

SELF-REFINED ATTENTION-BASED LIGHTWEIGHT DEEP LEARNING MODELS FOR PRECISE CANCER LOCALIZATION: OVERCOMING SPATIAL COARSENESS IN EDGE-HEALTHCARE

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ABSTRACT

Medical imaging-based localization of malignant lesions is currently a challenging problem, in part because of the spatial coarseness of imaging systems and the sizeable computational cost of modern deep-learning systems, especially in resource-constrained edge-healthcare systems. Though the current developments in deep-learning have increased the accuracy of the diagnostics, the current state-of-the-art architecture is unable to maintain the fine-grained, high-resolution spatial detail and at the same time meet the real-time processing demands and low-power specifications posed by clinical practitioners. The current paper presents an overall overview of self-refined, attention-based lightweight deep-learning frameworks that were developed to overcome these shortcomings. We thoroughly study

spatial (3D), channel, and hybrid attention mechanisms that are incorporated into highly efficient architectures, explaining their contribution to the enhancement of localization accuracy with a minimal computational cost. More importantly, the discourse involves a collection of methodological approaches, such as multi-scale feature learning, iterative attention refinement, and edge-based model optimization methods, such as pruning and quantization. Besides, the review also explores how different imaging modalities (including

MRI, CT, histopathology, and thermal imaging) affect the effectiveness of attention-based lightweight models with a specific focus on their ability to reduce spatial coarseness in cancer localization in addition to their ability to detect tumors in real-time as part of next-generation edge-healthcare. Lastly, the paper discusses the existing challenges, which are scarce data, high annotation expenses, poor interpretability, and lack of clinical validation of the available datasets, hence the need to advance future studies to create strong, efficient, and clinically implementable cancer localization systems and to describe future research directions in this area.

KEYWORDS: Cancer Localization; Deep Learning; Self-Refined Attention; Lightweight Neural Networks; Edge Healthcare; Medical Image Analysis; Spatial Coarseness; Computer-Aided Diagnosis

1. INTRODUCTION

Proper localisation of the malignant tissue is one of the pillars in the oncological assessment at all stages of the disease, thus, playing a central role in early diagnosis, therapeutic planning, and prognostication. With the introduction of new medical imaging technologies, the description of anatomical and functional tissue properties has become highly detailed, but, at the same time, the amount and volume of data requiring subject to accurate, highly automated and reliable analytical processes have also increased.^[1] Deep learning has become a highly promising framework whereby the automatic localisation of cancerous lesions is achieved by the hierarchical extraction of discriminative features in a variety of different imaging modalities. However, the basic problems of producing correct localisations at the same fine spatial resolution remain. Traditional deep learning designs that have large convolutional layers separated by a series of pooling and down-sampling steps to reduce computational costs invariably impair boundary faithfulness and, by extension, produce less accurate boundary delineation of small scale or early-stage tumours. Transformer-based and hybrid models have significantly enhanced the ability of the deep learning systems to encode global contextual information.^[2] Nevertheless, these architectures require large computational and memory resources to obtain the best performance. With the ongoing increase in the deployment of edge-healthcare systems, the need to have efficient and lightweight deep-learning solutions will only increase, especially with respect to portable diagnostic devices and point-of-care screening platforms, due to the strict constraints that are set by latency, power consumption, and the inaccessibility of specialised computing hardware. Because of

the inherent limitations of modern high-capacity architectures, there is still a need to explore models that provide high localisation accuracy and have a low computational cost.^[3] The requirement to achieve fine-grained spatial resolution and at the same time to be compatible with edge-deployment situations is a promising solution to the two requirements of attention-based models that can dynamically focus on relevant clinical entities and successively refine the salient feature representations. This review entails a methodic review of the existing self-refining attention-based lightweight deep-learning frameworks, along with an elucidation of existing attention processes, lightweight architectural frameworks, assessment strategies, and practical issues involved in implementation. The discussion concludes with the suggestion of the future research directions that should lead to the achievement of the exact, scalable localisation of tumours in edge-based healthcare systems.^[4]

1.1 Research Gap and Motivation

Although the current literature has made considerable advances in deep learning based cancer localisation algorithms in recent years, there are still a number of limitations to be overcome. Most of the best models are optimised to perform well in localisation, but require a large amount of computation, which limits their use in real time environments with limited hardware capabilities.^[5] Lightweight architectures whose focus is on computational efficiency, in turn, tend to make access to high-quality spatial resolution, which is needed in lesion localisation to detect small tumours or lesions in their early stages, and the boundary delineation process more difficult. Also, there has been no systematic integration of attention mechanisms in any of the compressed or edge-optimised deep-learning architectures, despite their use to improve feature representation. The inter-modal validation and the application of real-life clinical data are not well represented in the literature to date. There is, therefore, an immediate necessity to invent self-refining, attention-constrained, lightweight deep-learning models to support next-generation edge-healthcare systems, which can simultaneously provide the feasibility of computation as well as the spatial resolution.^[6]

2. Cancer Localization in Medical Imaging

CAD systems make use of medical imaging to localise neoplasms by allowing clinicians to define the area of concern using the analysis of images, define the boundaries of the tumour, and minimise inter-observer differences when interpreting medical images. In the past, CAD used only computer-generated rules to process imaging data in localising tumours.^[7] Alternatively, especially in modern practice, as medical imaging data has become highly

multifaceted, CAD systems have shifted away from the rule-based frameworks into the fully automated data-driven deep learning models that learn to detect the malignant patterns by reacting to the raw images. With the further development of CAD technologies, the accuracy of these technologies in enabling clinicians to (1) detect cancer earlier; (2) develop treatment plans based on the accurate location and size of the tumour; and (3) track the progress of the disease over time, becomes substantially higher.^[8] Medical imaging modalities can be utilised to localise cancer using a variety of modalities; the modalities provide different information. Magnetic resonance imaging (MRI) is one of the most popular modalities used to perform soft-tissue imaging and has been demonstrated to be better than most other imaging modalities in providing high-resolution and high-contrast images of the brain, breast, and prostate. Computed tomography (CT) images of lungs, liver dysfunctions, and abdominal areas are usually performed due to the possibility of providing significantly detailed cross-sectional tissue images; however, the lack of uniformity within the contrast of tissues tends to make it difficult to clearly define a tumour by colour. Positron emission tomography (PET) imaging also provides functional information, a measurement of metabolic activity, and hence makes it possible to identify malignancies that would otherwise be missed in anatomical images. Histopathological analysis at the microscopic level gives detailed and continuous information on tumour grading and sub-typing, and precise localisation of cellular abnormalities is often vital. During the last two years, non-invasive inexpensive modalities like thermal imaging and ultrasound have received interest as potential future lines of early screening or hidden physiological mass-market monitoring. These modalities create large amounts of data, which require effective and automated localisation measures. The wide range of imaging methods used to assess the condition of cancer underlines the necessity to create powerful and flexible deep-learning architectures that can help locate the tumour with high accuracy when using a wide range of medical images with significant differences in their characteristics.^[9]

3. Deep Learning Models for Cancer Localization

The use of deep learning as the methodology of choice in tumour localisation in medical imaging has become possible due to the ability to autonomously learn highly complex and hierarchical representations using large volumes of data which can be further used to develop evidence-based decisions. The most commonly applied deep-learning paradigm in extracting both spatial and textual features of medical images is the convolutional neural networks (CNNs). Empirical data has shown that CNN based models are very accurate at detecting the

existence or absence of tumours, where convolutional filters are used to extract local information or edges, shapes and intensity gradients of the image. However, even with this improved performance in classification, the standard CNNs have a significant disadvantage the pooling and striding operation result in a loss of spatial detail, lost border demarcations and loss of island fine localisation, especially in smaller or non-uniform lesions.^[10] In order to overcome these drawbacks, encoder-decoder designs have been suggested to carry out pixel-wise localisation of tumours. Other architectures (including U-Net and its variants) use the topos of which is a symmetric encoder-decoder, used where the encoder takes context information and the input signal and down-samples it in a systematic manner, and the decoder reincorporates that systematically to recover the original spatial information. By introducing skip connections across the matching encoder and decoder layers, the fine-grained spatial information is maintained and, therefore, the models can outline tumour boundaries in a meticulously precise manner. Encoder- decoder Architectures have seen impressive performance, however, these structures present significant computational and memory requirements that can be a barrier to implementation in resource constrained edge-healthcare environment. Recent developments of transformer-based and hybrid deep-learning models have been used to gain more and more popularity in cancer localisation tasks. They are successful because of the self-attention mechanisms that transformers have and help them to model global contexts and obtain long-range dependencies over the entire image. As an example, most tumours are subtle or diffuse; using a global perspective can be more accurate in detection than local techniques. Similarly, it is possible to consider hybrid structures, which combine convolutional neural networks (CNNs) with transformers so that the most suitable strategies could be reunited with the powerful feature numbers found in global contextual thinking. Although the use of these methods has been shown to provide significant performance improvements, the high computational cost of such methods highlights the importance of lightweight designs and focused attention mechanisms that can effectively and reliably offer real-time operation in an edge-based healthcare setting.^[11]

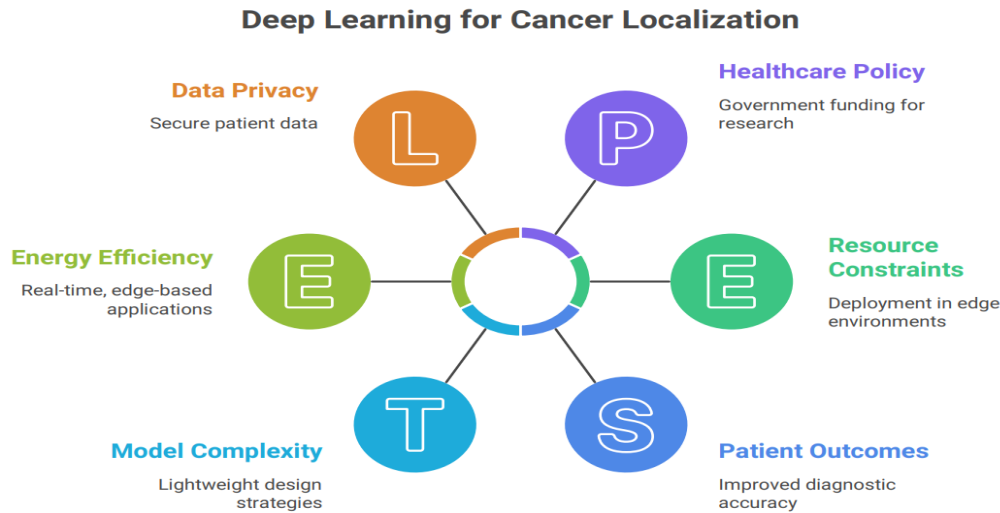


Figure 1: The illustration shows how convolutional neural network (CNN) architectures have evolved since the classical approaches up to encoder-decoder networks to modern hybrid CNN-Transformer networks, all of which are used to identify the type of tumor accurately.

Besides that, the figure reports the numerous issues surrounding the deployment of deep learning to localize tumors, such as model complexity, which is evidenced by high computational and memory demand, energy consumption, which is required to execute the computations in the edge of healthcare systems (e.g., real-time access), data privacy, including protection of patient information in HIPAA compliance, and a myriad of new solutions and methods that enable lightweight design, and consequently improved patient accuracy and outcomes.^[12]

4. Spatial Coarseness in Deep Learning

Spatial coarseness is an enormous hindrance to the precise localisation of tumours in deep learning approaches, which is due to the fact that fine-grained spatial data is lost in the feature extraction steps of the network. The standard convolutional neural network architectures usually include several pooling or down-sampling processes to lower the computational expenses, in order to increase the receptive fields, and thus, capture more abstract and global representations. However, the cumulative use of the pooling and down-sampling layers produce feature maps of reduced resolution thus undermining fidelity of results when defining tumour boundaries. This is especially true of small or early lesions which tend to have subtle textual patterns and highly detailed edges which when poorly maintained can result in false identification.^[13] The effect of the spatial coarsening on the

definition of the tumorous delimiting is of the utmost significance since even slight errors can change the diagnosis, treatment plan, or the prognosis based on a specific case. Moreover, when spatial fidelity is reduced in a neural network, it may cause a decrease or an increase in the tumor size, the wrong identification of nearby tissue, and poor performance of the segmentation models. This therefore means that the failure of the traditional models to precisely describe the heterogeneous morphologies of tumours impairs their ability to localize the entire tumorous tissue. To resolve spatial coarsening, it is consequently necessary to enhance the clinical reliability and accuracy of deep-learning methods in oncological localization, which requires the incorporation of attention mechanisms and self-refined feature learning in modern architectures.^[14]

5. Attention-Based Learning Strategies

Attention mechanisms are an effective methodological model that enhances the functions of deep-learning models in tumour localisation by separating clinically valuable objects of medical images and reducing or removing unrelated background factors.^[15] The spatial attention narrows the model down to particular points in the image, which allows the accurate capture of small details and structural components, which is critical in tumour detection. Channel attention, on the other hand, emphasizes the most informative elements of the disparate feature maps, which results in more accurate discriminative representations on the end of the entire hierarchy of features. The model therefore gains a deeper understanding of the visual content whereby both spatial and channel attentional strategies are combined which give it greater localisation ability without a significant penalty in terms of computational latency. Further statistics modulation over feature representations follows using self-attention modules used within the transformer architecture, which computes the long-range dependency among map constituents as well as the broader picture context of the image.^[16] This has been quite helpful especially in analysis of hard to classify medical images where potential tumours can be detected with different morphology and/or location in different anatomical sites. Hybrid attentional methods are effective to combine spatial, channel-based, and self-attentional characterization methods into one unified framework and, as a result, to allow a deep learning model to take advantage of information available locally and globally at the same time. Moreover, attentional learning is capable of dynamically sharpening the features of an image, thus reducing the coarseness of space whilst increasing the fine detail; sharpening of models used in cancer localisation can increase their robustness and

interpretability. The above-mentioned features make the attention-based algorithms a perfect candidate to be implemented in clinical and edge healthcare settings.^[17]

6. Lightweight and Edge-Optimized Architectures

The application of deep-learning models in cancer localisation in edge-healthcare systems, including portable diagnostic devices and point-of-care screening devices, demands models that are computationally efficient and highly accurate at the same time. Existing common deep-learning other designs often require large memory and computation assets, which limits their usefulness in executions in real time on resource-constrained equipment. The constraints are alleviated in the lightweight models through dimensionality reduction of the models, speeding up inference, and maintaining localisation accuracy. Many methods are used in the manufacturing of lightweight. Model- compression algorithms such as pruning, quantisation and knowledge distillation reduce the parameter count and floating-point operations (FLOPs), making them easier to infer more quickly with only a small accuracy loss. Optimisation approaches, e.g. the using of the efficient network back-bones (e.g. MobileNet, EfficientNet), are those, which utilise depthwise convolutions and parameter sharing that yield a favourable tradeover between computational cost and performance. In spite of these methodological improvements, there are more challenges related to the implementation of deep-learning models into edge-healthcare settings.^[18] Limitation of computer power, extreme latency demands and energy usage should be properly weighed against model fidelity. In addition, non-uniform hardware platforms and multiplicity of imaging modalities demand very flexible and strong architectures that can generalise through diverse clinical settings. Integration of attention and multi-scale learning of features in lightweight models has been provided to be a viable approach to address these issues without the need to compromise on spatial detail and localisation accuracy.^[19]

Table 1: Summary of Lightweight and Edge-Optimized Strategies for Cancer Localization.

Strategy	Technical Description	Advantages	Challenges	Representative Techniques
Lightweight CNN Architectures	Parameter-efficient neural networks employing depthwise separable convolutions and	Reduced memory footprint, faster inference speed, suitable for real-time edge deployment	Potential reduction in feature representation capacity	MobileNet, EfficientNet, ShuffleNet

	optimized building blocks to minimize computational overhead			
Model Pruning	Systematic removal of redundant or low-importance weights, filters, or neurons during or after training	Decreased model size, lower FLOPs, improved computational efficiency	Requires careful fine-tuning to avoid performance degradation	Magnitude-based pruning, Structured pruning
Quantization	Conversion of high-precision numerical representations (e.g., FP32) into lower-precision formats (e.g., INT8, FP16)	Faster computation, reduced energy consumption, hardware-friendly implementation	Accuracy degradation if aggressively applied without calibration	Post-Training Quantization (PTQ), Quantization-Aware Training (QAT)
Knowledge Distillation	Training a compact “student” model using soft predictions or feature representations from a larger “teacher” network	Maintains competitive accuracy with significantly smaller models	Complexity in designing effective teacher–student frameworks	Response-based distillation, Attention-based distillation
Edge Deployment Optimization	Hardware-aware model adaptation and runtime optimization for resource-constrained devices	Real-time processing, low latency, improved deployment feasibility	Heterogeneous hardware environments, limited GPU/CPU resources	TensorRT optimization, ONNX Runtime, EdgeTPU deployment

The main steps to be undertaken to create lightweight and edge-based streamlined deep learning models to localize cancer are highlighted in the table above. The former plan is the application of lightweight convolutional neural networks (CNNs) with a significantly decreased number of parameters and features efficient convolution functions. This is a faster and less memory-consuming method that does not significantly reduce accuracy. The second approach is model pruning, that helps to remove unnecessary parameters and/or neurons in the model, and reduce the computational cost without impairing performance. The third strategy is quantization of the numeric representation of the weight data, which allows the more efficient computation because it allows a larger temporal margin to perform the

operations on the fly. The technique eventually results in low total battery usage of the computation, resulting in run times efficiency, faster processing and lower power consumption.^[20] The fourth approach is knowledge distillation, in which a smaller student model is trained on the output probability and output of a larger capacity teacher network. The method provides the best models which have reduced size and/or footprint. The techniques mentioned above are essential elements in the creation of lightweight, edge-based optimized models which could perform with real time or near real time performance on various devices with limited resources which are not routinely available in a variety of clinical environments as part of an edge health care model.^[21]

7. Challenges, Future Directions, and Conclusion

Although there has been great advances in using deep learning to localize malignant tissue in biopsy specimens, there are still a number of significant challenges that need to be overcome before such systems can be widely implemented in realistic edge healthcare settings.^[22] Of greatest importance are these data scarcity and the prohibitive cost of data annotation, because supervised deep learning networks require large volumes of strictly annotated data in order to train. Also, the heterogeneity of imaging modalities used in different institutions and heterogeneity in studies of different groups of patients also creates significant inter-dataset variability; therefore, when models are applied to new datasets, they often perform worse because of the overfitting phenomena. Furthermore, deep learning models with their complicated architecture hinder interpretability and explainability, which creates severe obstacles in terms of clinical acceptance, regulatory support, and physician trust.^[23] Such systems are also hindered by real-time constraints, heterogeneous hardware platforms and power requirements of edge devices to real-time deployment. Future research efforts should hence aim at systematically resolving these issues so that both the accuracy and computational efficiency of deep learning based diagnostic tools can be improved. The use of weakly and semi-supervised learning paradigms can theoretically decrease the reliance on annotated datasets and, at the same time, produce localized predictions. Mechanisms of explainable attention may increase the transparency and make interpretability easier, further improving clinical acceptability of such methodologies.^[24] Federal learning and privacy-sensitive methods are some of the approaches that facilitate the creation of models in more than one institution and also provide security to patient information. It is anticipated that with the help of optimized, self-refining attention-based models, data can be processed in real-time, even in non-clinical environments, hence providing high-quality diagnostic information

to patients in resource-limited settings.^[25] To conclude, self-refining, lightweight attention-based deep learning systems offer a new way of localizing cancer with fine spatial granularity and reducing the effects of computational limitations. The addition of state-of-the-art attention-level processing, multi-scale feature apprehension and edge-calculation planning will allow these models to provide clinically meaningful predictions that can be implemented on handheld point-of-care devices. With such models achieving wider implementation, the time interval between the presentation of the patient and the correct diagnosis is likely to decrease, which benefits first-line treatment choices, patient outcome, and health scientists to come up with the next-generation edge health-care solutions to oncology patients.

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