# Convolutional neural networks for classification of transmission electron microscopy imagery

## Sergii Gryshkevych

Uppsala University
Supervisor: Max Pihlström
Reviewer: Ida-Maria Sintorn
Examinator: Justin Pearson
Opponent: Christopher Lagerhult

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#### Introduction

This MSc project is done in cooperation with Vironova AB.



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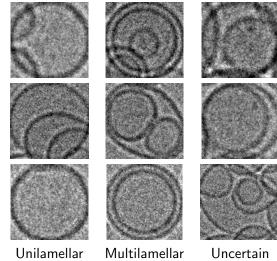
- Discuss the suitability of applying CNN method for classification of electron microscopy images
- Benchmark CNN models against SVM classifier for the selected problems
- Discuss Deep Learning software:
  - OS availability
  - Licenses
  - Performance
  - Community support

# 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%



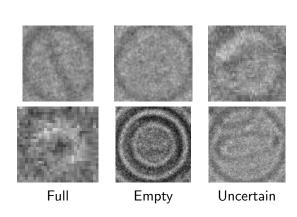
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# Problem description: Encapsulation

Determine presence of a liposomal encapsulation.

There are 24918 EM images and three classes:

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



# The data set of image features

- Maximum width
- Diameter
- Length
- Histogram
- Image Moments
- Radial Density Profile
- Edge Density Profile
- Signal to noise

SVM operates on feature representation of the image.

# 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?

- Scalability due to the following assumptions:
  - Local connectivity
  - Parameter sharing
- 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
- Documented success

## The Class Imbalance Problem

Lamellarity and Encapsulation data sets are imbalanced and it is a problem!

How to mitigate the class imbalance problem? I tried:

- Oversampling
- Undersampling
- SMOTE (Synthetic Minority Oversampling Technique)
- Artificial data
- Higher penalties for misclassification of minority classes

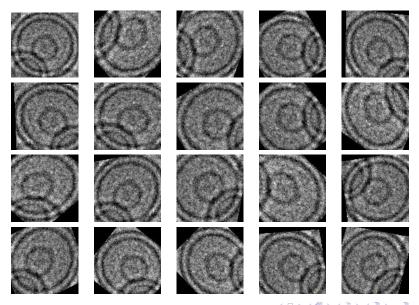
## Regularization

#### **Definition**

Regularization is any modification we make to a learning algorithm that is intended to reduce its generalization error but not its training error

- Weight decay
- Noise injection: label smoothing
- Dropout
- Early stopping
- Data augmentation

# Data augmentation example



# 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
- Cropped and masked

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## Performance measures

Accuracy is not enough when the data set is imbalanced.

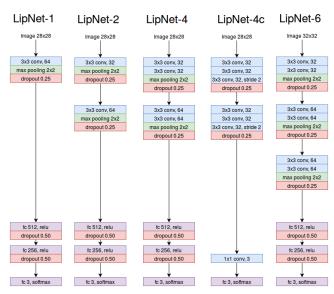
#### Confusion matrix

	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



## Network architectures



## Which LipNet model is the best?

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

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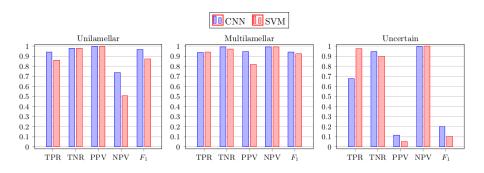
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# Which LipNet model is the best?

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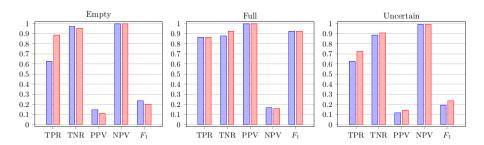
- The Lamellarity Problem: **LipNet-4** is the best
- The Encapsulation Problem: There is no clear leader. **LipNet-2** is selected for the final experiment. LipNet-6 performed worst.

# CNN vs SVM: Lamellarity



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

# CNN vs SVM: Encapsulation



- SVM is slightly better than CNN.
- 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*.

# Deep learning software

## OS and API

The path of least resistance:

- Linux
- Python

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## Licensing

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

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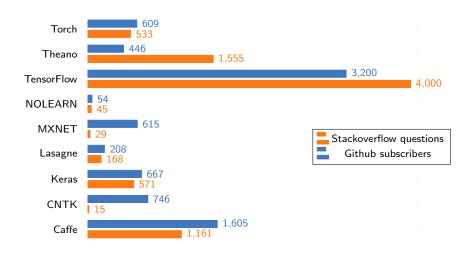
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### **GPU**

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 October 2016



## Conclusion and future work

#### Conclusions:

- Reasonable performance
- CNN is an excellent research tool

#### Future work:

- Fully convolutional networks with input of variable size
- Alternative ways to expand the training set
- Late fusing