especially in medical
images. Among the earliest was the work by Long et al.
[27], who adopted several well-known architectures using
transfer learning. In the same year, U-Net [32] became a
breakthrough model in medical imaging, achieving highly
promising results for medical image segmentation. Later
works such as UNet++ [47], DoubleUNet [17] and Coupled
U-Net [39] further improved and alleviated limitations in U-
Net. ColonSegNet [16] was a lightweight encoder-decoder
architecture that uses residual connections with squeeze and
excitation network as the main component. ColonSegNet
achieved a high inference speed but with sacrificing accuracy
a lot. DDANet [40] was another encoder-decoder design that
leverages the strength of residual connection and squeeze-
and-excitation modules. DDANet incorporated a single en-
coder followed by two dual decoders. The first decoder
is used for the segmentation mask, while the second one
acts as an autoencoder model that reconstructs the grayscale
image and helps strengthen the feature representation of
the encoder. Attention-U-Net [29] proposed attention gates
as a filter mechanism for selecting useful salient features.
Development on non-U-Net models in medical segmentation
has also remained active. DeepLabV3 [6] is a prominent
architecture that utilizes atrous convolutions for dense feature
extraction. Fan et al. [9] enhanced an FCN-like model with
parallel partial decoder and reverse attention to form PraNet,
a network that achieved state-of-the-art performance on
many benchmark datasets. HarDNet-MSEG [12] employed
an encoder-decoder structure with HarDNet as the encoder
backbone, achieving good performance on the Kvasir-SEG
dataset and very high inference speed. Meanwhile, TransFuse
[46] combined a CNN with the Transformer architecture
using a fusion module called BiFusion.

Many deep learning methods are also specially designed
for the polyp segmentation and detection problem. Qadir et al.
[30] proposed a framework that incorporates a CNN
architecture for labeling segmentation masks for polyps. The
framework allows doctors to receive pre-annotations from a
model trained in a semi-supervised manner. In [33], the au-
thors proposed a model with an Inception-ResNet backbone
combined with several post-learning methods to enhance
polyp detection accuracy. Shin et al. [34] used conditional
adversarial networks to generate abnormal samples for train-
ing polyp detection models. Liu et al. [24] applied different
CNN backbones including InceptionV3 [37], ResNet50 [11]
and VGG16 [36] to the SSD framework, whose accuracy
was much higher than other one-stage object detectors and
comparable to the Faster-RCNN two-stage one. In [23], Li et
al. compared the performance of eight state-of-the-art deep
learning object detectors and demonstrated promising results
in colonoscopy.

While there have been few works in the past several years concerning polyp neoplasm detection (such as that of Ribeiro et al. [31]), it was only very recently that neoplasm detection has been incorporated into polyp segmentation. Phan et al. [20] formally described the problem (denoted as PSND) and proposed NeoUNet, a UNet-based architecture that established the baseline for PSND. While NeoUNet strikes a balance between accuracy and inference speed, typical deployment scenarios for polyp segmentation systems require relatively low latency to ensure smooth operation. Moreover, such scenarios would have the neural network run on lightweight systems embedded within the colonoscopy device. Therefore, this paper focuses on building a network architecture optimized for speed and small in size.

III. POLYP SEGMENTATION AND NEOPLASM DETECTION

Polyp Segmentation and Neoplasm Detection (PSND) has been formulated as a type of fine-grained polyp segmentation problem [20]. Besides segmentation of polyps, this formulation further classifies a polyp pixel into two classes: non-neoplastic or neoplastic. In medical image analysis, non-neoplastic polyps are considered benign, while neoplastic polyps may further progress with a higher risk of cancer. During a colonoscopy, the operator must decide the types of polyps, neoplasm or non-neoplasm, to consider an optimal management strategy, i.e., removal or resection in endoscopy procedure or biopsy and operation. Figures 1 depicts the PSND problem as a semantic extension of the polyp segmentation problem.

In practice, an “undefined” class is labeled if there is not enough information from the endoscopic image to categorize the risk of neoplasm. This undefined subgroup is not a specific class we want to predict since such predictions would not bring any insight for the endoscopist. Therefore, the model only needs to learn to discriminate between neoplastic and non-neoplastic polyps. However, the undefined class still gives supplementary information about polyp regions that can be exploited to help the model gain more representation power in the training phase.

IV. PROPOSED METHOD

Figure 2 depicts three versions of the proposed BlazeNeo model. The models are developed based on HarDNet-MSEG [12], with several improvements tailored for the PSND problem. First, we use a simplified version of RFB [25] with smaller kernel sizes and apply different feature aggregation schemes. For the encoder layer, we keep the HarDNet-68 [4] backbone as in HarDNet-MSEG.

The three BlazeNeo variants differ in how outputs from the model are generated and processed. Inspired by NeoUNet [20], Single-headed Binary BlazeNeo (SB-BlazeNeo) solves two binary segmentation tasks corresponding to neoplastic and non-neoplastic classes. The second variant, Single-headed Trinary BlazeNeo (ST-BlazeNeo), predicts a trinary map for three classes in the neoplasm segmentation task. Finally, Multi-headed BlazeNeo (or BlazeNeo for short) uses two output branches. The main output branch is used for the neoplasm segmentation task, and the auxiliary branch is for the polyp segmentation task. The following subsections describe our design and motivations in detail.

A. LIGHTWEIGHT ENCODER: HARDNET

HarDNet (Harmonic Densely Connected Network) [4] is an improvement over DenseNet [13]. The primary goal in HarDNet’s design is to lower latency by reducing memory traffic. The authors argued that the connection pattern of Dense Blocks, in which each layer has skip connections toward every proceeding layer in the block, causes ineffective memory access during runtime that severely hinders performance. HarDNet reduces the number of skip connections to form a pattern similar to the harmonic wave function, as well as scaling channel width according to a layer’s influence level. We illustrate the difference between the two architectures in Figure 3.

Inside a HarDNet block, each layer is indexed from the input layer 0. A layer $l$ receives a skip connection from layer $l - 2^n$ if $2^n$ divides $l (n \geq 0, l - 2^n \geq 0)$. Given the initial growth rate $k$ and compression factor $m$, layer $l$’s channel width is equal to $k \times m^x$, where $x = \max\{\nu \mid l > 2^n\}$.

Chao et al. [4] further proposed HarDNet-68 for small-object detection problems. While most CNNs focus on stride-16 to enhance classification ability, HarDNet-68 distributes most of the layers on stride-8 to aid small-scale object detection, as shown in Figure 4. Experiments in [4] show that HarDNet-68 is not only 30% faster than ResNet-50 [11] but also more accurate than ResNet-101 [11] when used as backbone for SSD [26] in the object detection problem.

Our BlazeNeo also uses HarDNet-68 as the encoder backbone. For an input colonoscopy image $I$ with size $h \times w$, five levels of features $\{f_i, i = 1, 2, 3, 4, 5\}$ with resolution $[h/2^{i-1}, w/2^{i-1}]$ are produced from the encoder. Wu et al. [41] showed that low-level features (corresponding to $f_1$ and $f_2$) contribute less to performance while being computationally expensive due to their size. Therefore, our BlazeNeo discards $f_1$ and $f_2$, using only the final three feature maps for the decoder module to accelerate its inference speed.

B. PARALLEL PARTIAL DECODER

In all three variants of our BlazeNeo, the decoder module consists of a Receptive Field Block (RFB) series. Three last feature maps of the encoder are independently passed through the RFB blocks and then fused by the feature aggregation blocks.

1) Receptive Field Block

Polyps can appear in various scales on endoscopic images depending on their actual size, their distance to the colonoscopy camera, or the angle between them and the camera. This is a challenge for CNN architectures, in which the receptive field
FIGURE 1: PSND is an extension of polyp segmentation, which further discriminates whether a polyp is neoplastic or non-neoplastic. For a given input image shown on the top right corner, expected outputs for polyp segmentation and PSND are depicted on the middle and the bottom images on the right, respectively. The black color denotes background pixels, white color denotes polyp regions; green and red colors denote non-neoplastic and neoplastic polyps, respectively.

FIGURE 2: Proposed architectures of our BlazeNeo: (a) Single-headed Binary BlazeNeo (SB-BlazeNeo) has one output branch that produces two binary segmentation maps corresponding to neoplastic and non-neoplastic classes; (b) Single-headed Trinary BlazeNeo (ST-BlazeNeo) also has one output branch that directly predicts a trinary segmentation map; (c) Multi-headed BlazeNeo (or BlazeNeo for short) contains two output branches that are responsible for the two tasks: neoplasm segmentation treated as the main task, and polyp segmentation treated as the auxiliary task. Both branches share the same architecture of the feature aggregation module, but they are trained separately without sharing their parameters.

size is often fixed. Several studies have suggested different mechanisms to create more robust receptive fields, including the Inception block [37], ASPP block [5], and Deformable Convolution block [8]. Conceptually, these proposals are
FIGURE 3: Illustrations for DenseNet block and Harmonic DenseNet (HarDNet) block. Each of the layers is a $3 \times 3$ convolution. The value on each layer denotes the number of output channels.

FIGURE 4: An overview of HarDNet-68 architecture. Following each HarDNet block is a transitional Conv 1x1 layer. similar in that they all use multiple convolutional branches with different kernel sizes, merging the outputs to form adaptive receptive fields. However, they also have their own limitations. The Inception block samples all the kernels of each branch at their center, ignoring crucial edge details due to small sampling coverage. Meanwhile, the ASPP and Deformable Convolution blocks do not differentiate between different pixel positions, making it difficult for the model to focus on segmentation targets.

The Receptive Field Block (RFB) [25] has been proposed to address these limitations. RFB also uses the multi-branch convolution approach, with improvements inspired by the human visual cortex. In addition, it highlights the relationship between receptive field size and eccentricity, where the distance to the center is proportional to the weight specified or the importance level.

The RFB module used in PraNet [9] and HarDNet-MSEG [12] is modified with a larger kernel size and larger dilation rate. As this version of RFB is more computationally expensive, our BlazeNeo instead uses a simplified version of RFB (see Figure 5) as proposed in [25] for faster inference.

FIGURE 5: Structure of the Receptive Field Block (RFB).

2) Feature Aggregation

A high polyp miss rate is often associated with small and flat polyps (whose perimeters are below $10\text{mm}$) [18]. In order to detect these polyps, it is important to obtain high-resolution features from multiple image scales. Feature fusion (or aggregation) is a well-studied technique to achieve this for CNNs, in which feature maps from different scales are fused to form a multi-scale feature map. Figure 6 demonstrates four feature aggregation techniques, in order of increasing complexity [45].

Long Skip Connection (LSC) illustrated in Figure 6a is an early aggregation scheme used by segmentation networks such as UNet [32], UNet++ [47], and Attention UNet [29]. Given feature maps $X_1, X_2, X_3$, higher-level feature maps are upsampled and fused with their adjacent low-level features by a long skip connection, gradually restoring the spatial information. Each fusion module includes a concatenation layer and a convolutional layer with kernel size $3 \times 3$.

LSC is a well-tested and straightforward technique, but it is not without limitations. Zhang et al. [45] proposed three alterations to produce higher-quality features, as described below.

Iterative Deep Aggregation (IDA) depicted in Figure 6b produces finer feature maps by using multiple iterative convolutions for a single scale.
defined labels are excluded when calculating \( L \) for deciding on neoplasm class, they still can provide some information from data for the segmentation. We aim to exploit the information from data with the un-semantic meaning by re-combining the output with high-information flow and reduces overfitting.

From these observations, in our BlazeNeo, we propose to apply feature aggregation to the outputs of RFB modules at different scales. We examine variants with each of the aforementioned aggregation schemes, namely BlazeNeo-LSC, BlazeNeo-IDA, BlazeNeo-DIA, and BlazeNeo-DHA, in section \( V \).

### C. LOSS FUNCTION AND AUXILIARY TRAINING

We aim to exploit the information from data with the undefined labels for training in a way similar to [20]. The intuition is that while these data do not provide information for deciding on neoplasm class, they still can provide some semantic meaning from the data for the segmentation.

To training BlazeNeo, we propose the loss function \( L_{total} \) consisting of two components: a main loss \( L_{main} \) associated with the main task of neoplasm segmentation, and an auxiliary loss \( L_{aux} \) associated with the auxiliary task of polyp segmentation. The total loss can be expressed as follows:

\[
L_{total} = L_{main} + L_{aux}
\]

The main loss \( L_{main} \) drives the model toward making accurate class-specific segmentation. The pixels with undefined labels are excluded when calculating \( L_{main} \). The auxiliary loss \( L_{aux} \) drives the model toward making accurate foreground-background segmentation, in which all pixels are used for training.

To investigate this training strategy, we iterate through three different ways to incorporate it into BlazeNeo, which creates three different variants: Single-headed Binary BlazeNeo (SB-BlazeNeo), Single-headed Trinary BlazeNeo (ST-BlazeNeo), and Multi-headed BlazeNeo (the final version of BlazeNeo).

1) Single-headed Binary BlazeNeo

Our first variant, SB-BlazeNeo (Figure 2a), uses the same loss formulation as the NeoUNet model proposed in [20]. The final output layer produces two binary segmentation maps, one for the neoplastic class and another for the non-neoplastic class. Losses are calculated separately for each map and then averaged. The main loss is a combination of Binary Cross Entropy and Focal Tversky loss [1] as follows:

\[
L_{main} = L_{main}^\text{neo} + L_{main}^\text{non} = L_{BCE}(P_{main}^\text{neo}, G_{main}^\text{neo}) + L_{FT}(P_{main}^\text{neo}, G_{main}^\text{neo}) + L_{BCE}(P_{main}^\text{non}, G_{main}^\text{non}) + L_{FT}(P_{main}^\text{non}, G_{main}^\text{non}) \tag{2}
\]

where \( P_{main}^\text{neo} \) and \( P_{main}^\text{non} \) denote the prediction maps for the neoplastic and non-neoplastic classes, respectively; \( G_{main}^\text{neo} \) and \( G_{main}^\text{non} \) are ground truths. We choose the Focal Tversky loss for \( L_{main} \) to alleviate class imbalance due to small amount of non-neoplastic polyp pixels as shown later in Figure 8.

The auxiliary loss is a combination of Binary Cross Entropy and Tversky loss, which uses an auxiliary polyp segmentation map inferred from the two binary class-specific maps:

\[
L_{aux} = L_{BCE}(P_{aux}^\text{polyp}, G_{aux}^\text{polyp}) + L_{T}(P_{aux}^\text{polyp}, G_{aux}^\text{polyp}) \tag{3}
\]

where \( P_{aux}^\text{polyp} \) and \( G_{aux}^\text{polyp} \) denote the auxiliary polyp prediction map and the corresponding ground truth.

The auxiliary polyp prediction map \( P_{aux}^\text{polyp} \) is inferred using element-wise max:

\[
P_{aux}^\text{polyp} = \max(P_{main}^\text{neo}, P_{main}^\text{non}) \tag{4}
\]

2) Single-headed Trinary BlazeNeo

While the method using binary map [20] yielded promising classification results, we found that a lighter model can benefit from imposing an additional constraint on the outputs. Specifically, when the model outputs two class-specific maps for one image, it may make both maps have high prediction values for the same pixel. Therefore, a class constraint is needed to ensure that one class is chosen for each pixel. In our second variant, ST-BlazeNeo (Figure 2b), we use a 3-channel output map \( P_{trinary} \), denoting the probabilities for the neoplastic, non-neoplastic, and background class, respectively. A softmax activation is used on the channel dimension, meaning each pixel may only belong to one class.

The main loss is a combination of Categorical Cross Entropy and Focal Tversky loss as follows:
where $G_{\text{main}}$ is the trinary ground truth.

Similarly, the auxiliary loss is a combination of Categorical Cross Entropy and Tversky loss:

$$L_{\text{aux}} = L_{\text{CCE}}(P_{\text{aux}}^{\text{polyp}}, G_{\text{aux}}^{\text{polyp}}) + L_{\text{T}}(P_{\text{aux}}^{\text{polyp}}, G_{\text{aux}}^{\text{polyp}})$$

Here we apply element-wise max to the two channels of the map $P_{\text{main}}^{\text{trinary}}$, which correspond to the neoplastic and non-neoplastic classes, to produce the auxiliary polyp segmentation map $P_{\text{aux}}^{\text{polyp}}$.

3) Multi-headed BlazeNeo

For our final version of BlazeNeo, we further evolve the use of auxiliary loss by adding an auxiliary segmentation branch. Auxiliary training is the process of jointly learning a side or auxiliary task to enhance the main task’s performance [7], [44]. This idea is similar to multi-task learning, except the auxiliary branch does not activate in the inference phase.

The auxiliary branch uses an identical (with separate weights) feature aggregation module but outputs a binary segmentation map instead of a 3-channel multi-class map. The main loss and auxiliary loss are calculated exactly as in Eq. (5) and Eq. (6), respectively. However, there is no conversion between multi-class and polyp segmentation maps as in Eq. (4). Instead, the main loss is calculated with the 3-channel multi-class map, and the auxiliary loss is calculated with the output map from the auxiliary branch. Intuitively, we believe the model will benefit from adding an auxiliary network branch since it strengthens the supervised signal and better optimizes the training process.

Figure 2c describes how BlazeNeo incorporates the auxiliary branch for training in our BlazeNeo.

V. EXPERIMENTS

A. BENCHMARK DATASET

We use the NeoPolyp dataset as introduced in [20] to train and benchmark the proposed BlazeNeo. The dataset consists of 7,466 annotated endoscopic images captured directly during endoscopic recording and includes all four lighting modes: WLI (White Light Imaging), FICE (Flexible spectral Imaging Color Enhancement), BLI (Blue Light Imaging), and LCI (Linked Color Imaging). NeoPolyp is split into a training set of 5,966 images and a test set of 1,500 images. Some examples of the NeoPolyp dataset are shown in Figure 7. For comparison with baseline models, we also use the NeoPolyp-Clean dataset, which does not contain any polyps with undefined class labels. This dataset consists of 5,277 training images and 1,353 test images.

In practice, most non-neoplastic polyps are small, and the endoscopists can immediately remove them without the need to capture images or take a biopsy for lesions less than 5mm for post-checking. Due to that reason, neoplastic polyps take up a majority of the polyps present in NeoPolyp (see Figure 8). The number of neoplastic, non-neoplastic, and undefined polyps are 5113, 3185, and 1031, respectively. However, if we look at the pixel-wise level as shown in Figure 8b, we can observe a strong data imbalance between the three classes. The number of neoplastic polyp pixels takes up to 80% among all polyp pixels in the dataset. Meanwhile, these numbers for non-neoplastic and undefined classes are 13% and 7%, respectively. This data imbalance, combined with the inherent challenges of PSND, creates a difficult benchmark for models to overcome.

B. EXPERIMENT SETUP

Our experiments include several ablation studies to verify the effectiveness of each component in BlazeNeo, a comparison against several polyp segmentation methods, and benchmarks on the NVIDIA Jetson AGX Xavier developer kit 1, which closely resembles real deployments. The Jetson device is configured to run at MAXN power mode.

We oversample non-neoplastic polyps to account for class imbalance in the NeoPolyp dataset, as addressed by [20]. Images containing non-neoplastic polyps are duplicated such that $P_{\text{non}} \approx P_{\text{neo}}$, where $P_{\text{non}}$ and $P_{\text{neo}}$ are the number of pixels containing in non-neoplastic and neoplastic polyps, respectively.

The models are trained using Stochastic Gradient Descent (SGD) with Nesterov momentum and an initial learning rate of 0.001. The learning rate is adjusted according to a combination of linear warmup and a cosine annealing schedule.

Images used for training are at 3 different scales: $256 \times 256$, $352 \times 352$ and $512 \times 512$.

During training, augmentations including random scaling, rotation, horizontal/vertical flip, motion blur, and color jittering are added to improve generalization. These augmentations are performed on-the-fly with a probability of 0.5.

BlazeNeo and other baseline models are implemented in Python 3.7 using the PyTorch framework.

C. EVALUATION METRICS

Commonly used metrics Dice score and IoU score are employed to measure the model’s output quality. They are evaluated on three classes: neoplastic polyp, non-neoplastic polyp, and generic polyp (same as polyp segmentation). Dice and IoU are calculated pixel-wise on the entire test set (micro-averaged). Equations (7) and (8) describe how these metrics are calculated.

$$\text{Dice}_c = \frac{2 \times \sum_{i \in I} u_i^c v_i^c}{\sum_{i \in I} u_i^c + \sum_{i \in I} v_i^c}$$

$$\text{IoU}_c = \frac{\sum_{i \in I} u_i^c v_i^c}{\sum_{i \in I} u_i^c + \sum_{i \in I} v_i^c - \sum_{i \in I} u_i^c v_i^c}$$

1https://developer.nvidia.com/embedded/jetson-agx-xavier-developer-kit
FIGURE 7: Some examples from the NeoPolyp dataset. The first row displays original images from the dataset. The second row shows the ground truths for polyp segmentation. The last row shows the ground truths for neoplasm segmentation, where some polyps are undefined and marked by yellow color. From left to right, the color modes are WLI, BLI, LCI, FICE, and FICE, respectively.

FIGURE 8: Data distribution of polyp class labels in the NeoPolyp dataset. In the pixel-wise distribution on the right, percentages are calculated on polyp pixels only (not including background pixels.)

where \( i \in I \) denotes a prediction pixel within the entire test set. \( u^c_i = 1 \) if the model predicts pixel \( i \) to have class \( c \), and 0 otherwise. Similarly, \( v^c_i = 1 \) if the ground truth map states that pixel \( i \) has class \( c \), and 0 otherwise. For neoplastic and non-neoplastic class evaluation, \( I \) does not include undefined neoplasm pixels.

We also evaluate each model’s inference speed using the number of processed frames per second (FPS). This metric is measured by running each model with a batch size of 1 on 100 colonoscopy images. FPS is measured on a Google Colaboratory instance with an NVIDIA Tesla V100 GPU when not specified otherwise.

Finally, we log each model’s number of parameters and floating-point operations (measured in GFLOPs) to evaluate their size and complexity.

VI. RESULTS AND DISCUSSION
A. ABALATION STUDY
1) The effectiveness of different output architectures
Firstly, we compare our three BlazeNeo variants shown in Figure 2 to evaluate the effectiveness of different output architectures. Table 1 shows performance metrics for each variant on the NeoPolyp test set. Here we use the same DHA feature aggregation scheme for all three of BlazeNeo. The
final BlazeNeo model with multi heads achieves the best results on all metrics. Notably, this final variant outperforms the other two variants by over 6% in IoU score for the non-neoplastic class. This shows the effectiveness of the auxiliary branch, which helps anchor segmentation performance and makes use of undefined labels. We also see that ST-BlazeNeo outperforms SB-BlazeNeo, which justifies our use of trinary output in the final variant.

2) The effectiveness of different feature aggregation schemes

This experiment investigates the use of four different feature aggregation schemes in BlazeNeo: Long Skip Connection (LSC), Iterative Deep Aggregation (IDA), Dense Iterative Aggregation (DIA), and Dense Hierarchical Aggregation (DHA).

Table 2 shows performance metrics for each model variation on the NeoPolyp dataset. We can see that BlazeNeo-DHA produces the highest values of Dice and IoU on all classes. This is what we expected, as DHA is the most complex aggregation mechanism that preserves a lot of high-resolution features. However, this improvement comes at a cost as BlazeNeo-DHA is also the slowest variation at only 81.5 FPS, compared to the fastest BlazeNeo-LSC at 88.6 FPS. Interestingly, the nested IDA aggregation scheme performs worse than basic LSC in the segmentation task. This is alleviated in DIA and DHA with the use of skip connections.

3) The effectiveness of auxiliary training

This experiment looks into the effectiveness of enabling and disabling auxiliary training for each variation of BlazeNeo, namely BlazeNeo-LSC, BlazeNeo-IDA, BlazeNeo-DIA, and BlazeNeo-DHA.

Figure 9 shows that auxiliary training generally improves output quality. In fact, without auxiliary segmentation learning, BlazeNeo-IDA and BlazeNeo-DHA achieve even lower accuracy than BlazeNeo-IDA. The non-neoplastic class benefits the most from auxiliary training, improving BlazeNeo-LSC, BlazeNeo-IDA, BlazeNeo-DIA, and BlazeNeo-DHA by 3%, 1.9%, 4%, and 4.9%, respectively.
TABLE 2: Performance metrics on the NeoPolyp test set for BlazeNeo with different feature aggregation schemes

| Method     | Dice_{seg} | IoU_{seg} | Dice_{non} | IoU_{non} | Dice_{neo} | IoU_{neo} | FPS   |
|------------|------------|-----------|------------|-----------|------------|-----------|-------|
| BlazeNeo-LSC | 0.897      | 0.814     | 0.709      | 0.550     | 0.884      | 0.792     | **88.6** |
| BlazeNeo-IDA | 0.890      | 0.803     | 0.715      | 0.557     | 0.887      | 0.798     | 84.6   |
| BlazeNeo-DHA | 0.897      | 0.814     | 0.719      | 0.562     | **0.888**  | **0.800** | 84.0   |
| BlazeNeo-DHA | 0.901      | 0.820     | 0.728      | 0.572     | **0.888**  | **0.800** | 81.5   |

TABLE 3: Performance metrics for BlazeNeo-DHA when training on NeoPolyp and NeoPolyp-Clean, measured on the NeoPolyp test set

| Training dataset   | Dice_{seg} | IoU_{seg} | Dice_{non} | IoU_{non} | Dice_{neo} | IoU_{neo} | FPS   |
|---------------------|------------|-----------|------------|-----------|------------|-----------|-------|
| NeoPolyp-Clean      | 0.900      | 0.818     | 0.714      | 0.555     | 0.884      | 0.792     |       |
| NeoPolyp            | **0.901**  | **0.820** | **0.728**  | **0.572** | **0.888**  | **0.799** |       |

4) The effectiveness of including undefined polyps
This experiment examines the effectiveness of using undefined neoplasm pixels via the auxiliary module. Table 3 shows performance metrics for BlazeNeo-DHA, the best-performing BlazeNeo model, when trained on the NeoPolyp dataset (which contains undefined polyps) and the NeoPolyp-Clean dataset (which does not contain undefined polyps). Results show that the addition of these undefined pixels leads to improvements across the board, especially for the non-neoplastic class.

**B. COMPARISON WITH STATE-OF-THE-ART MODELS**

1) Quantitative comparison
We compare the performance of BlazeNeo-DHA, the best-performing BlazeNeo model, with seven state-of-the-art models for the polyp segmentation and PSND problem: U-Net [32], ColonSegNet [16], DDANet [40], DoubleU-Net [17], HarDNet-MSEG [12], PraNet [9], and NeoUNet [20]. Except for NeoUNet, the models mentioned above do not handle undefined neoplasm pixels during training. Thus, in the interest of a fair comparison, we use the NeoPolyp-Clean dataset for this experiment, which does not contain undefined polyps. Results are shown in Table 4.

We can see that while NeoUNet remains the most accurate model, BlazeNeo is a close second, with a difference of less than 1% on most accuracy metrics. At the same time, BlazeNeo is a much more lightweight and faster model. Compared to NeoUNet, BlazeNeo achieves higher FPS (81.5 versus 68.3), has half as many parameters (17, 143, 324 versus 38, 288, 397), and lower GFLOPs (11.06 versus 39.88). Notably, BlazeNeo-DHA is faster and more accurate than HarDNet-MSEG, while NeoUNet is slower than HarDNet-MSEG and U-Net. We attribute the speed improvement of BlazeNeo over HarDNet-MSEG to the different decoder designs, especially the use of the small RFB module.

Although achieving a high overall dice score, our BlazeNeo is not without limitations. The dice and IoU scores of BlazeNeo are still low for non-neoplastic polyps, and both of them are significantly reduced when the model is converted into the INT8 precision. The reason may be due to the small size of non-neoplastic polyps. When the weights are converted into integers ranging from -128 to 127 in the INT8 precision, the model seems to lose the capacity of representing detailed information and, therefore, is easier to miss small objects in the input images.

2) Qualitative comparison
Figure 10 shows examples outputs of BlazeNeo-DHA and other baseline models. Overall, BlazeNeo-DHA produces the most accurate segmentation and classification results for different types of polyps.

The first five rows of Figure 10 contain “easier” polyp examples. BlazeNeo-DHA and NeoUNet perform quite well in these examples, with similarly high accuracy. Meanwhile, PraNet, HarDNet-MSEG, DoubleU-Net, DDANet, U-Net and ColonSegNet produce predictions with less uniformity, with some polyps containing both neoplastic and non-neoplastic regions. For larger polyps such as the 5th row, PraNet is unable to fully segment the area.

The final five rows in Figure 10 represent more challenging examples, in which all models struggle to provide accurate segmentation masks. This is because non-neoplastic polyps are usually small in size and easier to be miss detected. BlazeNeo-DHA and NeoUNet produce fewer false positives in these situations, while U-Net and ColonSegNet create the most inaccurate masks.

The last two rows show two non-neoplastic polyps in BLI and FICE modes. Contributing factors for these struggles in enhanced color modes include their smaller proportions in the training dataset. Furthermore, the endoscopist put the camera scope close to the mucosa in these cases, making the polyps’ surface look very clear and sharp such that one can even observe small dots that are glandular holes on the surface. Therefore, these polyps are easily confused with angiogenesis in neoplastic lesions, which is why all models failed in classifying them.

**C. BENCHMARK FOR EMBEDDED DEVICE**
In this experiment, we apply model compression techniques via the NVIDIA TensorRT 7.1 toolkit [28] to BlazeNeo and the baseline models. The compressed models are then
TABLE 4: Performance metrics of different models on the NeoPolyp-Clean test set

| Method                | Diceseg | IoUseg | Dice non | IoU non | Dice neo | IoU neo | FPS   | Parameters | GFLOPs |
|-----------------------|---------|--------|----------|---------|----------|---------|-------|------------|--------|
| ColonSegNet [16]      | 0.738   | 0.585  | 0.505    | 0.338   | 0.732    | 0.577   | 44.9  | 5,010,000  | 64.84  |
| U-Net [32]            | 0.785   | 0.646  | 0.525    | 0.386   | 0.773    | 0.631   | 69.6  | 31,043,651 | 103.59 |
| DDANet [40]           | 0.813   | 0.684  | 0.578    | 0.406   | 0.802    | 0.670   | 46.2  | 6,840,000  | 31.45  |
| DoubleU-Net [17]      | 0.837   | 0.720  | 0.621    | 0.450   | 0.832    | 0.712   | 43.2  | 18,836,804 | 83.62  |
| HarDNet-MSEG [12]     | 0.883   | 0.791  | 0.659    | 0.492   | 0.869    | 0.769   | 77.1  | 17,424,031 | 13.11  |
| PraNet [9]            | 0.895   | 0.811  | 0.705    | 0.544   | 0.873    | 0.775   | 55.6  | 30,501,341 | 11.38  |
| NeoUNet [20]          | 0.911   | 0.837  | 0.720    | 0.563   | 0.889    | 0.800   | 68.3  | 38,288,397 | 39.88  |
| BlazeNeo-DHA (Ours)   | 0.904   | 0.825  | 0.717    | 0.559   | 0.885    | 0.792   | 81.5  | 17,143,324 | 11.06  |

FIGURE 10: Qualitative comparison of the proposed method with other baseline methods: (a) image, (b) ground truth, (c) BlazeNeo (Ours), (d) NeoUNet, (e) PraNet, (f) HarDNet-MSEG, (g) UNet, (h) DoubleU-Net, (i) DDANet, and (j) ColonSegNet.

benchmarked on the NVIDIA Jetson AGX Xavier developer kit, an embedded computation unit with an NVIDIA GPU specialized for edge AI deployments. This setup is more in-line with deployment scenarios for polyp segmentation and PSND models, i.e., embedded on-site into colonoscopy devices.

Three available precision modes are tested for compressing each model: FP32, FP16, and INT8. Each mode can be seen as a different trade-off level between accuracy and speed. FP32 precision applies techniques such as layer/tensor fusion while keeping parameters as 32-bit floating-point numbers. Hence, this mode provides some speed-up while minimizing accuracy degradation. FP16 precision converts suitable parameters to 16-bit floating-point numbers, greatly
reducing model size and latency but is subject to more degradation. Finally, INT8 precision mode quantizes model parameters to 8-bit integers. This precision mode requires an additional calibration procedure to maintain model integrity, which attempts to replicate the original model’s output on a small calibration dataset. Despite calibration, INT8 precision is susceptible to a lot more degradation. For this experiment, INT8 calibration is done on a randomized set of images.

Table 5 shows performance metrics in different precisions for U-Net, PraNet, HarDNet-MSEG, NeoUNet, and BlazeNeo-DHA. We can see a stark difference in FPS when running models on the Jetson AGX Xavier compared to the Google Colab environment. At FP32 precision, the fastest model (BlazeNeo) achieves only 53.3 FPS on the device, while the slowest model in the Colab environment (PraNet) without any compression still achieves 55.6 FPS. On the other hand, Dice and IoU measures are hardly affected at this precision level. In fact, U-Net and HarDNet-MSEG see improvements up to 1.5% across all metrics after compression. DoubleUNet and ColonSegNet achieve a slight improvement of about 0.5 − 1% after compression. DDANet suffers a little from compression, dropping by about 1.5% in segmentation metrics. Finally, PraNet is most affected after compression, dropping by 4.6% in segmentation metrics.

At FP16 precision, latency for all models are vastly improved, the fastest being BlazeNeo (121.9 FPS) and HarDNet-MSEG (118.7 FPS). In addition, accuracy metrics for all models are within 0.01% of their FP32 counterparts. This further shows that large neural networks do not require high float precision to remain effective.

INT8 precision gives the most speed gain out of the three modes, but at great expense in terms of accuracy. BlazeNeo runs at 155.6 FPS in this mode, whereas HarDNet-MSEG is the second fastest model at 143.7 FPS. However, HarDNet-MSEG also suffers the largest drop in accuracy at about 8.1% on all metrics. This drop is a bit lower for PraNet (≈ 3.3%), NeoUNet (≈ 6%) and BlazeNeo (≈ 3.6%).

In every precision mode, BlazeNeo is consistently the fastest model while being a close second in terms of accuracy behind NeoUNet. BlazeNeo also displays its robustness to compression techniques, incurring significantly less degradation compared to models such as PraNet. Its small size also gives the proposed model advantage in long-term deployment, as energy usage and equipment wear become factors. In Figure 11, we visualize the performance of BlazeNeo in terms of speed (FPS) and accuracy (dice score on polyp segmentation task) compared to other existing methods.

It should be emphasized that high FPS is essential in real scenarios because it helps endoscopists operate smoother and easier to monitor and detect lesions. According to endoscopists’ experience, the idea FPS for colonoscopy should be at least 60. In addition, the fast inference speed gives us the potential to deploy the model on even more low-cost devices with less computational power, such as NVIDIA Jetson TX1/TX2, while still satisfying the minimal required FPS. This is important because it allows us to deploy the application on a large scale to many medical facilities in remote areas where the economic conditions are difficult.

For further discussion, we compare the performance of the models quantitatively and qualitatively in different precisions.

Table 6 shows the accuracy of our BlazeNeo-DHA models in different precisions. One can observe that the models with FP32 and FP16 precisions give the same result, which is lower than the original model by a mean margin of 2.32%. The TensorRT INT8 model yields the worst accuracy, which is lower than the original model by a mean margin of 5.75%.

With lower precision, a model can reduce latency, throughput, and increase power efficiency. To compare the speed performance of the models in different precisions, we present detailed benchmarking results of them for 100 iterations on the Jetson AGX Xavier with two metrics: host latency and GPU compute time. Host latency is measured as the end-to-end execution time from the CPU point of view, while GPU computing time is the actual working time for GPU calculation.

As shown in Table 7, the model in INT8 precision has the shortest latency compared to all other models, less than one-third of the model in FP32 precision. However, for deep learning inference, we must consider the trade-off between accuracy and speed. Therefore, the model in FP16 precision is the best choice, which gives the best result in all precisions and has a median latency.

For a more intuitive understanding of the loss in accuracy of each compressed model, Figure 12 illustrates the sample results of BlazeNeo-DHA models in different precisions. As we can observe, the prediction result of models in FP32 and FP16 precisions are almost the same in every example. In general, the INT8 compressed model loses the ability to segment smaller polyps compared to other modes. For segmented polyps, the neoplasm prediction remains constant for every compression mode in all examples. This demonstrates that BlazeNeo can be quite robust to model compression and can be deployed in high compression modes such as FP16 with confidence.

VII. CONCLUSION

This paper has proposed BlazeNeo, a novel neural network architecture for the polyp segmentation and neoplasm detection problem, with an emphasis on speed and deployability. BlazeNeo is an extremely lightweight and fast neural network, thanks to the use of an efficient HarDNet backbone, a multi-level feature aggregation structure, and an auxiliary training module to take advantage of undefined labels. Our experiments show that BlazeNeo outperforms all other state-of-the-art models in terms of inference latency while providing competitive accuracy. We also show that BlazeNeo can be very robust against degradation caused by compression techniques. In general, the proposed model is highly suitable for lightweight deployments with real-time requirements. Our source code is available at https://github.com/tofuai/neoplasm-segmentation.
TABLE 5: Performance metrics of different models with FP16, FP32 and INT8 precision levels on NVIDIA Jetson AGX Xavier

| Model                  | Precision | Dice  | IoU  | Dice  | IoU  | Dice  | IoU  | Dice  | IoU  | FPS |
|------------------------|-----------|-------|------|-------|------|-------|------|-------|------|-----|
| ColonSegNet@FP32       | FP32      | 0.745 | 0.594| 0.528 | 0.359| 0.728 | 0.572|       |      | 9.4 |
| UNet@FP32              | FP32      | 0.800 | 0.667| 0.537 | 0.367| 0.781 | 0.641|       |      | 10.7|
| DDANet@FP32            | FP32      | 0.799 | 0.665| 0.557 | 0.386| 0.776 | 0.635|       |      | 16.6|
| DoubleU-Net@FP32       | FP32      | 0.840 | 0.725| 0.627 | 0.456| 0.835 | 0.717|       |      | 10.6|
| HarDNet-MSEG@FP32      | FP32      | 0.891 | 0.804| 0.685 | 0.521| 0.871 | 0.771|       |      | 52.2|
| PraNet@FP32            | FP32      | 0.849 | 0.738| 0.571 | 0.400| 0.844 | 0.730|       |      | 37.0|
| NeoUNet@FP32           | FP32      | 0.909 | 0.832| 0.725 | 0.568| 0.893 | 0.806|       |      | 25.4|
| BlazeNeo@FP32 (Ours)   | FP32      | 0.906 | 0.828| 0.721 | 0.563| 0.887 | 0.796|       |      | 53.3|

| Model                  | Precision | Dice  | IoU  | Dice  | IoU  | Dice  | IoU  | Dice  | IoU  | FPS |
|------------------------|-----------|-------|------|-------|------|-------|------|-------|------|-----|
| ColonSegNet@FP16       | FP16      | 0.746 | 0.594| 0.528 | 0.359| 0.728 | 0.572|       |      | 26.3|
| UNet@FP16              | FP16      | 0.800 | 0.666| 0.537 | 0.367| 0.781 | 0.641|       |      | 35.5|
| DDANet@FP16            | FP16      | 0.799 | 0.665| 0.557 | 0.386| 0.776 | 0.635|       |      | 31.8|
| DoubleU-Net@FP16       | FP16      | 0.840 | 0.725| 0.627 | 0.456| 0.835 | 0.717|       |      | 22.9|
| HarDNet-MSEG@FP16      | FP16      | 0.891 | 0.804| 0.685 | 0.521| 0.871 | 0.771|       |      | 118.7|
| PraNet@FP16            | FP16      | 0.850 | 0.740| 0.572 | 0.401| 0.845 | 0.731|       |      | 95.1 |
| NeoUNet@FP16           | FP16      | 0.908 | 0.832| 0.724 | 0.568| 0.893 | 0.806|       |      | 73.4 |
| BlazeNeo@FP16 (Ours)   | FP16      | 0.906 | 0.828| 0.721 | 0.563| 0.887 | 0.796|       |      | 121.9|

| Model                  | Precision | Dice  | IoU  | Dice  | IoU  | Dice  | IoU  | Dice  | IoU  | FPS |
|------------------------|-----------|-------|------|-------|------|-------|------|-------|------|-----|
| ColonSegNet@INT8       | INT8      | 0.672 | 0.507| 0.456 | 0.295| 0.633 | 0.463|       |      | 41.6|
| UNet@INT8              | INT8      | 0.764 | 0.618| 0.501 | 0.334| 0.753 | 0.604|       |      | 44.8|
| DDANet@INT8            | INT8      | 0.770 | 0.626| 0.492 | 0.326| 0.748 | 0.598|       |      | 46.4|
| DoubleU-Net@INT8       | INT8      | 0.835 | 0.717| 0.562 | 0.391| 0.830 | 0.709|       |      | 46.7|
| HarDNet-MSEG@INT8      | INT8      | 0.810 | 0.680| 0.594 | 0.422| 0.799 | 0.665|       |      | 143.7|
| PraNet@INT8            | INT8      | 0.817 | 0.691| 0.575 | 0.404| 0.815 | 0.688|       |      | 116.7|
| NeoUNet@INT8           | INT8      | 0.848 | 0.736| 0.638 | 0.468| 0.848 | 0.727|       |      | 100.3|
| BlazeNeo@INT8 (Ours)   | INT8      | 0.870 | 0.770| 0.678 | 0.513| 0.857 | 0.750|       |      | 155.6|

FIGURE 11: Comparison between different models in different precisions. Red, green and blue markers denote INT8, FP16 and FP32 precisions, respectively.

TABLE 6: Accuracy metrics on the NeoPolyp-Clean test set for BlazeNeo-DHA models in different precisions

| Model                  | Dice  | IoU  | Dice  | IoU  | Dice  | IoU  | Dice  | IoU  | Dice  | IoU  |
|------------------------|-------|------|-------|------|-------|------|-------|------|-------|------|
| PyTorch (w/o compression) | 0.904 | 0.825| 0.717 | 0.559| 0.885 | 0.792|       |      |       |      |
| TensorRT FP32          | 0.906 | 0.828| 0.721 | 0.563| 0.887 | 0.796|       |      |       |      |
| TensorRT FP16          | 0.906 | 0.828| 0.721 | 0.563| 0.887 | 0.796|       |      |       |      |
| TensorRT INT8          | 0.870 | 0.770| 0.678 | 0.513| 0.857 | 0.750|       |      |       |      |

In future works, we would like to exploit recent advancements in Transformer-based architectures to improve the
FIGURE 12: Qualitative comparison of BlazeNeo-DHA models in different precisions: (a) image, (b) ground truth, (c) Pytorch, (d) TensorRT FP32, (e) TensorRT FP16, (f) TensorRT INT8.
TABLE 7: Latency metrics for BlazeNeo-DHA models in different precisions. The latency is measured on Jetson Xavier AGX with power mode MAXN

| Precision    | Host Latency (ms) | GPU Compute (ms) |
|--------------|-------------------|------------------|
|              | min   | max   | mean  | median | min   | max   | mean  | median |
| TensorRT FP32| 18.50 | 22.04 | 18.67 | 18.55  | 18.40 | 21.94 | 18.57 | 18.45  |
| TensorRT FP16| 8.10  | 10.24 | 8.20  | 8.15   | 7.99  | 10.13 | 8.09  | 8.04   |
| TensorRT INT8 | 6.35  | 6.51  | 6.42  | 6.42   | 6.25  | 6.42  | 6.32  | 6.32   |

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