**Fast CapsNet for Lung Cancer Screening**

* We show that CapsNets significantly outperforms CNNs when the number of t**raining samples is small.**
* To increase the computational efficiency, our paper proposes a consistent **dynamic routing mechanism** that results in 3× speedup of CapsNet.
* Finally, we show that the original image reconstruction method of CapNets performs poorly on lung nodule data.
* We propose an efficient alternative, called **convolutional decoder,**that yields lower reconstruction error and higher classification accuracy.that is more powerful in reconstructing the input from the final capsules. The proposed decoder serves as a regularizer to prevent over-fitting issue, and yields higher classification accuracy than the original CapsNets.

**Why?**

* CNNs have a number of important drawbacks mostly due to their procedure of routing data. Routing is the process of relaying the information from one layer to another layer.
* **CNNs perform routing via pooling operations** such as max-pooling and average-pooling. These pooling operations discard information such as location and pose of the objects which can be valuable for classification purposes.
* Capsule Network, to address CNNs’ shortcomings. The idea is to encode the relative relationships (e.g., locations, scales, orientations) between local parts and the whole object.
* Encoding these relationships equips the model with a built-in understanding of the 3D space. This enables CapsNet to recognize objects from different 3D views that were not seen in the training data.
* **CapsNets employ a dynamic routing mechanism to determine where to send the information.**

**Capsule Networks against Medical Imaging Data Challenges**

* In this work, we compare the behavior of capsule networks against ConvNets under typical datasets constraints of medical image analysis, namely, small amounts of annotated data and class-imbalance.
* We evaluate our experiments on **MNIST, Fashion-MNIST** and medical(histological and retina images) publicly available datasets.
* Our results suggest that **capsule networks can be trained with less amount of data for the same or better performance** and are more robust to an imbalanced class distribution, which makes our approach very promising for the medical imaging community.
* We experimentally demonstrate that the **equivariance properties of CapsNets reduce the strong data requirements,** and are therefore very promising for medical image analysis.
* Focusing on computer-aided diagnosis(classification) tasks, we address the problems of the limited amount of annotated data and imbalance of class distributions.

**Capsule vs Convolutional Networks**

The main technical differences of CapsNets w.r.t. ConvNets are:

i) Convolutions are only performed as the **first operation of the primary caps**

**layer, leading as usual to a series of feature channels.**

ii) Instead of applying a non-linearity to the scalar outputs of the convolution filters, CapsNets build tensors **by grouping multiple feature channels**.

The non-linearity, **a squashing function**, becomes also a **multidimensional** operation, that takes the j −th vector sj and restricts its range to the [0,1] interval to model probabilities while preserving the vector orientation. The result of the squashing function is a vector vj , whose magnitude can be then interpreted as the probability of the presence of a capsule’s entity, while

the direction encodes its pose. vj is then the output of the capsule j.

iii) The weights Wij connecting the i primary capsule to the the j − **th secondary capsule are an affine transformation**. These transformations allow learning part/whole relationships, instead of detecting independent features by filtering at different scales portions of the image.

iv) The transformation weights Wij are not optimized with the regular backpropagation but with a **routing-by-agreement algorithm**.

v) Finally, the output of a ConvNet is typically a softmax layer with cross-entropy loss: Instead, for every secondary capsule**, CapsNet computes the margin loss for class k:**

**Abnormality Detection in Musculoskeletal Radiographs Using Capsule Network**

* Convolutional Neural Network has been used extensively in classifying images and segmentation problems.
* To achieve translation invariance MaxPooling is performed.
* Translation Invariance indicates that CNN will classify the input image in the same way regardless of how the information within the image is shifted and the features location information is lost at the Pooling layer.
* Again the performance of the neural network depends on the depth of the architecture. Adding more layers will reserve more information and improve performance.
* But that also increases the computational complexity and computational cost.
* In contrast information at the neuron level is stored as vectors in capsule network rather than scalars like neural networks.
* The vector output of a capsule uses a powerful mechanism, dynamic routing. These vectors contain information about: spatial orientation, magnitude/prevalence,and other attributes of the extracted feature.

**Objective**

* Find an improved architecture for estimating abnormality in the musculoskeletal condition which can maximize the abnormality detection rate
* Examine the ability of capsule network in the case of image classification and processing and also investigate the over-fitting problem in capsnet.
* And also want to find out whether capsnet can outperform the convolutional neural network

**Enhanced Capsule Network for Medical image classification**

Due to **robustness to rotation and affine transformation**, capsule network can effectively solve this problem of CNN and achieve the expected performance with less training data, which are very important for medical image analysis. The proposed capsule network, the feature decomposition module and multi-scale feature extraction module are introduced into the basic capsule network.

* The feature decomposition module is presented to extract richer features, which reduces the amount of calculation and speeds up the network convergence.
* The multi-scale feature extraction module is used to extract important information in the low-level capsules, which guarantees the extracted features to be transmitted to the high-level capsules.

Capsule networks use vectors to replace neurons in traditional neural networks. A capsule is a group of neurons that learns to detect a specific target in a given area image and outputs a vector. Compared to a scalar neuron, vector capsules can obtain more information, which also enable the capsule network to be promoted on less training data.

Capsule networks **use vector capsules instead of scalar neurons to** represent features, so they can extract richer features and prove to perform better on tasks with imbalance between classes

The **feature extraction module i**s added to extract richer features and feature decomposition is used to extract important information in the low-level capsules and transmit them to the high-level capsules. Experimental results show that the enhanced capsule network has faster convergence speed without any reduction in accuracy.