# Convolutional neural networks for classification of transmission electron microscopy imagery

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January 16, 2017



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- Pitfalls
- Deep Learning software:
  - OS availability
  - Licenses
  - Performance
  - Community support

### Convolutional neural networks (CNN)

### Convolutional neural network (CNN)

It is a special kind of neural network for processing data that has a known, grid-like topology. CNN are simply neural networks that use convolution in place of general matrix multiplication in at least one of their layers.

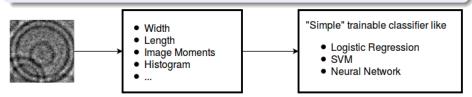
#### Why CNN?

- CNN operate on raw pixel data, i.e. minimum preprocessing
- CNN learn image features themselves, i.e. do not need expert knowledge for selecting feature
- Scalability due to the following assumptions:
  - Local connectivity
  - Parameter sharing
- Documented success

#### Motivation

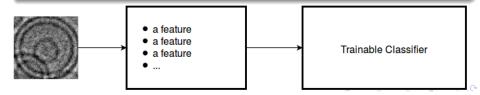
### Traditional Approach

Extract a number of features and then train a "simple" classifier.



#### **CNN** Approach

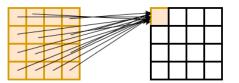
Feed raw pixel data to a model that trains both feature extractor and classifier.



### Local connectivity and parameter sharing

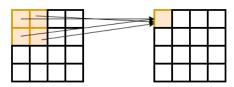
### **Full Connectivity**

All nodes (pixels) in input layer are connected to all nodes in the next layer. All weights are unique.



#### Local Connectivity

Each node in a layer is connected only to a small number of nodes (pixels) from the previous one. Weight are shared within each layer.



### Why now?

CNN are being successfully used for

- Classification
- Segmentation
- Super Resolution
- A lot of other examples

Three reasons why CNN have become so useful right now

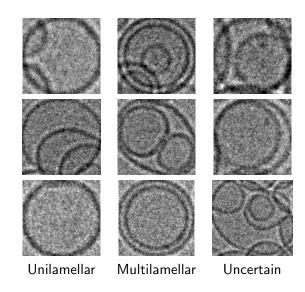
- Big datasets
- Powerful enough hardware
- Software

### Problem description: Lamellarity

Determine structure of a liposome according to the number of lamellae.

There are 14169 EM images and three classes:

- Unilamellar 12368, 87.29%
- Multilamellar 1717, 12.12%
- Uncertain 84, 0.5%

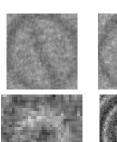


### Problem description: Encapsulation

Determine presence of a liposomal encapsulation.

There are 24918 EM images and three classes:

- Full 24255, 97.34%
- Empty 161. 0.65%
- Uncertain 502, 2.01%







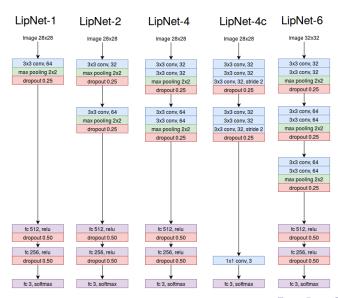


Full **Empty** 



Uncertain

#### Network architectures



### Which LipNet model is the best?

Five LipNet models are evaluated by recording their 5-fold cross validated  $F_1$  scores. Present performance measures.

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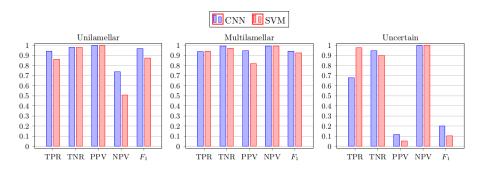
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### Which LipNet model is the best?

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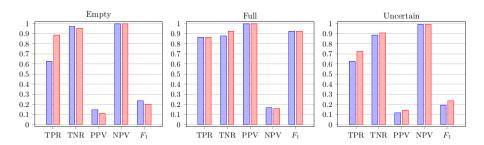
- The Lamellarity Problem: **LipNet-4** is the best
- The Encapsulation Problem: There is no clear leader. LipNet-4 is selected.

### CNN vs SVM: Lamellarity



- CNN is slightly better than SVM.
- Less false negative unilamellar by CNN than SVM.
- Less false positive multilamellar by CNN than SVM.
- Many false positive predictions of *uncertain*, mainly *unilamellar* is confused with *uncertain*.

### CNN vs SVM: Encapsulation



- Almost the same performance.
- Some full are falsely classified as empty and uncertain
  - Low NPV for full
  - ▶ Poor precision (PPV) for *empty* and *uncertain*
- PPV for *full* and NPV for *empty* and *uncertain* are almost 1, so hardly any false positive of *full*.

### Pitfalls and performance improvement techniques

- The Class Imbalance Problem. It is very problematic when a data set is unbalanced. They usually are!
  - Oversampling
  - Undersampling
  - Artificial data
  - Higher penalties for minority classes

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- Poor diversity of the training data
  - Data augmentation
- Regularization
  - Weight decay
  - Noise injection, for example label smoothing
  - Dropout
  - Early stopping

### Deep learning software

#### OS and API

The path of least resistance:

- Linux
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Nearly all libraries are distributed according to some of OSI-approved licenses like Apache, BSD, MIT, etc.

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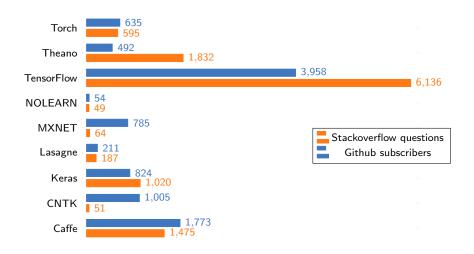
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#### **GPU**

All libraries benefit from GPUs. At the moment there is no study that shows superiority of any library in terms of performance.

### Popularity of deep learning software as of January 2017



#### Conclusion and future work

#### Conclusions:

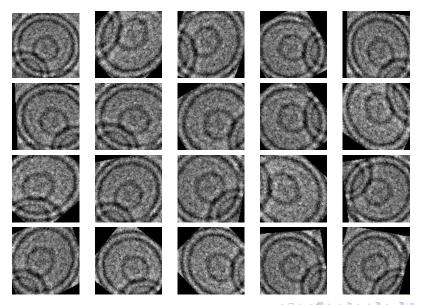
- CNN is a promising tool for research and production
- Reasonable performance
- CNN does not require feature representation
- Limited support for Windows

#### Future work:

- Fully convolutional networks with input of variable size
- Alternative ways to expand the training set
- Fusing, i.e. combine LipNet and another neural network trained on image features

## Thank you!

### Data augmentation example go back



### Performance measures go back

Accuracy is not enough when the data set is imbalanced.

#### Confusion matrix

	Predicted Positive	Predicted Negative
Actual Positive	True Positive	False Negative
Actual Negative	False Positive	True Negative

- True Positive Rate:  $TPR = \frac{TP}{TP + FN}$  (sensitivity or recall)
- True Negative Rate:  $TNR = \frac{TN}{TN+FP}$  (specificity)
- Positive Predicted Value:  $PPV = \frac{TP}{TP+FP}$  (precision)
- Negative Predicted Value:  $NPV = \frac{TN}{TN + FN}$
- F<sub>1</sub> score : harmonic mean of TPR and PPV



### Input images: surrounding and masking

Each image contains a liposome object and its surrounding which goes 50 pixels in each direction. Corresponding particle masks are also available.

#### Three choices:

- Images with surrounding
- Cropped images
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