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Deep Learning in Radiology: Recent Advances, Challenges and Future Trends

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Outline

- Introduction to Recent Artificial Intelligence Breakthroughs
- Deep learning Methodologies in Computed Tomography
- Deep learning in MRI
- Overview of Past and Present of CAD systems
- Challenges in deep learning methodologies for radiology applications
- Conclusion and future trends for deep learning in radiology
- References

Recent AI Breakthroughs: Deep learning

Deep learning (DL) is a computer technology inspired by the functioning of brain. Artificial neural networks automatically discover patterns in humongous amount of data. Data can be text, images, videos or any of your choice

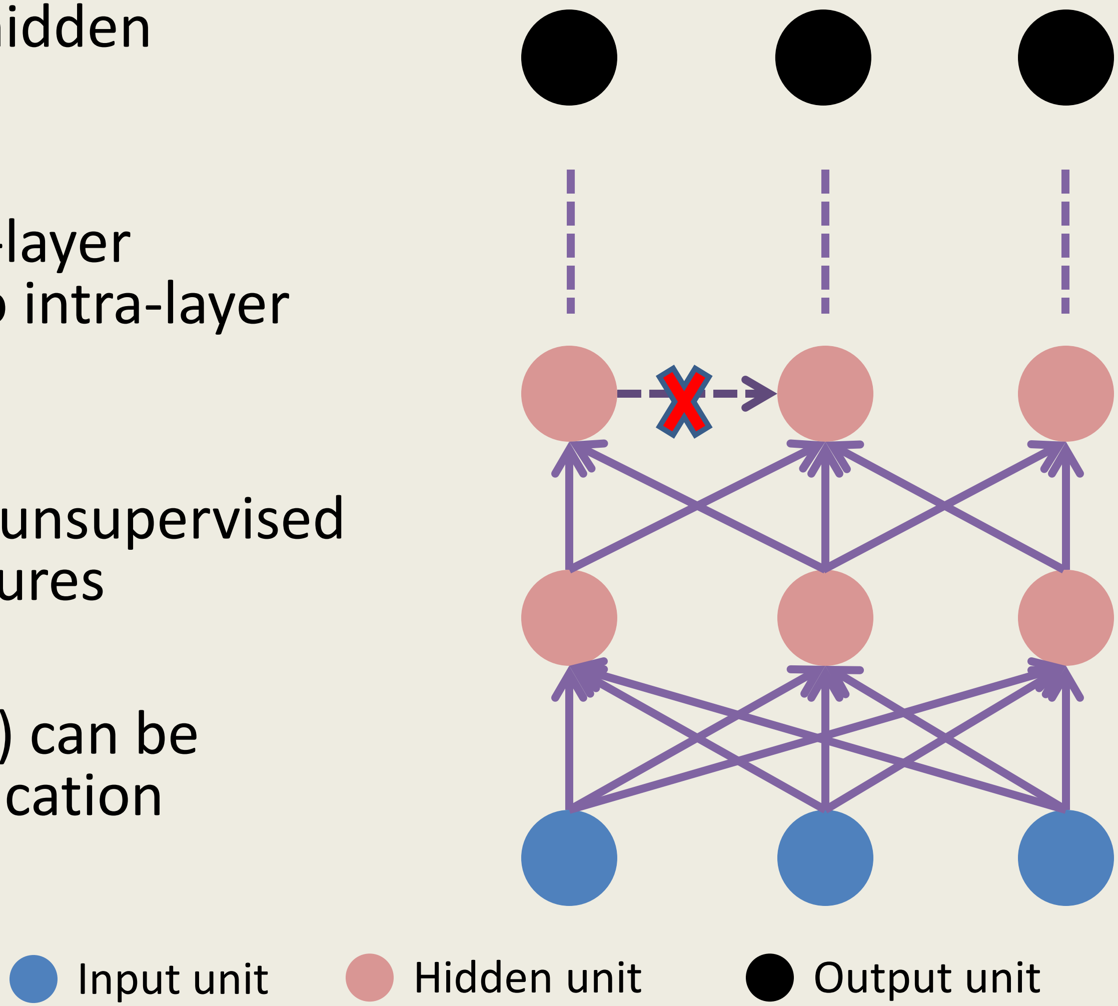
- Deep learning algorithms can facilitate clinicians and radiologists in diagnosis and treatment planning.

- Following are some popular categories in DL:
  - Deep Belief Networks
  - Convolutional Neural Networks (CNN)
    - 2D CNN
    - 3D CNN
  - Auto-encoders
  - Recurrent Neural Networks
    - Long Short Term Memory

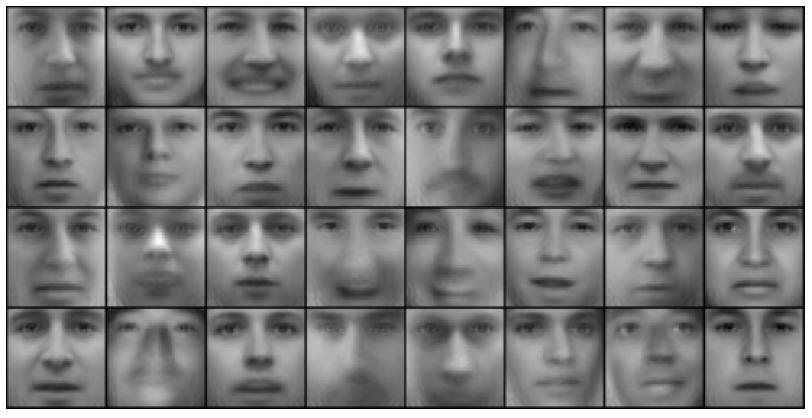
Images Credits: Nature, Science,

Deep Belief Network

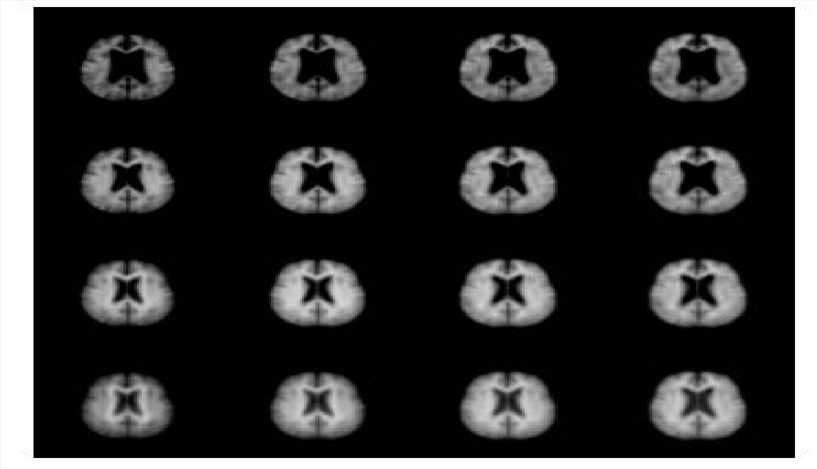
- Generative graphical model with multiple layers of hidden variables
- Comprises of inter-layer connections but no intra-layer connection
- Usually work in an unsupervised manner to get features
- Supervision (labels) can be supplied for classification purposes



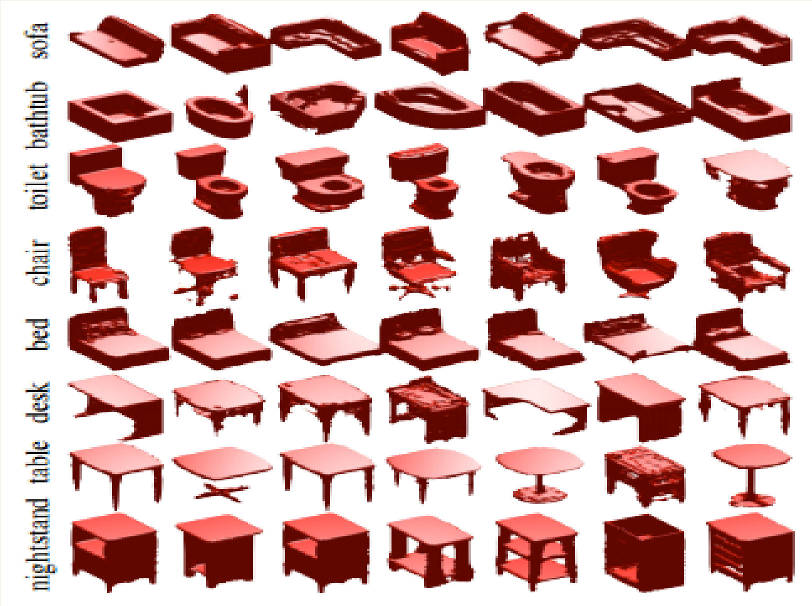
Deep Belief Network- Applications



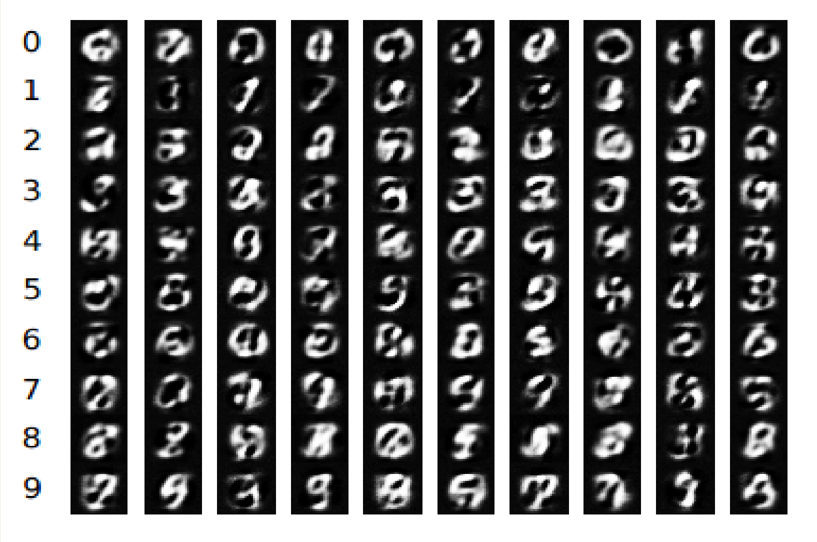
Face samples generated using DBN [1]



Generated axial slices of brain [2]



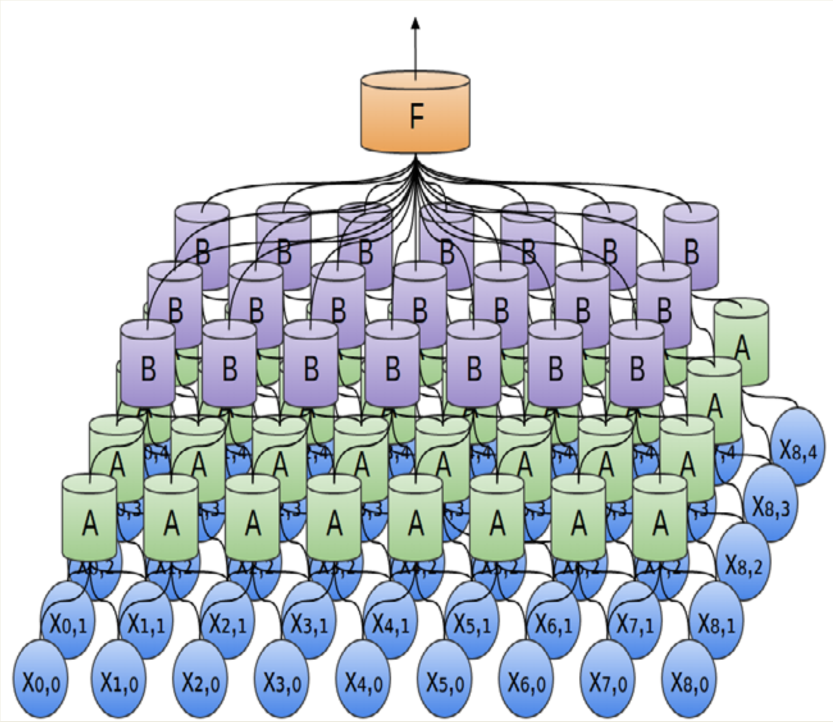
Samples generated using Convolutional DBN [3]



Images of digits generated using DBN[4]

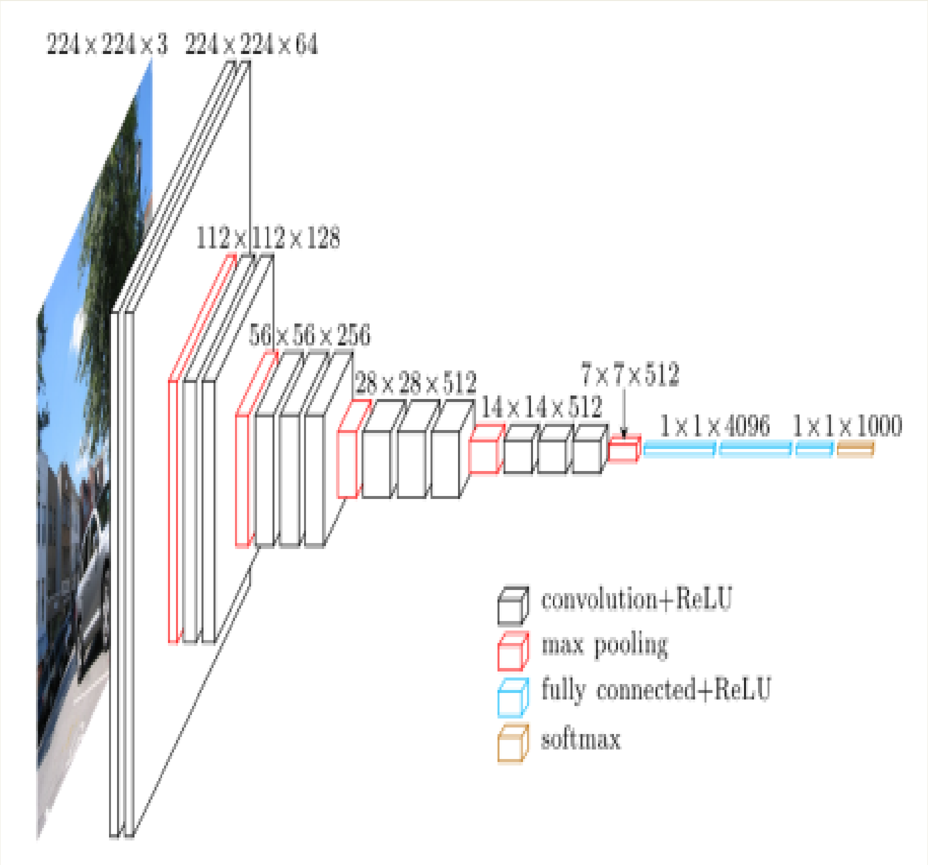
Convolutional Neural Networks

- In case of images there can be thousands/millions of neurons (units)
- Use local connectivity of neurons to address over-parameterization
- The higher level features are found to be useful for image recognition
- Comprises of the following 4 stages:
  - Convolution
  - Non-linearity
  - Sub-sampling
  - Classification

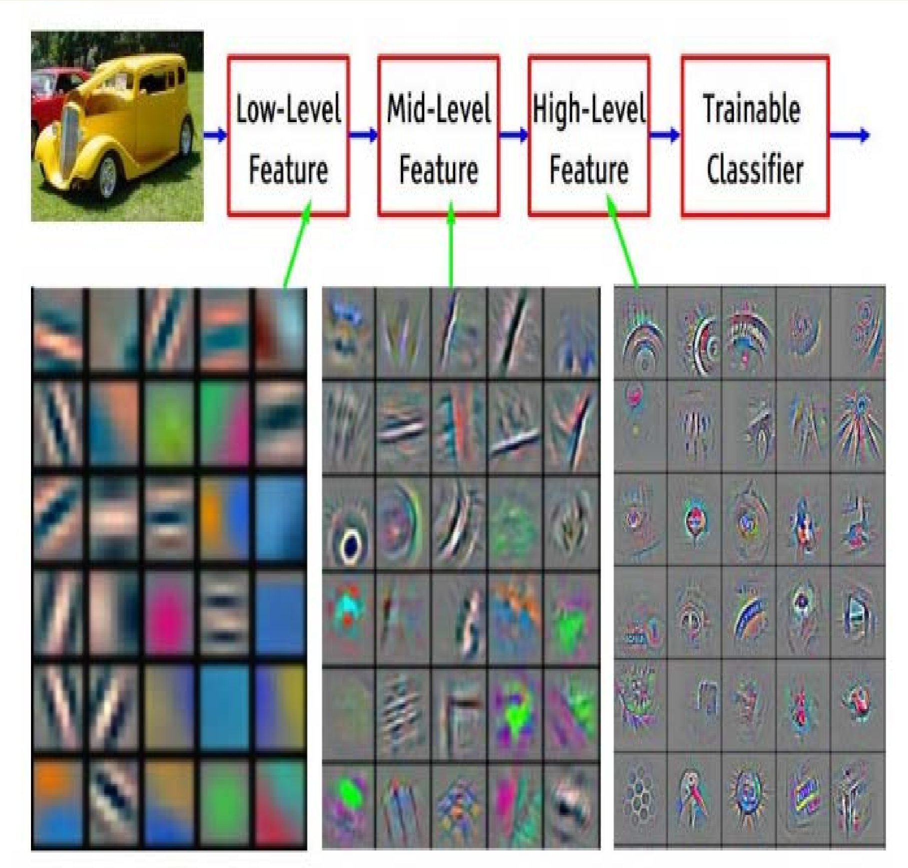


A and B are connected to only a group of units rather than all of them [5]

Convolutional Neural Networks (2D CNN)

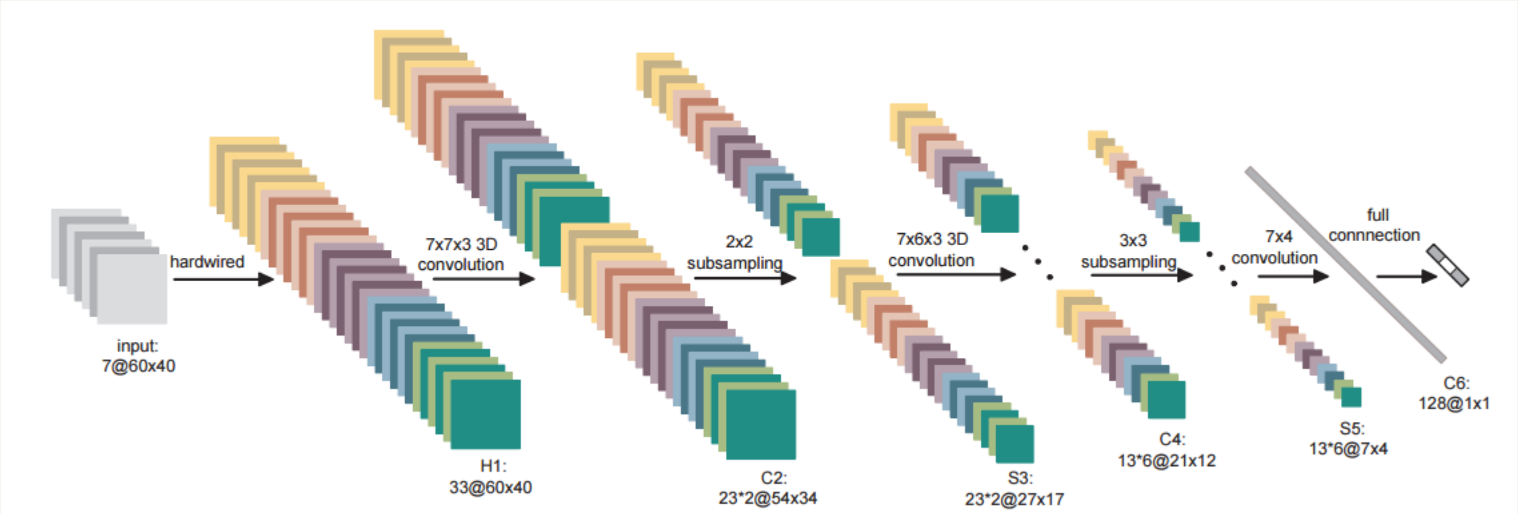


CNN architecture showing convolutional, max pooling, fully-connected and softmax (classification) layers [6]

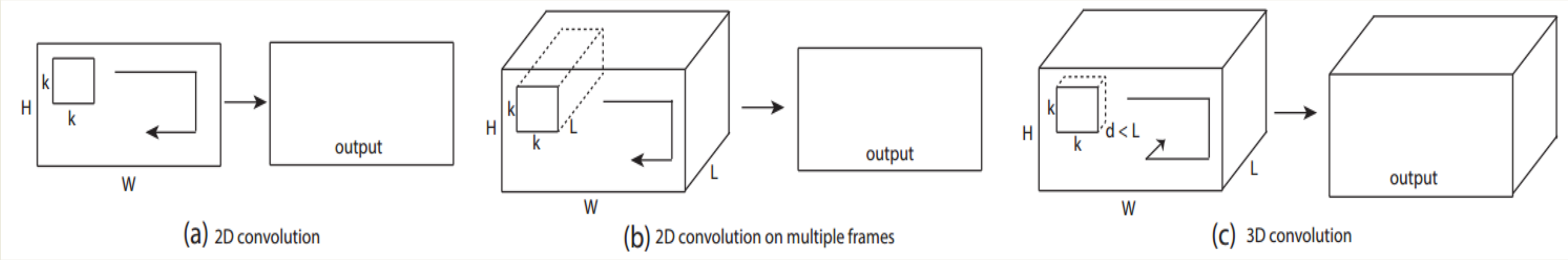


Visualizing learnt features from different layers of CNN [7,8]

Convolutional Neural Networks (3D CNN)



3D Convolutional Neural Network for Human Action Recognition [9]



Difference between 2D convolution when applied on (a) an image (b) video (volume) and (c) 3D convolution when applied on a volume [10]

Auto-encoders

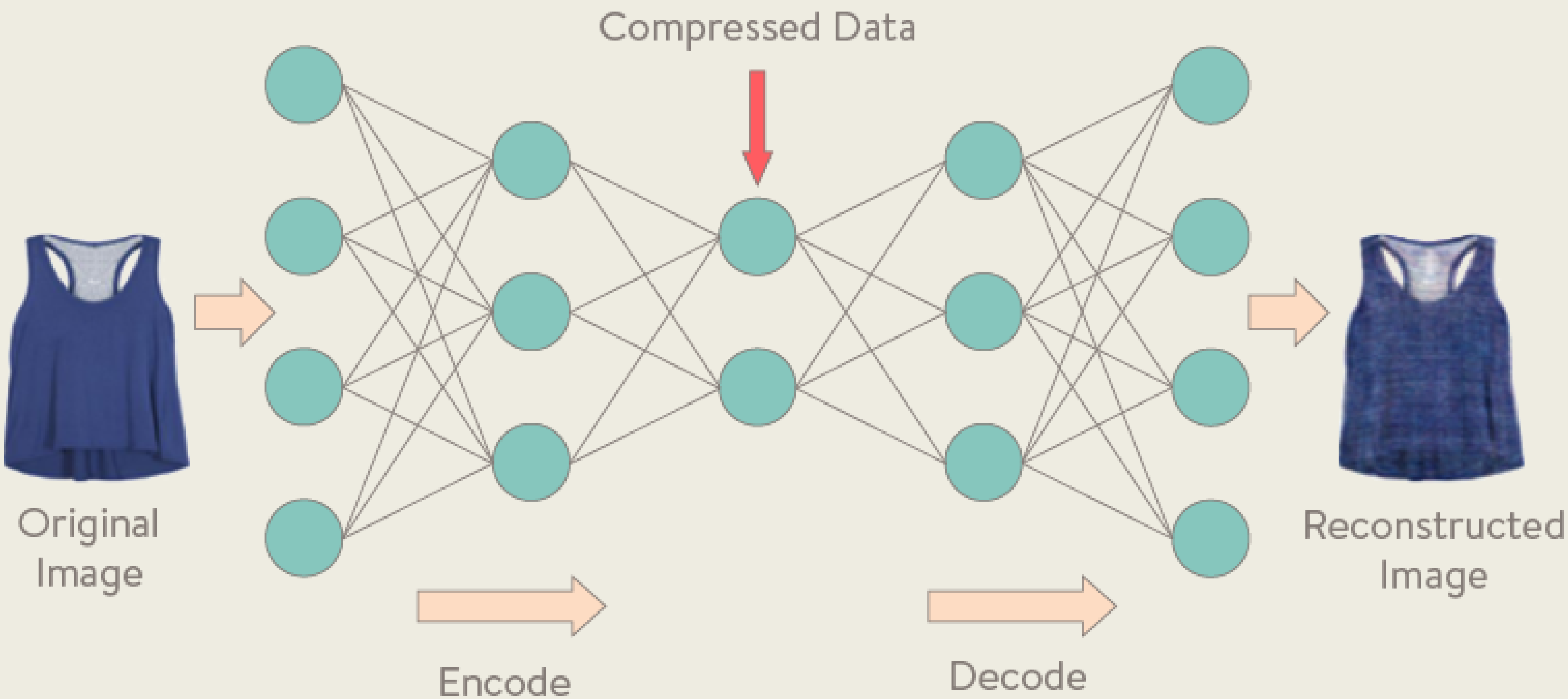
- An unsupervised neural network

- Weights in the network are learnt so as to make the target values equal to the input values

- Comprises of two stages:
  - **Encoding:** maps input to a hidden representation
  - **Decoding:** the hidden representation is mapped back so as to be as close to the input as possible

- In a denoising auto-encoder, the network is trained to reconstruct input from its corrupted version.

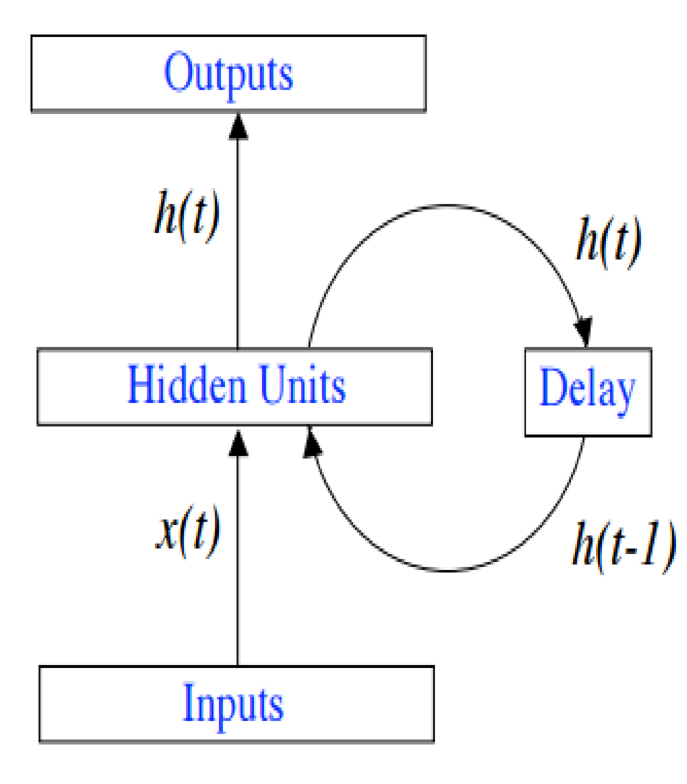
Auto-encoders [11]



- *Application of deep auto-encoder to learn the hidden units that can reconstruct the image of a dress.*
- *The original image of a dress is encoded into a compressed form and then decoded to generate the reconstructed image of the same dress.*
- *During the stages of encoding and decoding, the network learns the parameters (weights) [11]*

Recurrent Neural Network (RNN)

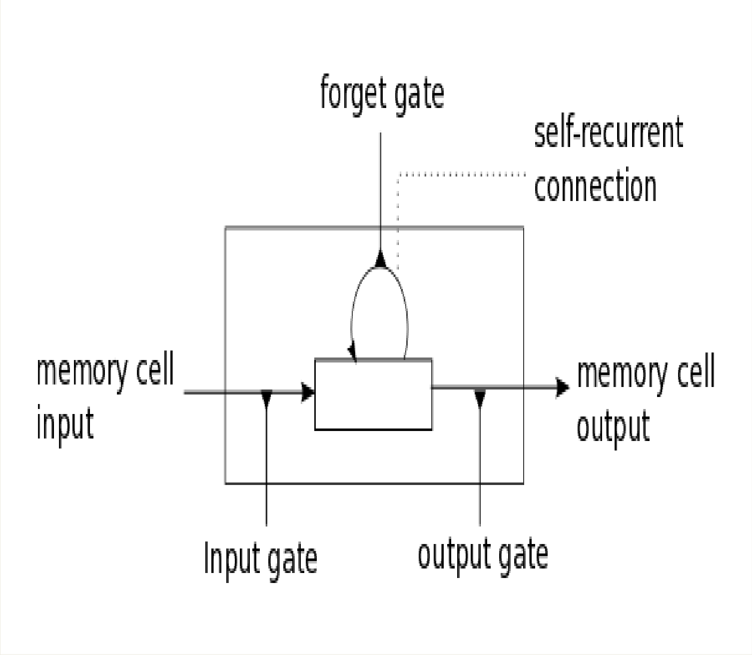
- A traditional neural network assumes independence between different inputs and outputs
- A recurrent neural network is a sequential network, where the current output depends upon the previous inputs/outputs.
- Contains atleast one feed-back connection (self-loop)
- Very useful for temporal processing and sequential learning. (Machine translation, video classification)



A recurrent neural network, with a delayed self-loop [12]

Long Short Term Memory (LSTM)

- RNNs struggle to model the long-term dependencies between different inputs
- As the time different between input increases, the gradients of error used to train RNN start vanishing.
- LSTMs are designed to solve the long-term dependency problem of RNN
- An LSTM memory unit comprises of 3 gates:
  - Input gate: Controls the input signal to pass or block
  - Forget gate: Decides whether to remember or forget the previous state
  - Output gate: Allows/disallows the output of the memory cell to pass to the next neurons



An LSTM memory cell with input gate, forget gate, output gate and a self-recurrent connection [13]

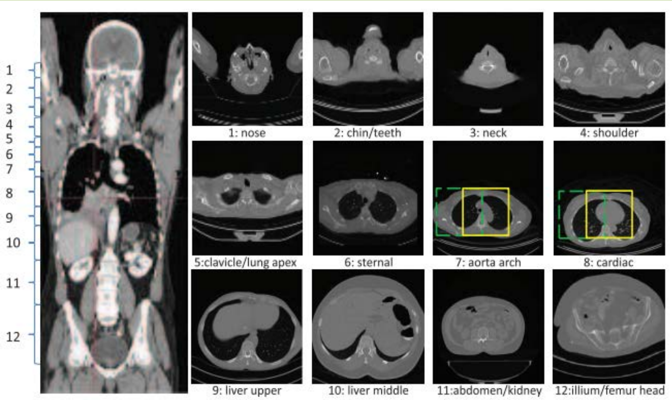
Deep learning Methodologies in Computed Tomography

- Deep learning has been applied to a range of problems in Computed Tomography including:
  - Anatomy recognition [14]
  - Organ segmentation
    - Pancreas Segmentation [15]
    - Unary Bladder segmentation [16]
  - Image Registration (X-ray) [17]
  - Lung texture classification and airway detection [18]
  - Computed Aided Diagnosis
    - Lymph node detection [19]
    - Lung nodule detection and classification [20]
    - Liver Lesion segmentation [21]

Anatomy Recognition [14]

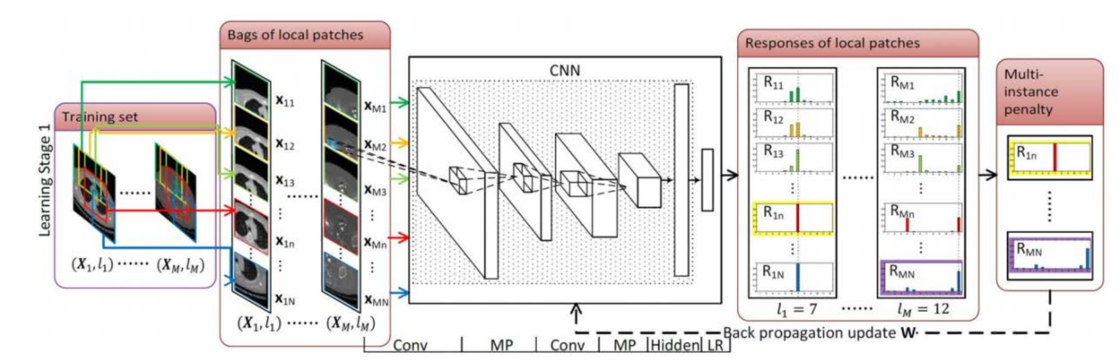
1. Objective:

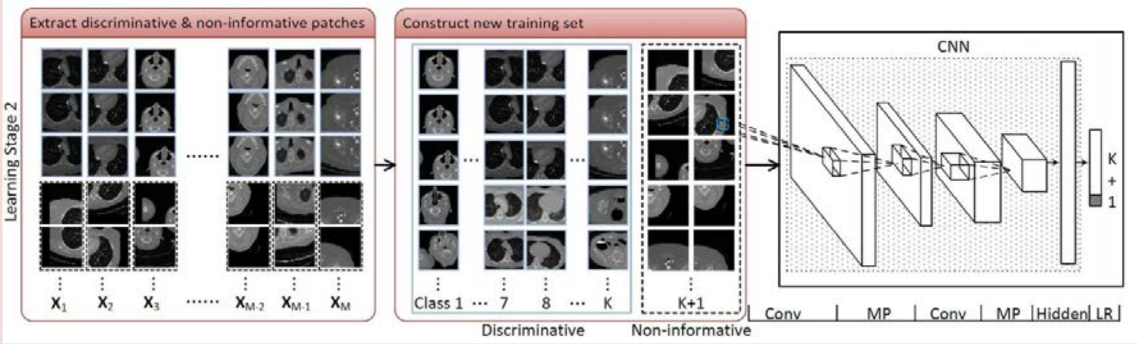
Recognition of 12 body parts in CT scans having 7489 transversal slices from 675 patients



2. Method:

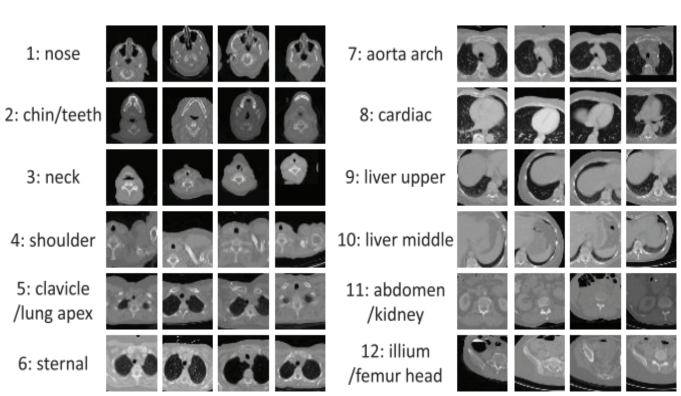
- Training CNN in 2 stages:
  - Multiple Instance learning based pre-training
  - CNN Boosting for improved recognition
- Multiple instance learning is used to automatically learn the discriminative local patches from the CT scans





3. Results

The proposed method reports Precision, Recall and F1 score of 92.25%, 92.21% and 92.23% respectively



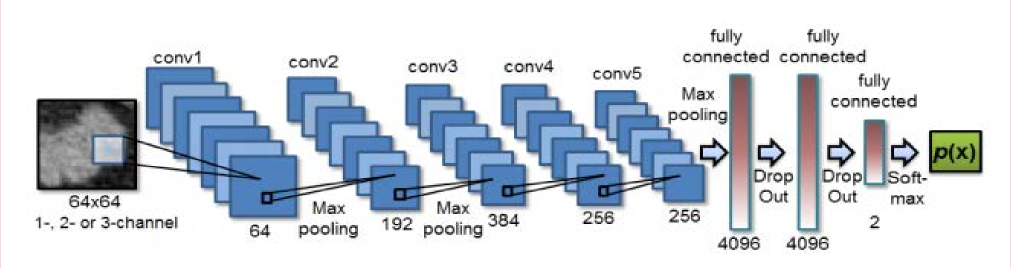
Pancreas Segmentation [15]

1. Objective:

Pancreas segmentation in 82 contrast enhanced CT images using Convolutional Neural Network

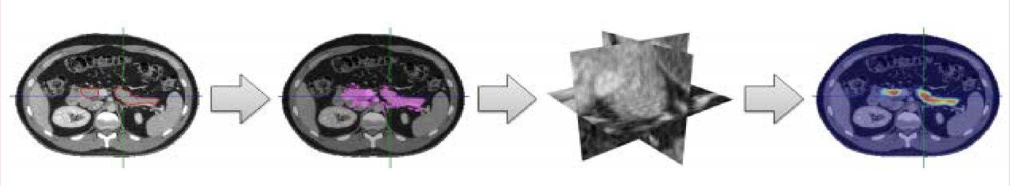
2. Method:

- Super-pixel segmentation on the CT image followed by Random Forest (RF) based classification to get initial pancreas segmentation.



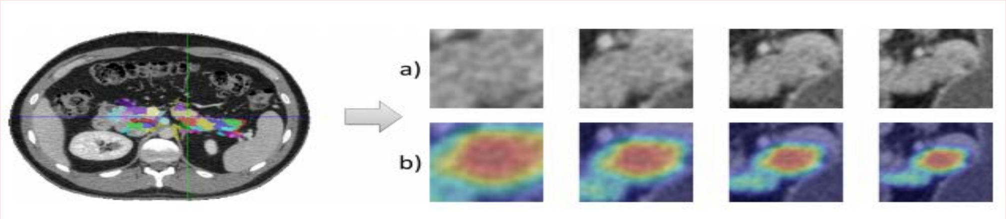
CNN architecture

- Classification of patches generated through sliding window using CNN (P-CNN)



(Left to Right) Red contour shows gold standard of segmentation, pink regions are classification results using RF, finally the probability map using P-CNN

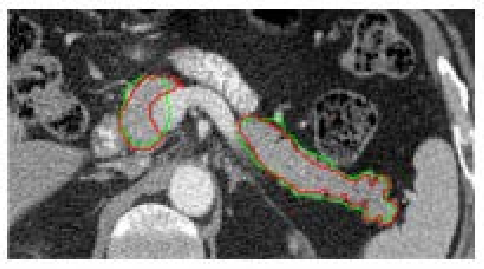
- Region based classification (R-CNN) at different scales.



(a) Region based CNN on different scales, (b) Additional channel of input from P-CNN

3. Results

- 4-fold cross validation
- Dice Similarity Coefficient (DSC) as evaluation metric.
- Mean DSC of 71.8%±10.7% in testing
- Computation in minutes

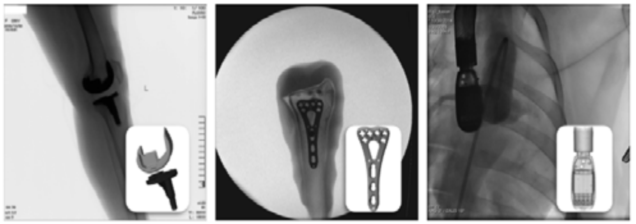


Qualitative results, ground truth in red and segmentation results in green

2D/3D Registration [17]

1. Objective:

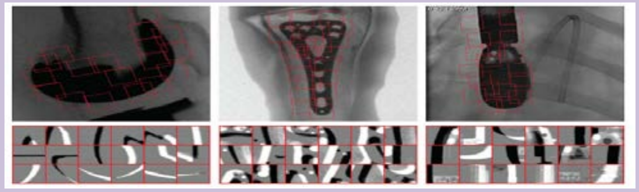
To perform realtime 2D/3D registration using CNN based regression



2D X-Ray image and a 3D model of the target object

3. Results

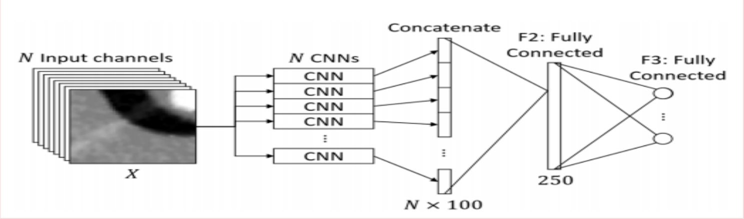
- Evaluation on knee-prosthesis, virtual implant system and X-ray echo fusion datasets
- Evaluation metric: Mean target registration error in the projection direction
- Significant improvement in performance as well as time.



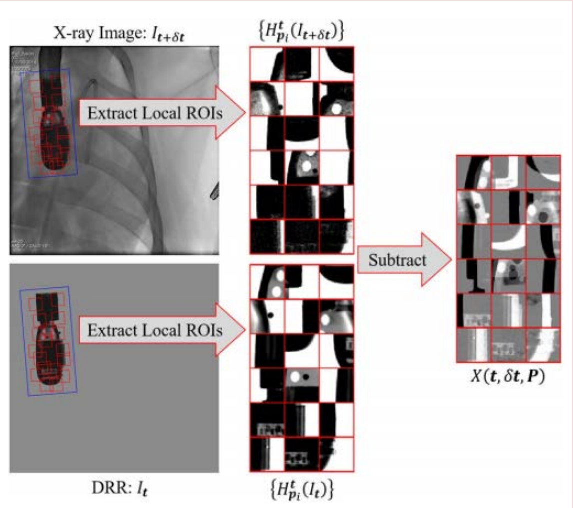
Examples of Region of Interest and Local Image Residuals from the 3 datasets

2. Method:

- The goal is to train a CNN regressor to map from 2D/3D image to their transformation parameter difference
- Local image residual features are extracted representing difference between rendered image and the X-ray image in local patches.
- Regression problem is simplified by partitioning the parameter space into 3 groups based on their difficulty
- The CNN architecture comprises of 2 convolutional, 2 maxpooling and 1 fully connected layers.



CNN Regression Model

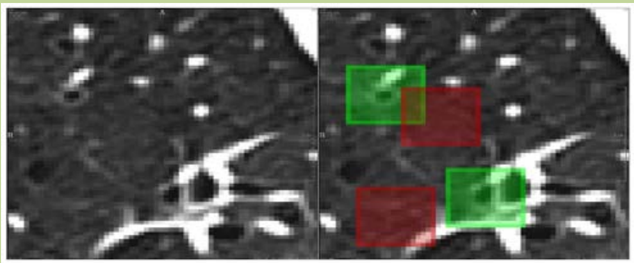


Local Image Residuals

Lung Texture Classification/Airway Detection [18]

1. Objective:

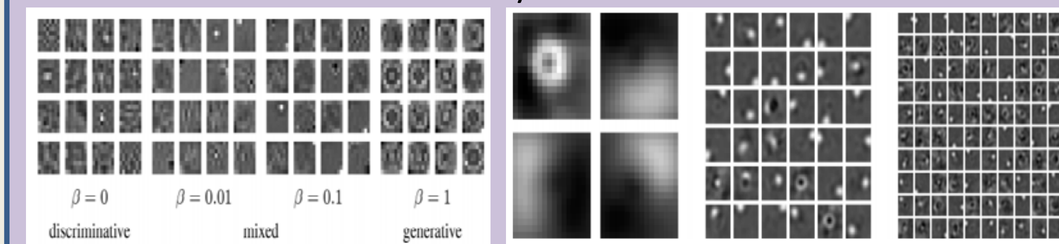
Lung texture classification and airway detection using Convolutional classification Restricted Boltzmann Machine (RBM)



Airway dataset ; airway centerline (green) and non-airway (red)

3. Results

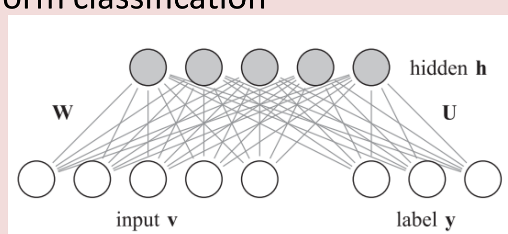
- Lung tissue classification on 73 scans, 40 scans for airway detection.
- A combination of generative and discriminative learning gives better classification accuracy than either of them alone.



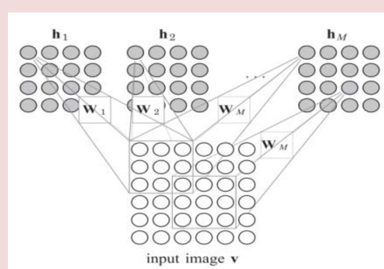
Features learnt from Lung texture (left) and Airway (right) datasets.

2. Method:

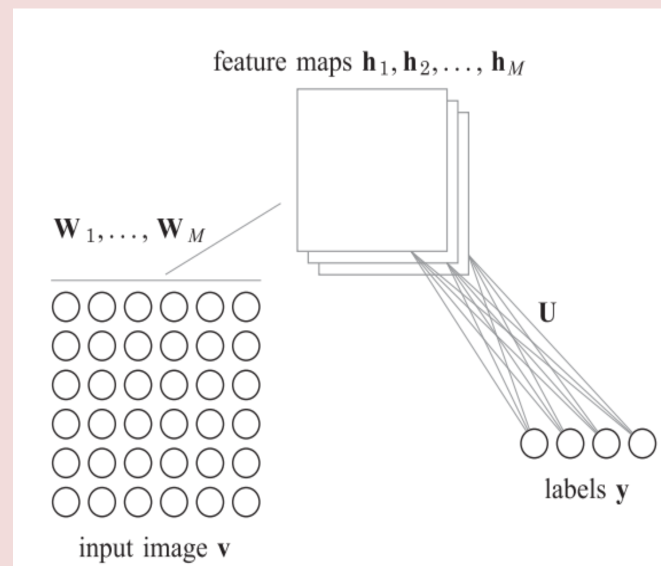
- A classification RBM is constructed by having a extra layer of labeled nodes to the visible layer.
- As in convolutional neural network, a convolutional RBM use the same weight sharing approach.
- A convolutional classification RBM (CC-RBM) have all visible, hidden and label layers
- A CC-RBM can be trained as a discriminative model and be tested to perform classification



A classification RBM



Convolutional RBM

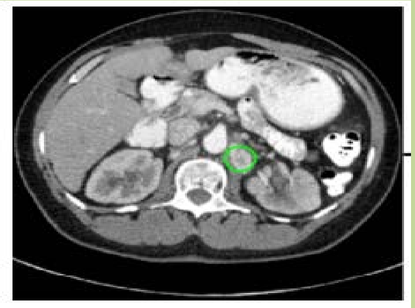


Convolutional Classification RBM

Lymph Node Detection [19]

1. Objective:

Lymph node (LN) detection in 176 CT scans using 2.5D Convolutional Neural Network.



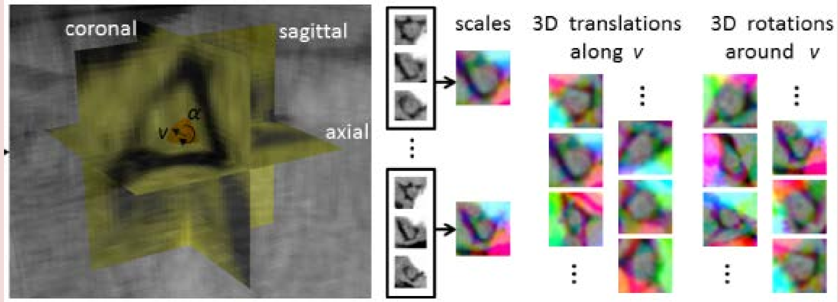
Lymph node in an axial CT slice marked in green

3. Results

- 3-fold cross validation
- 388 mediastinal and 595 abdominal lymph nodes
- Classification sensitivity of 70% for mediastinum and 83% for abdominal lymph node with 3 False Positives per patient

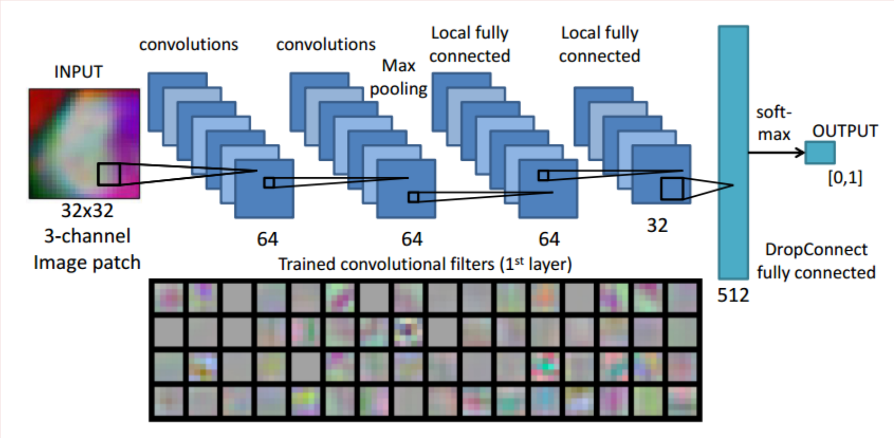
2. Method:

- The 3 views of CT are considered as different channels (RGB) of an image.
- Data augmentation is performed using random translation and rotation



Data augmentation by random translation and rotation

- 2 convolution, a max pooling, 2 locally fully connected and one drop-connect layers.

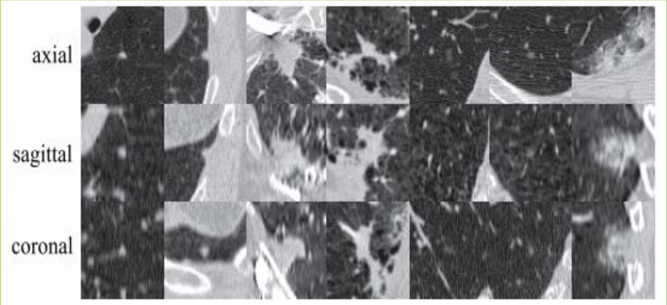


CNN Network and the learnt features from the first layer

Lung Nodule Detection [20]

1. Objective:

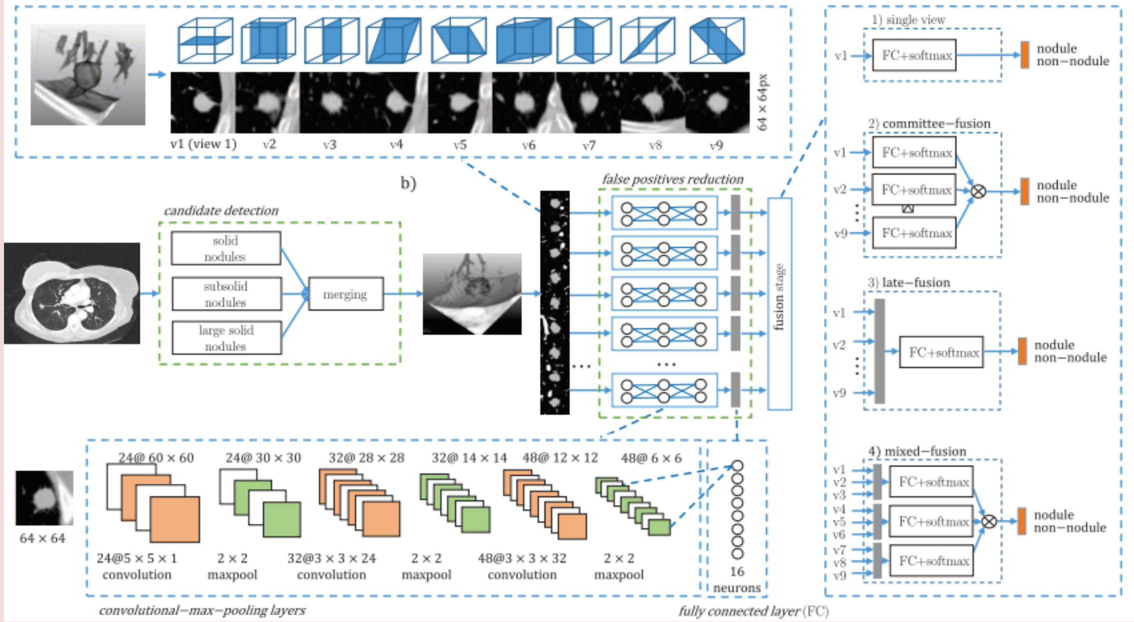
Detection of lung nodules in low dose CT images with CNN based False Positive rejection



Pulmonary Nodules across different views

2. Method:

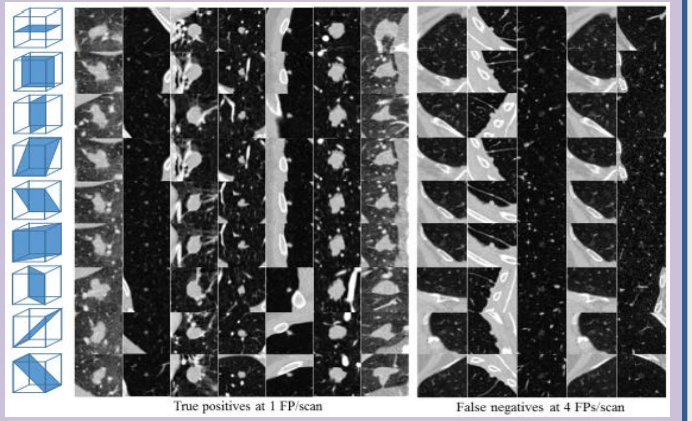
- Generating a substantial number of nodule candidates using 3 different methods.
- Separate candidate generation methods for solid, sub-solid and large solid nodules
- A 50x50mm patch is generated around each nodule candidate which serves as an input to 2D Convolutional Network
- For each of the candidate nodules, 9 different views are considered for classification
- Different strategies are employed to fuse the outputs corresponding to the 9 views



A figurative overview of the method

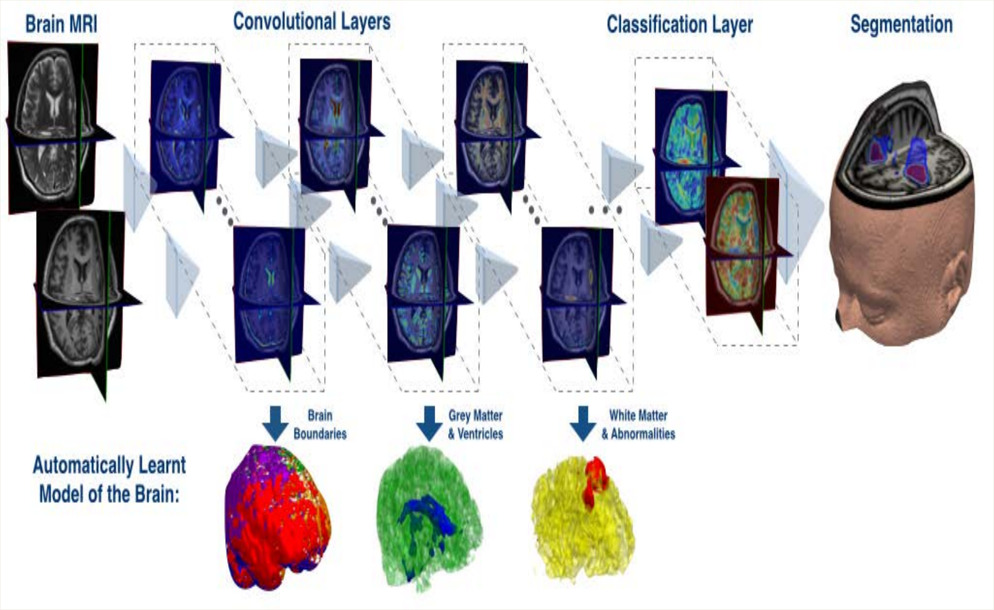
3. Results

- Evaluations on 3 Low Dose CT datasets with 1018, 55 and 612 scans
- Sensitivity of 90.1% with 4 False Positives per scan



Deep learning in MRI

- Deep learning has been applied to a range of problems in Magnetic Resonance Imaging including:
  - Segmentation
    - Prostate Segmentation [22]
    - Left Ventricle Segmentation [23]
    - Brain Tissue Segmentation [24]
  - Disease Diagnosis
    - Alzheimer’s disease diagnosis [25]
  - Organ Volume Estimation
    - Bi-ventricular volume estimation [26]
  - Survival Time Prediction [27]

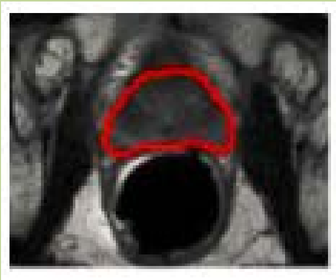


Deep learning architecture for Brain Lesion Segmentation [33]

Prostate Segmentation[22]

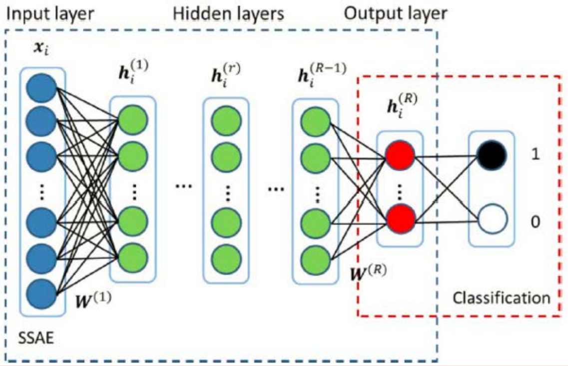
1. Objective:

Prostate segmentation in 66 T2-weighted MR images using Stacked Sparse Auto Encoder and Sparse Patch Matching.



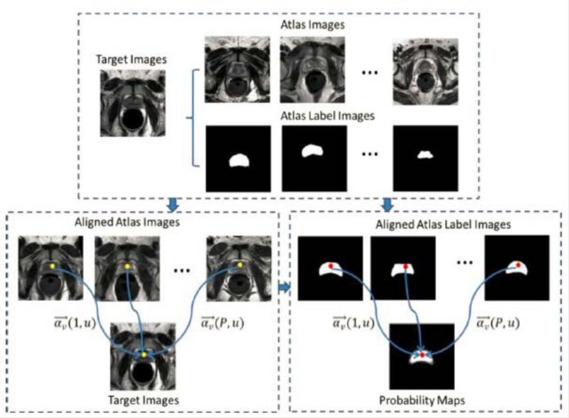
2. Method:

- High level feature representation of the image patch.



Supervised SSAE architecture

- Infer likelihood map of prostate gland by using sparse patch matching with all atlases.

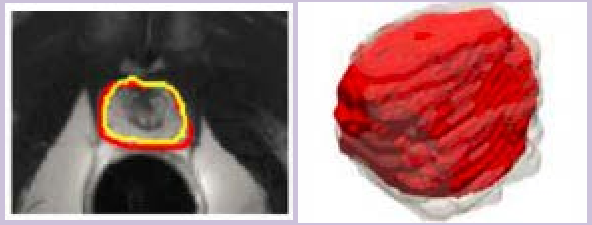


Sparse Patch Mapping schematic

- Use the likelihood map to identify initialization region for deformable segmentation as well as an appearance force to drive the segmentation.

3. Results

The proposed method reports Dice ratio, precision, Hausdorff distance, and average surface distance of 87.1±4.2, 87.1±7.3, 8.12±2.89 and 1.66±0.49 respectively.



Qualitative results: ground truth in red and segmentation results in yellow. 3D visualization: Ground truth in gray, segmentation result in red

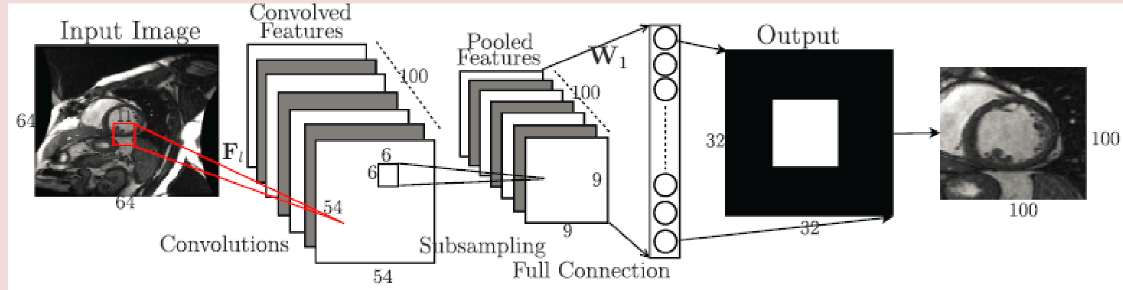
Left Ventricle Segmentation[23]

1. Objective:

Left Ventricle segmentation 45 Cardiac MR images using Convolutional Neural Networks, Stacked Auto Encoder and Deformable Segmentation.

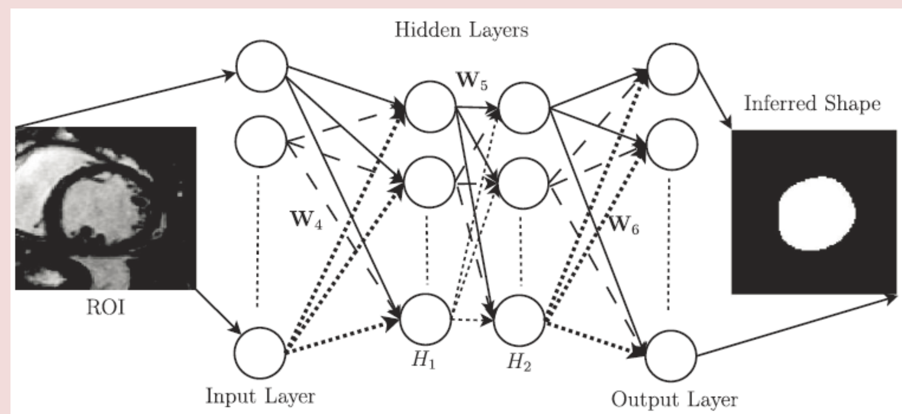
2. Method:

- Detect LV and compute ROI around it by training the CNN.



CNN Architecture

- Stacked Encoders are used to infer the shape of LV from the ROI image.

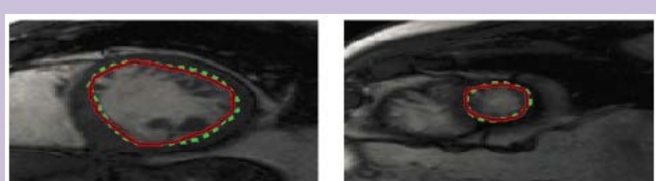


Stacked Auto Encoders

- Use the inferred shape as initialization for deformable segmentation of the LV.

3. Results

The proposed method reports percentage of good contours, Dice metric, average perpendicular distance and conformity, were computed as 96.69%, 0.94, 1.81 mm and 0.86 respectively.

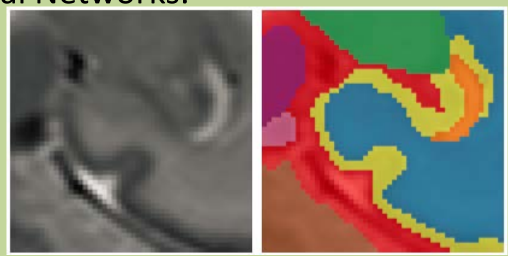


Qualitative results: ground truth in red and segmentation results green at the apex and mid LV

Brain Tissue Segmentation[24]

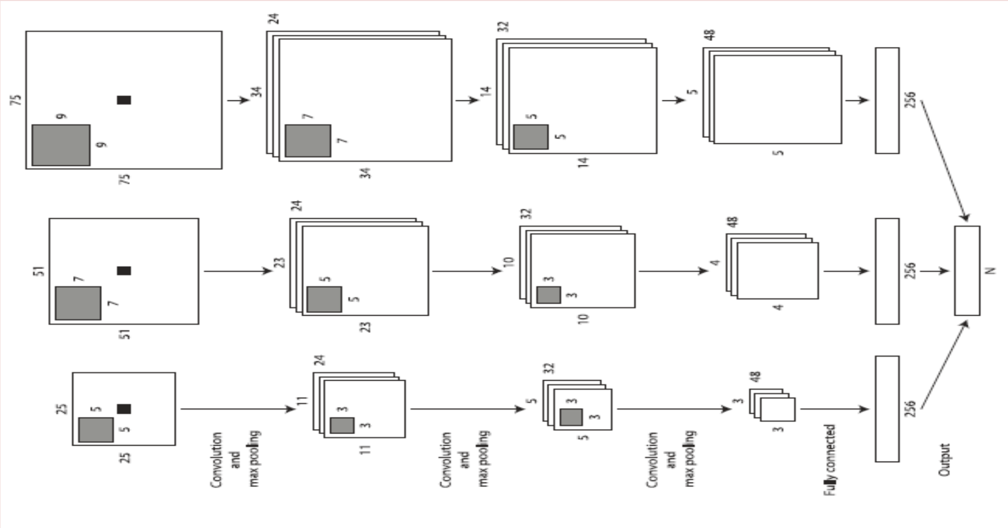
1. Objective:

Brain Tissue segmentation of developing neonates as well as young adults and ageing adults with T2-weighted or T-1 weighted MR images using Convolutional Neural Networks.

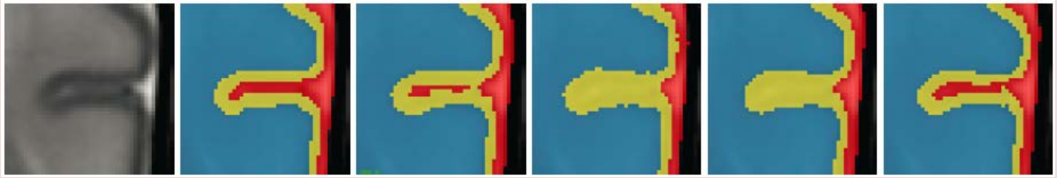


2. Method:

- Multi-scale patches are fed into the CNN for voxel-wise classification into different tissue classes.



CNN Architecture



30 weeks PMA (a) for the lateral sulcus using (from left to right), manual segmentation (b), only a patch of 25 25 voxels (c), only a patch of 51 51 voxels (d), only a patch of 75 75 voxels (e), and these 3 patch sizes combined (f). The tissues are labelled as follows: uWM in blue, cGM in yellow, and eCSF in red

3. Results

The method reported for preterm infants 30weeks PMA, 40weeks PMA, ageing adults and young adults Dice coefficients across all tissue classes as 0.87,0.82,0.86 and 0.91 respectively.

Qualitative results: T2-weighted Image, ground truth and automatic segmentation results

Alzheimer's Disease Diagnosis[25]

1. Objective:

AD, MCI, NC classification in 210 subjects using Convolutional Neural Networks.

Diagnosis	AD	MCI	NC
Number of subjects	70	70	70
Male / Female	36 / 34	50 / 20	37 / 33
Age (mean$_{\pm STD}$)	$75.0_{\pm 7.9}$	$75.9_{\pm 7.7}$	$74.6_{\pm 6.1}$

3. Results

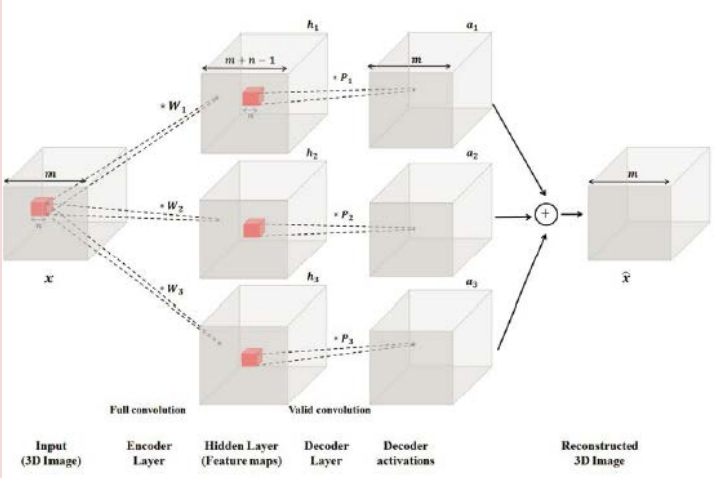
- Accuracy as evaluation metric
- five classification tasks: AD vs. NC, AD+MCI vs. NC, AD vs. MCI, MCI vs NC and AD vs. MCI vs. NC.
- Evaluated by 10-fold cross-validation

Task-specific classification [mean$_{STD}$,%].				
AD/MCI/NC	AD+MCI/NC	AD/NC	AD/MCI	MCI/NC
$89.1_{1.7}$	$90.3_{1.4}$	$97.6_{0.6}$	$95_{1.8}$	$90.8_{1.1}$

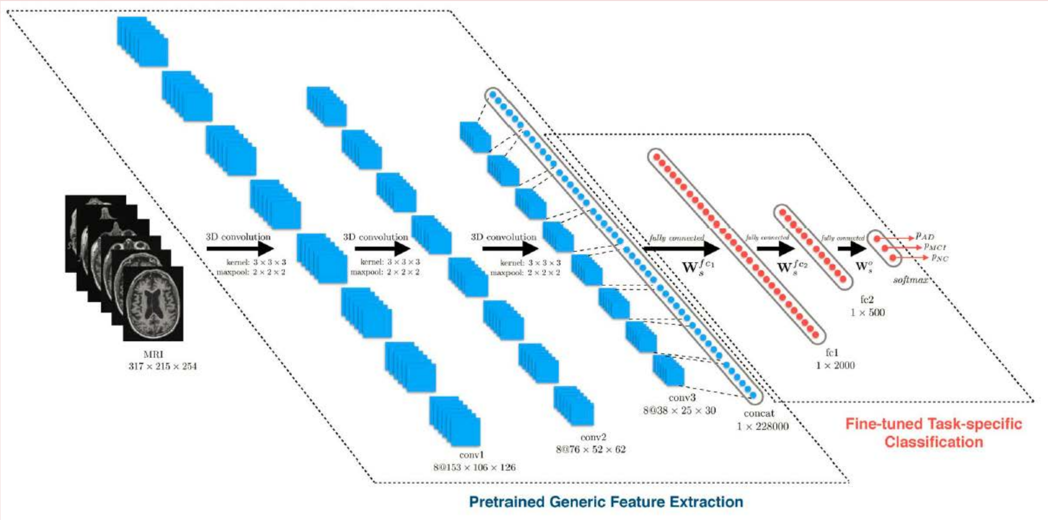
Mean Accuracy

2. Method:

- Feature extraction based on reconstructing the input



- Multi-scale patches are fed into the CNN for voxel-wise classification into different tissue classes.

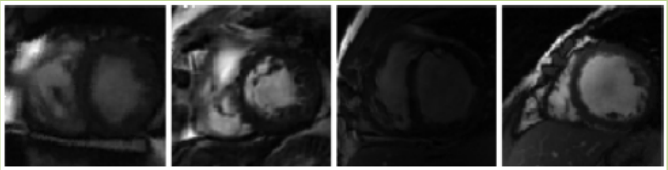


3D-ACNN Architecture

Bi-Ventricular Volume Estimation[26]

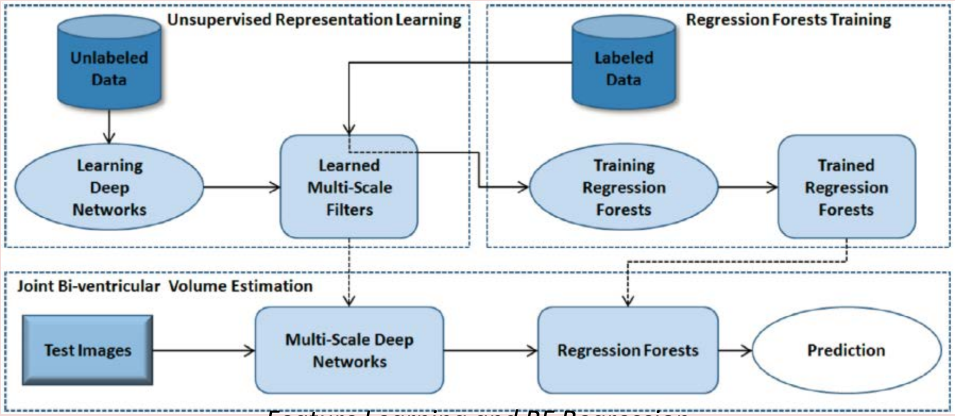
1. Objective:

Direct estimation of cardiac ventricular volumes using Recurrent Boltzmann Machines and Regression Forests.

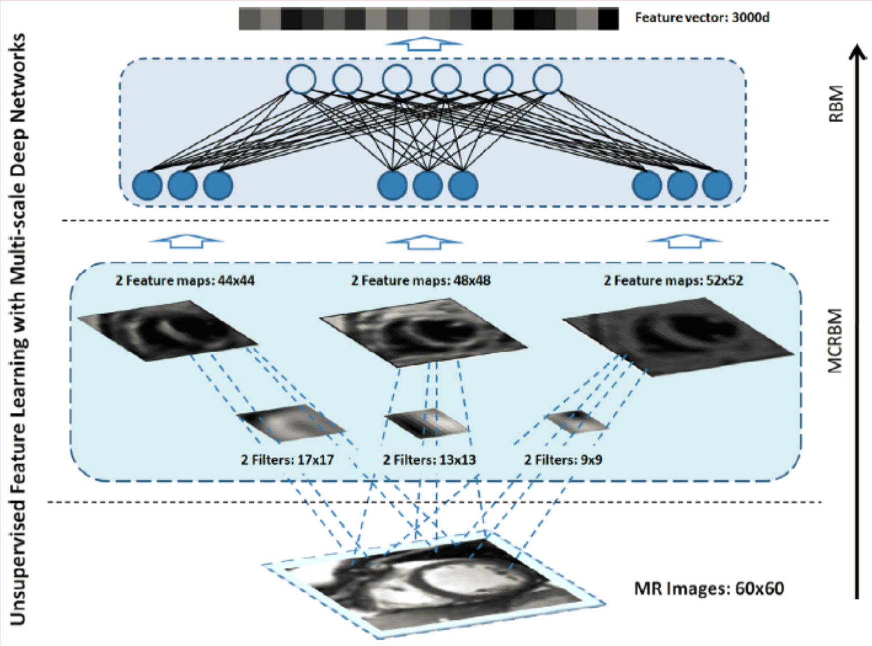


2. Method:

- Extract from multi-scale deep networks feature vector.
- Regression Forest to predict if feature vector is biventricular cavity.



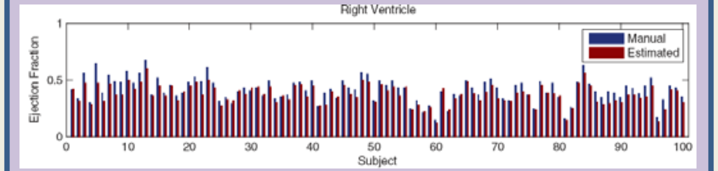
Feature Learning and RF Regression



Multi-Scale Deep Network Architecture

3. Results

- Ejection Fraction (EF) is used to estimate results.
- Correlation of EF with Ground-truth results in coefficient of 0.921 and .908 for LV and RV respectively.



EF: Manual(blue) vs Estimated (red)

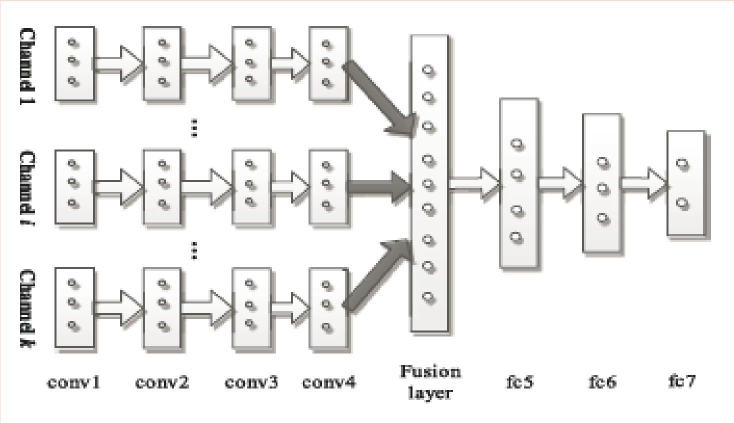
Survival Time Prediction[27]

1. Objective:

Predicting survival time for 69 patients high-grade glioma using T1-MRI,DTI,fMRI and Convolutional Neural Networks, Principal Component Analysis (PCA) and Sparse Representation (SR).

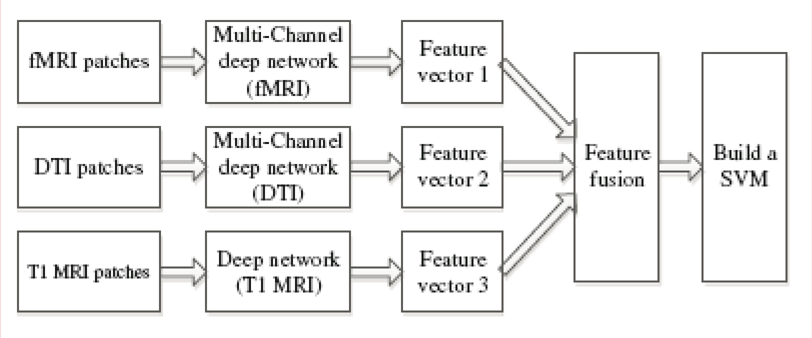
2. Method:

- Extract feature vector for fMRI and DTI from multi-channel CNN.



mCNN Architecture

- Extract feature vector for T1-MRI from single channel CNN
- Fuse the feature vectors and do PCA and SR to reduce dimensionality.
- SVM to predict.



Multi-modal Deep Network Architecture

3. Results

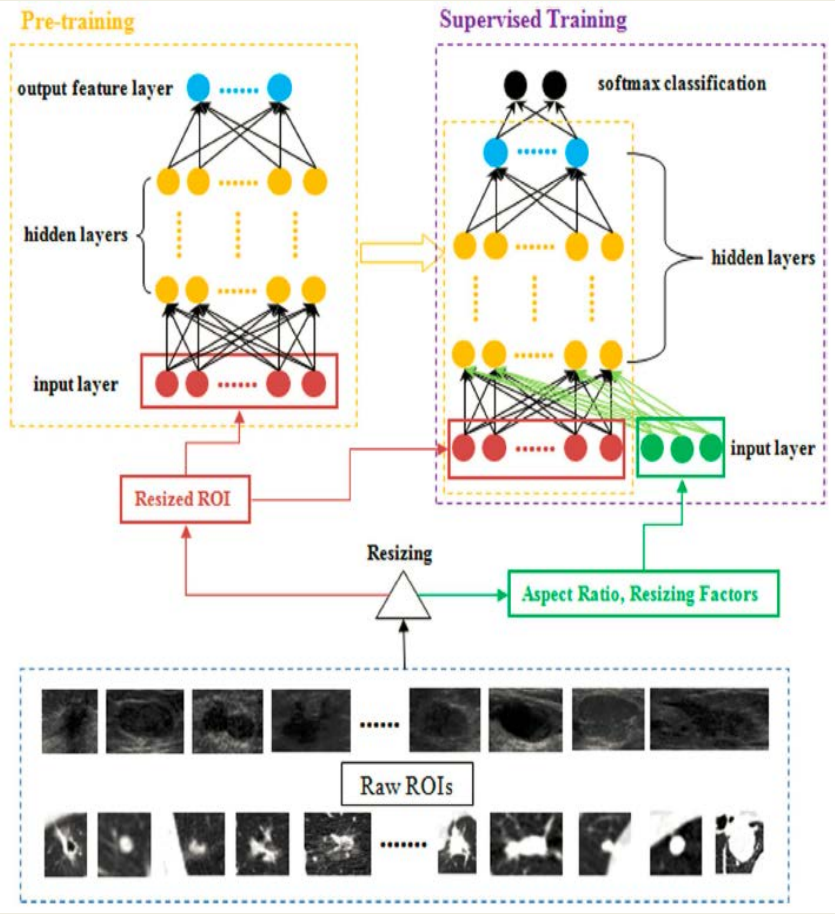
Accuracy ▲ 89%

	ACC (%)	SEN (%)	SPE (%)	PPR (%)	NPR (%)
HF	62.96	66.39	58.53	63.18	65.28
HF + SIFT	78.35	80.00	77.28	67.59	87.09
HF + 2D-CNN	81.25	81.82	80.95	74.23	88.35
fc7	80.12	85.60	77.64	71.71	87.50
fc6-PCA	80.55	84.85	76.92	75.68	85.71
fc6-SR	76.39	86.67	69.05	66.67	87.88
HF + fc7	**89.58**	92.19	**88.22**	84.44	95.57
HF + fc6-PCA	**89.85**	**96.87**	83.90	**84.94**	93.93
HF + fc6-SR	85.42	92.60	80.39	75.36	**96.83**

Prediction accuracy

Overview of Past and Present of CAD Systems

- Common Algorithms used
- Basic CAD System
- The popular applications of CAD systems include:
  - Breast cancer detection
  - Lung cancer detection
  - EEG Signals



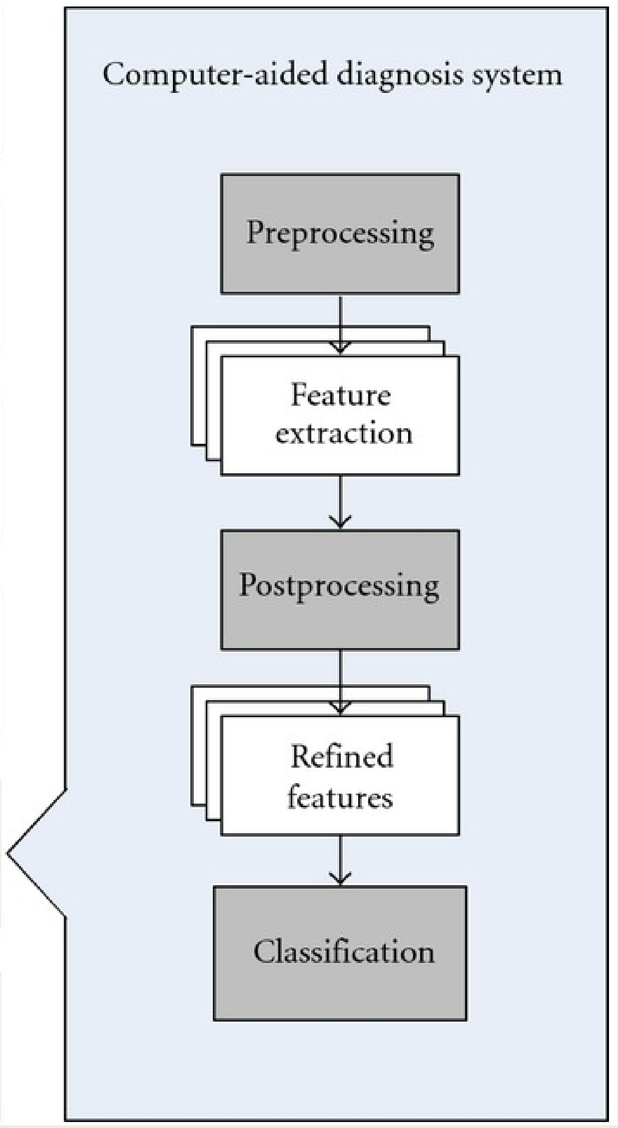
CAD for Breast Lesion and Lung Nodules using stacked denoising autoencoder [32]

Common Algorithms in CAD [28]

- K-nearest neighbors
  - Based on the closest training cases in feature space
- Decision Trees
  - Branching out from a node; similar to **tree branches** to reach the leaf node
- Fuzzy Logic
  - Fuzzification of input, followed by inference and then de-fuzzification to output.
- Artificial Neural Networks
  - Clustering, self-organizing maps, Support Vector Machines (SVM)
- Deep Learning
  - Using multiple layers of **non-linear processing units**
  - These layers can be ANNs

Basic CAD System[29]

- Preprocessing
  - Noise, artifact reduction
- Feature Extraction
  - Hand-crafted, trained (intensity, texture, etc.)
- Refined Features
  - ROI detection
- Classification
  - Common algorithms are used



Challenges in Deep learning for Radiology Applications

- Dearth of quality data
- Lack of collaboration between the clinicians and machine learning scientists
- Sensitivity in a few problems is better for clinicians
- Difficulty in modeling implicit knowledge and skills of clinicians which are developed with experience
- Deep learning can sometimes be a black-box for diagnostic purposes which leads to lack of trust by some radiologists
- High degree of complexity of human physiology as compared to traditional machine learning tasks of face recognition and object detection
- Diagnostic decision making heavily relies on rule based systems
- Large speed discrepancy between radiologists and algorithms in some cases.
- Stringent regulations
- Large variation in images due to sensors and other factors
- Annotations required to claim statistical significance of results

Potential Solutions: Data Dearth [30]

- Transfer learning
  - Transfer of knowledge from a non-radiological task but with a lot of annotated data (camera images, videos) to a radiological task
- Since the annotated medical data is limited, an alternative would be to just fine-tune a CNN model rather than train it from scratch.
- Fine-tuning requires a lot less data and outperforms (or performs as well) as network learnt from scratch.
- Fine tuning of CNN also increases the robustness to the size of training data as compared to the scratch trained CNN
- Experiments performed for 4 different clinical tasks with varying imaging modalities:
  - Polyp detection in colonoscopy videos
  - Pulmonary Embolism detection in CT pulmonary angiography
  - Colonoscopy frame classification
  - Intima-Media Boundary Segmentation in Carotid intima-media thickness (CIMT) images.

Potential Solutions to challenges

- Encouraging and facilitating close collaborations between radiologists and machine learning scientists.
  - Joint research proposals
  - Collective efforts to transfer the implicit diagnostic knowledge from clinicians to the machine learning researchers.
- Active use of feature map visualizing techniques to understand the decision basis of the CNN and convey that information to the radiologists
- Unsupervised deep learning
- The use of GPUs for fast processing is quickly bridging the speed gap between human and machines.
- Introduction of large publically available datasets such as LIDC, Cancer Imaging Achieves, MICCAI and ISBI challenges.
- Crowdsourcing for medical imaging annotations and labeling.

Conclusion and Future Trends

- There is a lot of untapped potential regarding the use of deep learning for radiology

- Healthcare will be most effected by the advancements in AI than other industries. [31]

- Transfer learning can help address the data dearth in short term

- Close collaboration between radiologists and ML scientists can further advance this field.

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