Tree-CNN: A Deep Convolutional Neural Network for Lifelong Learning

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Abstract—In recent years, Convolutional Neural Networks (CNNs) have shown remarkable performance in many computer vision tasks such as object recognition and detection. However, complex training issues, such as “catastrophic forgetting” and hyper-parameter tuning, make incremental learning in CNNs a difficult challenge. In this paper, we propose a hierarchical deep neural network, with CNNs at multiple levels, and a corresponding training method for lifelong learning. The network grows in a tree-like manner to accommodate the new classes of data without losing the ability to identify the previously trained classes. The proposed network was tested on CIFAR-10 and CIFAR-100 datasets, and compared against the method of fine tuning specific layers of a conventional CNN. We obtained comparable accuracies and achieved 40% and 20% reduction in training effort in CIFAR-10 and CIFAR 100 respectively. The network was able to organize the incoming classes of data into feature-driven super-classes. Our model improves upon existing hierarchical CNN models by adding the capability of self-growth and also yields important observations on feature selective classification.

Index Terms—Convolutional Neural Networks, Deep Learning, Incremental Learning, Lifelong Learning, Transfer Learning

1 INTRODUCTION

Deep Convolutional Neural Networks (DCNNs) have emerged as the leading architecture for large scale image classification in recent years [1]. In 2012, Krizhevsky, et al. [2] won the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) by implementing a Deep-CNN. This catapulted DCNNs into the spotlight, and since then, they have dominated ILSVRC and have surpassed human level performance on popular image datasets such as MNIST [3], [4] and ImageNet [5].

Today, with increased access to large amount of labeled data (e.g. ImageNet contains 1.2 million images with 1000 categories), supervised learning has become the leading paradigm in training DCNNs for image recognition. Traditionally, a DCNN is trained on a dataset containing large number of labeled images. The network learns to extract relevant features and classify these images. This trained model is then applied to other unlabeled images to classify them into these specific classes. In such training, all the training data is presented to the network during the same training process. However, in real world, we hardly have all the information at once. Instead, data is gathered incrementally over time. And we, humans, also learn in a similar incremental manner. We accumulate knowledge acquired in the past and use it to learn new things during our lifetime. Inspired by the way humans learn, Lifelong Machine Learning (LML) [6] is an emerging paradigm in machine learning that tries to address this limitation. Lifelong Learning [7], [8], is based on the principle that learning the $n^{th}$ task should be easier than learning the $(n-1)^{th}$ task. While, intuitively, this makes sense; the actual implementation of such a network faces several challenges that are discussed further.

A DCNN embeds feature extraction and classification in one coherent architecture within the same model. Modifying one part of the parameter space immediately affects the model globally. Another problem of incrementally training a DCNN is the issue of “catastrophic forgetting” [9]. When new data is fed into a DCNN, it results in the destruction of existing features learned from earlier data. This means when training on new data, all previous data must also be shown to the network.

Interestingly, it has also been observed that initial layers of DCNN learn to extract generic features, while deeper layers learn to identify higher level features. It has been demonstrated that initializing a new network with transferred features from a trained network can potentially boost the performance of the new one [10]. “Off the shelf” CNNs trained on large datasets are then fine-tuned for specific applications [11]. However, these solutions do not train the original network to learn the new classes. Rather a new network is created from the old one.

In this work, we propose a network that grows hierarchically as new classes are introduced. The branching is based on the similarity of features between new and old classes. The initial nodes of the Tree-CNN divide the dataset into coarse super-classes, and as we approach the leaves of the network, finer classification is done. Such a model allows us to leverage the convolution layers learned previously to be used in the new bigger network. Our objective is to present the advantages of such a network model in terms of incremental learning over transferring trained convolution layers and fine tuning a regular network.

The proposed Tree-CNN has the following salient features:

i. The network is initially trained to classify images into $N$ classes. When an image belonging to a new class is shown to the network, the network grows
to accommodate the new class.

ii. The network grows by adding a new branch or a new leaf node to the current structure. The decision is based on how closely the new class resembles a particular superclass and its sub-classes.

iii. The objective is to reduce the training effort, which is made up of 2 components: number of weights updated, and the number of examples (both old and new) required for training.

iv. The updates are localized to a section of the tree, while majority of the Tree-CNN is left untouched, therefore reducing the cost of learning new classes.

The rest of the paper is organized as follows. The related work on incremental learning in deep neural networks is discussed in Section 2. Next, in Section 3, we explain in detail our proposed network architecture and incremental learning method. In Section 4, we describe the two experiments we conducted using CIFAR-10 and CIFAR-100 datasets. It is followed by a detailed analysis of the performance of the network and its comparison with basic transfer learning and fine tuning in Section 5. Finally, in Section 6, we discuss the merits and limitations of our network, conclude our findings and suggest opportunities for future work.

2 Related Work

The modern world of digitized data produces new information every second, thus fueling the need for systems that can learn as new data arrives. Traditional deep neural networks are static in that respect, and several new approaches to incremental learning are currently being explored. “One-shot learning” [12] is a Bayesian transfer learning technique, that uses very few training samples to learn new classes. Fast R-CNN [13], a popular framework for object detection, also suffers from “catastrophic forgetting”. One way to mitigate this issue is to use a frozen copy of the original network compute and balance the loss when new classes are introduced in the network [14]. “Learning without Forgetting” [15] is another method that uses only new task data to train the network while preserving the original capabilities. However, here the original network is trained on an extensive dataset, such as ImageNet [5], and the new task data is a much smaller dataset. We, on the other hand, propose a network that knows only a handful of classes, and grows and learns over time.

Our work draws inspiration from transfer learning. It has been observed that initial layers of a CNN learn very generic features [10]. The same work also demonstrated that a new network, when initialized with “learned” layers from a trained network, performs better. Switching initial layers of deep neural networks with pre-defined Gabor filters have been shown to reduce training time and offer a more energy-efficient training process [16].

Common features shared between images of different objects has been exploited to build hierarchical classifiers. These features can be grouped semantically, such as in [17], in which authors built an “Attention-tree”, a visual semantic hierarchy to perform energy-efficient image classification. “FALCON: Feature driven selective classification” [18] is a classification methodology inspired by biological visual attention mechanism in the brain. They use characteristic features such as color and texture to break down the behemoth task of classifying large datasets into a set of hierarchical classifiers.

Similar to the progression of complexity of convolutional layers in a DCNN, the upper nodes of a hierarchical CNN classify the images into coarse super-classes using basic features, like grouping green-colored objects together, or humans faces together. Then deeper nodes perform finer discrimination, such as “boy” v/s “girl”, “apples” v/s “oranges”, etc. Such hierarchical CNN models have shown to perform at par or even better than standard DCNNs [19]. “Discriminative Transfer learning” [20] is one of the earliest works where classes are categorized hierarchically to improve network performance. “HD-CNN” [19], is a hierarchical CNN model that is built by exploiting the common feature sharing aspect of images. However, in these works, the dataset is fixed from the beginning, and prior knowledge of all the classes and their properties is used to build a hierarchical model. In this work, the Tree-CNN starts out as a single root node and generates new hierarchies to accommodate the new classes. Images belonging to the older dataset are required during retraining, but by localizing the change to a small section of the whole network, we try to achieve reduction in training effort. In [21], a similar approach is applied, where the new classes are added to the old classes, and divided into two super-classes, by using an error-based model. The initial network is cloned to form two new networks which are fine tuned over the two new super-classes. While their motivation was a “divide-and-conquer” approach for large datasets, we are interested in developing a model that can incrementally grow with new data. And, we sequentially add new data over multiple learning stages. In the next Section, we lay out in detail our design principle, network topology and the algorithm used to grow the network.

3 The Lifelong Learning Model

3.1 Network Architecture

The network model is inspired from hierarchical classifiers. It is built with nodes, connected as a directed acyclic graph. Each node acts a classifier, predicting a label for the input image. As per the label, the image is then passed on to the next node which further classifies the image, until we reach a leaf node, the last step of classification.

We begin by defining certain terms used frequently in our model. A Node represents the building block of our tree. Each node represents a group of 1 or more classes. Each node has following parameters.

- **Node-ID**: Each node is given a number that uniquely identifies it.
- **Parent**: This holds the Node-ID of the node previous to this node. Each node can have only one parent. A parent node can be inferred as coarse-classifier, whereas the child node does finer classification. Except for the root node, all other nodes have parent node. Each node can only have at max one parent node.
- **Children**: It is an array of Node-IDs belonging to the nodes linked with each output neuron of the current
Fig. 1. A generic model of Tree-CNN: The root node predicts super-classes whereas lower nodes predict finer classes.

node. The number of children each node has is equal to the number of output neurons.

- **Net**: This stores the convolutional neural network that processes the input image. In case of a leaf node, this is empty.

- **LT**: Acronym for "Labels Transform", LT is a lookup table that keeps track of the original label of a class, and the output neuron number it is associated with. For a leaf node, LT has just one record, the class label of that node.

The root node is the highest node of the tree. The first classification happens at this node. Each output neuron of the root is associated with a node. Next in hierarchy is the branch node. It has a parent and two or more children. It performs classification for at minimum 2 classes/super-classes. The leaf node is the last level of the tree. Each leaf node is uniquely associated to a class. No two leaf nodes have the same class. Fig. 1 shows the root node and branch nodes for a 2 stage classification network. Each output of the second level branch node is a leaf node.

### 3.2 Algorithm

To start with, one has two options when implementing the Tree-CNN. If there are only a handful of distinct classes that don’t seem like they can be grouped in a hierarchical fashion, then the network can be initialized as a single root node. The output of the root node are the distinct classes. However, if at the beginning we have data that is already grouped in hierarchical manner as coarse and fine classes, then a more detailed Tree-CNN can be initialized. The root node will be trained to classify the images into the highest level of super-classes. The branch nodes further down the tree are trained to classify the images into finer classes.

Now that we have a trained Tree-CNN, we discuss how it predicts classes and how it treats new classes. First, we describe how the network predicts the class of an input image. A recursive algorithm moves along the hierarchies of the network to reach a specific leaf node. At each node, beginning with the top node, the image is fed to the DCNN associated with that node. The output node with the highest classification probability is the next node the algorithm moves to. If it is a leaf node, then the class associated with that node is the predicted class. Else, the algorithm feeds the image to the DCNN of that node. The pseudo-code for class prediction is given under Algorithm 1.

#### Algorithm 1 Class Prediction

```
Initialize: Im = Input Image, node = root node of the Tree-CNN

procedure CLASSPREDICT(Im, node)
  if num(node.children) = 0 then
    Checks if it is a leaf node
    return class = node.LT
    For leaf node, LT = class label
  else
    NextNode = EvaluateNet(Im, node.net)
    EvaluateNet returns the node.ID of the child node
    having the largest output
    return CLASSPREDICT(Im, NextNode)
  end if
end procedure
```

Next we describe the process of incremental/lifelong learning. The Tree-CNN is already trained to classify, say, N classes. Now, data belonging to M new classes have been acquired and the network needs to learn to classify them while trying to minimize the change in network structure, and having a low training effort. A small sample of images (~ 10%) is selected from the training set of the new classes. At the root node these images are fed to the DCNN, one class at a time. We obtain a 3 dimensional matrix, $O^{K \times M \times I}$, where

- $K = \text{number of children of the root node}$
- $M = \text{number of new classes}$
- $I = \text{number of sample images per class}$

$O(k, m, i)$ denotes the output of the $k^{th}$ output neuron for the $i^{th}$ image belonging to the $m^{th}$ class where $k \in [1, K]$, $m \in [1, M]$, and $i \in [1, I]$. $O_{avg}^{K \times M}$ is the average of the outputs over $I$ images. $O_{avg}$ is taken over $O_{avg}$ to obtain the likelihood matrix $L^{K \times M}$ which indicates how strongly an image belonging to $m^{th}$ class on average associates to the $k^{th}$ node.

$$O_{avg}(k, m) = \frac{\sum_{i=1}^{I} O(k, m, i)}{I} \tag{1}$$

$$L(k, m) = e^{O_{avg}(k, m)} \sum_{k=1}^{K} e^{O_{avg}(k, m)} \tag{2}$$

Each column of $L$ can be represented as a $K \times 1$ vector, $l_m$, where $m \in [1, M]$ represents the $M$ new classes. We arrange $l_m$ in an ordered set, $S$, such that

$$S = [l_{m1}, l_{m2}, l_{m3} \ldots l_{mM}] \tag{3}$$

$$\max(l_{m1}(k)) >= \max(l_{m2}(k)) >= \ldots >= \max(l_{mM}(k)) \tag{4}$$
We analyze each vector of the set $S$ one by one to determine how a new class will be appended to the root node. There are 3 options:

i. **Add the new class to an existing child node:** If the value of $\max(l_m)$ is greater than a threshold (which can be set as per requirement) indicating a strong resemblance/association with a particular child node, the new class is added to child node $k$ such that $l_m(k) = \max(l_m(k'))$, $k' \in [1, K]$

ii. **Combine one or more child nodes and the new class to form a new child node:** If there are more than 1 child nodes that the new class has a strong likelihood for, we can combine them to form a new child node. Say, the top two likelihood values were 0.48 and 0.45, and at least one of them is a leaf node, we can combine the two and the new class to form a new child node which will be a branch node. We can set an upper limit to the number of child nodes that could be combined.

iii. **Add the new class as a new child node:** If the new class doesn’t have a single likelihood value greater than a threshold ($l_m(i) < \text{threshold}$ $\forall i \in [1, K]$), or certain network restrictions are applied to prevent addition of classes to child nodes, the network expands horizontally by adding the new class as a new child node. This node will be a leaf node.

Once this is complete for the $M$ classes at the root node, we move to the next level of the tree. The same process is applied on the child nodes that now have new classes to be added to them. For example, say, two new classes were added to a child node. If child node is a leaf node, it is changed into a branch node that now has 3 leaf nodes as children. If the child node is a branch node, then we repeat the process of calculating likelihood matrix and determining how these two new classes will get added to its output. As we can see, the decision on how to grow the tree is semi-supervised. The algorithm itself decides how to grow the tree, given the constraints by the user. We can limit parameters such as maximum children for a node, maximum depth for the tree, etc. as per our system requirements. Once the new classes are allotted locations in the tree, we do supervised gradient descent based training of the nodes that have been modified/added. Doing this saves us from modifying the whole network, and only affected portions of the network require retraining/fine-tuning.

4 **The Experiments**

We conducted two experiments using the datasets, CIFAR-10 and CIFAR-100. We used MatConvNet [22], an open-source toolbox for implementation of Convolutional Neural Networks in MATLAB [23].

The two experiments have very different initial conditions. In the first experiment on CIFAR-10 we show that given a trained Tree-CNN with one root node and two branch nodes how it expands as new classes arrive. We demonstrate a single incremental learning stage. In the second experiment with CIFAR-100, the network starts with one root node that can classify only 10 classes, and we progressively teach the network 90 new classes over time.

During training, we performed simple data augmentation. Training images were flipped horizontally at random with a probability of 0.5 [24]. All images were whitened and contrast normalized [24]. The activation used in all the networks is rectified linear activation ReLU, $\sigma(x) = \max(x, 0)$. The networks are trained using stochastic gradient descent with fixed momentum of 0.9. Dropout [25] is used between the final fully connected layers, and between pooling layers to regularize the network. We also employed batch-normalization (BNORM) [26] at the output of every convolutional layer. Additionally, a weight decay $\lambda = 0.001$ was set to regularize each model. The final layer performs softmax operation on the output of the nodes to generate class probabilities.

4.1 **Adding Multiple New Classes**

4.1.1 **Dataset**

We used CIFAR-10 dataset [27] for this experiment. It has 10 mutually exclusive classes, namely, airplane, automobile, bird, cat, deer, dog, frog, horse, ship, and truck. There are 50,000 training images and 10,000 test images equally distributed between 10 classes. Each image is a $32 \times 32$ color image, thus having 3 input channels for Red, Green and Blue pixels. We first train the network on 6 classes, and in the next stage of incremental learning, we train the network for the 4 remaining classes.

4.1.2 **The Network**

For ease of reference, we label this network as Tree-CNN A. The root node is a DCNN with two output nodes. It will classify the input image as either “Animals” or “Vehicles”. Each child node has a DCNN that does finer classification. The description of the layers in each of these sub-networks is given in Tables 1 and 2. Fig. 2 and Fig. 3 a) depict the initial model of Tree-CNN A.

For comparison, we took another network (Network “B”) with a complexity level similar to two stage complexity of this Tree-CNN. It has 4 convolutional blocks, each block having 2 sets of $3 \times 3$ convolutional kernels. The network is inspired from the architecture of VGG-net [28]. Detailed model is given in Table 3.

4.1.3 **Initial Training**

CIFAR-10 has classes that can easily be grouped into 2 distinct groups, “Vehicles” and “Animals”. We start with 6 classes, 3 belonging to each group. Automobile, ship, and
### TABLE 1
Root Node for Tree-CNN A (CIFAR-10)

| Layer | Description |
|-------|-------------|
| Conv1 | 5x5x3x64 ReLU stride 1 + BNORM |
| [2 2] Max Pooling stride 2 |
| Conv2 | 3x3x64x128 ReLU stride 1 + BNORM |
| Dropout 0.5 |
| [2 2] Max Pooling stride 2 |
| FC | Fully Connected 8x8x12x512 ReLU |
| Dropout 0.5 |
| Fully Connected 1x1x128x2 ReLU |
| Softmax Layer |

### TABLE 2
Branch Node for Tree-CNN A (CIFAR-10)

| Layer | Description |
|-------|-------------|
| Conv1 | 5x5x32 ReLU stride 1 + BNORM |
| [2 2] Max Pooling stride 2 |
| Conv2 | 5x5x32x64 ReLU stride 1 + BNORM |
| Dropout 0.25 |
| [2 2] Max Pooling stride 2 |
| Conv3 | 3x3x64x64 ReLU stride 1 + BNORM |
| Dropout 0.25 |
| [2 2] Avg Pooling stride 2 |
| FC | Fully Connected 4x4x64x128 ReLU |
| Dropout 0.5 |
| Fully Connected 1x1x128xN ReLU (N=number of children) |
| Softmax Layer |

truck are grouped as “Vehicles”, while cat, dog, and horse are grouped as “Animals”. The network at the root node is trained to classify the images as “Animals” or “Vehicles”. For this, the 30,000 training images belonging to the 6 classes are re-labeled as “Animals” or “Vehicles”. The root node is then trained for 300 epochs. The learning rate is kept at 0.1 for first 200 epochs, then reduced by 10 times every 50 epochs. We achieve a testing accuracy of 92.40%. The accuracy of tree-CNN A is within the range of network “B”.

#### 4.1.4 Incremental Learning
Next we want to train the networks to identify the remaining four classes, bird, frog, deer and airplane. There are 500 training images per class given to us. We select at random 50 images per class, and show these 200 images to the root node. We obtain the L matrix, which is a $2 \times 4$ matrix with each element $l_{ij} \in (0, 1)$. The 1st row of the matrix indicates the softmax likelihood of each of the 4 classes as being classified as “Vehicles”, while the second row presents the same information for “Animals”. Fig. 3 shows how likely a new class is to be classified as “Animals” or “Vehicles”. Note, that this is not the number of times out of 50, the images belonging to the class are classified as one of the two super-classes by the root node. Instead, we perform the softmax operation (eq. 2 on the actual values of the output layer, to see which output neuron gives a higher value for a particular class and by how much.

As per our algorithm, airplane gets grouped with “Vehicles” while bird, deer, and frog get added to the “Animals” coarse category. The decision making is done using Algorithm 2 based on the softmax likelihood output of the root node, as obtained in Fig. 4. The before and after structure of the Tree-CNN A is shown in Fig. 5. Next the root node
is retrained with 50,000 training images from all the 10 classes (old and new) to classify them into the two coarse categories. The root node is trained for 250 epochs, with learning rate 0.1 for first 100 epochs, then the learning rate is reduced by 10 every 50 epochs. Next we train the two branch nodes. For each of the two nodes, we train it with training images from both new and old classes. Each of the nodes is trained for 250 epochs and the learning rate variation is kept same as for the root node.

Algorithm 2 Incremental Learning for Tree-CNN A

**Inputs:** $L = 2 \times 4$ likelihood matrix, node = root node of the Tree-CNN, NewClass = array of new class labels

**procedure** TREEGROW($L$, node)

for (col = 1, col ≤ 4, col++) do

if $L(1, col) > L(2, col)$ then

AddClass(NewClass(col), node.children(1))

else

AddClass(NewClass(col), node.children(2))

end if

end for

end procedure

For comparison, we apply fine tuning to our already trained network “B”. We add the 4 new classes as 4 new output nodes of the final layer. As described in Table 3, it is made up of 4 convolutional blocks (CONV) and one fully connected block (FC). For network B, 5 fine tuning strategies have been used. Each method retrains/fine-tunes certain layers of the network. As listed below, we set 5 different depths of back-propagation when retraining with the whole dataset, i.e. all 10 classes.

1. Case I: FC
2. Case II: FC + CONV1
3. Case III: FC + CONV1 + CONV2
4. Case IV: FC + CONV1 + CONV2 + CONV3
5. Case V: FC + CONV1 + CONV2 + CONV3 + CONV4

Case V represents the extreme scenario where the previous network is completely retrained to learn the new classes. This is equivalent to training a new network with all the classes.

4.2 Sequentially Adding Multiple Classes

4.2.1 Dataset

For this experiment, we use a larger dataset, CIFAR-100 [27]. It has 100 classes, 500 training and 100 testing images per class. The image is a $32 \times 32$ color image with 3 input channels for Red, Green and Blue pixels. We divide the 100 classes into 10 groups, each group having 10 classes. This distribution is done at random. We first train the networks with 10 classes, and then incrementally add 10 new classes every stage. There are 9 learning stages to add the remaining 90 classes.

4.2.2 The Network

Initially, the Tree-CNN has a root node and 10 leaf nodes. We label this network as Tree-CNN C. The root node has a DCNN network, with 10 output nodes. The layers of the CNN are described in detail in Table 4. In subsequent learning stages, the network would extend branches. The DCNN model used in branch nodes is given in Table 5. For comparison, we use the same network “B” as used in previous experiment.

4.2.3 Initial training

For Tree-CNN C, the root node is trained to classify 10 classes. It is trained for 300 epochs, with learning rate of 0.1 for first 200 epochs. It is then reduced by 10 every 50 epochs. We obtain a testing accuracy of 84.90%. Network “B” is trained for 300 epochs as well, and the learning rate is same as for the root node. We achieve a testing accuracy of 85%. The starting accuracy for the two networks is almost the same.

4.2.4 Incremental Learning

We divided the remaining 90 classes into 9 groups, each containing 10 classes. These classes were added to the network in 9 incremental learning stages. At each stage, first 50 images belonging to each class are shown to the root node and a likelihood matrix $L$ is generated. The columns of the matrix are used to form an ordered set $S$, as described in equations 3 and 4. For this experiment, we applied the following constraints to the system.

- Maximum depth of the tree is 2
### TABLE 4
Root Node of Tree-CNN C (CIFAR 100)

| Layer  | Description |
|--------|-------------|
| Input  | 32x32x3     |
| Conv 1 | 5x5x3x64 ReLU stride 1 + BNORM |
| [2 2] Max Pooling stride 2 |
| Conv 2 | 3x3x64x128 ReLU stride 1 + BNORM |
| Dropout 0.5 |
| [2 2] Max Pooling stride 2 |
| Conv 3 | 3x3x128x128 ReLU stride 1 + BNORM |
| [2 2] Avg Pooling stride 2 |
| FC     | Fully Connected 4x4x1024 ReLU |
| Dropout 0.5 |
| Fully Connected 1x1x1024x1024 ReLU |
| Dropout 0.5 |
| Fully Connected 1x1x1024xN |
| (N = Number of Children) |
| Softmax Layer |

### TABLE 5
Branch Node of Tree-CNN C (CIFAR 100)

| Layer  | Description |
|--------|-------------|
| Input  | 32x32x3     |
| Conv 1 | 5x5x3x32 ReLU stride 1 + BNORM |
| [2 2] Max Pooling stride 2 |
| Conv 2 | 5x5x32x64 ReLU stride 1 + BNORM |
| Dropout 0.25 |
| [2 2] Max Pooling stride 2 |
| Conv 3 | 3x3x64x64 ReLU stride 1 + BNORM |
| Dropout 0.5 |
| [2 2] Avg Pooling stride 2 |
| FC     | Fully Connected 4x4x512 ReLU |
| Dropout 0.5 |
| Fully Connected 1x1x512x128 ReLU |
| Dropout 0.5 |
| Fully Connected 1x1x128xN |
| (N = Number of Children) |
| Softmax Layer |

- Maximum number of output/children for a *branch* node is 10

The depth of the tree is constrained for ease of conducting the experiment. The algorithm then needs to be implemented only at the *root* node level. It was observed during developing the algorithm that new classes tend to have a higher softmax likelihood value for *branch* nodes with higher number of children. To prevent the network from being lop-sided, by having one very large branch, we limit the number of children to 10 per *branch* node. Once the placement of the new classes is determined we train the *root* node and the modified *branch* nodes. The *root* node is trained for 250 epochs, with learning rate 0.1 for first 100 epochs, then the learning rate is reduced by 10 every 50 epochs.

To compare, we use same fine tuning test cases on network “B” as the previous experiment. We have 5 different cases, each having a different depth of back-propagation, as explained in Section 4.1.2.

## 5 RESULTS

Now, we discuss the results obtained from the two sets of experiments. To reiterate, the first experiment had only one incremental learning stage. While, the second experiment demonstrated how the network grew to accommodate new data over time. The network grows 10 folds in classification capacity, from 10 classes to 100 classes. We compare our proposed method against re-training final layers of a standard DCNN. The methods were compared against the following metrics:

- Training Effort = \( \sum_{nets}^{nets} \) (total number of weights × total number of training samples)
- Testing Accuracy

Every training sample generates a corresponding error that is back-propagated through stochastic gradient descent to update the network weights. Training Effort is the number of weight updates that happen per training epoch. As batch size and number of training epochs is kept the same, the product of number of weights and the number of training samples used gives us a good measure of the effort used in training a network. For *Tree-CNN* the training effort of each of the nodes (nests) is summed together. For network “B”, there is only one net in each case.

### 5.1 Adding multiple new classes (CIFAR-10)

In Fig. 5, we compare the test accuracy and the training effort for the 5 cases of fine-tuning network “B” against our *Tree-CNN C* for CIFAR-100. Retraining only FC layer of network “B” requires the least training effort. However, it gives us the lowest accuracy, 78.37% amongst all. And as more classes are introduced, this method causes much loss in accuracy, as shown with CIFAR-100 in Fig. 7. Our proposed model, *Tree-CNN A* has the second lowest normalized training effort, ~ 40% less than ‘B:Case V’, and ~ 30% less than ‘B:Case II’. At the same time, *Tree-CNN A* (86.25%) had comparable accuracy to ‘B:Case II’ (85.02%) and ‘B:Case III’ (88.15%), while just being less than the ideal case ‘B:Case V’ by a margin of 3.76%.
5.2 Sequentially adding new classes (CIFAR-100)

We compare Tree-CNN C against the 5 different fine-tuning cases of Network “B”. Fig. 6 shows the training effort for all the test cases for CIFAR-100 experiment. We normalized the training effort by dividing all the values with the highest training effort. i.e. ‘B:Case V’. ‘B:Case I’ has the lowest training effort, as we only fine tune the final fully connected layer. However, it performs the worst in accuracy as shown in Fig. 7. Tree-CNN C requires almost the same training effort as ‘B:Case II’, and achieves better accuracy than ‘B:Case II’ and ‘B:Case III’. It achieves accuracy within the same range as ‘B:Case IV’, while requiring 20% less training effort. ‘B:Case IV’ and ‘B:Case V’ require almost similar training effort, as the difference is only the extra training of the smallest CONV layer, i.e. the first layer. ‘B:Case V’ gives us the best accuracy, however, that is because we are retraining the entire network with all the images. There is no pre-trained kernel sharing and it is as good as starting anew, thereby requiring the highest training effort. The Tree-CNN achieves an accuracy of 60.46% on the full CIFAR-100 dataset. It is 2.59% less than the accuracy achieved by training the full network “B”, which gives us 63.05%. The overall accuracy of the Tree-CNN and the network we compared with is comparable to the range of reported accuracy of similar sized networks, such as 67.38% by HD-CNN [19], 67.68% by Hertel, et al [29]. Further improvements to accuracy can be done by modifying the CNN architecture of the nodes, and by adopting methods such as “all convolutional net” [30], “exponential linear units” [31].

In all 6 cases, the training effort required at a particular learning stage was greater than the effort required by the previous stage. This is because we had to show images belonging to old classes to avoid “catastrophic forgetting”. Our method had lower slope for Training Effort v/s Learning Stage, as compared to all but one (Case I) of network
TABLE 6
Root Node of Tree-CNN C classifying CIFAR-100 classes into 17 child nodes (after 9 Learning Stages)

| 1   | trout | dolphin | turtle | seal   | sea   | mouse | lizard | elephant | mushroom | maple tree |
|-----|-------|---------|--------|--------|-------|-------|--------|----------|----------|------------|
| 2   | bridge| mountain| palm tree| tank   | willow tree| castle | plain | train | bus | leopard |
| 3   | girl | man | woman | baby | boy | | | | | |
| 4   | caterpillar | bottle | can | bear | skunk | fox | tiger | telephone | rocket | porcupine |
| 5   | lawn mower | | | | | | | | | |
| 6   | possum | hamster | kangaroo | whale | shrew | dinosaur | beaver | flatfish | shark | snail |
| 7   | otter | chimpanzee | cloud | bowl | lion | ray fish | worm | raccoon | bee | rabbit |
| 8   | poppy | aquarium fish | sunflower | butterfly | cockroach | tulip | orchid | spider | beetle | crab |
| 9   | sweet pepper | apple | orange | pear | rose | | | | | |
| 10  | bicycle | chair | couch | table | house | bed | tractor | pickup truck | road | motorcycle |
| 11  | lobster | | | | | | | | | |
| 12  | clock | plate | wardrobe | keyboard | television | cup | lamp | snake | | |
| 13  | oak tree | streetcar | pine tree | forest | | | | | | |
| 14  | skyscraper | | | | | | | | | |
| 15  | squirrel | camel | cattle | | | | | | | |
| 16  | crocodile | | | | | | | | | |
| 17  | wolf | | | | | | | | | |

“B”. For Tree-CNN C, the normalized training effort incremented by 0.081 on average for every stage, while for network “B”, the increment was 0.041, 0.086, 0.097, 0.0997, and 0.1 for the 5 cases, in increasing order of number of layers trained in each case.

An interesting thing to note was similar looking classes, that were also semantically similar, were grouped under the same branches. At the end of the 9 incremental learning stages, the root node had 17 children nodes out of which 4 were leaf nodes and remaining 13 were branch nodes. The details of the classes associated with each of these 17 nodes is given in Table 6. These 13 branch nodes further had 3 to 10 leaf nodes. The final groups formed after training all the classes is given in Table 6. Certain similar objects grouped together is shown in Fig. 8. While there were some groups that had objects sharing semantic similarity as well, there were a few odd groups, such as Node 13 as shown in Fig. 8. The groups formed is dependent partly on the sequence in which the classes arrived. As we had limited the number of leaf nodes of a branch to 10, even when a new class matched which the classes arrived. As we had limited the number of classes is given in Table 6. Certain similar objects grouped with the trees because most images of streetcar in some cases, such as branch number 13, the street car was grouped with the trees because most images of streetcar in the dataset were green in color. Color and shape similarities led to grouping of very semantically dissimilar objects.

6 DISCUSSION
In this work, we explore a method for incremental learning when dealing with very large image databases. The motivation of this work stems from the idea that subsequent addition of new image classes to a network should be easier than retraining the whole network again with all classes. We observed that expectedly, each incremental learning stage required more effort than the previous, because images belonging to old classes needed to be shown to the CNNs. This is due to the inherent problem of “catastrophic forgetting” in deep neural networks. Our proposed method has a lower rate of increase of training effort over consecutive learning stages as compared to the effort need to fine-tune limited layers of a large network, while maintaining comparable accuracy. However, the Tree-CNN continues to grow in size over time, and the implications of that while implementing on hardware is an important future work. The Tree-CNN grows in a manner such that images that share common features are closer neighbors in the tree than those images that are very different. The final leaf nodes, and the distance between them can also be used as measure of how similar or different any two images are. Such a method of training and classification can be used to hierarchically classify large datasets. The correlation between image similarity and the location of the image classes in the Tree-CNN needs to be analyzed empirically. Our proposed method, Tree-CNN, thus offers a better incremental learning model that is based on hierarchical classifiers and transfer learning. It could, also, potentially be applied to large image search operations. During inferencing, we can choose to parse the network up to a certain depth to give us an idea of which “super-category” the search image belongs to. Hence, it could offer a quick solution to analyze incoming data.

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