

Article

PrimeNet: Adaptive multi-layer deep neural structure for enhanced feature selection in early convolution stage

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Abstract: The colossal depths of the deep neural network sometimes suffer from ineffective backpropagation of the gradients through all its depths. Whereas, The strong performance of shallower multilayer neural structures prove their ability to increase the gradient signals in the early stages of training which easily gets backpropagated for global loss corrections. Shallow neural structures are always a good starting point for encouraging the sturdy feature characteristics of the input. In this research, a shallow, deep neural structure called PrimeNet is proposed. PrimeNet is aimed to dynamically identify and encourage the quality visual indicators from the input to be used by the subsequent deep network layers and increase the gradient signals in the lower stages of the training pipeline. In addition to this, the layerwise training is performed with the help of locally generated errors which means the gradient is not backpropagated to previous layers, and the hidden layer weights are updated during the forward pass, making this structure a backpropagation free variant. PrimeNet has obtained state-of-the-art results on various image datasets, attaining the dual objective of (1) compact dynamic deep neural structure, which (2) eliminates the problem of backwards-locking. The PrimeNet unit is proposed as an alternative to traditional convolution and dense blocks for faster and memory-efficient training, outperforming previously reported results aimed at adaptive methods for parallel and multilayer deep neural systems.

Keywords: Deep neural structures; Deep learning; CNN; DNN; Dynamic training

1. Introduction

This decade has witnessed a remarkable reclaim of artificial neural structures in various forms of deep learning techniques. The evolving robust computing infrastructure efficiently leveraged the designs of bigger deep neural models on new larger datasets. The inculcation of new ideas in algorithms and complex neural structures in different domains has also contributed to high-quality image and vision results. The quest to build deep neural-based intelligent machines has reached the IoT and AI enabled light infrastructured interconnected devices, portable machines, and embedded systems. To devise efficient algorithms, eventually seeking minimal power and memory usage for such devices become an essential design paradigm.

¹ It is argued that the generalized linear models (GLM) like convolutional filters in convolutional neural networks (CNNs) have inadequate feature abstraction capability [1,2] because it assumes that the

¹ Keras implementation of PrimeNet is available at github: [PrimeNet](#)

latent concepts for the underlying sliding data patches are linearly separable. There could be a possible improvement by replacing the linear approximators with a multilayer perceptron (MLP) structure [3]. MLP structure is the universal function approximator that is also trainable by the backpropagation technique. Classically, backpropagation, in a typical deep neural-based classification scenario, is a way to inform the subsequent layers to adjust the weights to reduce the error, which is approximated by global loss functions. Intermediate layers carry a vast memory overhead during the forward and backpropagation phase. Weights cannot be updated until the forward, and backward phases are completed. This issue of backwards-locking restricts the parallelization and simultaneous update of the weight parameters[4].

Combining these two issues, we ought to refine the existing multilayer neural structures to encourage potentially the most vital visual indicators from the depths of the model and alleviate the problem of the backwards-locking loop using local loss update for a compact and faster training design outcome. The proposed method leverages upon the classical benefits of multiscale visual information abstraction. It also allows the broader deep neural structures with the increased number of units at each stage without demanding additional computational resources.

In this paper, we presented a dynamic MLP structure called PrimeNet. PrimeNet dynamically determines the layerwise local loss and relays only the layer configuration which has incurred a minimum loss. We argue that dynamic tracking of locally generated errors and operating over minimum loss in a multilayer structure organization will automatically relieve the necessity of higher depths to propagate gradients back through all the layers effectively. This research presents an advanced neural architecture combined with a more effective training method following the adaptive inference mechanism. The overall contributions of this work could be summarized as:

- A backwards-locking free novel dynamic MLP structure 'PrimeNet' is proposed to encourage the most vital distinctive attributes within highly correlated multiscale activations.
- PrimeNet builds a localized learning strategy to train the weight layers with locally generated errors.
- To avoid extreme compression of the information passing through PrimeNet and to avoid correlated regions concentrating in local regions, a summarized local translation-invariant features projection is utilized in this research.

PrimeNet has been trained and evaluated with different standard datasets and has obtained competitive results. The proposed 'PrimeNet' can reduce the computational complexities while retaining state-of-the-art results. The superior image classification performance and the result visualizations demonstrate that the backpropagation free variant of a complex deep neural structure is efficient and valuable for computationally constrained tasks.

The rest of the paper is organized as follows: Section 2 presents the most relevant research contributions in the category of adaptive and conditional neural computing. Section 3 discusses the methods. Section 4 presents the experiment and results and section 5 presents the component analysis. Finally, in section 6, the research is concluded with some suggested future work.

2. Relevant work

In our proposed work, an advanced complex deep neural structure is designed to enhance feature selection. Also, an adaptive inference technique with a local loss update procedure is incorporated to make it a backpropagation free version. Before the concoction of the proposed design, we meticulously reviewed several recent research contributions in different related categories as follows:

2.1. Conditional Computation

Conditional computation, also known as adaptive inference, has gained attention recently due to its compatibility, ease of use and high-performance advantages. Adaptive inference aims at achieving efficient dynamic computational resource allocation by strategically invoking lighter or complex deep

neural units depending on input [5–18]. Zhichao Li [12] has presented an extension work of *Recurrent Visual Attention Model* by Mnih et al [19] and proposed a *dynamic computational time model (DT-RAM)* to speed up the overall processing time. Rather than attention to a finite number of steps, they added one extra binary action, which dynamically decides to *continue/stop* for each input image. In DT-RAM, initially a pre-trained *Recurrent Attentional Model (RAM)* is utilized, and later it is fine-tuned with REINFORCE. The RAM model defines that every input has a corresponding attention measure. The internal state of local regions is computed and updated with a recurrent neural network over each previous time step. The model then computes over two branches which are location network and classification network. The location network models the attention policy and samples the attention location based on the learnt policy. Classification network computes simply classification score. IN DT-RAM, as an extension of RAM, a stopping network operation is introduced, which simply decides that when it should stop taking more 'attentions' and output results as an early exit. Since the intermediate supervision at every time-step is required to output the classification score, the loss is defined as average cross-entropy over N training samples and $T(n)$ time steps.

MSDNet [18] also Proposed a progressively updating deep learning model. They combined the convolutional and dense network so that the intermediate classifiers maximally and efficiently use the computation resource. They utilized the combined fine and coarse level features at two different scales to retain high-quality classification performance in the early stages. To update the losses between these intermediate classifiers, they targeted minimizing the weighted cumulative loss.

Li et al. [17] designed their adaptive inference model by setting up multiple intermediate classifiers (Multiple exits) and settling these early classifiers' gradient conflicts by introducing *Gradient Equilibrium* technique. To enhance the information sharing and collaboration between these classifiers, they also introduced *Inline Subnetwork Collaboration (ISC)* and *One-for-all Knowledge Distillation (OFA)* techniques. The multi-exit simple classifiers had the responsibility to learn discriminative features for themselves and maintain information to pass to complex classifiers at later stages. Here MSDNet [18] has calculated the weighted cumulative loss of all the intermediate classifiers and minimized it. In Li's [17] inference model, intermediate classifiers have the overlapping arrangement and the loss minimization strategy by MSDNet [18] may create an issue of *gradient imbalance* due to its overlapping model structure. To handle the issue of gradient balancing, they introduced *Gradient Equilibrium (GE)* method which normalizes the gradients by a two-level scaling method. With their *Inline Subnetwork Collaboration (ISC)* they attempted to collaborate between intermediate adjacent classifier by adding a *knowledge transfer path* function to promote forward knowledge transfer. In this stage, the early intermediate classifiers help to boost the performance of the latter classifiers. Similarly, the deepest classifiers at the farthest end help increase the learning of shallow classifiers in the *Backward Knowledge Transfer* approach.

The discussed conditional computation based research works have overall shown the strength and utility of shallow, intermediate classifiers. Zhichao Li, [12] in his proposed DT-RAM, has put a discrete decision unit on *Recurrent Visual Attention Model (RAM)*, which operates upon N training samples over n time steps for each sample, raising the computational cost of $O(n^2)$. MSDNet [18] has utilized the multiscale feature abstraction in the early stage of classification. To update the losses, they considered backpropagating the gradients to minimize the overall weighted cumulative loss. Backpropagation has always been considered a more computationally spendthrift procedure than the forward-propagation [Own Access Paper citation]. Li et al. [17] have also exploited the advantages of early and multi-exits in the form of shallow neural structures and presented sophisticated *ISC and OFA* techniques. They also relied on the backpropagation of gradients from weighted cumulative losses of several intermediate classifiers, resulting in slow training responses with added computational complexity than the standard training procedures.

2.2. Network Pruning and Distillation

Network pruning generally refers to the techniques of reducing weight parameters of a deep neural network. With similar objectives of adaptive inference, neural pruning techniques also tries to

minimize the computational complexities in dynamic deep neural decision surface without reducing the classification performance.[7,20–25]. While preserving the full network capacity Ji Lin [7] presented an input dependent adaptive layerwise pruning strategy. Markovian decision agent judges the convolution kernel's importance and performs channel-wise pruning for each input sample. Easy inputs are recognized by shallower (more pruned) networks, while full capacity could be utilized for complex input samples. Training is performed using reinforced learning. In another research, He et al. [20] indicated that the weight pruning models are unstructured and hence does not save much computational cost whereas, filter pruning is advocated in their research. Instead of layerwise hard pruning of filters, [20] suggested Soft Filter Pruning (SFP) in which filters are deactivated, and they named it 'soft pruning'. These deactivated (dynamically pruned) filters have the advantage that they are updated during training epochs and compete in the next iteration for their inclusion due to the soft pruned existence. The model preserves full capacity but operates on compressed deep CNN. Moreover, pruning is performed all at once in the model, which is another advantage from slower layerwise pruning. However, to update the weights during training, the global loss update procedure is again proven to be computationally expensive.

2.3. Knowledge Distillation

Our proposed method can also be aligned with knowledge distillation techniques. The ensemble model designed by Li et al. [17] have used a cascade arrangement of shallow and deep network models. They ensembled the specialist shallow and generalist full-networks to collaborate and share the knowledge. Generalist models supervise the learning of specialist networks with their knowledge (output). Our research proposes a knowledge distillation process within a deep neural structure that we named as PrimeNet.

2.4. Discussion

With this discussion, we intend to converge and highlight the salient points in our proposed research. The main focus of our research is to amalgamate the proven concepts of deep neural advances to their lowest unit level. To perform this, we devised a multiscale deep neural structure named as PrimeNet. From the studies, we inferred that advanced deep neural structures could easily replace the traditional convolution layer without much performance penalty. We also extended the knowledge distillation strategy [26,27] in our research by distilling and including the most promising visual indicators in training while soft pruning the sparsed ones. The backpropagation is proven to be costlier [self reference] than forward-propagation, and hence we introduced layerwise local loss update procedure to our proposed PrimeNet algorithm to further reduce the computational complexity.

We performed extensive experiments on MNIST, CIFAR-10, and SVHN datasets to evaluate the validity and effectiveness of the proposed method.

3. Method

The convolution architectures are proven for higher performance on image classification at lower computational penalties, and hence we preferred to use convolution architecture for our proposed network structure design. We implemented PrimeNet as a backpropagation-free version of the convolution block as a custom layer. PrimeNet is the advanced multiscale micro-network block that implements the soft pruning of entire layer parameters using adaptive inference on local loss. We also presented the mechanism to work with standard convolution blocks (ResNet variants) or layers to present robust generalized convolution operations with local loss. Both layers are backpropagation free and update their weights locally.

3.1. Local loss computation

To compute the local loss, we measure the cross-entropy between the local classifier predictions and the target. Our PrimeNet design has four intermediate classifiers that will separately predict the

output and compute the loss for the same one-hot-encoded target. We represent *local loss* as L_{local} , this can be defined as given below:

$$L_{local} = CE(y_i, f(x_i; \theta)) \quad (1)$$

where Y_i is the one-hot-encoded target and $f(x_i; \theta)$ is a result of the previous activation. We flattened the feature maps and applied soft-max activation to obtain the local loss in PrimeNet. To perform backpropagation free, layerwise training, we detached the computation graph to stop the gradient flow. Weights are updated using the cross-entropy loss function. ADAM [28] optimizer is used with β set to 0.99.

3.2. Convolution with local loss

Our proposed PrimeNet is a multiscale, backwards-locking free, adaptive inference neural structure. PrimeNet can be used with other traditional convolution layers, but the standard convolution and hidden layer weights are updated by sending the gradients back to the previous layers through the backpropagation process, and PrimeNet updates the weights layerwise. To facilitate the end-to-end backpropagation free convolution operation in PrimeNet, we customized and used a standard convolution layer enabled with inline layerwise training.[4].

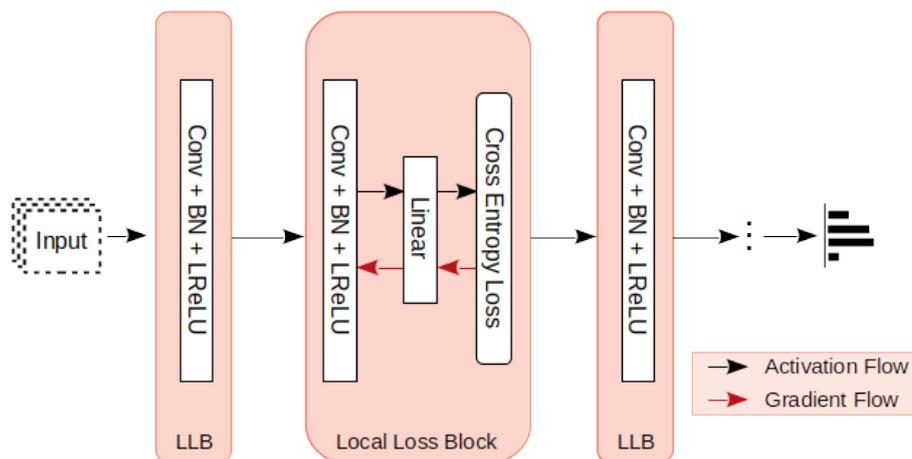


Figure 1. The backward-locking free, custom convolution block that updates the layer-wise local loss instead of sending the gradients back through backpropagation. Redrawn from figure source [4]

Each layer respective to each feature scale in PrimeNet block is constituted with this custom convolution operation enabled with local loss update. The $CONV \rightarrow BN \rightarrow LReLU \rightarrow FC \rightarrow SOFTMAX$ layer sequence is followed in order to compute the local loss.

3.3. Primenet

In the proposed Primenet framework, the shallow, deep learning structures work as a catalyst in the overall learning of the primary discriminative network. The capsule-like shallow structures present multiscale feature representations, and the dynamic selection logic encourages the representations with immediate minimum local loss. The learned feature representation is dynamically added to the secondary classifier network, which benefits the model into faster convergence. To design the PrimeNet block, we first set up the conditional computation model with multiple intermediate classifiers. Each classifier in this arrangement operates on a different feature scale. The shallow *Local Loss Block* layer order ($CONV \rightarrow BN \rightarrow LReLU \rightarrow FC \rightarrow SOFTMAX$) from Figure 1 is followed to compute local loss from each intermediate classifier.

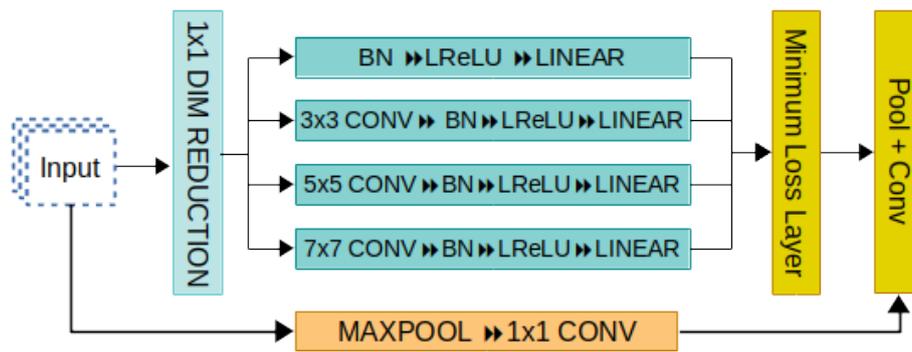


Figure 2. Proposed PrimeNet architecture. Multi-scale micro-network operates to perform intermediate classifications. Local loss is computed for each scale convolution and the adaptive convolution is performed. The other layers with higher losses are soft pruned and their weights are locally updated.

From figure 1, it can be seen that larger filter sizes (namely 5x5 and 7x7) are used, which will result in an increased number of parameters and require more computation power. A 1x1 convolution layer is used just after the input for dimensionality reduction while retaining the salient features from the input. The memory and computational savings by dimensionality reduction allowed us to use a 3x3 projection further to pool features across the channels and increase feature maps. The convolution layer feature maps are sensitive to the location of the features in the input. Moreover, there may be chances that the loss-based conditional computation may always choose and concentrate in a particular local region. In addition to that, the proposed multiscale feature abstraction process distills the most prominent visual indicators set, and the remaining features of the other layers are soft pruned. Sometimes, soft pruning could also result in the loss of essential features. The projection layer reduces the effect of extreme compression by soft pruning and presents a normalized local translation invariant feature presentation of the same input.

We set up our conditional computation block as a primary external network which consists of *four* intermediate classifiers respective to each feature scale.

$$[y_1, y_2, y_3, y_4] = f(x; \theta) = [f_1(x; \theta_1), \dots, f_4(x; \theta_4)] \quad (2)$$

where x is the input image and $f_{(1,2,3,4)}$ and $\theta_{(1,2,3,4)}$ represents the transformation operation ($conv \rightarrow fc \rightarrow softmax$) for y_i classifier. Similarly, from equation 1, the loss function can be expanded here as,

$$L(y, f(x; \theta)) = CE[y_1(f_1(x; \theta_1)), \dots, (y_4(f_4(x; \theta_4)))] \quad (3)$$

and then after loss based adaptive inference, the next layer convolution could be written as:

$$f_{min}(x; \theta) = MIN[L(y, f(x; \theta))] \quad (4)$$

at this stage, we obtain the most prominent visual indicators, and now we will apply pool projection on the obtained convolution feature map as follows:

$$f_{next}(x; \theta) = [f_{min}(x; \theta) \frown S(x; \theta)] \quad (5)$$

where $f_{next}(x; \theta)$ is the next layer input after concatenation (\frown) of convolution output with minimum loss $f_{min}(x; \theta)$ and pool projection $S(x; \theta)$.

3.4. Feature Representation with minimum loss local structure transferring

To implement the Primenet framework, we divided the model design into two parts. In the first part, we implemented a multiscale shallow neural structure for reusable feature representation. Each shallow neural structure will learn a feature representation at a specific convolutional scale. The

simultaneous feature representations will be analyzed for minimum batch input loss. The minimum loss feature representation will be forwarded to be inculcated in the second part of the model design. The weights for each lightweight network will be updated there itself using the local loss update procedure. The secondary part of the design is a classifier that takes the selected minimum loss feature representation as input and concatenates it with the batch input projection. With this feature projection, a summarized local translation invariant feature representation is obtained. The features are flattened, and a linear representation with a softmax activation function is used to obtain classification output.

3.5. Learning Algorithm

Various substantial implementation settings have been studied to design the learning algorithm, which primarily includes non-linear model topologies, shared input, and multiple model inputs and outputs. Typically, a deep learning model is a compound directed acyclic graph (DAG) structure of different layers. An extension to DAG is to build graphs of layers. In our training routine, the proposed deep learning structure runs multiple instances non-linearly and shares the input. We reused the unit architecture and its weights by running the multiple instances of the proposed PrimeNet structure. Further, to learn from the local multiscale representations (PrimeNet instances) and transfer the encoding for final classification, our iterative training strategy chains the dynamically selected Primenet output with the classification model. In the first part, we trained the batch input through the proposed PrimeNet network block and obtained the local representation for local loss computation. After computation of the local loss, we compared the PrimeNet for minimum loss and transferred the PrimeNet instance's convoluted output to the classifier block. In the classifier part of the training, the selected convoluted output from the PRIMENet is concatenated with input feature projection. The input feature projection presents a local translation-invariant version of the input, which further balances the domination of correlated regions in overall feature representation. The rest of the classifier block is designed as a simple convolutional network that facilitates a swift classification of dynamically learned feature representations.

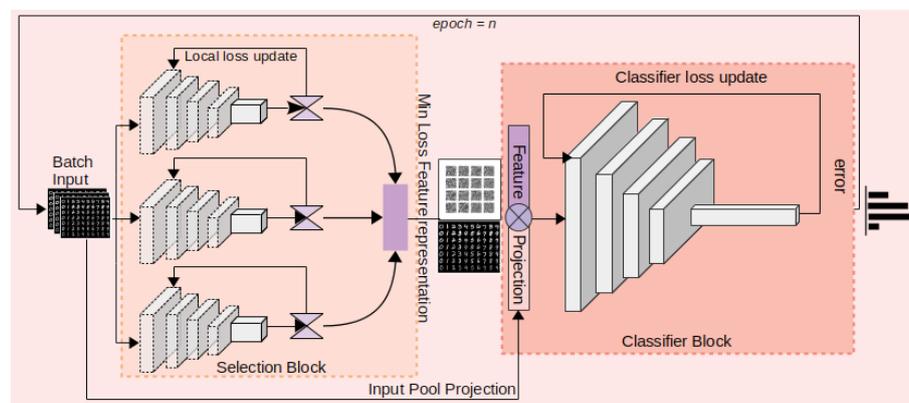


Figure 3. PrimeNet training flow. The shallow network inside the selection block convolve at different scale and the batch-wise loss is calculated and gradients are updated locally. The feature representation with minimum loss is forwarded as an input to the classifier and classification is performed on locally learned feature representation.

4. Experiments and Results

Our experiments present the Primenet as a shallow multiscale neural structure mainly for obtaining the prime discriminative characteristics from the input. We also present the backpropagation free layerwise gradient update procedure within PrimeNet, which combines with the other traditional layers and allows the weight update alternatively with the traditional backpropagation method. To evaluate the performance of the representation learning algorithm, we used PrimeNet as a feature extractor on various benchmarked datasets and evaluate the performance of linear models fitted on

top of these features. Moreover, we visualize and compare the feature representations generated by PrimeNet and ResNet models using t-Distributed Stochastic Neighbor Embedding (t-SNE) [29] feature visualizations. Finally, we presented the result analysis by comparing with different considered baseline performances.

4.1. Implementation Details

We utilized three simultaneous multiscale capsule-like networks in the initial step by following the structure from figure 1 ($Conv \rightarrow BN \rightarrow LReLU \rightarrow Flatten \rightarrow Dense$). For every iteration, one input batch is fed as an input to these shallow capsules. These small networks are trained with batch input, and we extract the feature representation occurring minimum loss from the convolved output of the same capsule. The selected feature representation is concatenated with input feature projection. The projection function $S(x; \theta)$ in equation 5 is implemented as $maxpool2D \rightarrow conv2D$ with ReLU activation function. We set the maximum iteration for 100 epochs in the training phase and use a mini-batch of size 200. For fine-tuning and evaluation, we use 50 iterations and a reduced batch size of 32. Moreover, we use the Adam optimizer with a default learning rate of 0.0002 with a beta value of 0.99. To recreate and compare with baseline ResNet50 and other SOTA models for computational results, we reshaped the MNIST input into three dimensions as per the experimental requirement. No data augmentation is used in PrimeNet experiments for any of the three datasets.

4.2. Experimental Setup

We selected three datasets for our experiments which includes MNIST, CIFAR-10 and SVHN. A brief description of the datasets is in the following table (table 1).

Table 1. Summary of the datasets used for the experiments.

Dataset	Input Size	No. of Classes	Train Size	Test Size
MNIST	28x28x1	10	60,000	10,000
CIFAR-10	32x32x3	10	50,000	10,000
SVHN	32x32x3	10	73,257	26032

4.3. Results

Table 2 presents the top-1 error rate performances of different state-of-the-art network models in the category of three related techniques, comparing with the proposed Primenet learning algorithm. For the MNIST digits dataset, Primenet has obtained a record performance surpassing all the results from considered baselines. MNIST is assumed to be too easy, but it is our first choice to test our algorithm because if an algorithm fails on MNIST, it is likely to fail on other tests. To further evaluate the performance of the proposed algorithm, we tested it on the Street View House Number (SVHN) dataset. With SVHN, the Primenet has obtained an acceptable performance close to the considered state-of-the-art method. We also evaluated our algorithm on the cifar-10 dataset for more generalized observations.

Table 2. Comparison of classification error rate on evaluation model. (%)

Dataset	PrimeNet Test Error (%)	Model	Baseline Error (%)	Baseline Technique
MNIST	0.58	DT-RAM [12]	1.46, 1.12	Conditional Computation
		Condensenet [18]	3.46, 3.76	Conditional Computation
		ITADN [17]	5.9	Conditional Computation
CIFAR-10	6.21	RNP [7]	15.05	Network Pruning
		SFP [20]	7.74, 6.32	Network Pruning
		ITADN [17]	3.13, 5.99	Knowledge Distillation
		ONE [26]	1.63	Knowledge Distillation
SVHN	1.71	ONE [26]	1.63	Knowledge Distillation

The observations are: (1) The proposed Primenet structure acts as a helper network for obtaining the prime visual indicators from the input and is most suitably applicable in early convolution stages. PrimeNet is helpful to reduce the size of large deep networks with lesser weight adjustment operations. (2) The Primenet is an independent adaptive deep neural structure with its own backpropagation free gradient update technique. PrimeNet infers that the complex deep neural networks can comprise a backwards-locking free mechanism to further reduce computational complexities. (3) The experiments also suggest that the standard convolutional layers can be easily combined with Primenet.

4.4. Computational Analysis

While achieving the state-of-the-art results, we have significant gains on the computational efficiency of the proposed algorithm. To evaluate the computational efficiency, we have considered and compared three key characteristics from each model. The considered characteristics are (i) number of FLOPs (floating-point operations.), (ii) model parameters and (iii) memory requirement.

Table 3. Summary of the computational results for MNIST, CIFAR-10 and SVHN experiments.

Model	Dataset	Params (Millions)	FLOPs (Millions)	epochs
ResNet[30]	All Three	23.6	409	50
PrimeNet (Ours)	All Three	0.41	2.7	100+50
Condensenet ^{light} [18]	CIFAR-10	0.33	122	300
Condensenet86 [18]	CIFAR-10	0.52	65	300
ONE [26]	SVHN	0.5	2.28	300, 40

Table 3² presents the computational gains achieved by PrimeNet and compares them with different considered baseline results depending on the information available in the original paper. The majority of related research results are obtained using ResNet architecture as a base model, so we also considered ResNet50 computational results as the first baseline to be compared. ResNet50 with pre-trained Imagenet weights has been recreated for our task data classifier with the same settings for each experiment.

Here, we have considered the combined computational information from the shallow dynamic deep neural structure and its classifier for computational analysis. Hence, the number of epochs for our algorithm is 100+50, which means 100 iterations for classifier network using shallow Primenet structure. Once the learned feature representation is extracted from the classifier, another 50 epochs are used for retraining. ResNet is trained for 50 epochs for the same purpose, and other baselines take 300 minimum epochs. Since we have used the same architecture for Primenet and ResNet baseline, we obtained the same number of parameters and FLOPs for all datasets. ResNet is one sizeable deep network that involves the highest computational cost. ONE [26] has produced the computational information for the experiment on SVHN, which has a precise, reduced number of FLOPs, whereas PrimeNet is just 15% more costlier, but on the other side, Primenet can reduce to number of parameters by 18%. Similarly for Cifar-10, Condensenet^{light} [18] can reduce the parameter size by 20% from PrimeNet, but PrimeNet has a tremendous gain of almost 99% reduced number of FLOPs. For another Condensenet experiment on the same dataset, PrimeNet has obtained almost 20% parameters and 95% FLOPs gain. Thus, the experiments suggest the proposed method's efficacy in various computational and classification performance categories.

5. Ablation Study

We perform an ablation study on MNIST data in which we investigate (1) the simultaneous local gradient updates from each Primenet instance with the effect of dynamic selection on the classifier

² Tensorflow or Keras model's computational information is obtained using model profiler function available at [model-profiler](https://github.com/GoogleCloudPlatform/ml-profiler).

network and (2) the quality of resultant features extracted from the classifier network to be used for evaluation and compared it with the ResNet50 feature visualization.

5.1. Local gradient update

The local gradient update strategy is simple and straight forward. The capsule-like instances are capable of computing the layerwise loss. Since these tiny networks are decoupled from the training loop, the layer-loss is computed locally as described in equation 3. Figure 4 presents a qualitative results for a single input instance.

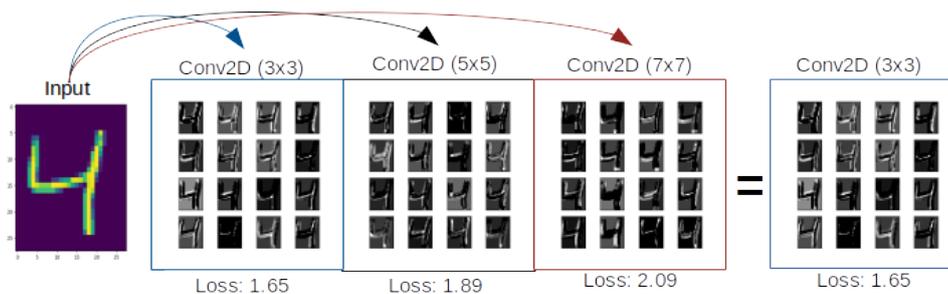


Figure 4. Qualitative output and dynamic selection strategy for capsule-like shallow networks.

In the training phase, we visualized the gradient updates by recording the loss values of each capsule in each iteration along with the resulting classifier's total loss value. The total loss of the classifier is the dynamically selected capsule loss added with the classifier's loss Figure 5. With this result, one can see the gradual loss update from all the intermediate capsule-like networks and their cumulative effect on the classifier model.

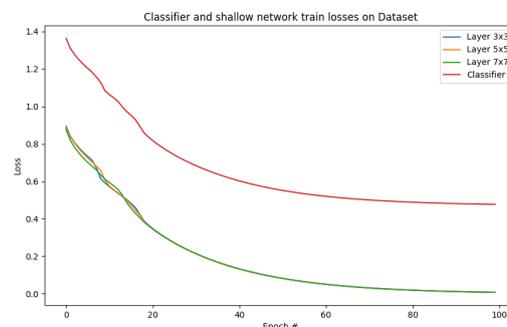
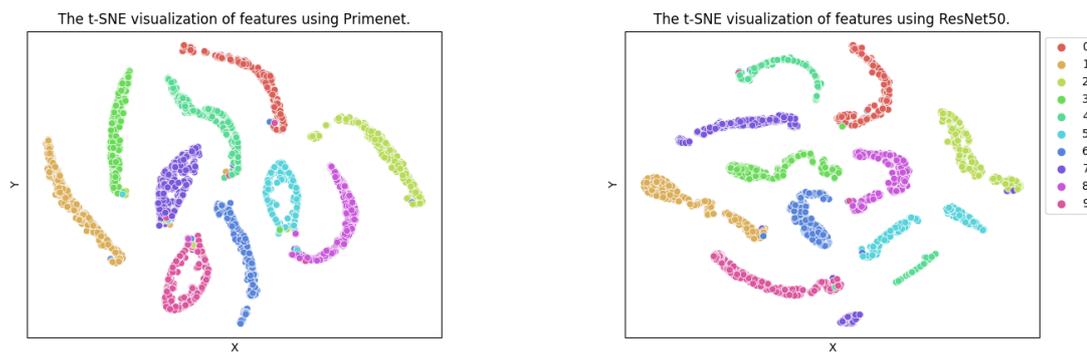


Figure 5. visualization of local gradient updates from shallow and classifier networks.

5.2. Adaptive cost-conscious Local structure transfer

To exhibit the efficiency of the cost-conscious local structure transfer technique, we extracted learned feature representations by proposed Primenet. We extracted the trained representation of the features and performed clustering using t-SNE visualization, then compared it with the ResNet50 baseline. From figure 6, this can be observed that the extracted feature representation using Primenet has more clear cluster margins than the ResNet features, proving that it could lead models to converge faster and obtain promising classification test results.

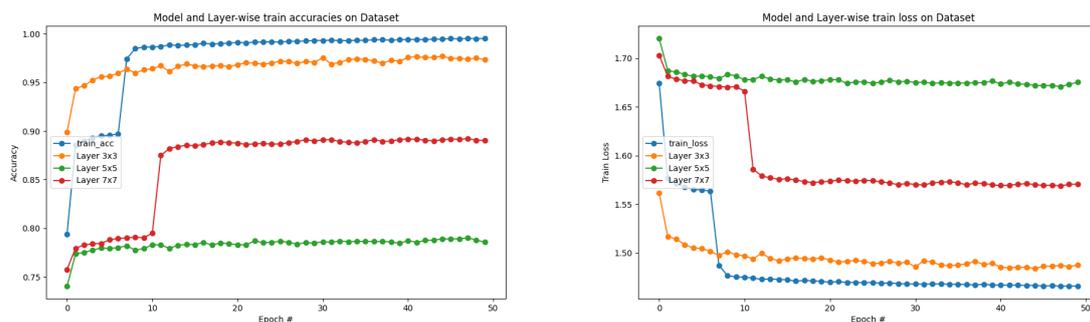


(a) Proposed Primenet feature visualization.

(b) Resnet feature visualization.

Figure 6. The t-SNE visualization of features from image representations by proposed Primenet (a) and ResNet50 (b).

Figure 6 also presents the impact of our adaptive convolution selection strategy over the linear convolution neural networks. The classifiers with standard convolution layers are presented with labels *Layer 3x3*, *Layer 5x5*, *Layer 7x7* and the evaluation model's loss is presented with label *train_acc* and *train_loss*.



(a) Train accuracies.

(b) Train losses.

Figure 7. Figure (a) and (b) presents the incremental model learning from the dynamically selected feature representations as a result of fine tuning on top of the classifier. Linear classifier network (simple convolutional) losses and accuracies are also presented to demonstrate the difference in performance.

Figure 6 also reflects the learned feature representation extracted from the secondary classifier, which helped faster convergence in fewer epochs (less than 10).

6. Conclusion

In this research, we introduced an adaptable deep neural structure called PrimeNet. Primenet is an efficient convolutional neural network design that encourages strong visual indicators and reuse of the same via backpropagation free convolutional layers. With its learned multiple multiscale convolutions, it attempts to soft prune the filters with less useful features. The simplistic adaptive and cost-conscious local structure transfer technique can reduce the overall computational cost of the models while retaining the latest SOTA performance. Due to its simple implementation, the Primenet structure is proven to replace traditional convolutional layers, combining the local or global gradient update methods. There are certain suggested future directions in which we would like to extend this research. (1) The PrimeNet can headway complex modules as layers like Inception, Attention or Residual modules. (2) PrimeNet can lead to find several other conditional computing operations in different applications.

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