Abstract—With time, machine learning models have increased in their scope, functionality and size. Consequently, the increased functionality and size of such models requires high-end hardware to both train and provide inference after the fact. This paper aims to explore the possibilities within the domain of model compression and discuss the efficiency of each of the possible approaches while comparing model size and performance with respect to pre- and post-compression.

Index Terms—quantization, pruning, model compression, machine learning, deep neural networks

I. INTRODUCTION

Deep Neural Networks have been efficiently and increasingly used in various applications of machine learning, computer vision, and other real-time applications. However, DNNs require high computational power and training and some of those models even on a high end machine might take hours and sometimes days to train. Not only are they intensive in terms of computation but also memory intensive due to a large number of weights taking up considerable storage and memory bandwidth. This makes it difficult to deploy them in resource-constrained environments like embedded systems. To address this limitation, techniques and methodologies for model compression have been attempted to reduce the storage requirement of deep neural networks without impacting the original accuracy.

Model compression can be done in three main ways: pruning, quantization and knowledge distillation. Pruning is the technique that helps develop smaller networks by zeroing out model weights during the training process to achieve model sparsity, eliminating specific connections between neurons. Quantization on the other hand, is the process of mapping values from a large set to a smaller set, leading to the output consisting of a smaller range than the input, without losing too much information. Models weights are typically stored as 32-bit floating point numbers and a common approach is to reduce these to 8-bit fixed points, reducing memory footprint by 4 times. Lastly, knowledge distillation employs a teacher-student architecture where knowledge is transferred from a deep ‘teacher’ model to a shallow ‘student’ model while maintaining the validity.

In this research we will focus on experimenting and testing the first two techniques that is pruning and quantization by utilizing previous works, and compare their performance and impact on the accuracy of the network models pre- and post-compression.

II. RELATED WORKS

Several work has been done regarding model compression. Yu Cheng and et al. in 2020 conducted a survey to discuss existing approaches regarding it [1]. Yu Cheng et al. discuss different techniques and methodologies to reduce the size and the computational requirement of the networks one of which is parameter pruning and quantization. The paper talks about different categories for pruning/quantization.

1) Quantization and Binarization: The best quantization practice among the many suggested in previous work is the method that proposes to quantize the link weights using weight sharing and then applied Huffman coding as well as the codebook to further reduce the rate. Started by learning the connectivity via normal network training, followed by pruning the small-weight connections. Finally, the network was retrained to learn the final weights for the remaining sparse connections. The main idea of the 1-bit representation or binary weight neural networks is to directly learn binary weights during the training itself. Several applications include BinaryConnect, BinaryNet and XNOR, but the networks trained with back propagation could be resilient to weight distortion which includes binary weights.

2) Network Pruning: There are several proposed ways for network pruning which includes reducing the number of connections based on the Hessian of the loss function. This suggested that such pruning gives better results than magnitude based pruning. One of the proposed data-free pruning methods is to remove redundant neurons. Another method is to use a low cost hash function to group group weights into hash buckets for parameter tuning. A significant drawback of using pruning is that it requires manual setup of sensitivity layers which requires fine-tuning of parameters which can be tedious. Network pruning reduces model size but plays no part in the improvement of the efficiency.

The general outcome of the survey suggests that if the applications require compact models from pre-trained complex deep neural networks, pruning and quantization is a preferable approach to consider.
Michael. H. Zhu and Suyog Gupta in [2] conduct a comparative study between two pruning approaches. 1, training a large model and then pruning it to obtain a sparse model with few parameters. 2. Training a small dense model. They propose an algorithm to prune the network during the training process by adding a binary mask variable of the same size and shape as the chosen layer’s weight tensor. The weights of that layer are sorted and the smallest weights are masked as 0 until the desired sparsity is reached. During back propagation the weights flow through the binary mask and the weights that were masked during forward propagation do not get updated. In the proposed algorithm the sparsity is increased from initial value 0 to a final value in n pruning steps.

\[ s_t = s_f + (s_i - s_f)(1 - \frac{t-t_0}{n\Delta t}) \]

for

\( t \in \{t_0, t_0 + \Delta t, t_0 + n\Delta t\} \)

Michael. H. Zhu and Suyog Gupta showed comparison between the performance of large-sparse models and small dense model on a large variety of datasets and shows that large sparse model outperforms the former.

Zhang, et al. in their paper Graph Pruning for Model Compression discuss in filter pruning used in conjunction with graph convolution [3]. Filter pruning is a method in which selected filters are removed and a narrower model is rebuilt. Filter pruning is usually applied to a single layer at a time but since some filters can be represented by filters from other layers. Zhang, et al. propose the use of AutoML pruning, Graph PruningNet, with meta-learning and reinforcement learning, in conjunction with graph convolution to take the relation between filters into consideration by extracting information from neighbouring nodes.

In this method, using graph convolution we first find the filters from the neighboring layer with a strong connection to the pruning layer then transform the network to form a topology. Each node has its features which are dynamically updated during training. During training the higher dimensional features are extracted by Graph PruningNet and each node of a layer is connected to a fully connected with the output of the node as the weight. Whereas during searching, a reinforcement algorithm searches for the best compression ratio using the Graph PruningNet output as the actor’s state and critic.

Zhang, et al. used the ImageNet-2012 dataset and after pruning and using the DDPG reinforcement learning algorithm for finding the optimal model, the best accuracy achieved was 53.1%. The results of this method were only slightly better than other AutoMLs but fully connected layers resulted in more parameters, which makes this method only suitable for smaller networks.

In a paper from Kozlov, et al. [4], the authors discuss Neural Network Compression Framework (NNCF) for fast model inference. This framework includes the quantization and pruning methods for model compression. The implementation of these techniques in NNCF is described as:

1) **Quantization:** In NNCF quantization is represented by affine mapping of integers \( q \) to real numbers \( r \) as follows:

\[ q = r \frac{s}{z} + z \]

where \( s \) is the scale factor, \( s \in \mathbb{R}^+ \) and \( z \) is the zero-point which is the quantized value \( q \) when \( r = 0 \). The zero-value is utilized for asymmetric quantization and has a value of zero if the quantization is symmetric. For symmetric quantization, the range is optimized using the scale parameter as:

\[ [r_{min}, r_{max}] = [- \text{scale} \cdot \frac{q_{min}}{q_{max}}, \text{scale}] \]

To quantize \( r \) to \( q \) we apply:

\[ q = \left\lfloor \frac{\text{clamp}(r; q_{min}, q_{max})}{s} \right\rfloor + z \]

where

\[ s = \frac{r_{max} - r_{min}}{2^{bits} - 1} \]

and

\[ z = \frac{-r_{min}}{s} \]

The symmetric mode is simpler to implement but the asymmetric mode has the advantage of utilizing the complete quantization range and consequently have a better accuracy. For a better trade-off between accuracy and performance, we can apply different levels of precision (e.g. 8, 6, 4 bits) to different layers based on the sensitivity of the layer. The sensitivity is calculated by taking the product of the trace of the Hessian of the layer with the Frobenius norm. For a better trade-off between accuracy and performance, we can apply different levels of precision (e.g. 8, 6, 4 bits) to different layers based on the sensitivity of the layer. The sensitivity is calculated by taking the product of the trace of the Hessian of the layer with the Frobenius norm. Lower sum of sensitivities corresponds to a more accurate quantized model.

2) **Filter Pruning:** NNCF supports pruning in the form of filter pruning based on an importance criteria. This criteria includes the L1-norm, L2-norm and geometric median.

To avoid large computation for geometric median for every individual filter, an approximation is used:

\[ G(F_i) = \sum_{i \neq j}^{n} \|F_i - F_j\|_2 \]

Where \( i \) denotes the \( i \)th filter in a layer. In case of pruning based on L2-norm, filters with a low average L2-norm are considered less important and are pruned
However if the geometric median were used as a criteria then the results showed a better accuracy. Pruned filters are not only zeroed out but completely removed from the model which speeds up the inference of the model.

The results of the experimentation using the ImageNet dataset on multiple models such as the ResNet models, etc were as follows: For the quantization, INT8 quantization of EfficientNet-B0 model was applied and there was a considerable difference in the accuracy drop between symmetric and asymmetric modes, 0.75% and 0.21% respectively. This shows asymmetric quantization has a higher accuracy. As for the pruning experiment, three ResNet Models were used with both geometric and magnitude based criteria and as mentioned above it was found that using the geometric median as criteria for pruning gave better results than when the norms were used. However, this difference was only a slight one. In both cases the accuracy only went down by around 1%.

Song Han et al. (2016) in [5] introduced a three-stage compression pipeline: pruning, quantization and Huffman coding, termed as 'Deep Compression' to address this limitation by reducing the storage requirement of deep neural networks without impacting the original accuracy.

For the first stage i.e pruning, Han et al. started by training connectivity, then connections with weights below a threshold were removed/pruned from the network and finally the network was retrained to learn the final weights for the remaining sparse connections. The results from pruning were then stored using compressed sparse row (CSR) or compressed sparse column (CSC) format. For further compression, they stored the index difference instead of the absolute positions. For the second stage i.e quantization, they further compressed the pruned network by reducing the number of bits, from 32 to 5, required for weight representation. By enforcing weight sharing between multiple connections and then fine-tuning these shared-weights, they limited the number of effective weights required to be stored. Finally they applied Huffman coding for encoding weights and indices which further improves the compression rate.

Han et al. applied this method on four networks: LENET-300-100, LENET-5, AlexNet and VGG-16 and examined the performance of two of them on MNIST and two on ImageNet datasets. Results showed that the compression pipeline saved 35x to 49x parameter storage across these four networks with no loss of accuracy. Most of the savings comes from pruning and quantization, while Huffman coding gives a marginal gain. Their experiment also showed that when pruning and quantization are applied individually, the accuracy of the pruned network as well as of the quantized network drops significantly when compressed below 8% of the original size. But when combined, the network can be compressed to 3% of original size without losing accuracy. This showed that quantization and pruning works well together. Further the results were compared with SVD, which is inexpensive but gives very poor compression rate.


1) Quantized distillation: This makes use of the distillation loss expressed with respect to the teacher network, a trained state-of-the-art deep model, and incorporates it into the training of the student network, a compressed model with quantized weights and shallower than the teacher network.

2) Differentiable quantization: This technique is used to improve the accuracy of the quantized student network to best fit the teacher model, and hence utilizes non-uniform quantization function that takes a set of s quantization points \{p_1,...,p_s\} as input and quantizes each element \(v_i\) to the closest of these points, deterministically [6].

Polino et al. experimented these two methods over various small and large datasets. Results showed that the combination of distillation and quantization through the proposed methods can compress models by up to an order of magnitude in terms of size while preserving accuracy.

Pierre Stock and et al. (2020) in [7] propose a strategy for network compression that works towards small reconstruction error for the output layers instead of for the weights itself. According to their proposed algorithm they are trying to find the codebook through weighted K means algorithm which is trying to minimize the difference between the output activations and their reconstructions. They start by sampling K uniform vectors among those which are to be quantized. Clustering is done through the following equation.

\[
c_j = \arg\min_{v} \|x(c - v)\|_2^2
\]

Following equation is used to compute the solution of least square problem.

\[
c^* = \arg\min_{p \in I_c} \sum_{p \in I_c} \|x(c - v)\|_2^2
\]

Building on top of this they propose an algorithm for not just quantizing a single layer but the whole neural network. Quantization starts from lowest layer to the highest layer. It is a two step process where first a the input activations are obtained by passing a batch of images through the quantized lower layer and the current layers are quantized using those activations. Next the codebook is fine-tuned using distillation in [8]. This approach produces state of the art results on ResNet architecture and is also generalized to architectures such as Mask R-CNN. This method does not require labeled data and the resulting models are byte aligned which aids in efficient inference on CPU.

III. Experiment

Our main focus is to test the efficacy of pruning and quantization, both individually and in tandem. The experiment that we’re conducting focuses on creating a Convolutional Neural Network using the popular ML library called Keras. The model will take inputs of size 28x28 which
is then reshaped into a 784-vector. The vector is then passed through a 2D convolution with a size of 3x3, activated with the ReLu function. Finally, with some maxpooling and flattening, the model produces a probabilistic output regarding the class of the given input that serves as our prediction that is then compared against the ground truth labels in order to calculate the accuracy of the model.

Following is a visualization of the model architecture, as implemented:

Since the experiment warranted numerous rounds of iterations and changes to many hyperparameters, we resorted to limiting our scope to the MNIST handwritten digit classification.

We focused on first establishing a baseline model with a sparsity of 0% and no post-training quantization. We then trained 4 different models that were pruned at varying levels of sparsity. After training the pruned models, we changed the back-end of our models from Keras to TensorFlowLite before quantizing both the models to a precision of 8-bit integers.

In terms of the hyperparameters, the initial model training was done for a total of 4 epochs with a validation set split being of 10% of the original dataset. For models that were pruned, the process occurred over 2 epochs with a batch size of 128, a validation dataset split of 30% and an initial sparsity of 50%. Each model was then evaluated on 10,000 data points in order to calculate an average accuracy rate, which was then compared to the test set accuracy of the baseline model for the accuracy delta metric to showcase the impact of each approach on the overall performance of the model. A second and more important metric was the reduction factor which was calculated by tabulating the raw size of gzipped versions of all our trained models and then compared against the baseline model size by calculating the ratio between the sizes.

Finally, to present the results based on a single metric, we use the normalized product of Accuracy Delta and Reduction Factor so that we’re allowed to recognize the most optimally compressed model based on a single point of data.

### IV. Results

Following is a table with the observed accuracy of the various models along with the delta against the baseline model.

<table>
<thead>
<tr>
<th>Model</th>
<th>Accuracy</th>
<th>Acc. Delta</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>97.89%</td>
<td>0</td>
</tr>
<tr>
<td>Pruned (50% sparsity)</td>
<td>97.77%</td>
<td>-0.12%</td>
</tr>
<tr>
<td>Pruned (75% sparsity)</td>
<td>97.35%</td>
<td>-0.54%</td>
</tr>
<tr>
<td>Pruned (90% sparsity)</td>
<td>94.68%</td>
<td>-3.21%</td>
</tr>
<tr>
<td>Pruned (95% sparsity)</td>
<td>58.49%</td>
<td>-39.4%</td>
</tr>
<tr>
<td>Quantized (16-bit float)</td>
<td>97.94%</td>
<td>0.05%</td>
</tr>
<tr>
<td>Quantized (8-bit int)</td>
<td>94.86%</td>
<td>-3.03%</td>
</tr>
<tr>
<td>Pru. (75%) + Quant. (8-bit int)</td>
<td>96.84%</td>
<td>-1.05%</td>
</tr>
<tr>
<td>Pru. (90%) + Quant. (8-bit int)</td>
<td>94.67%</td>
<td>-3.22%</td>
</tr>
</tbody>
</table>

We can see that the smallest delta is that of the full integer quantized model i.e. only 0.02%, whereas the highest is of the model that has had 95% of its weights zeroed out, leading to a drop of 39.4% in test set accuracy, in contrast with the baseline model. We will now go on to see the difference between the size of the models when pruned, quantized or when both methods are applied. Following is the table with model sizes and the size ratio between the baseline and the given models.

<table>
<thead>
<tr>
<th>Model</th>
<th>Size (bytes)</th>
<th>Reduction Factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>78,041</td>
<td>1.00</td>
</tr>
<tr>
<td>Pruned (50% sparsity)</td>
<td>48,380</td>
<td>1.61</td>
</tr>
<tr>
<td>Pruned (75% sparsity)</td>
<td>48,850</td>
<td>1.60</td>
</tr>
<tr>
<td>Pruned (90% sparsity)</td>
<td>17,409</td>
<td>4.48</td>
</tr>
<tr>
<td>Pruned (95% sparsity)</td>
<td>12,979</td>
<td>6.01</td>
</tr>
<tr>
<td>Quantized (16-bit float)</td>
<td>39,572</td>
<td>1.97</td>
</tr>
<tr>
<td>Quantized (8-bit int)</td>
<td>18,553</td>
<td>4.21</td>
</tr>
<tr>
<td>Pru. (75%) + Quant. (8-bit int)</td>
<td>12,792</td>
<td>8.91</td>
</tr>
<tr>
<td>Pru. (90%) + Quant. (8-bit int)</td>
<td>5,518</td>
<td>14.14</td>
</tr>
</tbody>
</table>
It is evident that compared to an unadulterated model, both pruning and quantization allow for huge increase in model size reduction. In our testing, pruning helped reduce the overall size of the model by 3.43 times on average, with the highest reduction factor being just above 6 times. Similar with quantization, where we saw an average reduction factor of 4.55, meaning that despite the precision of the quantization, we can expect a size reduction that will be smaller than a quarter of the original baseline model’s size. However, the biggest gains were yielded when we implemented pruning and quantization on the same model, with our smallest reduction factor being higher than the highest factor observed in the individually pruned/quantized models. Even better, with the sweet spot of 90% sparsity and full-interger quantization, we were able to observe the size of the model decreasing by more than 14 times, from 78,041 bytes to a paltry 5,518 bytes.

Now, in terms of discussing the size-to-accuracy tradeoff, we will look at the normalized product of Accuracy Delta and Reduction Factor, as tabulated below:

<table>
<thead>
<tr>
<th>Model</th>
<th>Norm. AD x RF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pruned (50% sparsity)</td>
<td>0.493</td>
</tr>
<tr>
<td>Pruned (75% sparsity)</td>
<td>0.484</td>
</tr>
<tr>
<td>Pruned (90% sparsity)</td>
<td>0.317</td>
</tr>
<tr>
<td>Pruned (95% sparsity)</td>
<td>-2.43</td>
</tr>
<tr>
<td>Quantized (16-bit float)</td>
<td>0.496</td>
</tr>
<tr>
<td>Quantized (8-bit int)</td>
<td>0.338</td>
</tr>
<tr>
<td>Pru. (75%) + Quant. (8-bit int)</td>
<td>0.379</td>
</tr>
<tr>
<td>Pru. (90%) + Quant. (8-bit int)</td>
<td>-0.067</td>
</tr>
</tbody>
</table>

The highest score is achieved by the model that had undergone only 16-bit float quantization, giving us a reduction factor of almost 2 while having the only positive accuracy delta compared to the rest of our models, thereby showcasing that a model can be most effectively compressed by quantization without little loss of accuracy, unless it is at a reduced precision, as showcased by the drop in accuracy when decreasing the precision down to 8-bit fixed-interger. While the normalized product is not a universal metric to decide on the best combination of model compression technique and hyperparameter combination, we can still extrapolate some semblance of logic that can help us dictate the right choice when it comes to model compression.

V. CONCLUSION

Through this paper we have discussed several types of pruning and quantization methods and experiments for model compression while retaining its performance. Pruning has allowed us to make our converged MNIST model such that 90% of the weights in the matrices are 0, thus increasing our sparsity by a lot. It also allowed us to reduce the size of our model by more than 400% while only losing a maximum of 3% in terms of test set accuracy compared to our baseline. Post-training quantization further reduced the model size by changing most of the weights and output activations from being 32-bit floats to 8-bit integers. Our final model with both pruning and quantization was just above 1400% smaller with no loss in accuracy compared to our pruned model.

REFERENCES