

Adaptive Inference through Early-Exit Networks: Design, Challenges and Directions

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ABSTRACT

DNNs are becoming less and less over-parametrised due to recent advances in efficient model design, through careful hand-crafted or NAS-based methods. Relying on the fact that not all inputs require the same amount of computation to yield a confident prediction, adaptive inference is gaining attention as a prominent approach for pushing the limits of efficient deployment. Particularly, early-exit networks comprise an emerging direction for tailoring the computation depth of each input sample at runtime, offering complementary performance gains to other efficiency optimisations. In this paper, we decompose the design methodology of early-exit networks to its key components and survey the recent advances in each one of them. We also position early-exiting against other efficient inference solutions and provide our insights on the current challenges and most promising future directions for research in the field.

CCS CONCEPTS

- Computing methodologies → Neural networks;
- Human-centered computing → Ubiquitous and mobile computing systems and tools.

KEYWORDS

Early-exit networks, Dynamic inference, Adaptive computing, Deep learning, Mobile systems

1 INTRODUCTION

During the past years, there has been an unprecedented surge in the adoption of Deep Learning in various tasks, ranging from computer vision [22] to Natural Language Processing (NLP) [69] and from activity recognition [72] to health monitoring [62]. A common denominator and, undoubtedly, a key enabler for this trend has been the significant advances in hardware design [1, 31] (e.g. GPU, ASIC/FPGA accelerators, SoCs) along with the abundance of available data, both enabling the training of deeper and larger models. While the boundaries of accuracy are pushed year by year, DNNs often come with significant workload and memory requirements, which make their deployment on smaller devices cumbersome, be it smartphones or other mobile and embedded devices found in the wild. Equally important is the fact that the landscape of deployed devices is innately heterogeneous [78], both in terms of capabilities (computational and memory) and budget (energy or thermal).

To this direction, there has been substantial research focusing on minimising the computational and memory requirements of such networks for efficient inference. Such techniques include architectural, functional or representational optimisations in DNNs [71], aiming at faster forward propagation at a minimal cost. These include custom – hand or NAS-tuned – blocks [26, 66], model weights sparsification and pruning [19] as well as low-precision representation and arithmetics [46, 59]. Given there is no free lunch in

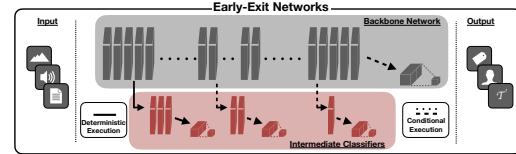


Figure 1: Early-exit network architecture

Deep Learning, most of the aforementioned approaches trade off model accuracy for benefits in latency and memory consumption. Moreover, while some of these approaches may work out-of-the-box, others do require significant effort during or post training to maintain performance or to target different devices [19].

A complimentary family of solutions further pushing the efficiency envelope exploits the accuracy-latency trade-off at runtime, by adapting the inference graph [11, 25, 75, 79] or selecting the appropriate model [20, 43] for the device, input sample or deadline at hand. This category includes early-exiting (EE) [68]. Early-exit networks leverage the fact that not all input samples are equally difficult to process, and thus invest a variable amount of computation based on the input's difficulty and the DNN's prediction confidence; an approach resonating with the natural thinking mechanism of humans. Specifically, early-exit networks consist of a backbone architecture, which has additional exit heads (or classifiers) along its depth (Fig. 1). At inference time, when a sample propagates through the network, it flows through the backbone and each of the exits sequentially, and the result that satisfies a predetermined criterion (exit policy) is returned as the prediction output, circumventing the rest of the model. As a matter of fact, the exit policy can also reflect the target device capabilities and load and dynamically adapt the network to meet specific runtime requirements [41, 42].

Reaping the benefits of early exiting upon deployment, however, is not as trivial as jointly training a backbone network with randomly placed exits. One needs to carefully design the network and the training sequence of the exits relative to the backbone before choosing the exit policy for the deployment at hand. These decisions can be posed as a Design Space Exploration problem that can be efficiently traversed through a “train-once, deploy-everywhere” paradigm. This way, the training and deployment processes of early-exit networks can be detached from one another [41].

This paper provides a thorough and up-to-date overview of the area of early-exit networks. Specifically, we first describe the typical architecture and major components of these networks across modalities. Next, we survey the state-of-the-art techniques and bring forward the traits that make such models a compelling solution. Last, we conclude by discussing current challenges in existing systems, the most promising avenues for future research and the impact of such approaches on the next generation of smart devices.

2 EARLY-EXIT NETWORKS

DNNs can be thought as complex feature extractors, which repre-

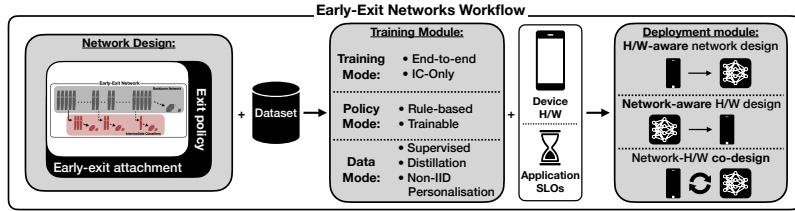


Figure 2: Early-exit networks workflow

sent inputs into an embedded space and classify samples based on the separability of classes in the hyperplane manifold. Typically, shallow layers extract low-level features, such as edges, whereas deeper ones build upon higher level semantics. Under that framework, early exits can be thought as early decisions based on the shallower representations. The hypothesis behind their operation lays on the fact that such features on easier samples might be enough to offer the desired distinguishability between classes.

Several important decisions arise when designing, training and deploying such networks, however, as different designs affect the dynamics the network precision, performance and efficiency. In this and the following sections we go through the workflow of deploying an early-exit network (Fig. 2).

2.1 Designing the architecture

Model & Exit Architecture. Initially, one needs to pick the architecture of the early-exit model. There are largely two avenues followed in the literature: i) *hand-tuned end-to-end designed networks* for early-exiting, such as MSDNet [30], and ii) *vanilla backbone networks, enhanced with early exits* along their depth [12, 35, 41, 68]. This design choice is crucial as it later affects the capacity and the learning process of the network, with different architectures offering varying scalability potential and convergence dynamics.

In the first case, networks are designed with progressive inference carved into their design. This means that the model and the architecture of its early exits are co-designed – and potentially trained jointly. Such an approach allows for more degrees of freedom, but potentially restricts the design’s performance across different circumstances and deployment scenarios, since this decision needs to be made early in the design process. For example, the existence of residual connections spanning across early exits can help generalisability of the network. On the other hand, some properties, such as maintaining multiple feature size representations, can prove detrimental in terms of model footprint [30].

On the other hand, when disentangling the backbone network’s design from the early exits, one can have the flexibility of lazily selecting the architecture of the latter ones. Although this might not yield the best attainable accuracy, since the two components are not co-designed, it enables case-driven designs of early-exits that can be potentially trained separately to the main network and selected at deployment time [41].

It is worth noting that early exits can adopt a uniform or non-uniform architecture, based on their placement. While the latter enlarges the design space of early-exit networks, it creates an interesting trade-off: The number (and type¹) of exit-specific layers accuracy vs. their overhead. While the adaptive and input-specific nature of early-exit networks is highly praised, when an early output does not meet the criteria for early-stopping, the runtime of the exit-specific layers are essentially an overhead to the inference

computation. As such, the early exits need to be designed in comparison with the backbone network (i.e. relative cost) and with the exit policy at hand (i.e. frequency of paying that cost).

Number & Position of Early-exits. In parallel with the architecture, one also needs to select the number and positioning of early exits along the depth of the network. This decision not only affects the granularity of early results, but also the overall overhead of early-exiting compared to the vanilla single-exit inference. Too densely placed early exits can yield an extreme overhead without justifying the gains achieved by the extra classifiers, whereas too sparse placements can offer large refinement period until the next output is available. Moreover, having too many early classifiers can negatively impact convergence when training end-to-end. With respect to positioning a given number of early exits, they can be placed equidistantly or at variable distances across the depth of the network. The decision depends on the use-case, the exit rate and the accuracy of each early exit. It is worth noting that this inter-exit distance is not actual “depth”, but can be quantified by means of FLOPs or parameters in the network.

2.2 Training the network

After materialising its architecture, the early-exit model needs to be trained on given dataset. As hinted, there are largely two ways to train early-exit networks: i) *end-to-end (E2E)* and ii) *intermediate classifiers (IC) only*. Each approach presents different trade-offs in terms of achieved accuracy vs. flexibility for target-specific adjustments. Here, we discuss these trade-offs along with orthogonal training techniques that can boost the overall accuracy of the model.

2.2.1 End-to-end vs. IC-only training.

End-to-end training. The approach comprises jointly training the network and early exits. Normally, a joint loss function is shaped which sums intermediate and the last output losses ($L_{task}^{(i)}$) in a weighted manner (Eq. 1) and then backpropagates the signals to the respective parts of the network. While the achieved accuracy of this approach can be higher both for the intermediate ($y_{i < N}$) and the last exit (y_N), this is not guaranteed due to cross-talk between exits [47]. Concretely, the interplay of multiple backpropagation signals and the relative weighting (w_i) of the loss components [27] needs to be carefully designed, to enable the extraction of reusable features across exits. As such, while offering a higher potential, E2E training requires manual tuning of the loss function as well as co-design of the network architecture and the populated exits [35].

$$L_{e2e}(y_0, \dots, y_N, y) = \sum_{i=0}^N w_i * L_{task}^{(i)}(y_i, y) \quad (1)$$

IC-only training. Alternatively, the backbone of the network and the early exits can be trained separately in two distinct phases. Initially, the backbone of the network, which may or may not be early-exit aware, is trained - or comes pretrained. In the subsequent phase, the backbone network is frozen², early-exits are attached at

¹Type can refer to the type of convolutions, such as regular vs. depthwise separable.

²Meaning that the weights of this submodel are not updated through backpropagation.

different points of the network and are trained separately (Eq. 2). This means that each exit is only fine-tuning its own layers and does not affect the convergence of the rest of the network. Therefore, the last exit is left intact, there is neither cross talk between classifiers nor need to hand-tune the loss function. As such, more exit variants can be placed at arbitrary positions in the network and be trained in parallel, offering scalability in training while leaving the selection of exit heads for deployment time [41]. Thus, a “*train-once, deploy-everywhere*” paradigm is shaped for multi-device deployment. On the downside, this training approach is more restrictive in terms of degrees of freedom on the overall model changes, and thus can yield lower accuracy than an optimised jointly trained variant.

$$L_{ic\text{-}only}^{(i)}(y_i, y) = L_{task}^{(i)}(y_i, y) \quad (2)$$

2.2.2 Training with distillation. An ensuing question that arises from the aforementioned training schemes is whether the early-exits differ in essence from the last one and whether there is knowledge to be distilled between them. To this direction, there has been a series of work [44, 47, 53, 58, 88] that employ knowledge distillation [23] in a self-supervised way to boost the performance of early classifiers. In such a setting, the student i is typically an early exit and the teacher j can be a subsequent or the last exit ($j \geq i$). As such, the loss function for each exit is shaped as depicted in Eq. 3 and two important hyperparameters emerge, to be picked at design time; namely the distillation *temperature* (T) and the *alpha* (α). The temperature effectively controls how “peaky” the teacher softmax (soft labels) should be while the alpha parameter balances the learning objective between ground truth (y) and soft labels (y_j).

$$L_{distill}^{(i)}(y_i, y_j, y) = L_{task}^{(i)}(y_i, y) + \alpha L_{KL}(y_i, y_j, T) \quad (3)$$

2.2.3 Training personalised early-exits. Hitherto, early exits have been trained for the same task uniformly across exits. However, when deploying a model in the wild, user data are realistically non-IID³ and may vary wildly from device to device. With this in mind, there has been a line of work [33, 44] that personalises early exits on user data, while retaining the performance of the last exit in the source global domain. In [44], this is effectively accomplished through IC-only training, where the backbone network is trained on a global dataset and early-exits are then trained on user-specific datasets in a supervised or self-supervised manner. In the latter case, data labels are obtained from the prediction of the last exit. Orthogonally, knowledge distillation can still be employed for distilling knowledge from the source domain to the personalised exits, by treating the last exit as the teacher [33, 44].

2.3 Deploying the network

At this stage, an early-exit network has been trained and ready to be deployed for inference on a target device. There are largely three inference modes for early exits, each relevant to different use cases:

Subnet-based inference. A single-exit submodel is selected (up to a specified early exit) and deployed on the target device. The main benefit here is the single training cycle for models of varying footprint, which, in turn, can target different devices or SLOs⁴.

Anytime adaptive inference. An adaptive inference model is deployed and each sample exits (early) based on its difficulty, the confidence of the network prediction and potential app-specific SLOs.

This mode offers progressive refinement of the result through early-exiting and latency gains for easier samples.

Budgeted adaptive inference. Similar to anytime inference, but with throughput-driven budget. Concretely given a total latency budget, the goal is to maximise the throughput of correct predictions. This means that the model elastically spends more time on some examples at the expense of early-exiting on others.

Next, we are focusing on the last two use-cases and more specifically how the exit policy is shaped.

2.3.1 Deploying for adaptive inference. Exit policy is defined as the criterion upon which it is decided whether an input sample propagating through the network exits at a specified location or continues. Picking the appropriate depth to exit is important both for performance and to avoid “overthinking”⁵ [35]. Overall, there are i) *rule-based* and ii) *learnable* exit policies.

Rule-based early-exiting. Most works in progressive inference have been employing the softmax of an exit to quantify the confidence of the network for a given prediction [2]. On the one hand, we have approaches where the criterion is a threshold on the entropy of the softmax predictions [68]. Low entropy indicates similar probabilities across classes and thus a non-confident output whereas higher entropy hints towards a single peak result. On the other hand, other approaches use the top-1 softmax value as a quantification of confidence. An overarching critique for using confidence-based criteria, however, has been the need to manually define an arbitrary threshold, along with the overconfidence of certain deep models. Solutions include calibrating the softmax output values [18] or moving to different exit schemes. Alternative rule-based exit policies include keeping per class statistics at each layer [17], calculating classifiers’ *trust scores* based on sample distances to a calibration set [32] or exiting after n exits agree on the result [89].

Learnable exit policies. Expectedly, one may wonder why not to learn network weights and the exit policy jointly. To this direction there has been work approaching the exit policy in differentiable [6, 60] and non-differentiable [8] ways. In essence, instead of explicitly measuring the exit’s confidence, the decision on whether to exit can be based on the feature maps of the exits themselves. The exit decision at a given classifier can be independent of the others (adhering to the Markov property) or can be modelled to also account for the outputs of adjacent exits.

3 EARLY-EXITS & TARGET HARDWARE

Early-exiting not only provides an elegant way to dynamically allocate compute to samples based on their difficulty, but also an elastic way to scale computation based on the hardware at hand. Although we have presented so far design, training and deployment as three distinct stages, these can, in fact, be co-designed and co-optimised for targeting different devices and SLOs.

First, a considerable benefit of early-exit networks, as aforementioned, is their “*train-once, deploy-everywhere*” paradigm. Essentially, this means that an overprovisioned network – e.g. a network with densely placed early-exits – can be trained and then different parts of it be deployed according to the device’s computational budget, memory capacity or energy envelope and application’s latency,

³Non Identically and Independently Distributed.

⁴Service Level Objective: e.g. max latency or min accuracy.

⁵Overthinking refers to the non-monotonic accuracy of ICs; i.e. later classifiers can misclassify a sample that was previously correctly classified.

throughput or accuracy objectives. In essence, tweaking i) the classifier architecture, ii) the number and positioning of early-exits and iii) exit-policy to the hardware at hand can be posed as a Design Space Exploration (DSE) problem with the goal of (co-)optimising latency, throughput, energy or accuracy given a set of restrictions, posed in the form of execution SLOs [41]. Accurately modelling this optimisation objective subject to the imposed restrictions is important for yielding efficient valid designs for the use-case at hand and shaping the Pareto front of optimal solutions.

Traversing this search space efficiently is important, especially since it needs to be done once per target device. Therefore, end-to-end training is usually avoided in favor of the more flexible IC-only approach. It should be noted, though, that the search is run prior to deployment, and its cost is amortised over multiple inferences.

Instead of searching for the optimal network configuration for fixed hardware, another set of approaches is to design the hardware specifically for early-exit networks [13, 36, 37] or co-design the network and hardware for efficient progressive inference [57, 73].

4 ADAPTIVE INFERENCE LANDSCAPE

Offline accuracy-latency trade-off. DNNs have been getting deeper and wider in their pursuit of state-of-the-art accuracy. However, such models still have to be deployable on devices in the wild. As such, optimising DNNs for efficient deployment has been an extremely active area of research. Approaches in the literature exploit various approximation and compression methods [71] to reduce the footprint of these models, including quantisation of network weights and activations [16, 46, 59] or weight sparsification and pruning [9, 19, 51]. A common denominator amongst these techniques is that they inherently trade off latency or model size with accuracy. This trade-off is exploited offline in a device-agnostic or hardware-aware [84] manner. Alongside, recent models tend to become less redundant, and thus more efficient, through careful hand-engineering [26], or automated NAS-based design [50, 66] of their architecture. These approaches remain orthogonal to adaptive inference, thus offering complementary performance gains.

Dynamic Networks. Techniques in this family take advantage of the fact that different samples may take varying computation paths during inference [52], either based on their intricacy or the capacity of the target device. Such methods include dynamically selecting specialised branches [55], skipping [70, 75, 79] or “fractionally executing” (i.e. with reduced bitwidth) [63] layers during inference, and dynamically pruning channels [11, 15, 25, 49] or selecting filters [7, 85, 86]. These approaches typically exploit trainable gating/routing components in the network architecture. This, however, complicates the training procedure and restricts post-training flexibility for efficient deployment on different hardware.

Inference Offloading. Orthogonally, there has been a series of work on adaptive inference offloading, where part of the computational graph of a DNN is offloaded to a faster remote endpoint for accelerating inference to meet a stringent SLO [34]. Some [42, 45] even combine early-exit networks with offloading.

Model Selection & Cascades More closely related to early-exiting come approaches that train a family of models with different latency-accuracy specs, all deployed on the target device. This is achieved by trading off precision [38], resolution [83] or model capacity [20, 74] to gain speed, or by incorporating efficient specialised models [77].

At inference, the most appropriate model for each input is selected through various identification mechanisms [43, 67], or by structuring the model as a cascade and progressively propagating to more complex models until a criterion is met [39]. Although seemingly similar to early-exiting, “hard” samples may propagate through numerous cascade stages without re-use of prior computation.

Early-exiting. Early-exiting has been applied for different intents and purposes. Initially, single early-exits were devised as a mechanism to assist during training [65], as a means of enhancing the feedback signal during backpropagation and to avoid the problem of vanishing gradients. In fact, these exits were dropped during inference. Since then, however, early-exits have proven to be a useful technique of adaptive inference and have been applied successfully to different modalities and for different tasks. These previously discussed techniques are concisely presented in Table 1 and organised by their optimisation goal, input modality and trained task.

Other surveys. There have been certain previous surveys touching on the topic of early-exiting, either only briefly discussing it from the standpoint of dynamic inference networks [21] or combining it with offloading [54]. To the best of our knowledge, this is the first study that primarily focuses on early-exit networks and their design trade-offs across tasks, modalities and target hardware.

5 DISCUSSION & FUTURE DIRECTIONS

Having presented how early-exiting operates and what has been accomplished by prior work, here we discuss the main challenges and most prominent directions for future research in the field.

5.1 Open Challenges.

Modalities. A lot of research efforts in early exits have focused on the task of image classification through CNNs, and only most recently NLP through Transformer networks. However, a large variety of models (e.g. RNN, GAN, seq2seq, VAE) are deployed in the wild, addressing different tasks including object detection, semantic segmentation, regression, image captioning and many more. Such models come with their own set of challenges and require special handling on one or more of the core components of early-exit networks, which remain largely unexplored to date.

Early-exit Overhead. Attaching early exits to a backbone network introduces a workload overhead for the samples where the exit at hand cannot yield a confident enough prediction. This overhead heavily depends on the architecture of the exit, its position in the network, the effectiveness of the exit policy and the task itself. Hence, instantiating the optimal configuration of early exits on a backbone network, which balances this overhead against the performance gains from exiting early, remains a challenging task.

Architectural Search Space As previously established, there is a large interplay between the building blocks of early-exit networks. It is therefore desirable to co-optimise many design and configuration parameters such as exit number, placement, architecture and policy. This inflates the architectural search space and makes it computationally challenging to traverse, in search for optimal configurations. Structured or NAS-based approaches to explore this space could provide an efficient solution to this end.

Training Strategy. Training early-exit networks is inherently challenging. Normally, early layers in DNNs extract lower-level appearance features, whereas deeper ones extract higher-level semantics,

Table 1: Work in early exiting.

Category	Title	Modality/Task	Description
Early-exit network-specific techniques	MSDNet [30, 47]	Vision/Classification	Hand-tuned multi-scale EE-network.
	Not all pixels are equal [48]	Vision/Segmentation	Pixel-level EE based on difficulty for semantic segmentation.
	Phuong et al. [58]	Vision/Classification	Distillation-based EE from later to earlier MSDNet exits.
	RBQE [82]	Vision/Enhancement	UNet-like network with EE, for Quality Enhancement.
	The Right Tool for the Job [61]	NLP	Jointly trained EE on BERT.
	DeeBERT [81]	NLP/GLUE	Jointly trained EE on Ro(BERT)a models.
	FastBERT [53]	NLP	Distillation-based EE on BERT models.
	Depth-Adaptive Transformer [10]	NLP/BLEU	Transformer-based EE for translation.
	Bert Loses Patience [89]	NLP/GLUE	Patience-based EE on (AL)BERT models.
Early-existing network-agnostic techniques	Cascade Transformer [64]	NLP/QA	Transformer-based EE rankers for Question Answering.
	MonoBERT [80]	IR/Document Ranking	Asymmetric EE BERT for efficient Document Ranking.
	Chen et al. [5]	Speech	Speech separation with EE-transformers.
Early-existing network-agnostic techniques	CDLN [56]	Vision/Classification	Primary early-exit work based on linear classifiers.
	BranchyNet [68]	Vision/Classification	Entropy-based fixed classifier EE-technique.
	SDN [35]	Vision/Classification	E2E & IC-only overthinking-based training EE.
	HAPI [41]	Vision/Classification	Hardware-aware design of EE-networks via DSE.
	Edgent [45]	Vision/Classification	Submodel selection for offloading through EE training.
	SPINN [42]	Vision/Classification	Partial inference offloading of EE-networks.
	FlexDNN [12]	Vision/Classification	Footprint overhead-aware design of EE-networks.
	DDI [76]	Vision/Classification	Combines layer/channel skipping with early exiting.
	MESS [40]	Vision/Segmentation	Image-level EE based on difficulty for semantic segmentation.
Variable label distributions	Bilal et al. [3]	Vision/Classification	Hierarchy-aware ee-CNNs through confusion matrices.
	Bonato et al. [4]	Vision/Classification	Class prioritisation on EE.
	PersEPhonEE [44]	Vision/Classification	Personalised EE-networks under non-IID data
Learnable exit policies	Scardapane et al. [60]	Vision/Classification	Differentiable jointly learned exit policy on EE-networks.
	EpNet [8]	Vision/Classification	Non-differentiable exit policy for EE-networks.
	Chen et al. [6]	Vision/Classification, Denoising	Jointly learned variational exit policy for EE-networks.
Adversarial robustness	Triple-wins [29]	Vision/Classification	Accuracy, robustness, efficiency multi-loss.
	DeepSloth [24]	Vision/Classification	Adversarial slowdown-enducing attack.
EE-H/W (co-)design	Kim et al. [37]	Vision/Identification	Low-power & robust EE model+H/W for continuous face recognition.
	Farhadi et al. [13]	Vision/Classification	FPGA partial reconfiguration for progressive inference.
	Kim et al. [36]	Vision/Classification	Single-layer EE and H/W synthesis for thresholding.
	Paul et al. [57]	Vision/Classification	Efficient EE inference on FPGA.
	DynExit [73]	Vision/Classification	Trainable weights in joint EE loss and FPGA deployment.

important for the respective task. In the realm of early-exiting, classifiers placed shallowly are natively pushing for the extraction of semantically strong features earlier in the network, which causes tension between the gradients of different exits, and may harm the overall accuracy in the case of e2e training. Conversely, IC-only trained early exits may lead to inferior accuracy or increased overheads. Developing a training strategy that can combine the best of both worlds remains an open question.

Exit Policy. Current hand-tuned exit policy treat prediction “confidence” as a proxy to accuracy. Exit placement and training strategy may cause this predictions to become naturally under- or over-confident, leading to a probability distribution over layers that does not reflect the network’s innate uncertainty [18]. Developing exit strategies that better reflect the networks readiness-to-exit and potential ability-to-improve its prediction by propagating to the next exit is a challenging area of research. Additionally, it is important to allow such methodologies to remain adaptable post-training, in order to facilitate efficient deployment to use-cases with varying requirements and devices with different computational capabilities.

5.2 Additional future directions

Temporal-Awareness. In video or mobile agent applications, strong correlations typically exist between temporally and spatially adjacent input samples, and hence their underlying predictive difficulty given previous predictions [28]. There is therefore space to integrate historical or codec information to further optimise early-exiting.

Hierarchical Inference. In latency critical applications, having some higher-level actionable result from early on may be more important than waiting for an accurate finer-grained classification prediction. Early-exit networks can facilitate this paradigm, through

hierarchical inference, with earlier exits providing more abstract – and therefore easier to materialise – predictions (e.g. “dog”), before specialising their prediction in deeper exits (e.g. “beagle”) [3, 87].

Personalisation. At deployment time, deep learning models often meet narrower distributions of input samples than what they have been originally trained for (i.e. detecting a single user or their relatively stationary environment). In such cases, early exits can act as a self-acceleration mechanism, trained on the spot, e.g. through knowledge (self-)distillation from the final exit [44], to maximise their performance by specialising to the target distribution.

Heterogeneous Federated Learning (FL). In FL deployments, participating devices can have very heterogeneous computational and network capabilities [25]. As such, submodels of varying depth may be distributed to clients to train on their local dataset, thus improving participation and fairness while avoiding stragglers.

Probabilistic Inference. Probabilistic models (e.g. Bayesian Neural Networks) have a native way of quantifying the predictive uncertainty of the network across all stages of inference [14]. This property of stochastic models can be exploited by the exit policy, rendering BNNs a natural fit for early exiting methodologies.

REFERENCES

- [1] Mario Almeida et al. 2019. EmBench: Quantifying Performance Variations of Deep Neural Networks Across Modern Commodity Devices. In *EMDL*.
- [2] Konstantin Berestizshevsky et al. 2019. Dynamically sacrificing accuracy for reduced computation: Cascaded inference based on softmax confidence. In *ICANN*.
- [3] Alsallakh Bilal et al. 2017. Do convolutional neural networks learn class hierarchy? *IEEE Transactions on Visualization and Computer Graphics* 24, 1 (2017).
- [4] Vanderlei Bonato and Christos Bouganis. 2021. Class-specific early exit design methodology for convolutional neural networks. *Applied Soft Computing* (2021).
- [5] Sanyuan Chen et al. 2021. Don’t shoot butterfly with rifles: Multi-channel Continuous Speech Separation with Early Exit Transformer. In *ICASSP*.
- [6] Xinshi Chen et al. 2020. Learning to stop while learning to predict. In *ICML*.

- [7] Zhourong Chen, Yang Li, Samy Bengio, and Si Si. 2019. You look twice: Gaternet for dynamic filter selection in CNNs. In *CVPR*.
- [8] Xin Dai, Xiangnan Kong, and Tian Guo. 2020. EPNet: Learning to Exit with Flexible Multi-Branch Network. In *CIKM*.
- [9] Lei Deng et al. 2020. Model compression and hardware acceleration for neural networks: A comprehensive survey. *Proc. IEEE* 108, 4 (2020).
- [10] Maha Elbayad et al. 2020. Depth-Adaptive Transformer. In *ICLR*.
- [11] Biyi Fang et al. 2018. NestDNN: Resource-Aware Multi-Tenant On-Device Deep Learning for Continuous Mobile Vision. In *MobiCom*.
- [12] Biyi Fang et al. 2020. FlexDNN: Input-Adaptive On-Device Deep Learning for Efficient Mobile Vision. In *Symposium on Edge Computing (SEC)*.
- [13] Mohammad Farhadi et al. 2019. A novel design of adaptive and hierarchical convolutional neural networks using partial reconfiguration on FPGA. In *HPEC*.
- [14] Yarin Gal and Zoubin Ghahramani. 2016. Dropout as a bayesian approximation: Representing model uncertainty in deep learning. In *ICML*.
- [15] Xitong Gao, Yiren Zhao, Łukasz Dudziak, Robert Mullins, and Cheng-zhong Xu. 2019. Dynamic channel pruning: Feature boosting and suppression. *ICLR*.
- [16] Amir Gholami et al. 2021. A Survey of Quantization Methods for Efficient Neural Network Inference. *arXiv preprint arXiv:2103.13630* (2021).
- [17] Alperen Gormez and Erdem Koyuncu. 2021. Class Means as an Early Exit Decision Mechanism. *arXiv preprint arXiv:2103.01148* (2021).
- [18] Chuan Guo et al. 2017. On Calibration of Modern Neural Networks. In *ICML*.
- [19] Song Han et al. 2016. Deep Compression: Compressing Deep Neural Network with Pruning, Trained Quantization and Huffman Coding. *ICLR* (2016).
- [20] Seungyeop Han et al. 2016. MCDNN: An Approximation-Based Execution Framework for Deep Stream Processing Under Resource Constraints. In *MobiSys*.
- [21] Yizeng Han et al. 2021. Dynamic neural networks: A survey. *arXiv:2102.04906*
- [22] Kaiming He, Xiangyu Zhang, Shaoqiu Ren, and Jian Sun. 2015. Deep Residual Learning for Image Recognition. (2015). *arXiv:1512.03385*
- [23] G. Hinton et al. 2015. Distilling the Knowledge in a Neural Network. In *NIPS*.
- [24] Sanghyun Hong et al. 2021. A Panda? No, It's a Sloth: Slowdown Attacks on Adaptive Multi-Exit Neural Network Inference. In *ICLR*.
- [25] Samuel Horvath, Stefanos Laskaridis, et al. 2021. FjORD: Fair and Accurate Federated Learning under heterogeneous targets with Ordered Dropout. *arXiv:2102.13451*
- [26] Andrew G. Howard et al. 2017. MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications. (2017). *arXiv:1704.04861*
- [27] Hanzhang Hu et al. 2019. Learning anytime predictions in neural networks via adaptive loss balancing. In *AAAI*.
- [28] Ping Hu et al. 2020. Temporally distributed networks for fast video semantic segmentation. In *CVPR*.
- [29] Ting-Kuei Hu et al. 2020. Triple Wins: Boosting Accuracy, Robustness and Efficiency Together by Enabling Input-Adaptive Inference. In *ICLR*.
- [30] Gao Huang et al. 2018. Multi-Scale Dense Networks for Resource Efficient Image Classification. In *ICLR*.
- [31] Andrey Ignatov et al. 2019. AI Benchmark: All About Deep Learning on Smartphones in 2019. In *ICCVW*.
- [32] Heinrich Jiang, Been Kim, Melody Guan, and Maya Gupta. 2018. To Trust Or Not To Trust A Classifier. *arXiv:1805.11783* (2018).
- [33] Junguang Jiang, Ximeie Wang, Mingsheng Long, and Jianmin Wang. 2020. Resource Efficient Domain Adaptation. In *ACM Int. Conf. on Multimedia*.
- [34] Yiping Kang et al. 2017. Neurosurgeon: Collaborative Intelligence Between the Cloud and Mobile Edge. In *ASPLoS*.
- [35] Yigitcan Kaya, Sanghyun Hong, and Tudor Dumitras. 2019. Shallow-Deep Networks: Understanding and Mitigating Network Overthinking. In *ICML*.
- [36] Geonho Kim and Jongsun Park. 2020. Low Cost Early Exit Decision Unit Design for CNN Accelerator. In *2020 International SoC Design Conference (ISOCC)*.
- [37] Youngwoo Kim et al. 2020. A 0.22–0.89 mW Low-Power and Highly-Secure Always-On Face Recognition Processor With Adversarial Attack Prevention. *IEEE Transactions on Circuits and Systems II: Express Briefs* 67, 5 (2020).
- [38] Alexandros Kouris et al. 2018. CascadeCNN: Pushing the Performance Limits of Quantisation in Convolutional Neural Networks. In *FPL*.
- [39] Alexandros Kouris et al. 2020. A throughput-latency co-optimised cascade of convolutional neural network classifiers. In *DATE*.
- [40] Alexandros Kouris, Stylianos I. Venieris, Stefanos Laskaridis, and Nicholas D. Lane. 2021. Multi-Exit Semantic Segmentation Networks. (2021). *arXiv:2106.03527*
- [41] S. Laskaridis et al. 2020. HAPI: Hardware-Aware Progressive Inference. In *ICCAD*.
- [42] Stefanos Laskaridis et al. 2020. SPINN: Synergistic Progressive Inference of Neural Networks over Device and Cloud. In *MobiCom*.
- [43] Royson Lee et al. 2019. MobiSR: Efficient On-Device Super-Resolution Through Heterogeneous Mobile Processors. In *MobiCom*.
- [44] Ilias Leontiadis et al. 2021. It's Always Personal: Using Early Exits for Efficient On-Device CNN Personalisation (*HotMobile*).
- [45] E. Li et al. 2020. Edge AI: On-Demand Accelerating Deep Neural Network Inference via Edge Computing. In *IEEE Trans. on Wireless Communications (TWC)*.
- [46] Fengfu Li and Bin Liu. 2016. Ternary Weight Networks. (2016). *arXiv:1605.04711*
- [47] Hao Li et al. 2019. Improved Techniques for Training Adaptive Deep Networks. In *Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV)*.
- [48] Xiaoxiao Li et al. 2017. Not All Pixels Are Equal: Difficulty-Aware Semantic Segmentation via Deep Layer Cascade. In *CVPR*.
- [49] Ji Lin et al. 2017. Runtime Neural Pruning. In *NeurIPS*.
- [50] Hanxiao Liu et al. 2019. DARTS: Differentiable architecture search. *ICLR* (2019).
- [51] Jiayi Liu et al. 2020. Pruning Algorithms to Accelerate Convolutional Neural Networks for Edge Applications: A Survey. *arXiv:2005.04275* (2020).
- [52] Lanlan Liu and Jia Deng. 2018. Dynamic Deep Neural Networks: Optimizing accuracy-efficiency trade-offs by selective execution. In *AAAI*.
- [53] Weijie Liu, Peng Zhou, Zhiruo Wang, Zhe Zhao, Haotang Deng, and Qi Ju. 2020. FastBERT: a Self-distilling BERT with Adaptive Inference Time. In *ACL*.
- [54] Yoshitomo Matsubara et al. 2021. Split computing and early exiting for deep learning applications: Survey and research challenges. *arXiv:2103.04505*
- [55] Ravi Teja Mullapudi et al. 2018. Hydranets: Specialized dynamic architectures for efficient inference. In *CVPR*.
- [56] Priyadarshini Panda, Abhraboli Sengupta, and Kaushik Roy. 2016. Conditional deep learning for energy-efficient and enhanced pattern recognition. In *DATE*.
- [57] Debdeep Paul, Jawar Singh, and Jimson Mathew. 2019. Hardware-Software Co-design Approach for Deep Learning Inference. In *ICSCC*.
- [58] Mary Phuong and Christoph H. Lampert. 2019. Distillation-Based Training for Multi-Exit Architectures. In *ICCV*.
- [59] Mohammad Rastegari et al. 2016. Xnor-net: Imagenet classification using binary convolutional neural networks. In *ECCV*.
- [60] Simone Scardapane et al. 2020. Differentiable branching in deep networks for fast inference. In *ICASSP*.
- [61] Roy Schwartz et al. 2020. The Right Tool for the Job: Matching Model and Instance Complexities. In *ACL*.
- [62] Sandra Servia-Rodriguez et al. 2017. Mobile Sensing at the Service of Mental Well-Being: A Large-Scale Longitudinal Study. *WWW*.
- [63] Jianghao Shen et al. 2020. Fractional skipping: Towards finer-grained dynamic CNN inference. In *AAAI*.
- [64] Luca Soldaini et al. 2020. The Cascade Transformer: an Application for Efficient Answer Sentence Selection. In *ACL*. 5697–5708.
- [65] Christian Szegedy et al. 2015. Going deeper with convolutions. In *CVPR*.
- [66] Mingxing Tan and Quoc Le. 2019. EfficientNet: Rethinking Model Scaling for Convolutional Neural Networks. In *ICML*.
- [67] Ben Taylor et al. 2018. Adaptive deep learning model selection on embedded systems. *ACM SIGPLAN Notices* 53, 6 (2018).
- [68] Surat Teerapittayanon, Bradley McDanel, and HT Kung. 2016. BranchyNet: Fast Inference via Early Exiting from Deep Neural Networks. In *ICPR*.
- [69] Ashish Vaswani et al. 2017. Attention is All you Need. In *NeurIPS*.
- [70] Andreas Veit and Serge Belongie. 2018. Convolutional networks with adaptive inference graphs. In *ECCV*.
- [71] Erwei Wang et al. 2019. Deep neural network approximation for custom hardware: Where We've Been, Where We're going. *ACM CSUR* 52, 2 (2019).
- [72] Jindong Wang et al. 2019. Deep learning for sensor-based activity recognition: A survey. *Pattern Recognition Letters* 119 (2019).
- [73] Meiqi Wang, Jianqiao Mo, Jun Lin, Zhongfeng Wang, and Li Du. 2019. DynExit: A Dynamic Early-Exit Strategy for Deep Residual Networks. In *SiPS*.
- [74] Xin Wang et al. 2017. Idk cascades: Fast deep learning by learning not to overthink. *arXiv preprint arXiv:1706.00885* (2017).
- [75] Xin Wang, Fisher Yu, Zi-Yi Dou, Trevor Darrell, and Joseph E Gonzalez. 2018. Skipnet: Learning dynamic routing in convolutional networks. In *ECCV*.
- [76] Yu Wang et al. 2020. Dual Dynamic Inference: Enabling more efficient, adaptive, and controllable deep inference. *Selected Topics in Signal Processing* 14, 4 (2020).
- [77] Zhihua Wei et al. 2019. A self-adaptive cascade ConvNets model based on label relation mining. *Neurocomputing* 328 (2019).
- [78] Carole-Jean Wu et al. 2019. Machine learning at facebook: Understanding inference at the edge. In *HPCA*.
- [79] Zuxuan Wu et al. 2018. Blockdrop: Dynamic inference paths in residual networks. In *CVPR*.
- [80] Ji Xin et al. 2020. Early Exiting BERT for Efficient Document Ranking. In *Proceedings of SustaiNLP*. ACL. <https://doi.org/10.18653/v1/2020.sustainlp-1.11>
- [81] Ji Xin, Raphael Tang, Jaejun Lee, Yaoliang Yu, and Jimmy Lin. 2020. DeeBERT: Dynamic Early Exiting for Accelerating BERT Inference. In *ACL*.
- [82] Qunliang Xing et al. 2020. Early exit or not: resource-efficient blind quality enhancement for compressed images. In *ECCV*.
- [83] Le Yang, Yizeng Han, Xi Chen, Shiji Song, Jifeng Dai, and Gao Huang. 2020. Resolution adaptive networks for efficient inference. In *CVPR*.
- [84] Tien-Ju Yang et al. 2018. Netadapt: Platform-aware neural network adaptation for mobile applications. In *ECCV*.
- [85] Jiahui Yu et al. 2019. Slimmable Neural Networks. *ICLR* (2019).
- [86] Jiahui Yu and Thomas S Huang. 2019. Universally Slimmable Networks and improved training techniques. In *ICCV*.
- [87] Amir R Zamir et al. 2017. Feedback networks. In *CVPR*.
- [88] Linfeng Zhang et al. 2019. Be your own teacher: Improve the performance of convolutional neural networks via self distillation. In *ICCV*.
- [89] Wangchunshu Zhou et al. 2020. BERT Loses Patience: Fast and Robust Inference with Early Exit. In *NeurIPS*.