HierNet: Image Recognition with Hierarchical Convolutional Networks

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Abstract: Convolutional Neural Networks (CNNs) have proven to be an effective method for image recognition due to their ability to extract features and learn the internal representation of the input data. However, traditional CNNs disregard the hierarchy of the input data, which can lead to suboptimal performance. In this paper, we propose a novel method of organizing a CNN into a quasi-decision tree, where the edges represent the feature-extracting layers of a CNN and the nodes represent the classifiers. The structure of the decision tree corresponds to the hierarchical relationships between the label classes, meaning that the visually similar classes are located in the same subtree. We also introduce a simple semi-supervised method to determine these hierarchical relations to avoid having to manually construct such a hierarchy between a large number of classes. We evaluate our method on the CIFAR-100 dataset using ResNet as our base CNN model. Our results show that the proposed method outperforms this base CNN between 2.12-3.77% (depending on the version of the architecture), demonstrating the effectiveness of incorporating input hierarchy into CNNs. Code is available at https://github.com/levtempfli/HierNet

1 INTRODUCTION

In the area of Deep Learning, the problem of image classification is one of the most fundamental and heavily researched problems. The introduction of Convolutional Neural Networks (CNNs) was a major breakthrough in the field (LeCun et al., 1998; Krizhevsky et al., 2012). Since then, the appearance of more sophisticated architectures and training algorithms built on CNNs has increased the performance of models year by year (Krizhevsky et al., 2012; Simonyan and Zisserman, 2015; He et al., 2016; Tan and Le, 2019).

Traditional CNNs are built sequentially with layer after layer starting with an input layer and ending with some flattening and fully connected layer(s). The idea behind these networks is that the convolutional operation acts on a small area of the input, thus detecting small details. Convolutions can extract lower-level features in the earlier layers, while higher-level features in the last layers. This way, a stack of convolutional layers can learn the general visual representation of an object accurately. However, these sequential models disregard the hierarchy of the data classes and treat every class equally distinguishable. In reality, groups of classes have similar visual appearances (e.g., a dog is similar to a cat, while a tulip is much more similar to other flowers than to animals).

In this paper, we introduce *HierNet*, a CNN architecture that exploits the hierarchy between the classes. HierNet is organized in a tree-like architecture and can be conceptualized as a decision tree (see Figure 1). The difference is that the edges in our tree represent convolutional, feature-extracting operations, and in the nodes happens the classification of which route should be taken next (based on the extracted features in the preceding edge). The categories outputted by the leaf nodes represent the predicted class. Although we have to train the whole tree, during inference we only have to evaluate just one route from the root node to a leaf node based on the outputs of the classifications in the nodes.

To construct our model, we need the hierarchy of the classes represented as a tree. In such a tree, the classes are the leaves, and the internal nodes are the *super-classes* (or groups of classes) of its child nodes. While a small number of categories can be constructed manually, we introduce a method for creating such a hierarchical tree in an automated way to handle classification problems with hundreds of cate-

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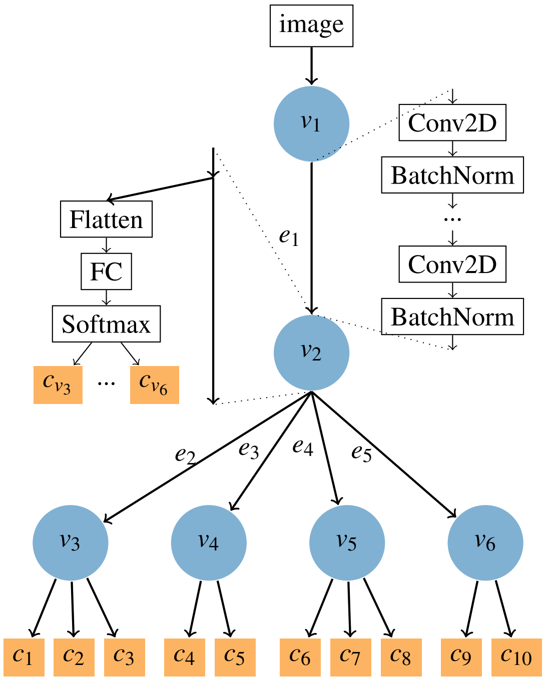


Figure 1: Basic architecture of HierNet. The edges contain the operations the same as the backbone. In the nodes, the output of the previous edge is connected to subsequent edges and to the classification module that outputs the next node.

gories.

Introducing the hierarchy of classes and internal nodes also improves the explainability of the network's decision: compared to a traditional convolutional neural network (where one can only get the output probabilities), HierNet also outputs the probabilities produced by the internal nodes. This information helps to understand why a certain prediction is made, and in case of an incorrect decision, it also facilitates architectural improvement by indicating which part of the architecture needs to be extended to improve accuracy.

We summarize our main contributions as follows:

- We introduce HierNet, a tree-like CNN architecture that exploits the hierarchy between classes.
- We present a semi-supervised method to cluster classes into super-classes based on their hierarchical relations.
- We analyze and compare the results of HierNet and its backbone model using the CIFAR-100 dataset.

2 RELATED WORK

One of the first papers that introduced a hierarchical deep CNN architecture for image classification is HD-CNN (Yan et al., 2015). This work uses a coarse category CNN classifier to separate easy classes, and fine category classifiers for more challenging classes. The method is built upon a building block CNN, which can be chosen from top-ranked single CNNs. HD-CNN probabilistically integrates predictions from fine category classifiers and achieves lower error with a manageable increase in memory and classification time. The main disadvantages of this method are the slow training time (due to the separate training of coarse and fine classifiers) and the lack of possibility to scale to hierarchical classification tasks that have more than two levels.

A similar approach to ours is the Adaptive Neural Trees (ANT) (Tanno et al., 2019). ANT has a tree-shaped architecture with convolutional layers on the edges (so-called ”transformers”) and classifiers in the nodes (so-called ”routers” in the internal nodes and ”solvers” in the leaf nodes.). During inference, only one route is selected. Compared to our method, the main difference is that their leaf nodes output all of the classes, and the hierarchy of the tree is not based on the logical hierarchy between classes: their hierarchy is built dynamically during training by randomly adding leaf nodes and edges, keeping them if they improve the model accuracy, and discarding the change if they don't.

Attention Convolutional Binary Trees (ACNet) is another tree-shaped architecture with convolutional operations along the edges and routers in the nodes (Ji et al., 2020). ACNet is constrained to use a binary tree structure with a pre-defined depth, the operations on the edges are asymmetrical, and the results are from the accumulation of leaves.

(Zhu and Bain, 2017) introduces Branch Convolutional Neural Network or B-CNN. This work also uses a predefined hierarchical tree of classes. Although it has a sequential model, there are classifiers at various depths of the CNN to predict super-classes and, finally, the classes in the last classifier. Considering the classifiers of the super-classes are earlier than those of the child classes, this paper showed that the feature extractions learned to classify a super-class could be reused for subsequent classifiers.

3 MODEL DESCRIPTION

The task of HierNet is learning to classify image samples into c categories, formally to learn the conditional distribution $p(y|x)$ from a $\{x^{(i)},y^{(i)}\}_{i\in[\![1,N]\!]}$ dataset, where $x^{(i)} \in X$ denotes an image, $y^{(i)} \in Y$ the corresponding label, and N the number of training samples; X and Y is the set of training images and the set of c labels, respectively. Next, we present the basic architecture of HierNet, how the training is performed, and three techniques to enhance the model's accuracy.

3.1 Basic Architecture

The architecture is organized around a decision tree, so we define the architecture with a $H = (T,F,C)$ triad, where T denotes the topology of the tree, F the feature extracting operations performed on the edges and C the classifier operations conducted in the nodes.

Topology Considering it is a tree, the T topology of the tree consists of a V set of nodes and E set of edges, where $V = \{v_1,v_2,...v_n\}$ and $E = \{e_1,e_2,...,e_m\} = \{(a,b) : a,b \in V, a \neq b\}$, where (a,b) means that b is the child of a. There is one and only one root node $root \in V$ without a parent ($|\{(a,b) : b = root, a \in V\} \cap E| = 0$) and every other $v \in V \backslash \{root\}$ node has only one parent ($|\{(a,b) : b = v, a \in V\} \cap E| = 1$). This topology is constructed from the hierarchy between the c classes obtained either manually based on the logical hierarchy or with an algorithm based on a confusion probability matrix (as described in Section '4).

Operations Every edge is assigned with zero or more feature-extracting operations $f \in F$.

We denote with $f_{i,j}$ the j-th operation of the e_i edge, where $i \in \{1,m\}$, $j \in \{1,k_i\}$ and k_i is the number of operations in the i-th edge. The direction of the operations is from the parent node to the child node. The edge e_i can be considered as the function $f_{i,k} \circ f_{i,k-1} \circ \cdots \circ f_{i,2} \circ f_{i,1}$, where $f_{i,1}$ gets the input from the preceding edge (except from $f_{1,1}$, where the input is the model input – the image). $f_{i,k}$ operation's output is fed into the next edges (if there are any) as well as to the classifier of the v_{i+1} node. Technically, a feature extracting operation could be any continuous, derivable function with arbitrary input and output dimensions, but considering that our task is image classification, we use the usual operations used in convolutional neural networks, like convolutional layers, batch normalization (Ioffe and Szegedy, 2015), max pooling and ReLU. It is important to note that an operation's output dimension must match the next operation's input dimension requirements.

Classification Every node v_i (where $i > 1$) contains a classifier function c_i The role of these nodes is the same as the nodes of a decision tree: to decide towards which child node to send the samples from the current node route (to which sub-tree). The c_i function is the composition of 3 functions/operations, $c_i(x) = c_{i,3}(c_{i,2}(c_{i,1}(x)))$, where the input of $c_{i,1}$ is the output of the incoming edge. The role of $c_{i,1}$ is to flatten its input by applying a simple flattening or a Global Average Pooling. The $c_{i,2}$ is a fully connected layer with $v_{i_{out}}$ output neurons, where $v_{i_{out}}$ is the number of child edges (or child nodes) of v_i. Formally: $c_{i,2}(x) = W \cdot x + b$ with W weights and b biases. $c_{i,3}$ is a Softmax function, that outputs a probability distribution over the $v_{i_{out}}$ options. This is used for deciding the next route by selecting the one with the highest probability. Let $c_i^{e_j}$ be the probability predicted for the direction towards edge e_j (or v_k), where $e_{j_{parent}} = v_i$ and $e_{j_{child}} = v_k$.

The root node of the tree is an exception since there is no need to classify the input image without feature extraction. So the root node simply forwards the input image to $f_{1,1}$.

Backbone model For the operations on the edges, we use the same operations in the same order that are present in standard CNNs, like ResNet (He et al., 2016) or VGG16 (Simonyan and Zisserman, 2015). We call these the "backbone" models of HierNet. Every operation (or layer) present in the backbone model is spread out from the edge after the root node to the edges before the leaves. Since the output of an edge is connected to the inputs of every subsequent edge, operations from the root node to a leaf node are the same as the operations from the input to the output of the backbone model. The classifications in the nodes are an exception because the backbone model only has a classification function at the end of the model. In contrast, HierNet has classifiers at every node (except the root node), and the number of possible output classes at a leaf node is much smaller. It is configurable how we would like to split up the operations of the backbone model among the edges on a root-to-leaf path, but we made a constraint that every edge at an i level must have the same operations. Figure 2 illustrates the relation between our model and a backbone model.

During prediction We carry out the classification of the input image the following way: apply all the operations on the edge after the route node; feed the output of the operations to the classification function in the first node after the root; choose a sub-branch based on the output of the classification function; apply all the operations in the sub-branch on the feature

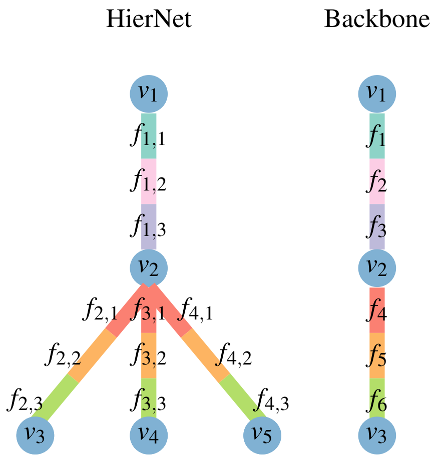


Figure 2: Relation between the HierNet and a backbone network. The different colors represent the different operations/layers. The operations follow the same architecture and order as in the backbone model. The edges on the same level have the same set of operations.

map obtained previously; feed the output of the last operations to the first node on the sub-branch; continue the cycle until reaching a leaf; the classifier in the leaf should give back the correct class of the inputted image in that node. An outputted class in a leaf node can be transformed easily into a global class number because we know the order of leaf nodes. Considering only the operations from the root to a leaf are evaluated, and the operations on a root-to-leaf route are exactly the same as the backbone model, the evaluation time during prediction should be similar to the backbone model with the slight addition of the classifiers in the nodes. The pseudocode of the algorithm used during prediction is presented in Algorithm 1.

```
Input: $input$ - an RGB image
$e \leftarrow e[1]$;
$x \leftarrow e(x)$ // $e(x) = f_k(\dots f_2(f_1(x))\dots)$
$v \leftarrow v[2]$ // $v(x) = c(x)$, where $c = c_i$
$class \leftarrow v(x)$;
while $v \notin V_{leafs}$ do
    $e \leftarrow v_{child\ edges}[class]$;
    $v \leftarrow v_{child\ nodes}[class]$;
    $x = e(x)$;
    $class = v(x)$;
end
$class \leftarrow$ global class prediction form $class$
  and $v$;
```

Algorithm 1: HierNet prediction algorithm.

3.2 Training

HieNet can be trained end-to-end, like the baseline model. To achieve this, each of the outputted probabilities of the leaf nodes is multiplied by all the outputted probabilities of the ancestor nodes leading to that leaf. Formally, let R_{v_i} be the set of edges on the route from the *root* to v_i and o_i is the new outputted probability distribution of v_i. In this case $o_i = c_i * \prod_{j \in R, k \in \{k : v_k = e_{j_{parent}}\}} c_k^{e_j}$. Then the new classification outputs of the leaf nodes are concatenated from left to right. Because only one route corresponds to an outputted class, there are altogether c number of categories outputted by the leaf nodes, and we got our output.

It's important to note that the order of the outputted classes depends on the hierarchical tree given. Hence, it is necessary for every model to reorder the labels in the dataset; the categories of the true label's one-hot representation match the intended place of that label in the hierarchy.

We can report two accuracies for every model: a ”conditional accuracy” and a ”routing accuracy.” The former is calculated from the predictions by the output during training (the concatenated o_j-s), while the latter is by following the route from the root to a leaf based on the classifier outputs of the nodes (the method outlined in section 3.1 or Algorithm 1).

We use Categorical Cross-entropy loss for the training of HierNet As far as the training algorithm, learning rate, or other similar hyperparameters are concerned, we usually use the same configuration as the baseline model.

3.3 Additional Layers Before the Classifier

We present a modification of the architecture in the nodes to increase their accuracy: Adding a few additional layers between the input from the edge and the flattening by the classification function. An illustration of this modification is shown in Figure 3.

The motivation behind this is that categorizing into super-classes might require different, independent features extracted. Previously the feature map used by the classifier in the nodes was the same as the feature map passed to the subsequent layer. But with this modification, there are additional operations on that feature map that are only used for the classifications. These extra layers might extract the features specific for super-classes categorized by that node.

The additional layers added after the edge input also follow the backbone model's architecture. Considering the last operation from the previous edge cor-

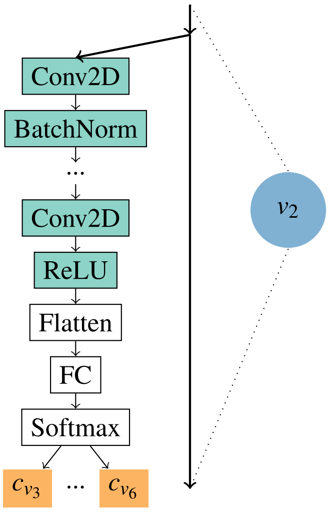


Figure 3: Slight modification of the node: Additional feature extracting layers (with green background) before the classifiers to increase node accuracy.

responds to a layer from the backbone model, the few k added layers in the node correspond to the following k layers in the backbone model.

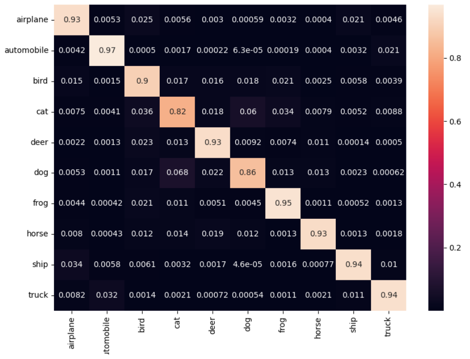
The leaf nodes are an exception because we cannot assign any additional layers to them. The reason behind this is that the architecture of a root-to-leaf path is the same as the backbone architecture; hence the input of the leaf nodes is the output of the last layer of the backbone model therefore, there are no remaining layers after the last one to add to the nodes.

The drawback of this approach is the slightly increased model size. Previously during prediction, the evaluation complexity of a route from the root to a leaf was similar to the evaluation complexity of the backbone model, just with a small surplus of the evaluation of the classifier functions in the nodes. With this approach, this difference increases by the evaluation complexity of the added operations in every touched node, so it is crucial not to overshoot the number of added layers.

4 HIERARCHY CONSTRUCTION

The topology of our model is constructed from a tree that represents the hierarchy between the c classes of the dataset. The leaves of this tree are the c classes, and the internal nodes represent the *super-classes*. In an ideal hierarchical tree, if the visual difference is small for two classes, the probability of being in the same super-class is high.

While a hierarchy can be constructed manually for a few dozen classes, this could be time-consuming when there are hundreds or thousands of classes.



	airplane	utomobile	bird	cat	deer	dog	frog	horse	ship	truck
airplane	0.93	0.0053	0.025	0.0056	0.003	0.00059	0.0032	0.0004	0.021	0.0046
automobile	0.0042	0.97	0.0005	0.0017	0.00022	6.3e-05	0.00019	0.0004	0.0032	0.021
bird	0.015	0.0015	0.9	0.017	0.016	0.018	0.021	0.0025	0.0058	0.0039
cat	0.0075	0.0041	0.036	0.82	0.018	0.06	0.034	0.0079	0.0052	0.0088
deer	0.0022	0.0013	0.023	0.013	0.93	0.0092	0.0074	0.011	0.00014	0.0005
dog	0.0053	0.0011	0.017	0.068	0.022	0.86	0.013	0.013	0.0023	0.00062
frog	0.0044	0.00042	0.021	0.011	0.0051	0.0045	0.95	0.0011	0.00052	0.0013
horse	0.008	0.00043	0.012	0.014	0.019	0.012	0.0013	0.93	0.0013	0.0018
ship	0.034	0.0058	0.0061	0.0032	0.0017	4.6e-05	0.0016	0.00077	0.94	0.01
truck	0.0082	0.032	0.0014	0.0021	0.00072	0.00054	0.0011	0.0021	0.011	0.94

Figure 4: The confusion probability matrix of the 10 CIFAR-10 classes from the validation set evaluated on the ResNet backbone ($n = 5$).

Moreover, a hierarchy constructed by humans may not be the best option for CNNs: one could say that a bird and an airplane should belong to the same super-class since both of them have wings but for the network, their visual similarity is not close at all. To tackle this problem, we construct the hierarchy based on the confusion probability matrix of the network.

Confusion probability matrix To group the categories, we need to have some information about the visual similarity relations between the classes. For this, we create a *confusion probability matrix* (CPM) similar to a confusion matrix. In a CPM's row (corresponding to a true label) the predicted probabilities are accumulated instead of the predicted classes. Then every row is divided by the number of examples belonging to that true label, so the row contains the average probabilities that represent the chance of a true class being predicted as another class. $CPM[i][j] = p$ represents the probability of an image with i class being predicted as j class. We construct the CPM with the trained backbone evaluated on the validation set. An example with the CPM matrix is shown in Figure 4.

Grouping algorithm To group c number of classes into g groups based on the CPM, we define the proximity of classes c_1, c_2 as $dist(c_1, c_2) = CPM[c_1][c_2] + CPM[c_2][c_1]$ – the back and forth confusion probabilities). The proximity of two groups is defined by $dist(G_1, G_2) = \frac{1}{|T|} \sum_{(c_1,c_2) \in T} (CPM[c_1][c_2] + CPM[c_2][c_1])$, where $T = G_1 \times G_2 = \{(c_1, c_2) : c_1 \in G_1, c_2 \in G_2\}$ – the average of proximities of all combinations of classes from the two groups.

The grouping works by first considering every class a different group. It merges the two groups with the highest proximity at every iteration until there are no more possible group pairs to merge. During grouping, the following constraints are considered: (1) The combined sizes of the two groups cannot exceed the g_{max} predefined value; (2) The proximity of the two groups has to exceed the p_{min} value. The second one is necessary to only group classes together that are close enough and the first one is to avoid too large groups when the others are small by cardinality.

Although this algorithm only creates groups of classes from a set of classes, thus resulting in a hierarchical tree with a depth of 2 (level 0: root; level 1: nodes representing the groups, level 2: nodes representing the classes), applying it recursively on the created groups will result in sub-groups, thus deeper trees.

5 Experiments

In this section, we will discuss the results of our method. First, we will discuss the hyperparameters that define our model, the range of these parameters that we tested, and what we found to be the recommended values. Then we will discuss the metrics and datasets used, followed by the reference models used, software/hardware configurations, and finally the results and comparisons.

5.1 Hyperparemeters

Besides the backbone (or reference) model used and the traditional hyperparameters (e.g. learning rate, batch size, number of epochs), each HierNet is defined by 4 specific parameters.

Split point of backbone CNN Since the convolutional and other feature-extracting layers are in the same order on a route from root to leaf as in a sequential backbone network, we need to define a split point. Such a point defines how many of the first layers belong to the common edge before the first classifier, while the rest belong to the edges leading to the leaf nodes. We tested with split points ranging from 30% to 85% of the total number of layers. According to the experiments, lower split points ($30-50\%$) performed worse, while higher ones yielded higher accuracy, meaning that our model seems to require more feature extraction for the superclass decision than for the fine class decision. Although high split points generally performed better, too high of a split point ($85-90\%$) also resulted in a decrease in accuracy, meaning that the optimal range is around $70-75\%$.

Number of additional classifier layers We presented in 3.3 a modification that increases the accuracy of our model by adding some independent layers for the superclass classifier node. We empirically showed that the more layers added, the better the performance, which is understandable because the model has more parameters to learn the representation, but it also increases the evaluation time. Adding just $4\%-12\%$ of the total number of layers as additional independent layers had a significant increase in performance compared to not adding any layers at all. While adding $16\%-25\%$ gave even better results, the leap was not as big as going from 0% to $4\%-12\%$.

Minimum proximity of group members The structure of our tree is defined by the hierarchy or groups created by our grouping algorithm. One of the parameters that define the groups produced is the minimum required proximity of the members of a group (as described in 4). We have found this to be the much more important parameter because it generally defines the allowed variety of objects in a group, and hence the number of groups. Having too few or too many groups resulted in a significant drop in performance, and in our case of 100 classes, the optimal number of groups we found was around $6-8$. The minimum proximity parameter should be set to achieve a similar number of groups, in our case it was around $0.005-0.0075$.

Maximum size of each group Restricting the size of a group turned out to be a much less useful parameter than minimum proximity. We compared several cases where the number of groups was the same, but in one case it was produced by high p_{min} and low g_{max}, and in the other by low p_{min} and high g_{max}. We found that controlling the size of a group with p_{min} was much more beneficial, so we later decided to just set g_{max} to 50. This allowed quite large groups but still didn't allow more than half of the classes to belong to just one group, which would defeat the purpose.

5.2 Metrics

For our task of classification, we use accuracy as the metric to measure performance, just like the authors of (He et al., 2016; Shah et al., 2016). A HierNet model can be evaluated in two ways, so naturally we can calculate two different accuracies for each model. The fast evaluation method is to evaluate only one branch or path of the decision tree based on the decision in the superclass classifier node, thus making the prediction in only one leaf node. The much slower but slightly more accurate evaluation method is to evaluate every branch of the decision tree for an input image and, similar to training, we can construct a probability vector by multiplying the output probabilities along the path to a leaf node, thus predicting from all classes. Having two evaluation methods means having two reportable accuracies. The fast scoring method can be used in cases where higher accuracy is desired with similar performance as the backbone network. Conversely, the slower scoring method can be used when performance is less important.

5.3 Dataset

We use the CIFAR-100 (Krizhevsky et al., 2009) dataset for our experiments. It consists of 60000 RGB images with a resolution of 32×32 containing 100 classes, each class containing 600 images.

This dataset is more suitable for our purposes than the CIFAR-10 dataset by the same authors (Krizhevsky et al., 2009), because it has significantly more classes that are less feasible to group manually, allowing us to test the effectiveness of our grouping algorithm. On the other hand, it has much fewer images of much lower resolution than ImageNet (Russakovsky et al., 2015), allowing us to train it on our own hardware.

Originally, the dataset is split into two sets, one containing 50000 images, and the other 10000. We use the first set for training, but we further split the second set into a validation set and a test set, both containing 5000 images with the same number of images per class. We use the validation set to evaluate the backbone model, to construct the groupings from the confusion probability matrix, and then to perform hyperparameter tuning. In this way, we avoid leaking information from the test set into the training, and we may evaluate the test set only once. The reported accuracies are measured on the test set.

We use the same 2 image augmentations as the authors of (He et al., 2016), namely: random horizontal flip and random translation with a factor of 0.125 on both the horizontal and vertical axis, where the pixels outside the image are filled with grey.

5.4 ResNet: The Backbone Model

We use two types of ResNet (He et al., 2016) architectures as our backbone reference models: the original ResNet (He et al., 2016) and a ResNet that uses ELUs (Shah et al., 2016) (Exponential Linear Units (Clevert et al., 2015)).

Architecture Like the authors of (Shah et al., 2016), we do not use the regular ResNet architecture tailored for ImageNet, but the smaller version used by the original authors of ResNet (He et al., 2016) for classifying CIFAR-10 images. The original authors(He et al., 2016) define network sizes of $n = \{3, 5, 7, 9, 18\}$, where they first have a convolutional layer, followed by $3 \times n$ stacks of residual blocks, where each stack of residual blocks has half the feature map size and twice the number of filters of the previous stack, starting from $32x32$ and 16. In the case of the ResNet with ELU activations (Shah et al., 2016), they are also based on this architecture, the difference is in the structure of the residual blocks. In both cases, we use the same architecture, i.e. a route from the root node to a leaf node corresponds exactly to a ResNet (or ELU ResNet), with the slight difference of the additional superclass classifier branch and the reduced fully connected layer (and softmax output) sizes in the leaves. We define the number of additional classifier layers and split points in terms of the number of residual blocks rather than individual layers (but to get the number of layers, multiply by 2 and add 2).

Training In terms of training, we trained with almost the same hyperparameters as the original authors (He et al., 2016). Namely, we use gradient descent with a batch size of 128, a weight decay of 0.0001, and a momentum of 0.9, but there is a slight difference in the learning rate schedule. All HierNets use a similar schedule to the $n = 18$ ResNet, namely, we use 0.01 to warm up the network for 2000 iterations, then we use 0.1 to 32K, 0.01 to 48K, and 0.001 after that. We have found that transfer learning (transferring the weights of a trained backbone CNN to a HierNet) is very beneficial, so we perform it before each training of a HierNet. We re-implemented the backbone models, trained them, and used the resulting accuracies as a reference.

5.5 Software and Hardware Configurations

For ease of implementation, all HierNet and backbone ResNet models were implemented in Python 3.8.10 using TensorFlow v2.7.0. The *tf.Data* input pipeline was used to load the dataset and a custom non-sequential keras. The model was defined to contain the HierNet architecture. We ran the tests on a machine equipped with 16GB of RAM, an Intel 7600K CPU, and an Nvidia GTX 1080TI GPU. The training time was about 1.5-2 hours for the smaller ResNet models of size 20 and 4-5 hours for ResNets

Table 1: Comparison of the accuracy of our HierNet and the backbone ResNet for different network sizes.

n	#layers	ResNet	Ours w/ slow eval.	Ours w/ fast eval.
3	20	65.96	***68.89***	**68.08**
5	32	67.08	***70.65***	**70.45**
7	44	68.12	***71.25***	**70.75**
9	56	68.38	***72.15***	**72.01**
18	110	71.33	***73.45***	**73.27**

Table 2: Comparison of the accuracy of our HierNet and the backbone ELU ResNet for different network sizes.

n	#layers	ELU ResNet	Ours w/ slow eval.	Ours w/ fast eval.
3	20	65.54	***68.30***	**68.16**
5	32	67.88	***70.71***	**70.43**
7	44	68.79	***70.83***	**70.79**
9	56	69.03	***72.47***	**72.29**
18	110	72.93	***74.37***	**74.15**

with 110 layers.

5.6 Grouper Algorithm Results

We would like to briefly present the results of our grouping algorithm to show that the groups produced do indeed contain visually similar classes. The following groupings have been generated based on the confusion probability matrix of the backbone ResNet ($n = 9$) with the settings $p_{min} = 0.0075$ and $g_{max} = 50$:

- GROUP 1: baby, girl, woman, boy, man
- GROUP 2: palm tree, forest, pine tree, willow tree, maple tree, oak tree
- GROUP 3: aquarium fish, trout, flatfish, ray, shark, dolphin, whale
- GROUP 4: wardrobe, chair, television, bed, couch, keyboard ...
- ...

5.7 HierNet Results

Finally, we present the performance of our HierNet model in comparison to the ResNets (He et al., 2016; Shah et al., 2016). The accuracies are reported for the test set, which was evaluated only once after the hyperparameter tuning had been completed.

Table 1 shows the performance improvements provided by our HierNet architecture compared to using a regular, sequential ResNet. As well as improving for each network size, the accuracy of the smallest HierNet ($n = 3$) is comparable to that of the second largest ResNet ($n = 9$), and the second largest HierNet outperforms the largest ResNet ($n = 18$) by 0.82%, despite being half the length. In terms of parameters, each run had the grouping parameters $g_{m}ax = 50$ and $p_{m}in = 0.0075$, additional classifier blocks of $\{2,3,4,5,4\}$ and split points of $\{5,9,12,16,38\}$. The latter two were defined in residual blocks, not layers.

Table 2 shows the results with the ResNet using ELU activations. As in the previous case, our HierNet has better performance for each network size, and smaller HierNets come close to or even exceed the performance of much larger ResNets. In every case, $g_{m}ax$ was set to 50 and $p_{m}in$ was set to 0.005, additional classifier blocks to $\{2,3,2,5,4\}$ and split points to $\{6,9,15,19,38\}$.

We can see a slight difference between our two evaluation methods, with the slower one tending to have a slightly higher accuracy. This is understandable because by training the whole tree, not just a branch, we are training the network on the output of the slow evaluation method, so the increase in accuracy of the faster method is just a 'by-product' of the training.

6 Conclusion

This paper presented HierNet, a convolutional neural network architecture. HierNet exploits the visual similarities and hierarchy between classes. We achieved this by constructing a tree for the hierarchical relationships, where the edges represent the feature extraction convolutions and the nodes have the classifier or routing function. In this way, classes in the same group can share the feature extraction operation, but be independent of the other groups.

The results of our experiments confirm that this architecture works as intended. And although we outperformed the backbone networks in almost every case, there is room for improvement.

An improvement might be a more sophisticated grouping algorithm. Our grouping algorithm often produces group trees where, for example, one group has 40 classes while others have only a few. Although it's probably impossible to construct a completely balanced tree, because some classes are more distinct while another large set of classes are more similar, we could improve our algorithm to take into account how balanced the hierarchy tree is.

Regarding training, since we used the same optimizer, learning rate schedule, and weight decay as for the backbone models, it is very likely that what works for the baseline models is not optimal for HierNet, so we could also investigate the training settings more.

Finally, it might be useful to investigate which features are extracted by the shared edges and which features are extracted by the edges of the individual groups. We could visualize this with an approach similar to the one described in (Zeiler and Fergus, 2014).

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