Quantitative Analysis of Image Classification Techniques for Memory-Constrained Devices

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Abstract
Convolutional Neural Networks, or CNNs, are undoubtedly the state of the art for image classification. However, they typically come with the cost of a large memory footprint. Recently, there has been significant progress in the field of image classification on memory-constrained devices, such as Arduino Unos, with novel contributions like the ProtoNN, Bonsai and FastGRNN models. These methods have been shown to perform excellently on tasks such as speech recognition or optical character recognition using MNIST, but their potential on more complex, multi-channel and multi-class image classification has yet to be determined. This paper presents a comprehensive analysis that shows that even in memory-constrained environments, CNNs implemented memory-optimally using Direct Convolutions outperform ProtoNN, Bonsai and FastGRNN models on 3-channel image classification using CIFAR-10. For our analysis, we propose new methods of adjusting the FastGRNN model to work with multi-channel images and then evaluate each algorithm with a memory size budget of 8KB, 16KB, 32KB, 64KB and 128KB to show quantitatively that CNNs are still state-of-the-art in image classification, even when memory size is constrained.

1. Introduction
Image classification is a task which comes with several innate challenges: occlusion, intra-class variability, varying lighting conditions and, more recently, adversarial examples form only the start of a long list of problems which need to be overcome. Significant progress has been made towards solving this open problem via deep learning, in particular in the form of Convolutional Neural Networks, or CNNs (Krizhevsky et al., 2012), but the field has increasingly come to rely on training huge models to obtain state-of-the-art performance (Simonyan & Zisserman, 2015). This means that when carrying out image classification on memory-constrained devices such as surveillance cameras, one is left with little option but to offload the inference to a data centre. Such offloading has an effect on the overall system cost (Yu et al., 2017) and as a result there has been a recent push towards developing methods which can carry out inference locally on the embedded devices (Li et al., 2018). Although many of these methods have been applied to simple image recognition tasks such as optical character recognition, they have, to our knowledge, not yet been applied to a task as complex, relative to the available memory, as 3-channel CIFAR-10 image classification. In this paper, we contribute an analysis of how the state-of-the-art methods for machine learning on the memory-constrained devices compare on this data set. We also contribute a novel architecture for multi-channel image classification, called Multi-FastGRNN.

The move towards carrying out inference on the embedded devices directly has been motivated by several factors. First of all, the matter of privacy has received significant attention in the popular press in recent years (Viega & Thompson, 2012). Secondly, 5G internet connectivity, which would offer greater reliability and stability to the inter-device communication, has recently faced major resistance due to concerns regarding involvement from foreign powers (Bowler, 2020) and potential impacts on human health (e.g. The Brussels Times 2020). Finally, some argue that minimising external communication can maximise battery life whilst potentially also reducing latency, given appropriate hardware (Norman, 2019).

Constructing models with memory size in mind has lead to various diverse streams of research and the applications targeted in these works have been equally diverse. As far as image classification goes, experimental results have thus far been centred around the MNIST data set (Lecun et al., 1998). This data set consists of \(8 \times 8\) single-channel images containing handwritten digits (0-9). As each image only takes up \(8 \times 8 \times 1 = 64\) bytes, with 1 byte per pixel, it leaves a majority of the memory available to the model even when memory is very constrained. However, in the present day the usefulness of this data set is becoming increasingly limited, due to three reasons:

- Users are increasingly expecting even embedded devices to be capable of carrying out tasks significantly more complicated than black-on-white low-resolution digit recognition.

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Recent works are starting to reach saturating levels of performance, i.e. above 99% test set accuracy (Gural & Murmann, 2019).

The single-channel nature of the dataset may bias the state of the art towards methods which may not generalize well when the input images consist of several channels, e.g. coloured images in RGB or HSV encoding.

Motivated by this insight, this paper instead sets out to compare the state-of-the-art methods from the present literature on a significantly more challenging task: the CIFAR-10 data set (Krizhevsky, 2009), discussed in detail in Section 3. To make the scope of the paper tractable, we limit our resource constraints to memory, rather than latency or energy efficiency, and carry out analysis when the methods are allowed to use up to 8KB, 16KB, 32KB, 64KB and 128KB of memory. We introduce the specific methods, which we have identified as forming the state of the art, in the following section.

2. Literature review

In this section, we introduce the recent models from the literature which we set out to analyse in this project, all chosen as the state-of-the-art for their respective approaches.

We will discuss Direct Convolutions as the state-of-the-art CNN approach to memory constrained image classification (Gural & Murmann, 2019), ProtoNN as a method to reduce memory requirements of a k-NN model (Gupta et al., 2017), Bonsai as a decision-tree based model (Kumar et al., 2017) and finally FastGRNN, a state-of-the-art tiny RNN model (Kusupati et al., 2018).

2.1. Direct Convolutions

The Direct Convolution neural network proposed by Gural & Murmann 2019 is a method which significantly reduces the memory overhead of using Convolutional Neural Networks through clever re-use of memory. Memory used to store the pixels of an input feature map is progressively replaced with the activations of the layer as the inputs become stale, i.e. all activations depending on the input pixel have been computed (Gural & Murmann, 2019).

Though deceptively simple, this method is made significantly more complicated when a layer increases the channel depth: that is, when the number of channels in the input is strictly less than that in the output. In such scenarios, naively processing the pixels in row-major order would cause the memory to be freed in a manner which fragments it and makes it difficult to store the output activations (Gural & Murmann, 2019). To deal with this case, Gural & Murmann 2019 propose a herringbone strategy where the pixels are traversed in alternating row- and column-major order, which provably uses the minimal amount of extra space (Gural & Murmann, 2019).

As of writing, this method holds the current record performance (99.15% test accuracy) on 10-class MNIST classification for models with memory footprints on the order of kilobytes, and it does so with a model of only 2KB of memory (Gural & Murmann, 2019). However, Gural & Murmann 2019 do not present results for any data set other than MNIST.

2.2. ProtoNN

A different approach to object recognition on resource-scarce systems is given in Gupta et al. 2017. This paper introduces the ProtoNN algorithm, which takes inspiration from the familiar k-Nearest-Neighbours method (described amongst other places in Mucherino et al. 2009). Operating analogously to k-NN for inference, i.e. assigning a data point to a class based on the most frequent class of its nearest neighbours, ProtoNN distinguishes itself by requiring several orders of magnitude less space and time. This is achieved by learning a small set of informative prototype datapoints to compare against at time of inference, along with a sparse projection onto low-dimensional space (Gupta et al., 2017).

Compared to Direct Convolutions (Gural & Murmann, 2019), ProtoNN achieves a less impressive 95.88% accuracy on 10-class MNIST classification and requires 64KB of memory to do so (Gupta et al., 2017). However, unlike Gural & Murmann 2019, Gupta et al. 2017 compare ProtoNN against a wider range of data sets, including a 2-class version of CIFAR on which they achieve 76.35% accuracy at 16KB. As such, there is more evidence that it will obtain comparable performance in a wider range of tasks.

2.3. Bonsai

Kumar et al. 2017 propose a decision-tree based algorithm for resource-constrained machine learning which they dub Bonsai, which along with learning a non-linear tree also learns a low-dimensional projection matrix. The model size is kept small by training a single tree rather than an entire forest on the low-dimensional projected data and by making sure that the learned projection matrix is sparse (Kumar et al., 2017).

Though the authors carry out experiments targeting several data sets, the results are mainly compared to those of pruned version of large networks, rather than architectures which directly target the resource-constrained systems. Though it may have been state-of-the-art at the time of its publication, Bonsai’s 97.01% 10-class MNIST test set accuracy at 84KB (Kumar et al., 2017) is now outperformed by Direct Convolutions (Gural & Murmann, 2019).

Like Gupta et al. 2017 did with ProtoNN, Kumar et al. 2017 carry out more varied experiments than just 10-class MNIST classification with Bonsai. One result Kumar et al. 2017 obtain is 73.02% accuracy on the 2-class version of CIFAR by only using up 2KB of memory; at 16KB it reaches 76.64%, just about beating out ProtoNN (Gupta et al., 2017). As such, we believe Bonsai to still be an interesting contender in the memory-constrained image classification space.
10,000 for testing. The training images are split into five 10-class MNIST (Kusupati et al., 2018). As such, it makes sense that the model is able to accurately capture the wake word “Hey Cortana” with a model size of only 1KB (Kusupati et al., 2018).

Somewhat surprisingly, Kusupati et al. 2018 also find that FastGRNN is apt at image recognition, achieving 98.20% accuracy with a 6KB model on a pixel-by-pixel version of 10-class MNIST (Kusupati et al., 2018). As such, it makes for an interesting contender in our analysis.

2.4. FastGRNN

FastGRNN is a gated recurrent neural network proposed in Kusupati et al. 2018. As an RNN, its primary focus is on handling sequential data, such as speech. Indeed, one of the most impressive results of the paper is that the model is able to accurately capture the wake word “Hey Cortana” with a model size of only 1KB (Kusupati et al., 2018).

In either of these cases the dimensionality of the feature space is either small (MNIST has 28 × 28 single-channel images) or the number of target classes is low. For our analysis, we therefore choose the CIFAR-10 data set, as we argue that it is more complex. Additionally, it allows us to establish a new benchmark for the models described in Section 2.

The CIFAR-10 data set consists of 60,000 32×32 3-channel colour images, divided into 10 classes such as airplane, automobile and dog (Krizhevsky, 2009). CIFAR-10 comes split into 50,000 images for training and 10,000 for testing. The training images are split into five training batches of 10,000 images each and the test images are kept in one test batch of 10,000 images (Krizhevsky, 2009). The test batch is balanced with respect to the 10 classes, featuring 1,000 randomly-selected images from each class, but the five training batches may be unbalanced (Krizhevsky, 2009). However, together the training batches contain exactly 5,000 images from each class (Krizhevsky, 2009).

The task for which we will be training the models described in Section 2 is 3-channel image classification, comparing each model by its test set accuracy. We also examine Direct Convolution (Gural & Murmann, 2019) and FastGRNN (Kusupati et al., 2018) on a version which has been grey-scaled using the luminosity formula (Cook, 2009), for reasons which are detailed in Section 4.4. However, we have purposefully decided against any other augmenting or pre-processing of the CIFAR-10 data set, as we want to keep the number of variable elements in our experiments to a minimum to achieve a fair comparison of the methods.

4. Methodology

In this section we will detail the experimental setup for each model introduced in Section 2. Since the models we are comparing in this analysis differ wildly in what hyper-parameters they expose, we introduce each of the methods in more detail to motivate our experiments detailed in Section 1. As explained in Section 1 we will compare the models in groups based on their model size, which we will constrain to 8KB, 16KB, 32KB, 64KB or 128KB.

4.1. Direct Convolutions

As outlined in Section 2.1, Direct Convolutions is a protocol implementing CNNs memory-optimally (Gural & Murmann, 2019). The main result in Gural & Murmann 2019, which introduced this method, was a 99.15% classification accuracy on the single-channel images of the 10-class MNIST data set. We will seek to extend these results to the 3-channel images of the CIFAR-10 data set (Krizhevsky, 2009).

In order to obtain 99.15% classification accuracy on 10-class MNIST, Gural & Murmann 2019 performed a sampling-based neural architecture search. The candidate layers for this search, their fixed parameters and the variable parameters are given in Table 1. The 16 possible combinations of these layers searched over by Gural & Murmann 2019 are given in Table 2. Given the strong performance of these models, we will also use them in an attempt to find the best models for the CIFAR-10 data set image classification for each memory size budget.

Our search starts by generating all of the possible models, i.e. all combinations of architectures and variable parameters, and then calculating the memory requirements for each. From the list of generated models, we sample 150 models in each range of memory size budget, i.e. 0-8KB, 8-16KB, etc., train these 750 models for 5 epochs each and identify the model with the best test set accuracy for each range of memory size budget. Bergstra & Bengio 2012 present empirical and theoretical evidence that randomly searching for hyper-parameters is more efficient than a guided or grid search, and thus we believe this sampling approach to be reasonable. Finally, we train the models which were identified as being the strongest contenders after 5 epochs for a full 100 epochs, using early stopping with a patience value of 3.
As introduced in Section 2.2, ProtoNN is a classification algorithm which learns a set of prototype data points which can be considered as the ‘training data’ in the normal inference procedure associated with the $k$–NN algorithm (Mucherino et al., 2009). Given that the algorithm does not assume any spacial relationship between elements of the feature vectors, single- as well as multi-channel images can be flattened out into feature vectors. In this paper, the data points will be flattened out in order of channel and then columns of that channel. To obtain the best performing model, both the dimensionality of the projected space as well as the number of prototypes to learn require tuning. We will make trade-offs between these given our imposed limitations on the memory footprint of the model.

4.3. Bonsai

As described in Section 2.3, the Bonsai models is a decision-tree based algorithm that learns a low-dimensional projection matrix alongside the decision tree itself. As such, a Bonsai model is parameterised by the depth of the decision tree and the dimensionality of the projection matrix, both integer-valued (Kumar et al., 2017). We can hence iterate, for any give depth, over the values of the dimensionality of the projection matrix until we reach a model size above our largest memory size budget of 128KB.

Since the Bonsai model takes the an entire image as a singular vector, with all channels concatenated (Kumar et al., 2017), Bonsai is already built for multi-channel images and so we run the search described above only for 3-channel CIFAR-10 images.

### Table 1. Direct Convolution candidate layers with abbreviations and their respective parameter spaces.

| Layer Abbreviation & Name | Fixed Parameters | Variable Parameters |
|---------------------------|-----------------|---------------------|
| (A) Average Pooling 2D    | $pool\_size = (2, 2)$ | - |
| (M) Maximum Pooling 2D    | $pool\_size = (2, 2)$ | - |
| (D) Dense with activation | $activation = ReLU$ | $output\_dim \in \{16, 32, 64\}$ |
| (D*) Dense without activation | $activation = None$ | $output\_dim = 10$ |
| (C1) 2D Convolutional     | $strides = (1, 1)$ | $output\_dim \in \{4, 6, 8, 10, 12, 16, 32, 64\}$ |
| (C2) Depthwise 2D Convolution | $multiplier = 1$ | $output\_dim \in \{4, 6, 8, 10, 12, 16, 32, 64\}$ |
| (Dr) Dropout              | $rate = 0.1$ | - |

Table 2. Enumeration of model architectures considered in Direct Convolution approach. See Table 1 for abbreviations. Note that $C$ denotes either $C_1$ or $C_2$.

| Direct Convolution Architectures | A, D, D, Dr, D* | A, C, M, D, Dr, D* |
|----------------------------------|----------------|--------------------|
| A, C, D, Dr, D*                  | A, C, M, C, Dr, D* |
| A, C, M, D, Dr, D*               | A, C, C, M, Dr, D* |
| A, C, M, C, Dr, D*               | A, C, M, C, D, Dr, D* |
| A, C, C, D, D*                   | A, C, C, D, Dr, D* |
| A, C, C, M, C, Dr, D*            | A, C, C, C, Dr, D* |

4.4. FastGRNN

As introduced in Section 2.4, FastGRNN is a recurrent neural network architecture which has shown surprising potential in simple image classification domains (Kusupati et al., 2018). However, to our knowledge we are the first to apply it to a domain with multi-channel images, which raises the question of how to model the input data as a time series in order to benefit from the recurrent nature of the network.

In simple single-channel images such as those found in MNIST (Lecun et al., 1998), the input data can be turned into a time series, fitting the recurrent neural network, by considering each row in the input as one data point (Kusupati et al., 2018). Multi-channel images complicate this process by introducing an implicit trade off between proximity in the time series between the same row in different channels and different rows in the same channel.

In this paper, we devote significant attention to comparing FastGRNN’s performance on the CIFAR-10 data set image classification for different modes of sequencing the input data. We hypothesise that concatenating the channels and treating the image as single-channel will not be a satisfactory solution, because doing so increases the number of
input dimensions and hence leaves us with less memory for the hidden neurons.

To combat the aforementioned issue, we propose three different methods for classifying multi-channel images with the FastGRNN architecture which share the basic assumption that each data point in the time series is one row of one channel in the input. The methods then differ in how they feed these data points into the network:

- **Row-major**: Feed the data into a single FastGRNN unit, followed by a fully-connected layer, starting first with all red rows, then all green rows and finally all blue rows. See Figure 2.

- **Channel-major**: Feed the data into a single FastGRNN unit, followed by a fully-connected layer, starting with the first red row, the first green row, the first blue row, then the second red row, the second green row and the second blue row, etc. until the last red row, the last green row, the last blue row. See Figure 3.

- **Multi-FastGRNN**: A novel architecture we propose. Feed the data into three separate FastGRNN units, one for each channel, followed by a fully-connected layer. Feed each unit with the rows of the channel corresponding to the unit, in order. See Figure 4.

For an RNN, learning features from several elements in its input sequence is strongly tied to their temporal latency, i.e. distance between them in the sequence. With the row-major method in Figure 2, we focus on features that relate the pixels in the first red row to those in the second red row and so on, where it takes time to see the next channel. With the channel-major method in Figure 3, we focus on features that relate pixels in the first rows of each channel, where it takes time to see the next row. As such there is a trade-off between setting up for intra- and inter-channel features.

Intuitively, our proposed Multi-FastGRNN architecture as seen in Figure 4 alleviates the trade-off explained above by explicitly separating the channels and training one FastGRNN unit per channel. We hypothesise this to allow each unit to learn strong, predictive features without risk of polluting the internal state with data from the other channels. By then concatenating their outputs into a fully-connected layer, we retain the ability to still learn cross-channel features.

**5. Experiments**

In this section we set up and perform experiments following the methodology outlined in the previous section. For ProtoNN, Bonsai, and the FastGRNN methods we use the versions included in the the EdgeML library (Dennis et al.), while for Direct Convolutions we base our experiments of the software provided by Gural. To ensure that the reported performance of each method is as accurate of a reflection of its potential in this space as possible, we devote significant time to individually optimising each method in our experiments.

**5.1. Direct Convolutions**

In the methodology section, a sampling based neural architecture search for this method was outlined. This search will be applied to two different datasets, the standard CIFAR-10 dataset and the grey-scaled CIFAR-10 dataset which was derived using the luminosity formula (Cook, 2009). The best models after 5 epoch in terms of test set accuracy are given in Table 3 and the final results, after full training of these models, is given in Table 6. For optimization of the weights we used the Adam optimizer (Kingma & Ba, 2014) with initial learning rate 0.01; no thought was paid to optimizing this value, given that it is impossible to calculate this value a priori (Reed & Marks, 1998).

**5.2. ProtoNN**

To train ProtoNN models with less than 128KB of memory size, we perform a grid search over the hyper-parameters that define the number of prototypes and dimensionality...
As Section 4.3 described, we have a discrete search space for the depth and the dimensionality of projection matrix that parameterise a Bonsai model. We start by sampling Bonsai models going over a grid of depths ranging from 0 to 5 and dimensionality of projection matrix of 5, 10, 20 and 30 to understand the search space. These values are based on suggestions within example code provided by Kumar et al. 2017. For this and any further experiments relating to Bonsai we use an initial learning rate of 0.1 with the Adam Optimiser (Kingma & Ba, 2014), a sigmoid sharpness (Kumar et al., 2017) of 1 and a batch size of 224, the square root of the number of training samples, see Section 3. We also use a regulariser of 0.0001 with sparsity 0.2 for predictor parameters $W$ and $V$ and branching parameter $\theta$ (Kumar et al., 2017) and a regulariser of 0.0001 with sparsity 0.2 for projection parameter $Z$ (Kumar et al., 2017).

We sample by training the Bonsai models from the described grid using the code provided by Kumar et al. 2017 with early stopping. We expect that the Bonsai model size and accuracy will increase proportionally to depth and projection matrix dimensionality, as well as likely reaching the limit of our maximum memory budget of 128KB. The results of this sampling can be found in Table 4.

Based on the results in Table 4, we observe that indeed, test set accuracy as well as model size increase with respect to an increase in depth and projection matrix dimensionality of the Bonsai model, with the exception of the decision trees of depth 0, where we are likely observing underfitting. We note further that for every depth, the model size with a dimensionality of projection matrix of 30 is above and of 10 below our maximum memory budget of 128KB. The only exception is at depth 5 where dimensionality of projection matrix of 10 is already beyond 128KB.

Having established upper bounds for depth and dimensionality of projection matrix in Table 4, we run the full search for depths 0 to 5 and dimensionality of projection matrix 1 to 20. For depths 0 to 4 we additionally try to increase the dimensionality of projection matrix one at a time until a

| Model Size | Best Model |
|------------|------------|
| Grey-Scaled Images | |
| ≤ 8KB | $A, C_{1}(10, (3, 3)), C_{1}(12, (1, 1)), M, \ldots C_{1}(64, (3, 3)), D, R, D^*$ |
| ≤ 16KB, 32KB, 64KB, 128KB | $A, C_{1}(10, (3, 3)), C_{1}(8, (1, 1)), \ldots C_{1}(64, (3, 3)), M, D, R, D^*$ |
| 3-Channel Colour Images | |
| ≤ 8KB | $A, C_{2}(6, (3, 3)), C_{1}(8, (3, 3)), \ldots C_{2}(32, (3, 3)), M, D, R, D^*$ |
| ≤ 16KB | $A, C_{2}(6, (3, 3)), C_{2}(32, (1, 1)), M, \ldots C_{2}(64, (3, 3)), D, R, D^*$ |
| ≤ 32KB | $A, C_{1}(8, (1, 1)), C_{2}(16, (3, 3)), \ldots C_{1}(64, (5, 5)), D, R, D^*$ |
| ≤ 64KB, 128KB | $A, C_{1}(64, (3, 3)), M, C_{2}(64, (1, 1)), \ldots C_{2}(64, (5, 5)), D, R, D^*$ |

Table 3. The best network architectures for the Direct Convolution method. The bound on the model size is given in the first column, the best model architecture in the second. See Table 1 for abbreviations. Convolutional layers $C_1$ and $C_2$ are followed by the value of their variable arguments, in the order output_dim then kernel_size.

| Model Size | Best Model |
|------------|------------|
| Grey-Scaled Images | |
| ≤ 8KB | $A, C_{1}(10, (3, 3)), C_{1}(12, (1, 1)), M, \ldots C_{1}(64, (3, 3)), D, R, D^*$ |
| ≤ 16KB, 32KB, 64KB, 128KB | $A, C_{1}(10, (3, 3)), C_{1}(8, (1, 1)), \ldots C_{1}(64, (3, 3)), M, D, R, D^*$ |

Table 4. Test set accuracies for sampled Bonsai models with given depth (rows) and dimensionality of projection matrix (columns). Model sizes in KB within square brackets.

| Model Size | Best Model |
|------------|------------|
| Grey-Scaled Images | |
| ≤ 8KB | $A, C_{1}(10, (3, 3)), C_{1}(12, (1, 1)), M, \ldots C_{1}(64, (3, 3)), D, R, D^*$ |
| ≤ 16KB, 32KB, 64KB, 128KB | $A, C_{1}(10, (3, 3)), C_{1}(8, (1, 1)), \ldots C_{1}(64, (3, 3)), M, D, R, D^*$ |

Table 5. Best Bonsai models for each memory budget.

| Depth | Test Accuracy |
|-------|--------------|
| 5     | 0.110        |
| 10    | 0.157        |
| 20    | 0.308        |
| 30    | 0.310        |

| Depth | Test Accuracy |
|-------|--------------|
| 5     | 0.106        |
| 10    | 0.267        |
| 20    | 0.318        |
| 30    | 0.322        |

| Depth | Test Accuracy |
|-------|--------------|
| 5     | 0.135        |
| 10    | 0.286        |
| 20    | 0.345        |
| 30    | 0.355        |

| Depth | Test Accuracy |
|-------|--------------|
| 5     | 0.130        |
| 10    | 0.318        |
| 20    | 0.360        |
| 30    | 0.386        |

| Depth | Test Accuracy |
|-------|--------------|
| 5     | 0.120        |
| 10    | 0.354        |
| 20    | 0.389        |
| 30    | 0.390        |

| Depth | Test Accuracy |
|-------|--------------|
| 5     | 0.126        |
| 10    | 0.143        |
| 20    | 0.143        |
| 30    | 0.337        |

| Depth | Test Accuracy |
|-------|--------------|
| 5     | 0.126        |
| 10    | 0.143        |
| 20    | 0.143        |
| 30    | 0.337        |

Table 6. Best Bonsai models for each memory budget.
model exceeds 128KB. With this method, we find all feasible models with maximum depth 5. The final results for test accuracy and model size are shown in Table 6, the precise configuration of decision tree depth and dimensionality of projection matrix can be found in Table 5.

From the results in Table 5 we can conclude that there is a non-linear relationship between the depth of the decision-tree together with the dimensionality of projection matrix and the test set accuracy. We note in particular that for a limit of both 16KB and 32KB, the model with depth 1 and dimensionality 2 is the best found. Furthermore, it appears that only increasing the depth or the dimensionality alone does not yield better results but rather that there are critical combinations of a depth and dimensionality of projection matrix that yield optimal results.

5.4. FastGRNN

For FastGRNN, our first experiment is grey-scaling CIFAR-10 according to the luminosity formula (Cook, 2009) and feeding it row by row into a single FastGRNN unit. We do so to give a baseline similar to the 10-class MNIST results in Kusupati et al. 2018. The results for the grey-scaled experiment can be found in Table 6.

Next, we construct a model where the input channels of the CIFAR-10 3-channel images are simply concatenated into one to verify our hypothesis from Section 4.4 that this will impede performance due to reducing the amount of memory available for the hidden units. The results for this can also be found in Table 6. Then we carry out experiments with each of the three methods discussed in Section 4.4. The results of all of these are summarised in Table 6.

To target the different memory sizes, we varied the hidden dimensionality of the FastGRNN cells. Compared to the other learning experiments discussed in this paper, this gave fine-grain control of the sizes of the models, allowing us to approach the bounds tightly. It also allowed us to get the exact same model sizes, for the grey-scaled, row-major and channel-major models, see Table 6, since they only differ in how the input data is sequenced.

The large number of FastGRNN models to compare meant that performing extensive search for the optimal setting of the rest of the hyperparameters proved infeasible. Instead, we only carry out experiments for models where the predictor parameters U and W (Kusupati et al., 2018) are kept full-rank and dense. We also fix the update and gate non-linearities to be the hyperbolic tangent and sigmoid function, respectively. These are identified as good defaults by the original authors (Kusupati et al., 2018). Finally, we fix the batch size to 100 and use early stopping.

For optimization we used an Adam optimizer (Kingma & Ba, 2014) with initial learning rate 0.01. For the 64KB and 128KB models, see Table 6, we decay this learning rate by a factor of 0.1 every 30 epochs. We also do this for every Multi-FastGRNN model regardless of size, as initial experiments indicated that this model was even more susceptible to overfitting the training data.

As hypothesised in Section 4.4, the grey-scaled and channel-concatenated models perform the worst, with the latter initially performing significantly worse than any other model but then overtaking the former as the model size increases. This matches our intuition that the channel-concatenated model is penalized by the increased number of input units, a problem which is partially alleviated as the memory size budget increases.

| Model                      | ≤ 8KB | ≤ 16KB | ≤ 32KB | ≤ 64KB | ≤ 128KB |
|----------------------------|-------|--------|--------|--------|---------|
| Direct Convolution (grey-scaled) | 0.576 (5.20KB) | 0.592 (13.40KB) | 0.592 (13.40KB) | 0.592 (13.40KB) | 0.592 (13.40KB) |
| Direct Convolution (3-channel) | 0.604 (5.39KB) | 0.629 (8.65KB) | 0.6433 (19.91KB) | 0.657 (58.23KB) | 0.657 (58.23KB) |
| ProtoNN                    | –     | –      | –      | 0.100  | 0.100   |
| BONSAI                     | 0.126 (4.95KB) | 0.143 (9.90KB) | 0.143 (9.90KB) | 0.337 (56.82KB) | 0.383 (119.96KB) |
| FastGRNN (Channel-concatenated) | 0.418 (7.80KB) | 0.482 (14.9KB) | 0.514 (30.9KB) | 0.540 (63.0KB) | 0.538 (126.7KB) |
| FastGRNN (Grey-scaled)     | 0.441 (7.92KB) | 0.480 (15.7KB) | 0.506 (31.2KB) | 0.530 (61.2KB) | 0.523 (127.6KB) |
| FastGRNN (Row-Major)       | 0.463 (7.92KB) | 0.490 (15.7KB) | 0.534 (31.2KB) | 0.546 (61.2KB) | 0.556 (127.6KB) |
| FastGRNN (Channel-Major)   | 0.468 (7.94KB) | 0.507 (15.1KB) | 0.546 (31.1KB) | 0.567 (63.9KB) | 0.583 (126.1KB) |
| Multi-FastGRNN             | 0.463 (7.94KB) | 0.508 (15.1KB) | 0.548 (31.1KB) | 0.550 (63.9KB) | 0.563 (126.1KB) |
| Direct Convolution + FastGRNN | –     | –      | –      | 0.612  | 0.628   |

Table 6. Test set accuracies for methods described in Section 2 for different memory size budgets. Actual model size given in square brackets. Bold entries denote best model for each column, i.e. memory size budget.
The best performance is split between the Multi-FastGRNN and the channel-major models, with the former only narrowly beating out the latter in the 16KB and 32KB memory ranges. Overall, the results show that FastGRNN is surprisingly apt at multi-channel image classification tasks such as CIFAR-10, although its performance is still far from that of the Direct Convolution method, as seen in Table 6. The results in Table 6 also highlight the large weight which is placed on the mode of sequencing the input data when applying FastGRNN to image recognition problems, sometimes being the sole driver of a difference of 5% test set accuracy.

5.5. Enhancing FastGRNN with Direct Convolutions

In the preceding section, we found that the FastGRNN algorithm is sensitive to the way in which the input data is sequenced due to the impact this has on the features which the network can extract from the data. This begs the question of whether we can improve performance by first using Direct Convolution layers to extract intermediate features, which are then fed into a FastGRNN unit. If the recurrent nature of the FastGRNN is capable of combining these intermediate features into more powerful ones than the CNN layers can produce on their own, this could potentially rival even the dominant Direct Convolution models shown in Table 6.

To test this hypothesis without straying too far from the main analysis of this paper, we focus our attention on the 64KB and 128KB memory size budgets, as these give us the most flexibility, and pre-train the CNN part of the combined network separately. Specifically, we take the best Direct Convolution model from Table 6 but remove the layers following the final convolution, leaving us with a CNN of 57.54KB. We then attach a FastGRNN unit at the end, fix the weights of the CNN, and train the FastGRNN unit.

When we combine the Direct Convolution model with the FastGRNN unit, we find that simply doing row-major or channel-major sequencing becomes prohibitively slow to train due to the CNN outputting many feature maps, 64 in this case. A Multi-FastGRNN architecture as described in Section 4.4 also becomes infeasible with this many feature maps, as each FastGRNN unit would be restrained to a tiny fraction of memory. Instead, we flatten each feature map and then input these in sequence into the FastGRNN unit. As in Section 5.4 we vary the total model size by setting the number of hidden dimensions of the FastGRNN unit. We also keep all hyperparameters as in Section 5.4, with the exception that we reduce the initial learning rate to 0.005 and learning rate decay step to 20 epochs for the 128KB model in order to further combat overfitting.

The results of the above experiments are included in Table 6. These show that while combining Direct Convolution layers with a FastGRNN unit improves performance compared to a pure FastGRNN model, it performs significantly worse than the model from which the convolutional layers were extracted. Furthermore, scaling up the size of the FastGRNN has little impact on performance. This indicates that most of the useful features have already been extracted by the convolutions, and that the FastGRNN was not able to add anything to the model’s representational power. We leave it to future work to evaluate this architecture and possible training methods more, as well as to consider the trade-off between allocating memory to convolutions and FastGRNN units.

6. Conclusions and Future Work

In conclusion, we have seen that the state-of-the-art methods proposed in the last few years in the memory-constrained image classification literature vary wildly in how well they adapt to the more complex task of classifying CIFAR-10 images.

In our experiments, ProtoNN failed to fit the data at all, despite Gupta et al. 2017 presenting a 76.35% accuracy on a 2-class version of CIFAR. This suggests that the ProtoNN training procedure struggles to keep up as the complexity of the task increases, and we believe the poor performance of this model is thus likely due to the training procedure getting stuck in a locally optimal region of the error function. In comparison, Bonsai, which slightly outperforms ProtoNN on the 2-class version of the CIFAR data set (Kumar et al., 2017; Gupta et al., 2017), peaked at 38.3% test set accuracy on CIFAR-10 image classification, see Table 6.

On the other end of the spectrum, FastGRNN proved surprisingly apt at multi-channel image classification, obtaining a maximum of 58.3% test set accuracy in the 128KB memory range. However, it also proved very dependent on the way that the input image was turned into a time series, models for this were presented in Section 4.4. Ultimately, CNNs using Direct Convolution (Gural & Murmann, 2019) dominate our analysis in this paper, obtaining a 65.7% test set accuracy with less than 60KB of model memory usage. All this leads us to the conclusion that further progress in the field of memory-constrained image classification will most likely come through research into fitting deeper CNN models into the memory size budgets or through a general paradigm shift in image classification. That is to say, we have shown that the techniques that dominate the field of image classification at large memory scales also dominate it at small memory scales when carefully applied such as by Gural & Murmann 2019.

For future work, we would like to extend the comparative analysis presented in this paper to more image classification data sets to, as we hypothesise, strengthen the result that CNNs dominate this domain. We would also like to consider tasks other than image classification, as this is by far not the only use case for memory-constrained machine learning models.

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