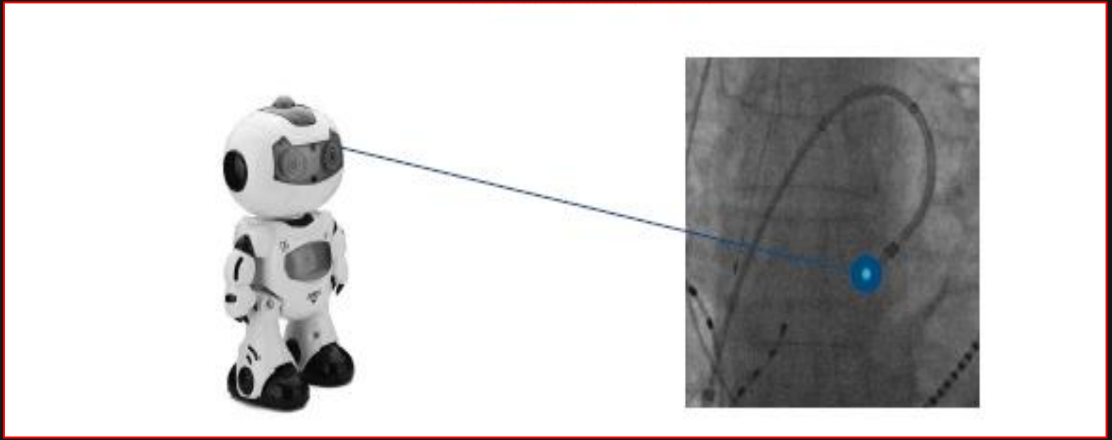
Jasbir S Sra, MD

COI: Many features invented and being used in Navik 3D Product

AI IN ELECTROPHYSIOLOGY

- Background
- Data Analysis/Training
- Diagnosis/Treatment
- Prediction

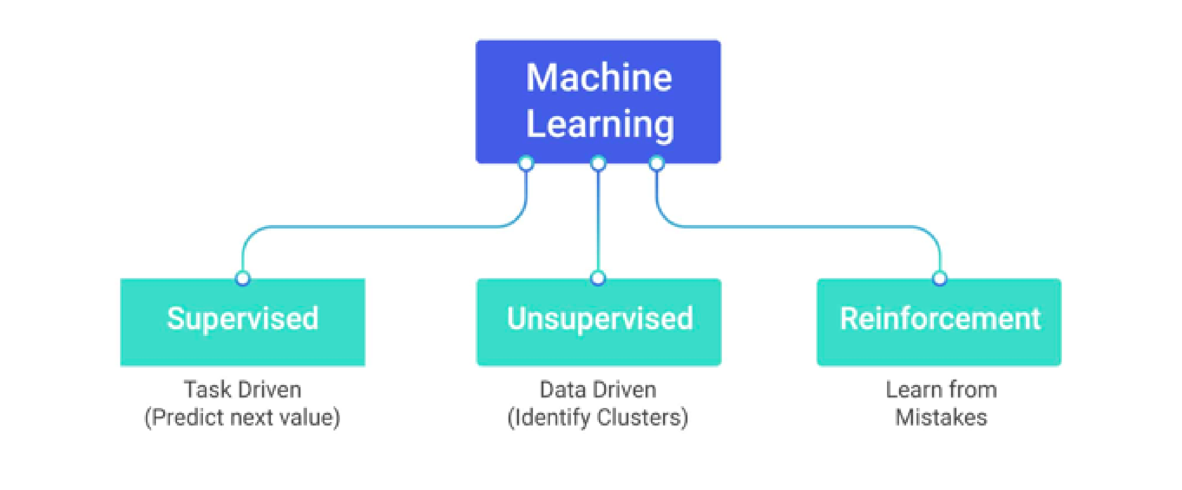


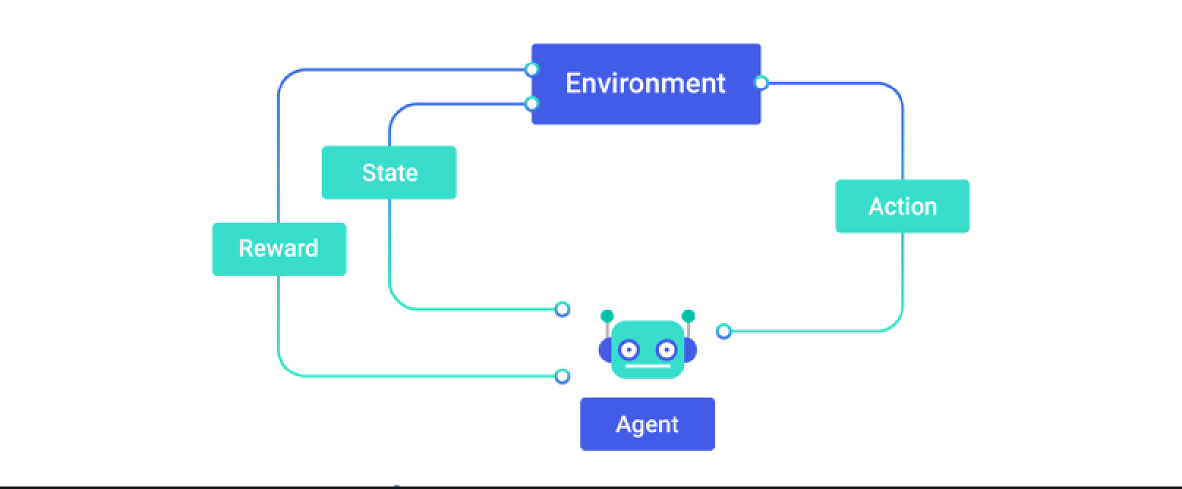
- ✓ **Image Recognition- Catheters, cryoballoon**, left atrial appendage devices, valves, leads for heart failure
- ✓ Signal Processing
- ✓ **Inference**
- ✓ Prediction

Next Generation EP Solutions

[redacted]

MACHINE LEARNING TECHNIQUES OVERVIEW





Supervised learning

- labeled data (Frames from Fluoro) is used to train Knowing the results for every input, we let the algorithm determine a function that maps it to an output
- We keep correcting the model every time it makes a prediction/classification mistake

Conventional unsupervised

- Data is without labels and we introduce the dataset to our algorithm hoping that it'll unveil some hidden structure within it.

Reinforcement learning

- Solves a different kind of problem
- In RL, there's an agent that interacts with a certain environment, thus changing its state, and receives rewards (or penalties) for its input

Supervised and Unsupervised Machine Learning

[redacted]

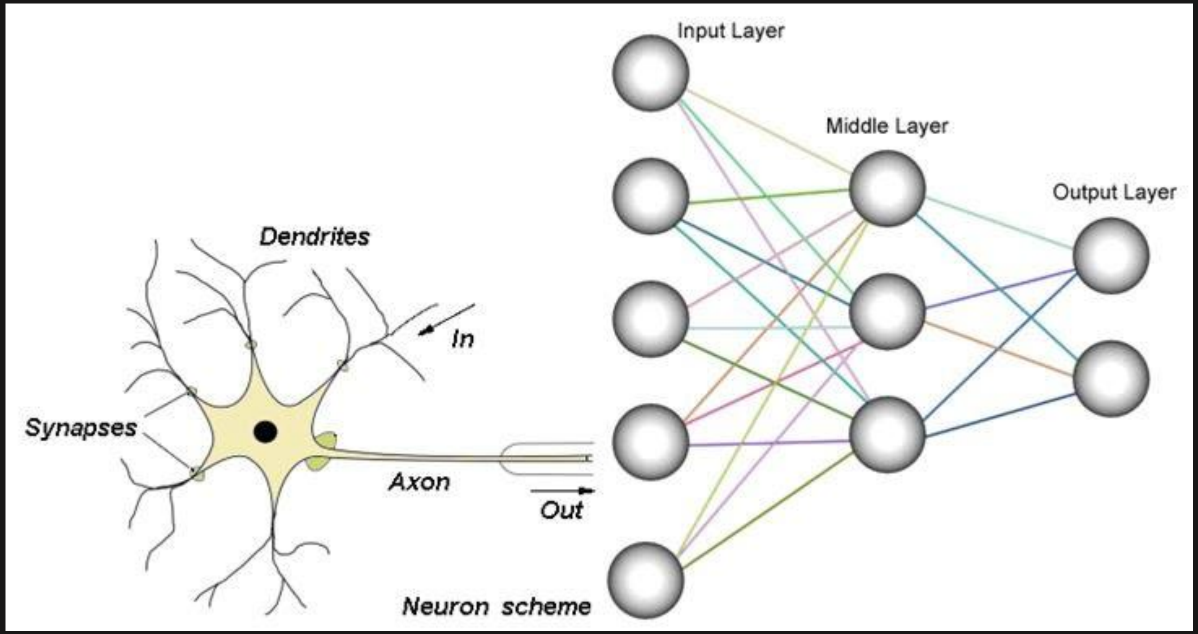
Background

- Artificial neural networks are computing systems that are inspired by, but not identical to, biological neural networks

- In a fully connected AI neural network each neuron has a mathematical model that defines if it is activated or not based on the activation in the connections with neurons in the previous layer and a weights assigned to each connection.

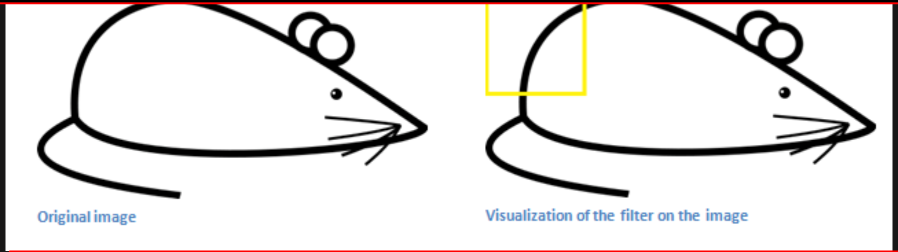
- The mathematical model of the neuron usually is a non linear function, that has a threshold (which can be adjusted) that defines if there is an activation based on the activations in the previous layer or not.

Artificial neural network
A computer representation of knowledge that attempts to mimic the neural networks of the human brain.



CONVOLUTIONAL NEURAL NETWORKS (CNN)

Simple but best for Image processing



Visualization of the receptive field

0	0	0	0	0	0	30
0	0	0	0	50	50	50
0	0	0	20	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0
0	0	0	50	50	0	0

Pixel representation of the receptive field

$*$

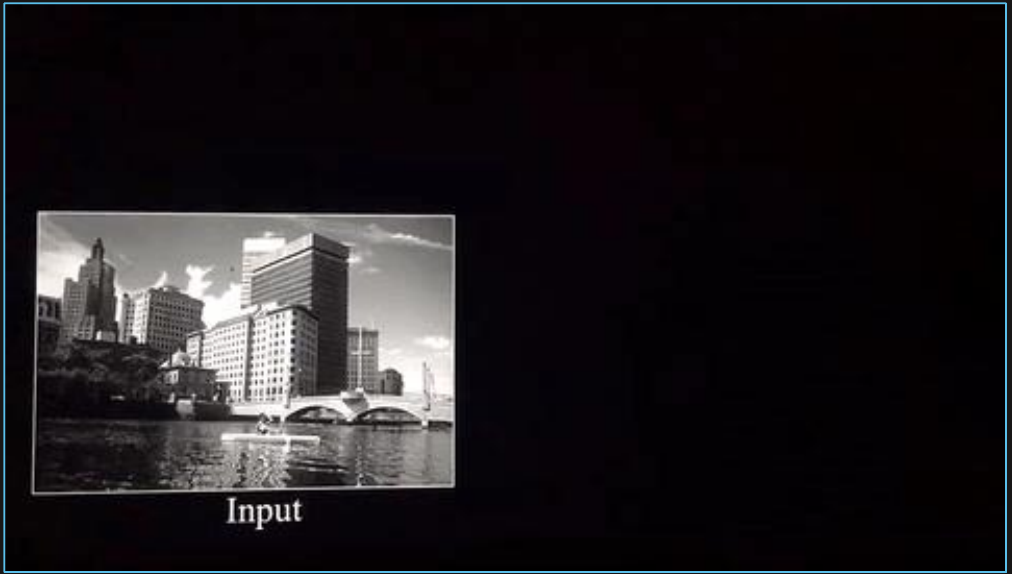
0	0	0	0	0	30	0
0	0	0	0	30	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	30	0	0	0
0	0	0	0	0	0	0

Pixel representation of filter

Multiplication and Summation = (50*30)+(50*30)+(50*30)+(20*30)+(50*30) = 6600 (A large number!)

Example 1 (Learning features)

ResNets are currently by far state of the art Convolutional Neural Network models and are the default choice for using convolutional neural network in practice



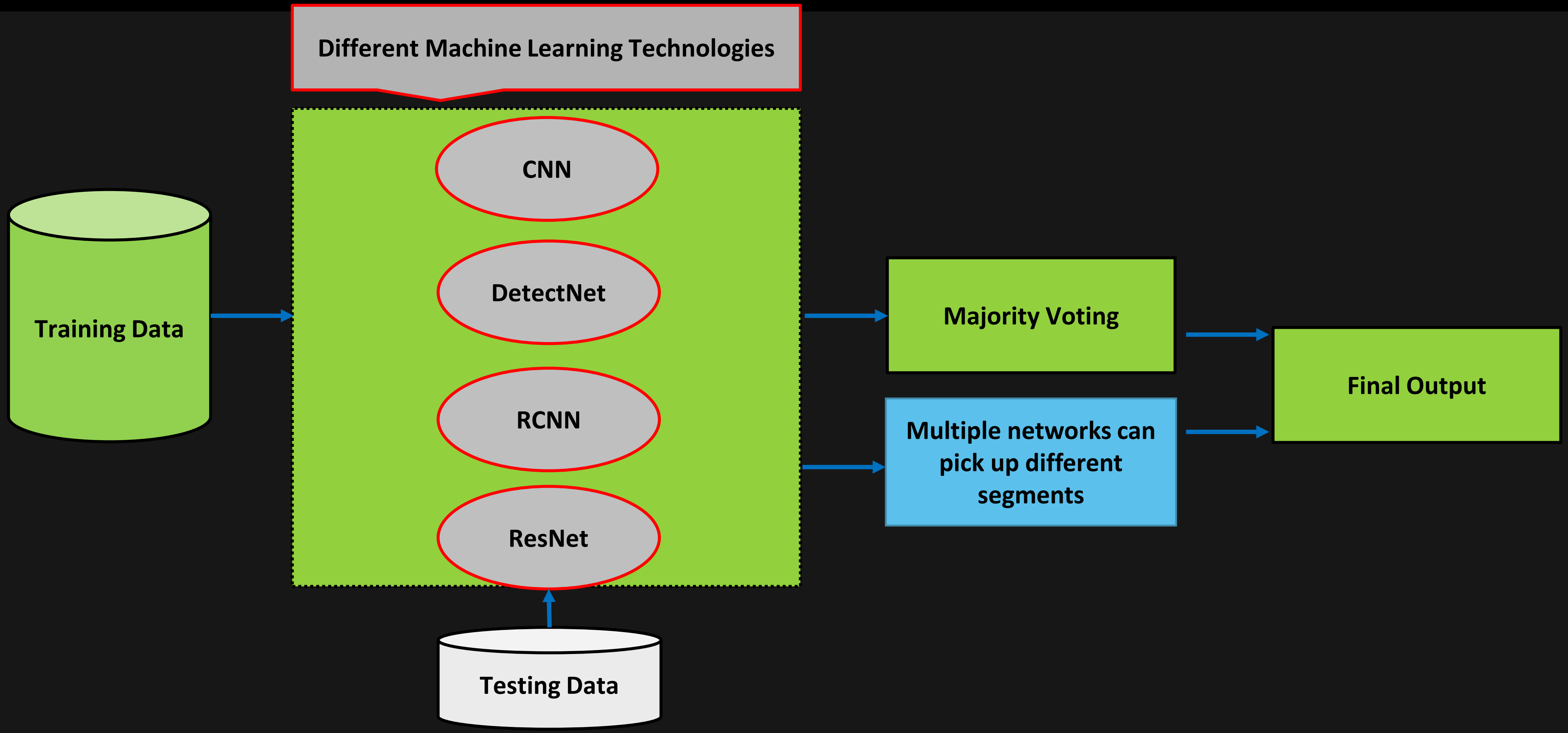
Example 2 (Strides)

Stride is how much a filter is shifted on an image with each step. It is the size of the small rectangle that is moved over the image to get the feature map

CNN are the neural network most commonly applied to analyzing visual imagery

[redacted]

Ensemble Learning



Using Multiple Neural Network Models Simultaneously

AI: Progress and Roadmap

2017-2018

- ✓ Live Tracking using CNN and blob detection
- ✓ Auto Correct using ResNet 20

April 2018

- ✓ Generic Model for Multiple Catheter
- ✓ System Retraining architecture & Dashboards

June 2018

- ✓ Using DGX for Training multiple models
- ✓ Replace CNTK with TensorFlow
- ✓ Faster RCNN for object detection and classification

October 2018

- ✓ Ensemble Model for Live tracking with RCNN and ResNet
- ✓ Mask RCNN for pixel wise segmentation
- ✓ Initiation of other work

CNN → ResNET → Faster RCNN → Mask RCNN

Artificial Intelligence Progress

Ultra Rapid Data Analysis and Optimization

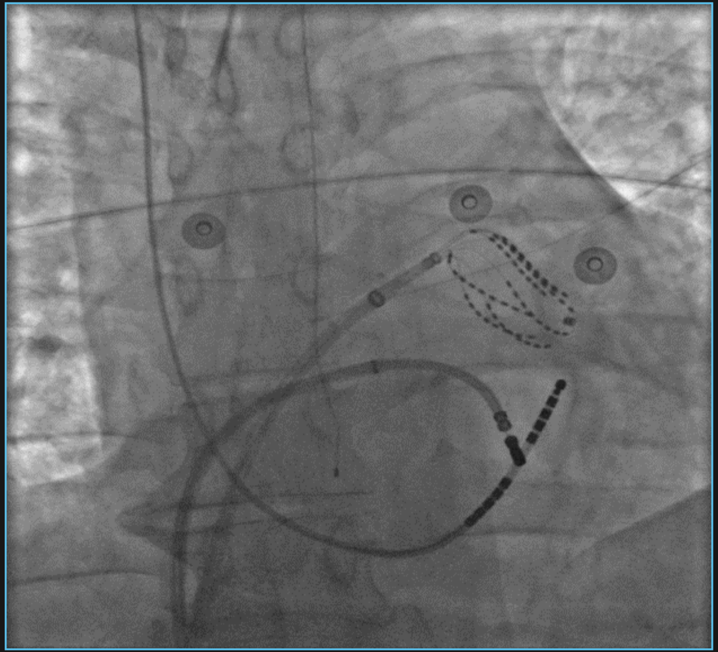
- ✓ **Image Recognition-Catheters, cryoballoon**, left atrial appendage devices, valves, leads for heart failure
- ✓ Signal Processing
- ✓ **Inference**
- ✓ Prediction
- ✓ Voice
- ✓ **Product Hardware (GPU)**

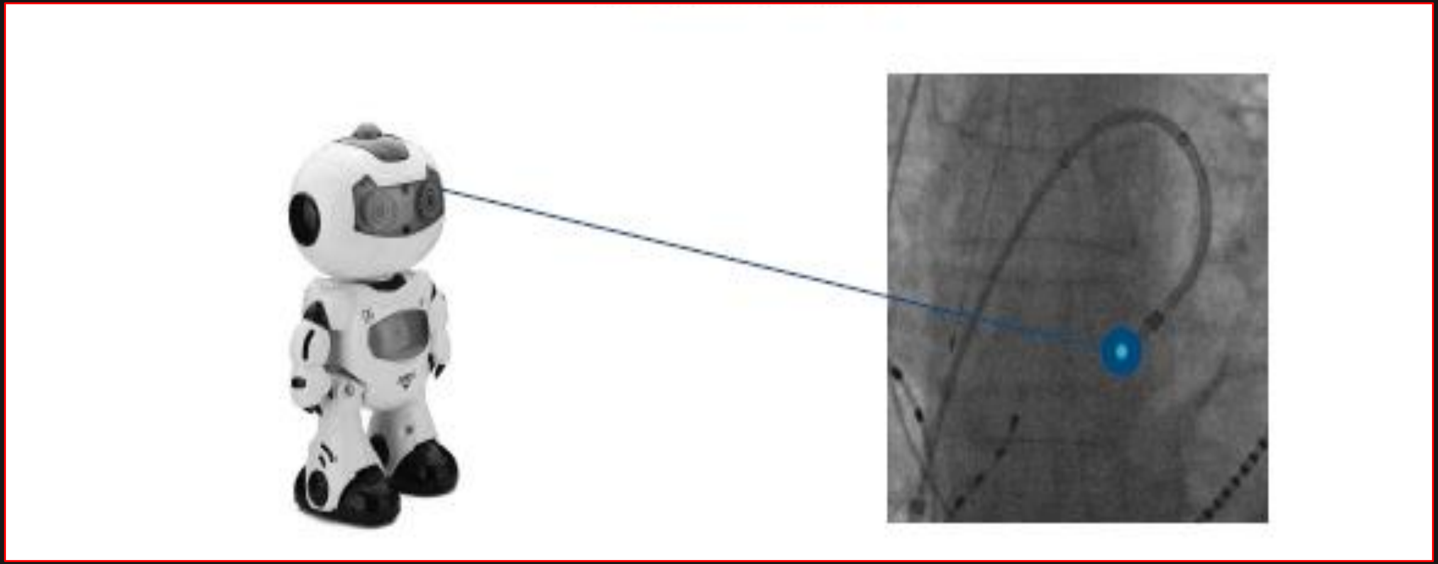
- AI Server
  - 15 hours for epoch (1 iteration of data)
  - 20 epochs (14 days)
- Nvidia-DGX Server
  - 8 mins-epoch using 7 GPUS
  - 100 epochs - 18 hrs., 200 epochs – 1day-15hrs

Training Time Using DGX

[redacted]

AI IN EP-Training and Analysis

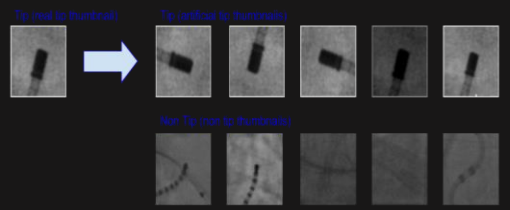


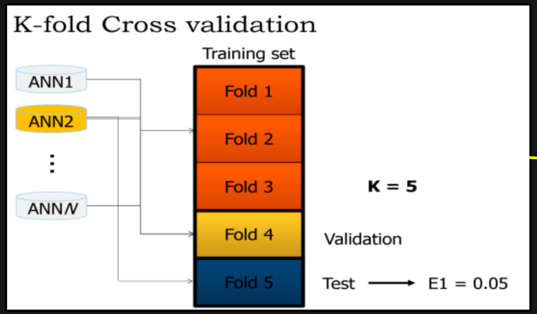


Catheter Detection

AI Architecture for Training

TRAINING THE AI MODEL

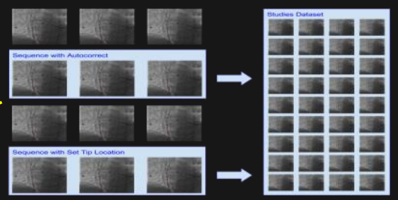




CNN Model
3 layers for live tracking

Out put of training (older model)

LIVE TRAINING



- Catheter may present in many orientations
- Training both ways what is a catheter and what is not

ResNet 20-Layers Model-Autocorrect

Improvement of CNN-- Transfer Learning Plus Dynamic Training

Tip X,Y

REAL TIME INFERENCE

Sometimes over learns-K fold validation is performed
Shuffle the 10 images-randomization is called K fold validation

Input frame → Scaling ¼ factor → Histogram equalization → Blob detection → AI tip classification

Resnet due to 20 layers provides better classification between catheter vs non catheter objects

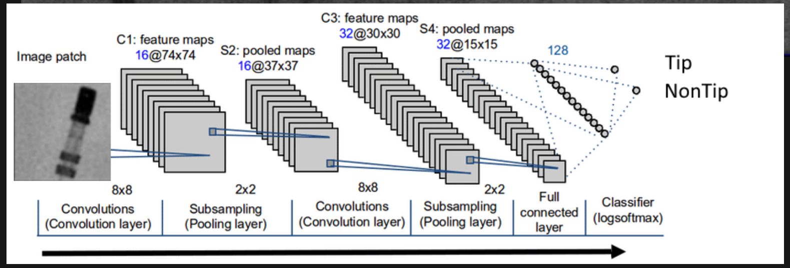
[redacted]

AI IN ELECTROPHYSIOLOGY- *Training*

On each layer we have a set of filters, the weights of these filters are adjusted during training

Each filter generates a feature map -the rectangles that we can see on the convolutional neural network diagram

On each layer we are detecting more features and the relation with other features detected in the neural network, e.g. catheter and number on rings.



In current mapping technique- Faster RCNN being used using 101 layers which analyzes the whole frame

[redacted]

Catheter Tip Detection-First Research Using AI

Catheter Tip Detection-1000 hours of Patient Data

Cloud Architecture Roadmap-over 1000 hours of Patient Data

Real-time Data

Historical Data

Information Management
- Data Factory
- Data Catalog
- Event Hubs

Big Data Store
- Data Lake Store
- SQL Data Warehouse

Machine Learning and Analytics
- Machine Learning
- Data Lake Analytics
- Stream Analytics

Services
- Training Services
- AI Algorithms
- Block Chain

Dashboards & Visualizations
- Power BI

Visualization

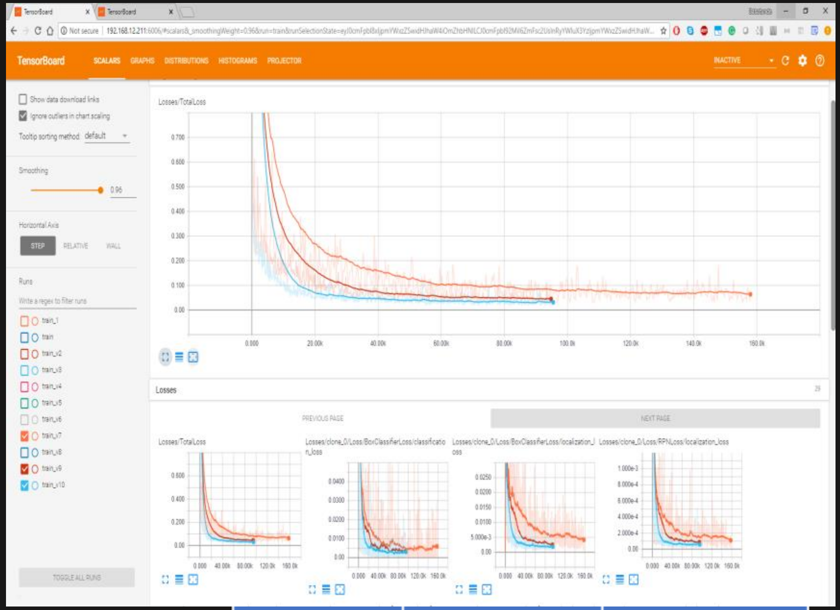
Realtime Inference at the edge

Data → Intelligence → Action

Automatic Detection of Catheters and Other Objects

Rapid Analysis of Data (within minutes)

Tensorboard shows training metrics across different models with different training configuration



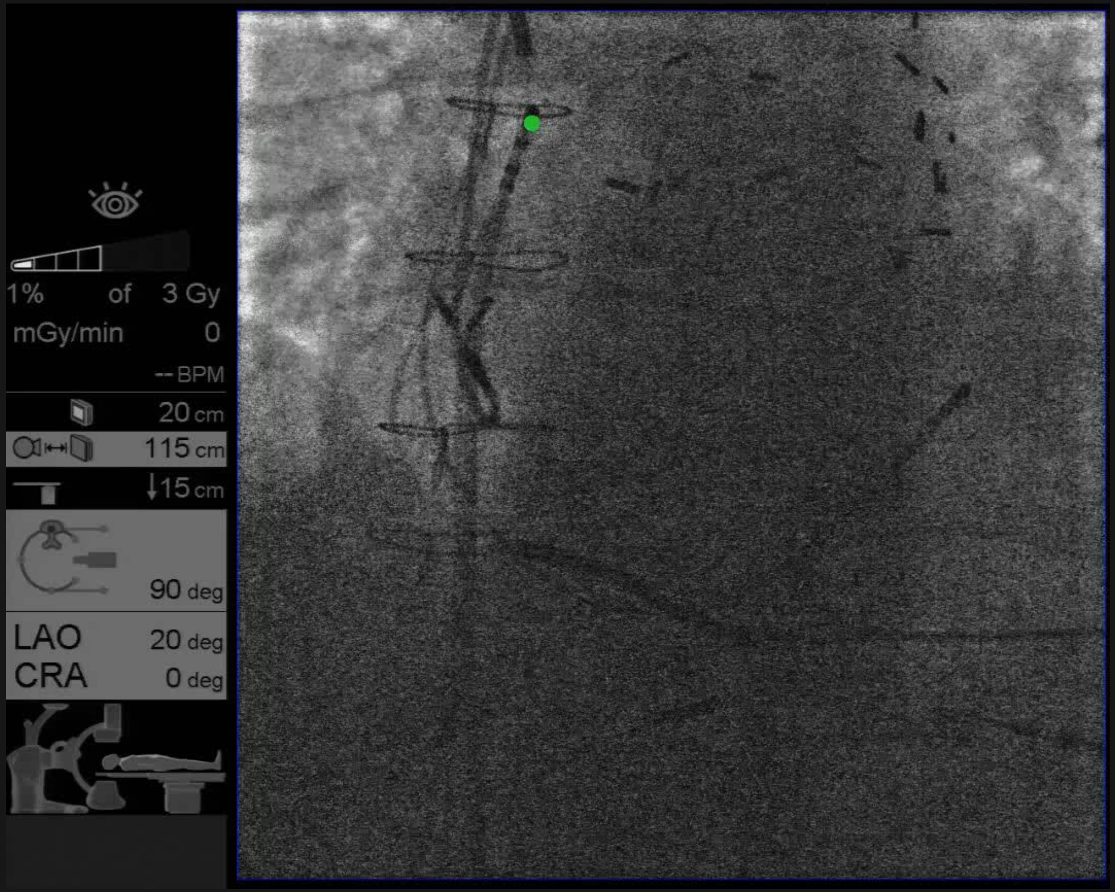
	Predicted True	Predicted False
Actual True	TP = 1701	FN = 0
Actual False	FP = 3	TN = 1867

Accuracy: 0.9992
Misclassification: 0.0008

Input Data-Mathematical Algorithms to Process-Output Data

[redacted]

Real Time Catheter Tip Detection



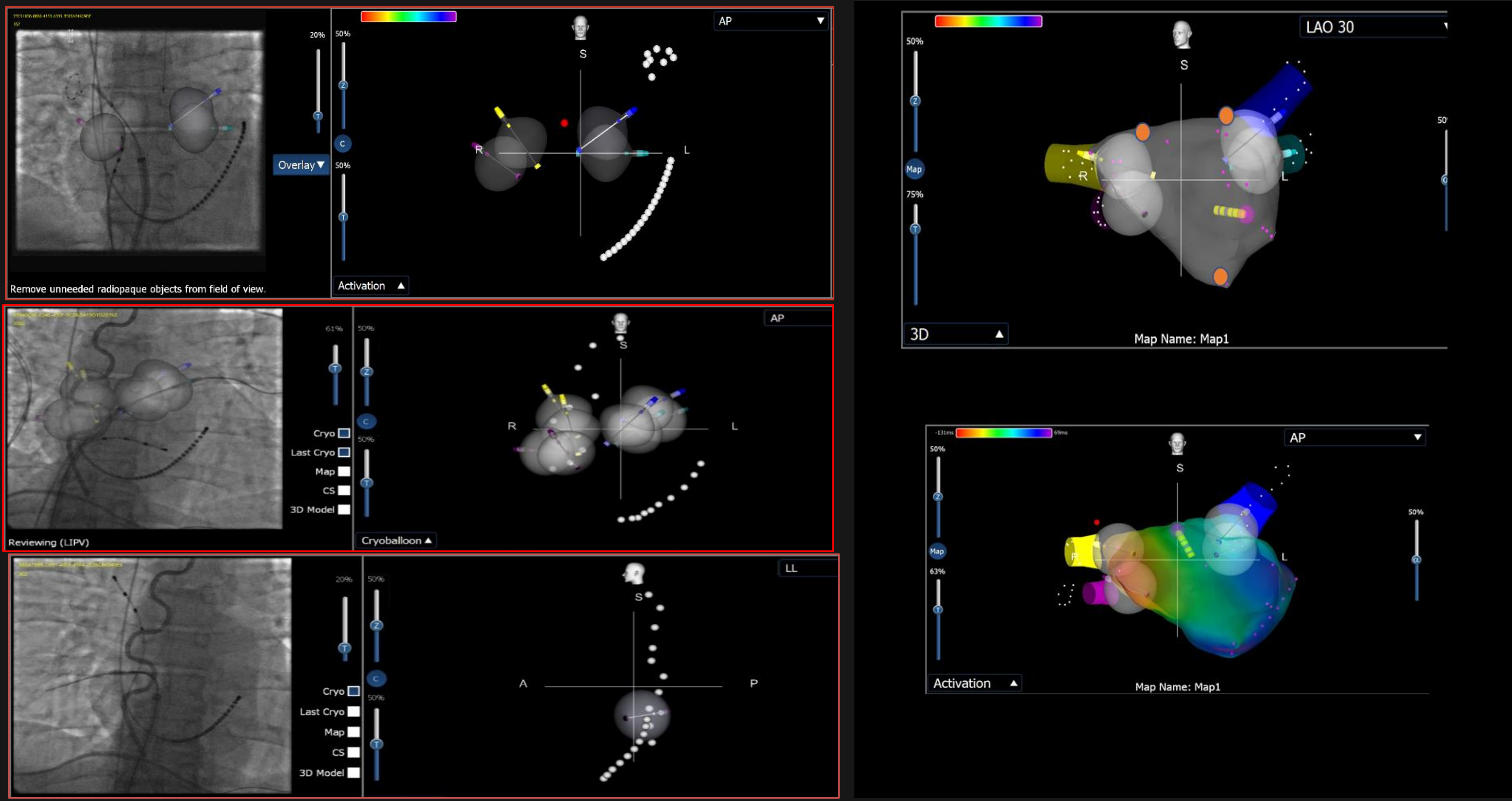
AI Enabled Catheter Tip Detection-Using Faster RCNN with 101 layers

[redacted]

Current Technology

Standard Mapping

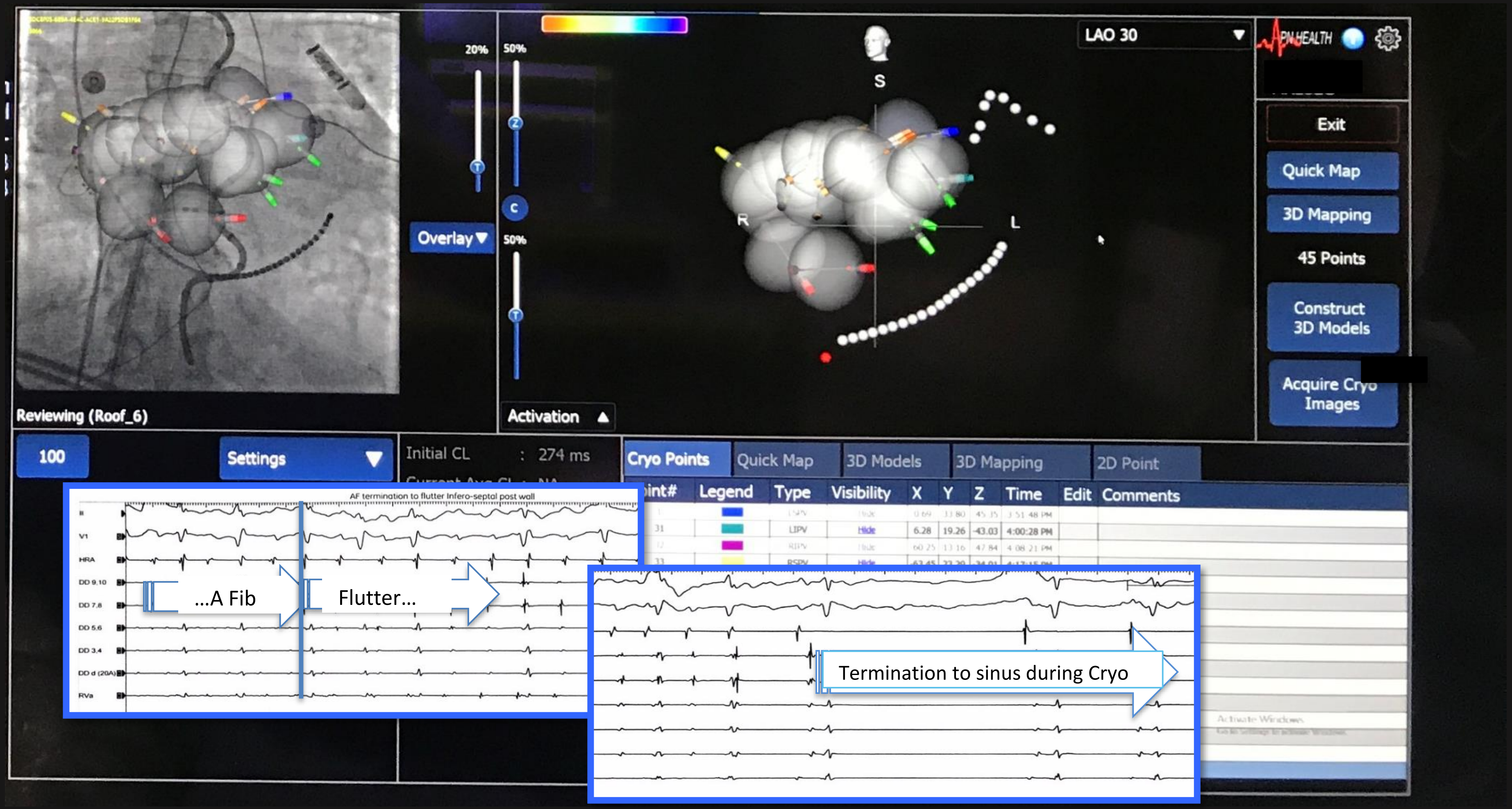
Integration of Cryoballoon and 3D Maps



3D Mapping from 2D Images and 3D localization of Balloon

[redacted]

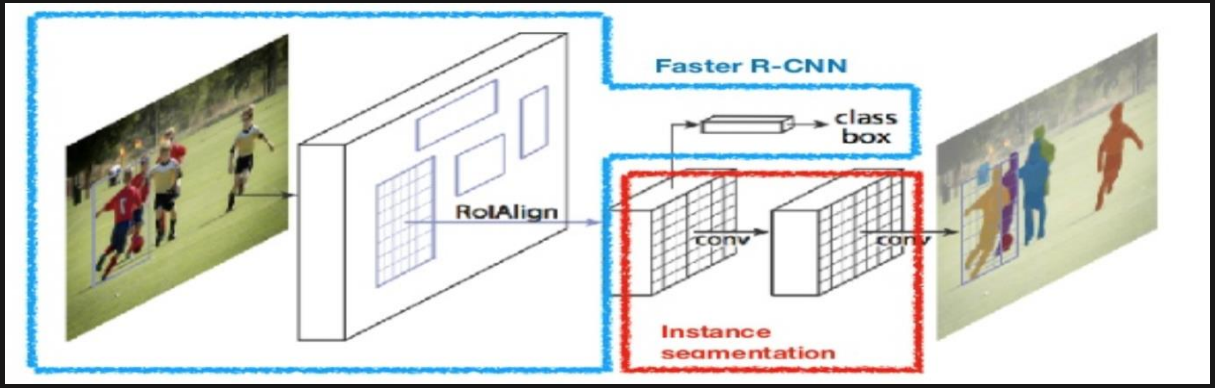
3D localization of Balloon

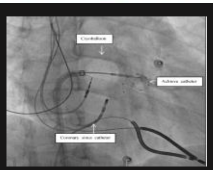


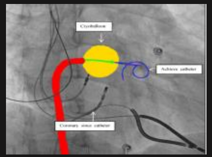
Over 300 Procedures Performed

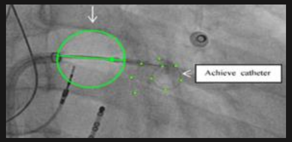
[redacted]

Automatic 3D localization of Balloon- *Mask RCNN*







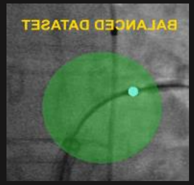


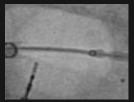
Fluoro Image

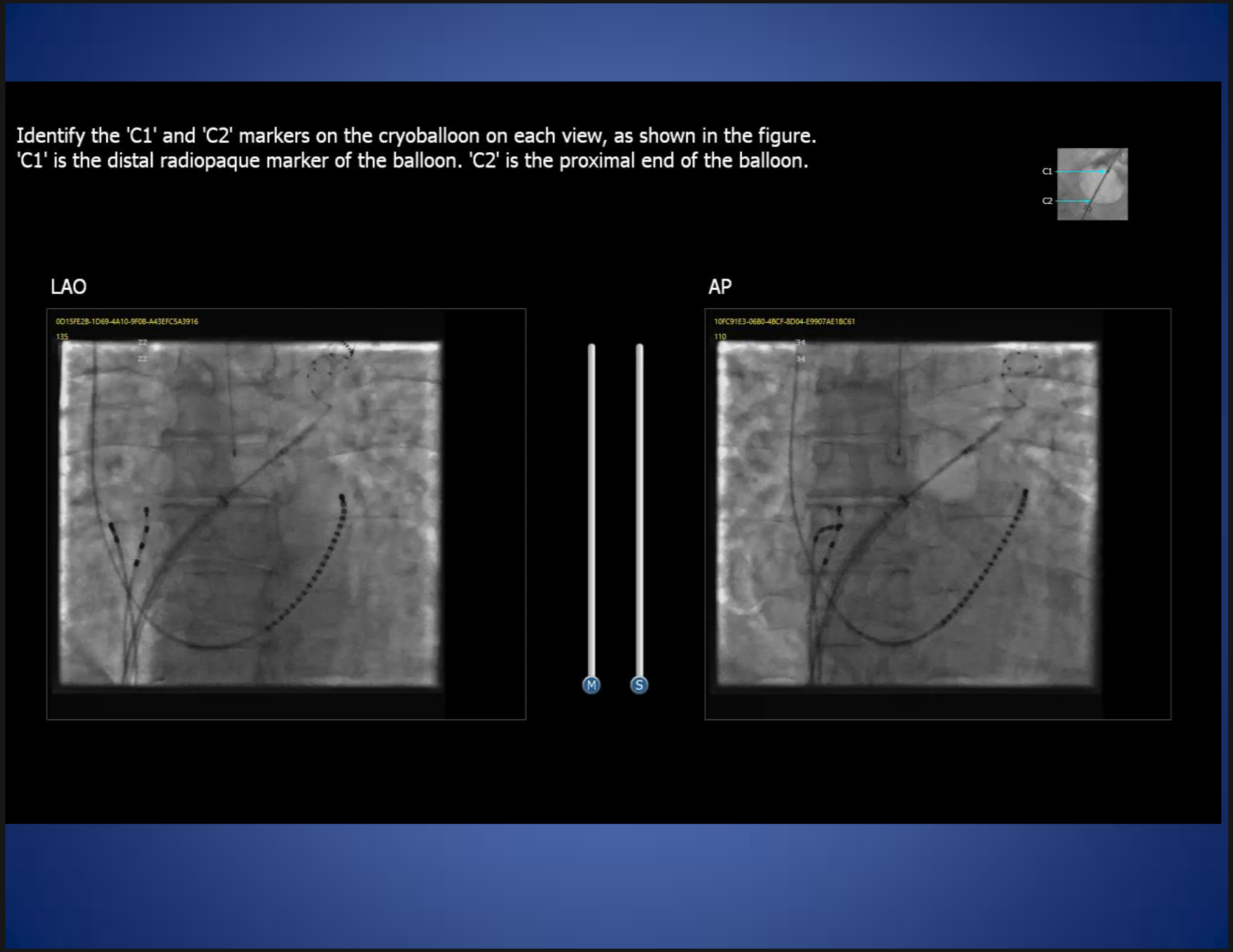
Mask RCNN
(ResNet 101)

Post Processing:
Position and
Orientation

ResNet 50
(Classification
Only)

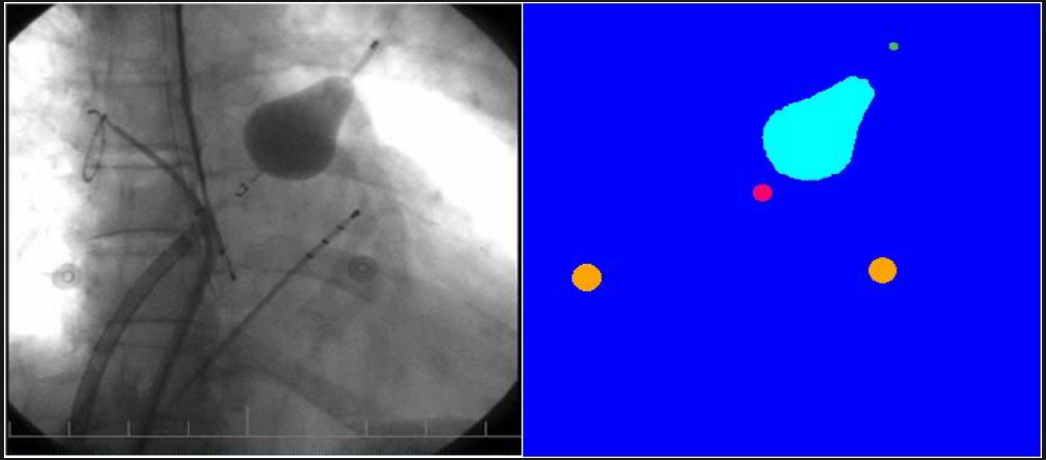


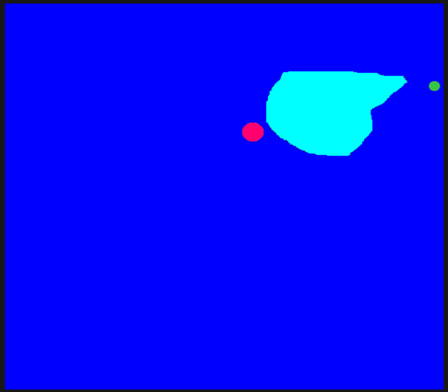


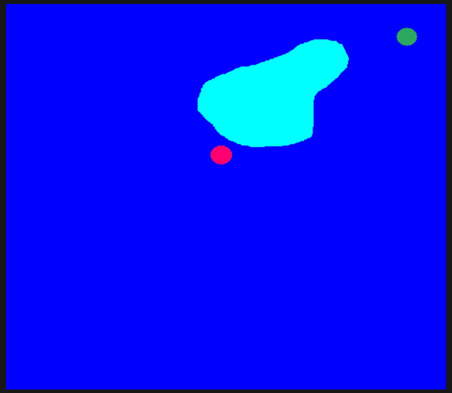


AI Enabled Automatic 3D location of Cryoballoon

Laser Balloon-Detection of Variable Shapes





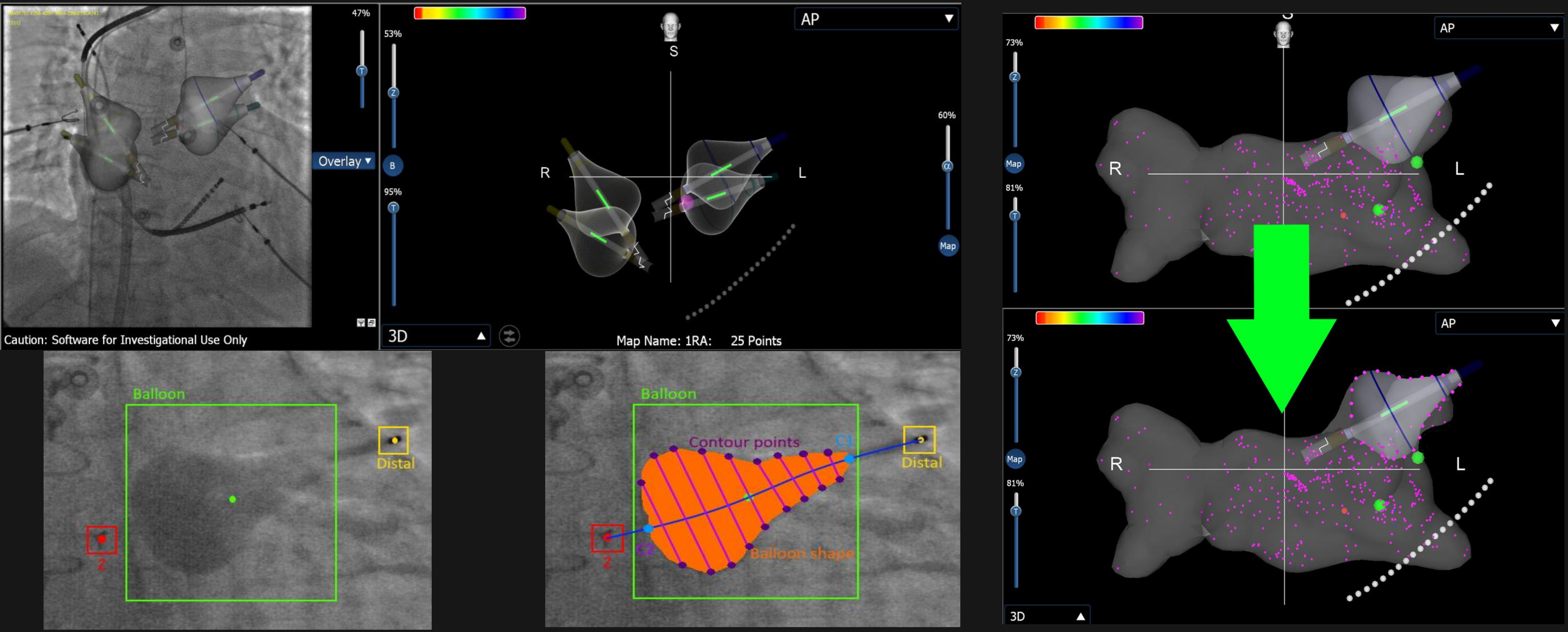


- Includes the balloon shape before, during and after the ablation
- Over 6000 datasets used

Training and automatic detection for Multiple Shapes

[redacted]

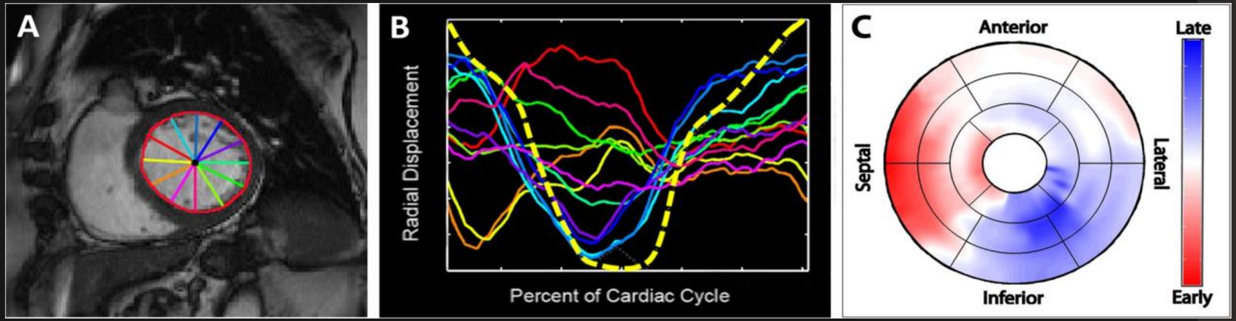
3D localization of Balloon With Deformable Shapes



Automatic detection of balloon and different markers

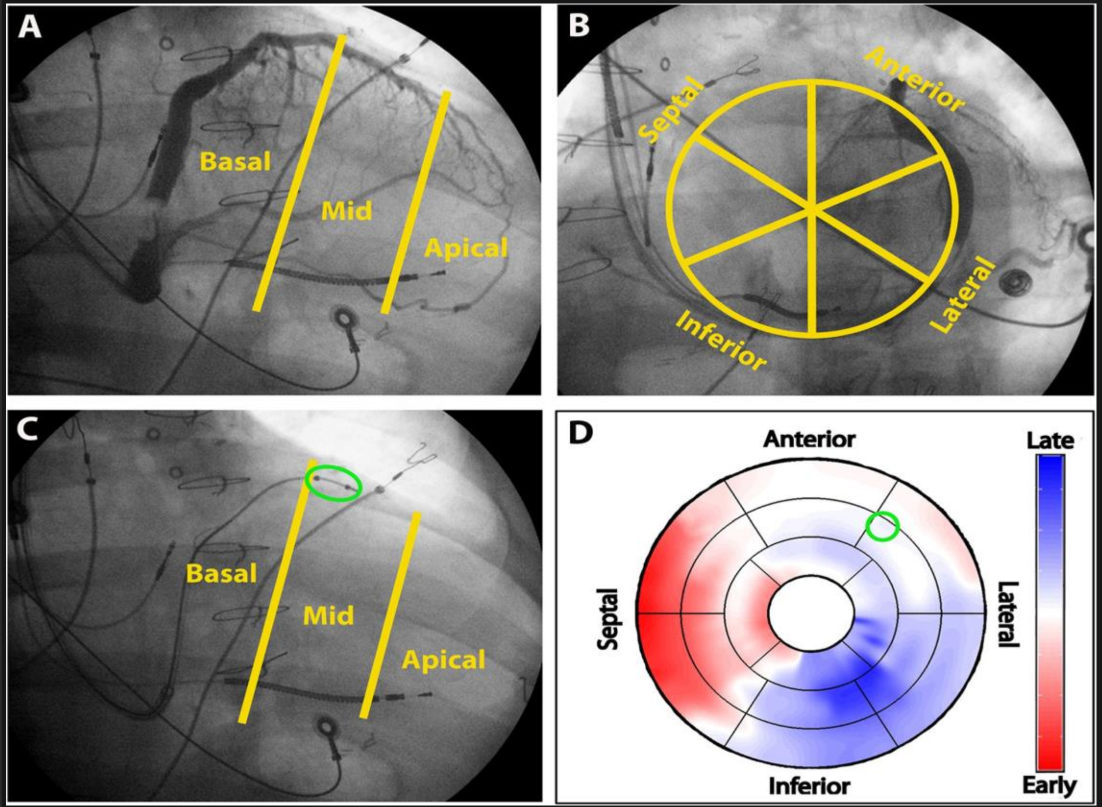
[redacted]

Prediction of response to cardiac resynchronization therapy using LV pacing lead position



There is evidence that a left ventricular (LV) lead localized to the latest contracting LV site predicts superior response, compared to an LV lead localized remotely from the latest contracting LV site.

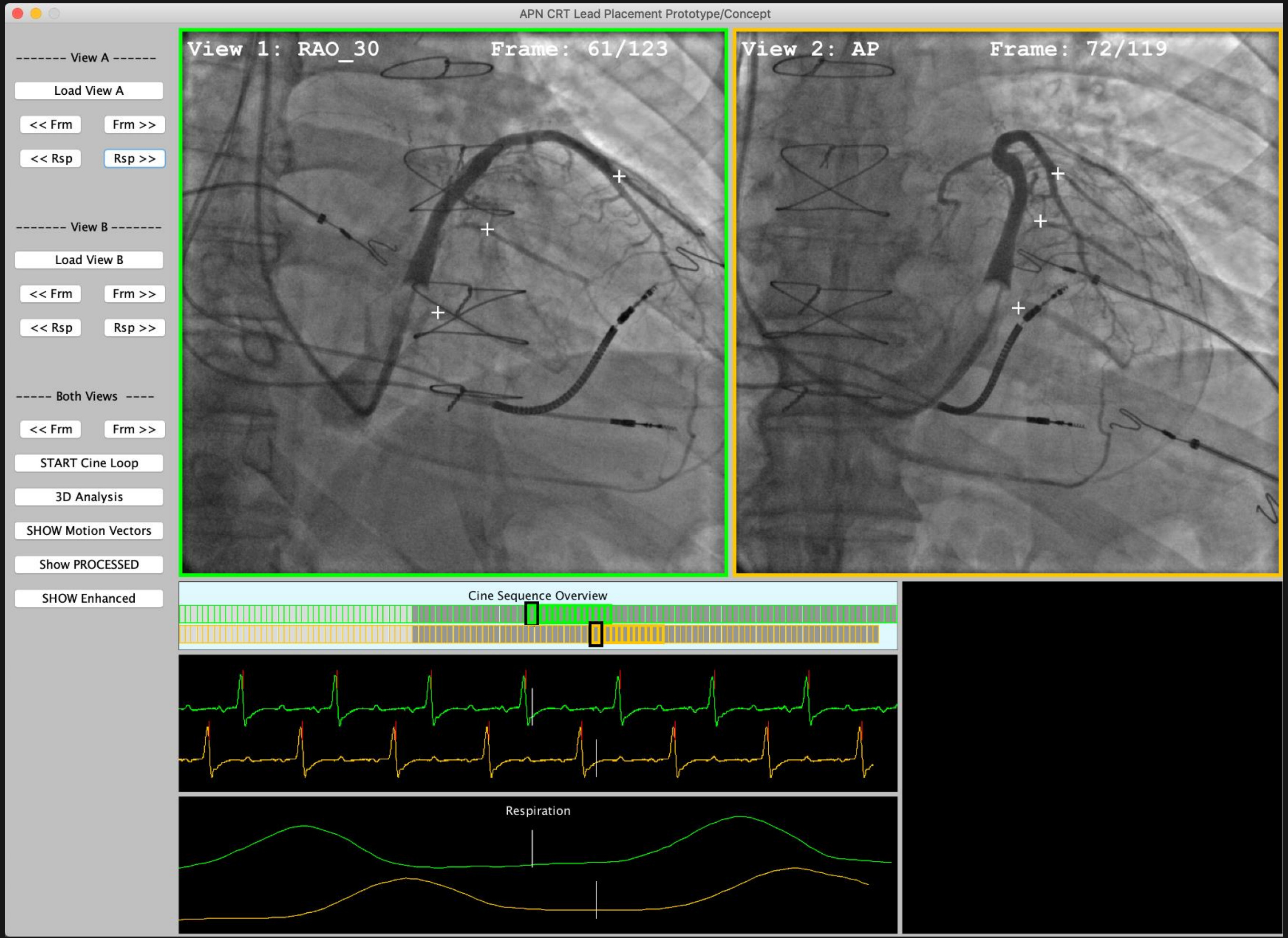
- 33 patients meeting conventional indications for CRT with a mean New York Heart Association class of 2.8 ± 0.4 and mean LV ejection fraction of 28 ± 9 %.
- Overall, 55 % of patients were echocardiographic responders by ESV criteria. Patients with
- LV lead concordant to the latest contracting site (T2CL) had a response rate of 92 %, compared to a response rate of 33 % for those without T2CL (p = 0.003).



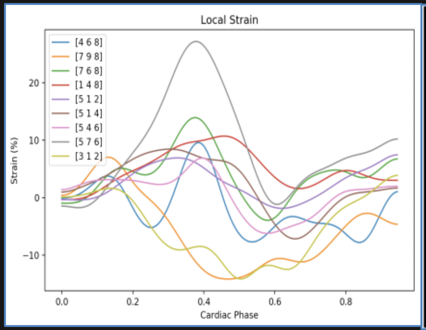
Hartlaae et al. Journal of Cardiovascular Magnetic Resonance (2015) 17:57

CRT Response Based on Site of Latest Activation

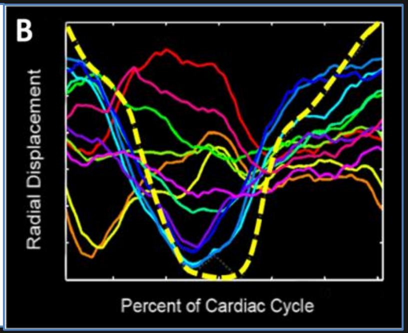
Identifying Appropriate Pacing Site



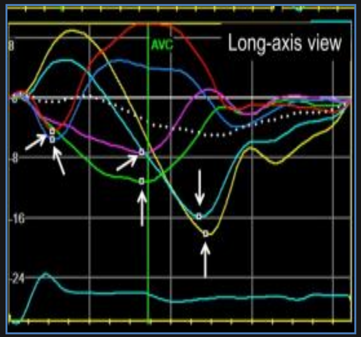
Displacement/Strain Measurement – Comparison



Fluoro Images



MRI

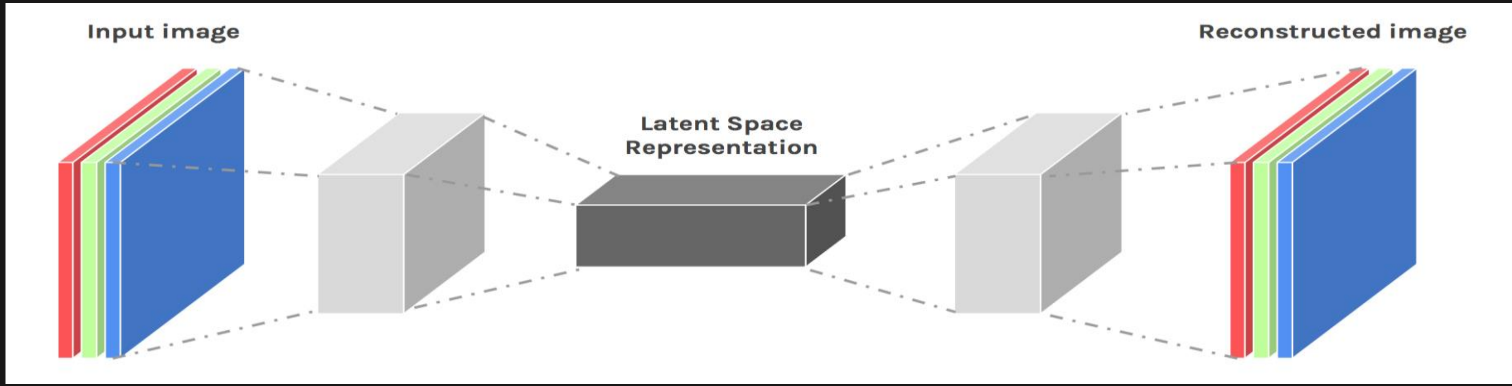


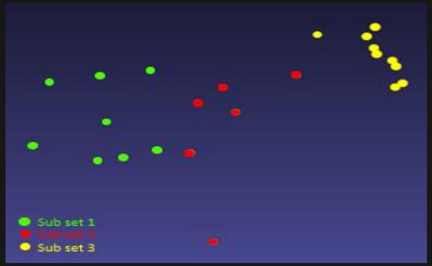
ECHO

Pacing Site Prediction in CRT

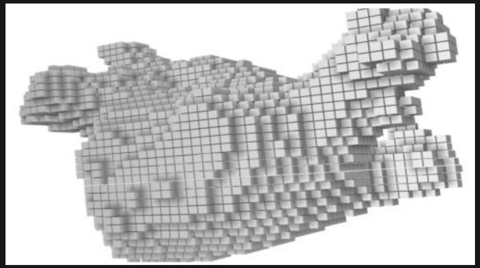
[redacted]

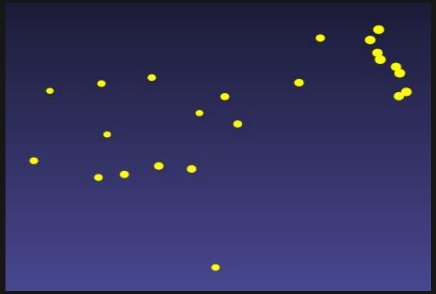
3D Reconstruction Using Minimal Points



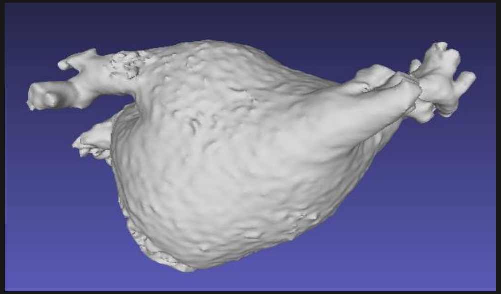


Autoencoder





Transform:
Translation
Rotation
Scaling



Using 3D images and CT models to create 3D reconstruction using AI

[redacted]

AI IN ELECTROPHYSIOLOGY

- Background
- Data Analysis/Training
- Diagnosis/Treatment
- Prediction

AI Enabled Platform LAA Occlusion Device

- **Cost**
- **Need for multiple specialties:**
  - EP : Cardiology
  - Anesthesia
  - ECHO
- **Need for General anesthesia-Many cases**

AI Based Solution

- **Appendage size prediction for device in advance**
- **Real time integration of CT in 3D and 2D**
- **Real time navigation of device to the LAA**
- **3D localization of Watchman**

Predicting Size and Real Time Navigation

[redacted]

ECG/EGM/Map Analysis-Reinforcement Learning

**Fast Catheter Mapping:
Automatically find out the best points to include in the map**

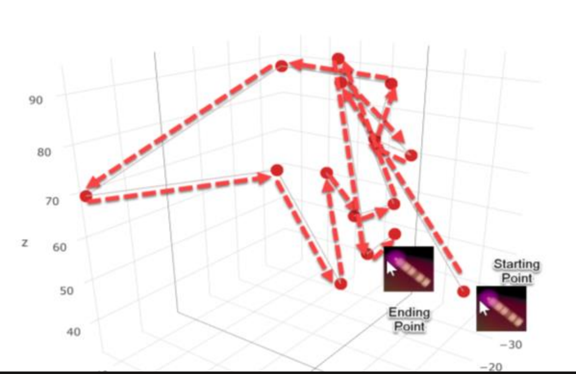
A reward function is created based on the acceptance or rejection of a selected point and a policy gets defined by Q-Learning

**Catheter Tissue Contact
Given the mapping characteristics and outcomes, find out if optimal contact force is currently in use**

From the impedance and other data, identify the point characteristics that were used in an accepted map. Dynamically determine the range of values that will result in an optimal contact

Intelligent Catheter Mapping:

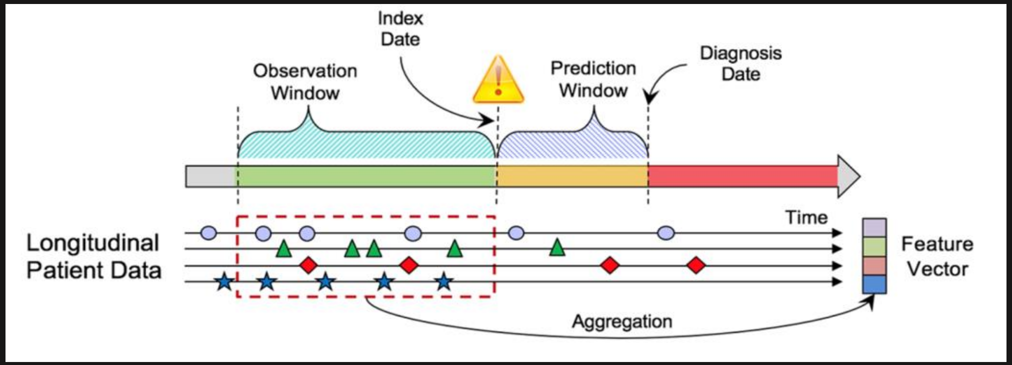
Find out the optimal path to arrive at the region of interest.

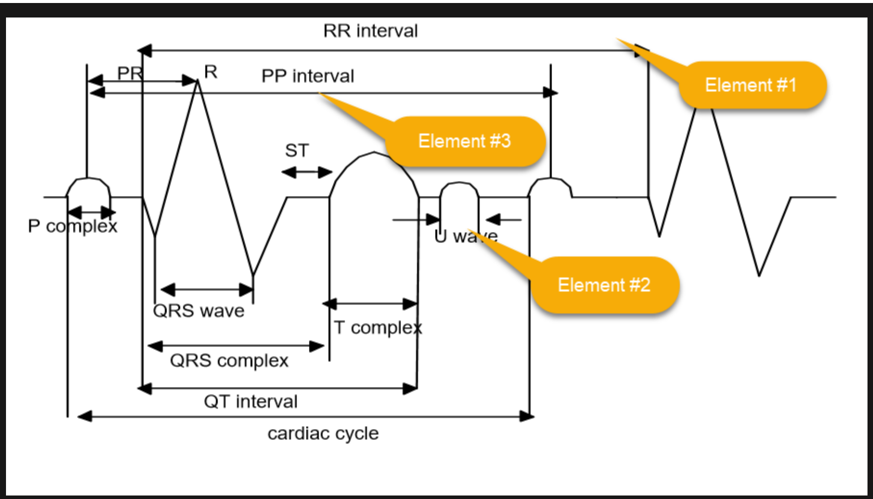


AI Enabled Prediction

[redacted]

Arrhythmia Site Prediction

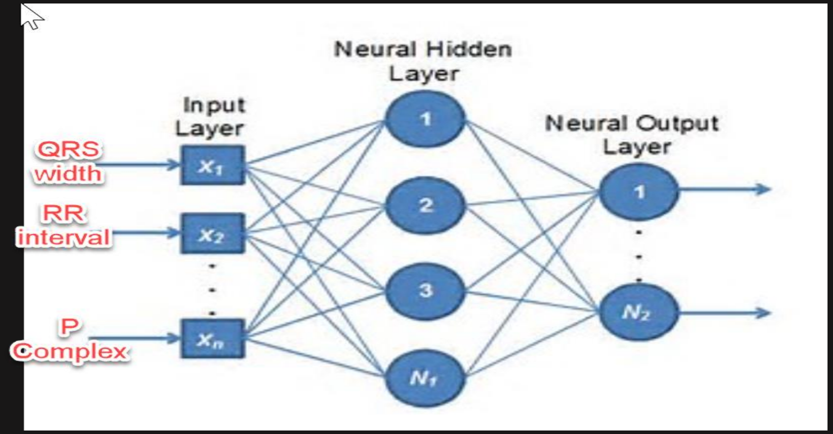




DATA FORMAT FOR THE ECG QRS COMPLEX

- ResNet-like architecture with 1D Convolution layers and Dropouts
- MIT-BIH Arrhythmia Database
  - https://www.physionet.org/physiobank/database/html/mitdbdir/mitdbdir.htm

Algorithms tested with

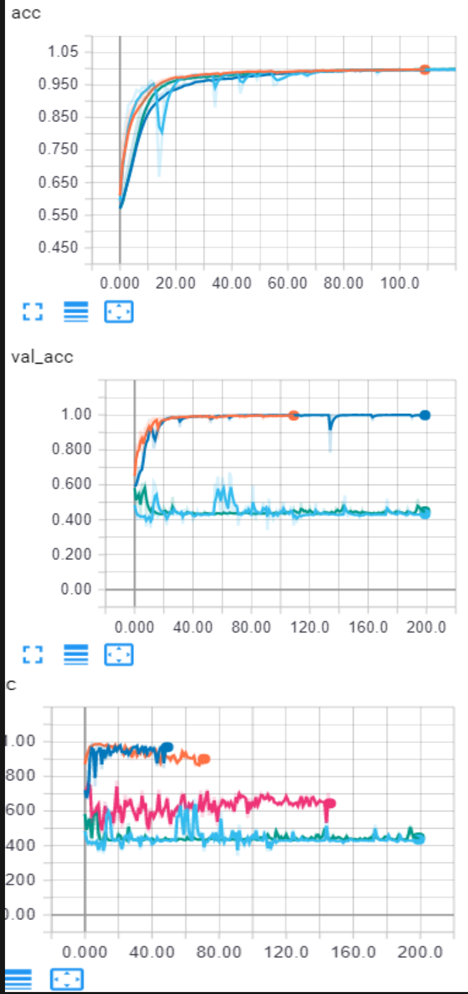


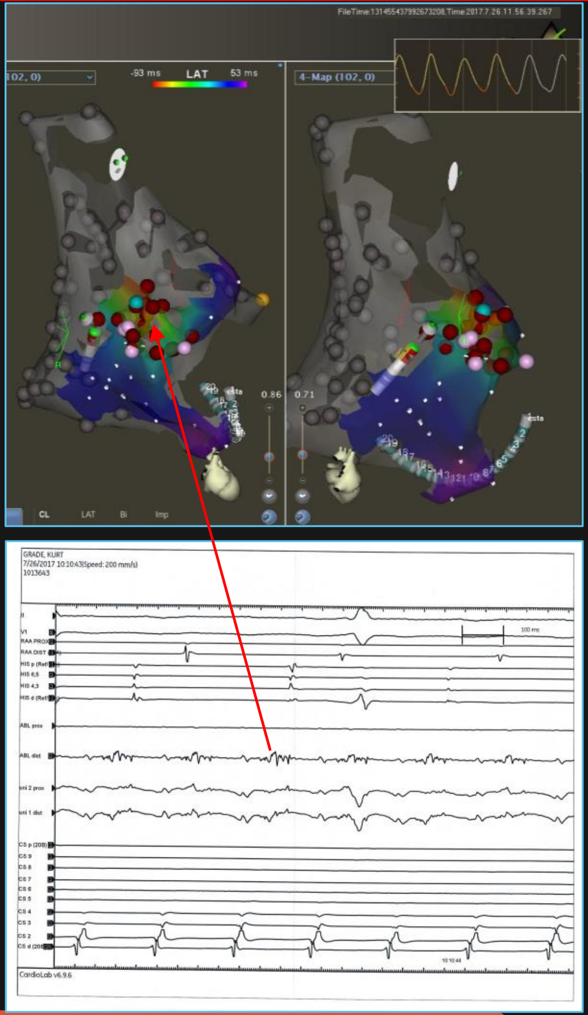
AI Enabled Analysis

[redacted]

Trials for Arrhythmia Site Prediction

Trial 1-Model	Comment
Bidirectional **LSTM** (Long/Short Term Memory)	Correctly predicts ECG signals with ~99% test accuracy
Conv1D-6conv1fc (in-sample dist.)	
Bidirectional LSTM (out-sample dist.)	Models didn't generalize well for signals (with significantly different pattern) it has not seen before
Conv1D-6conv1fc (out-sample dist.)	
Trial 2-ResNet1D with Dropout (out-sample dist.)	**~98% accuracy after adding dropouts after each max-pooling layer and to the last fully connected layer for better regularization.**
ResNet1D with Dropout (out-sample dist.) – different optimizer configuration	
BiLSTM, Conv1D-6conv1fc (out-sample dist.)	

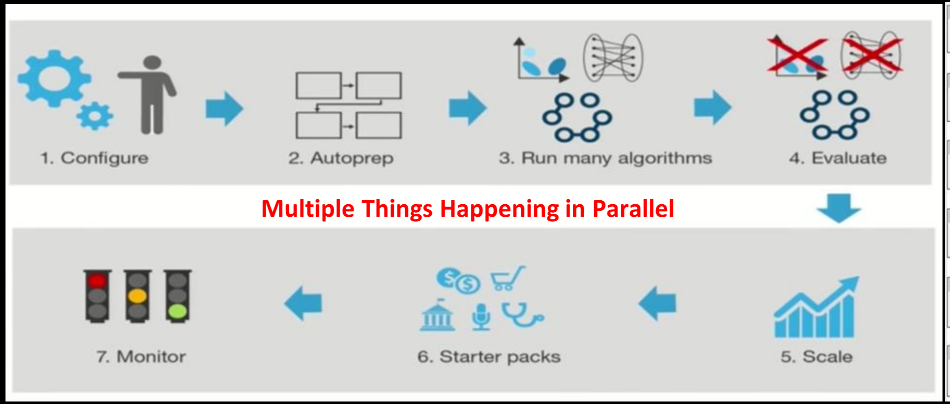


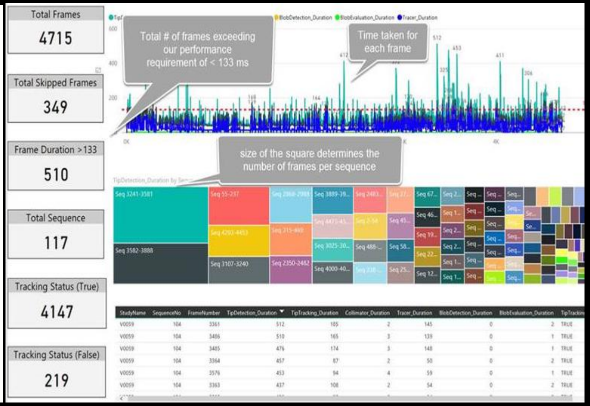


Drop out function forces neural network to learn more robust features to help with random subsets

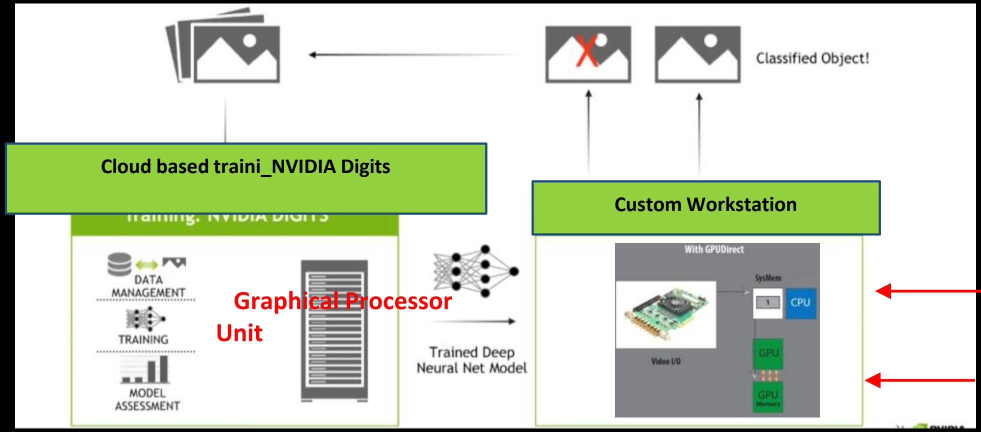
[redacted]

Infrastructure (Continuous AI TRAINING)-Hardware (fast computing power)





Prediction
Real Time Analysis
Mapping
Navigation



X-Ray/Other data

ECG

Deep Learning GPU Training System

AI in EP

[redacted]

Summary

- **Neural Network Models**
  - Convolutional - CNN
  - Residual – ResNet

- **Companies enabling AI**
  - Nvidia
  - Microsoft
  - Google

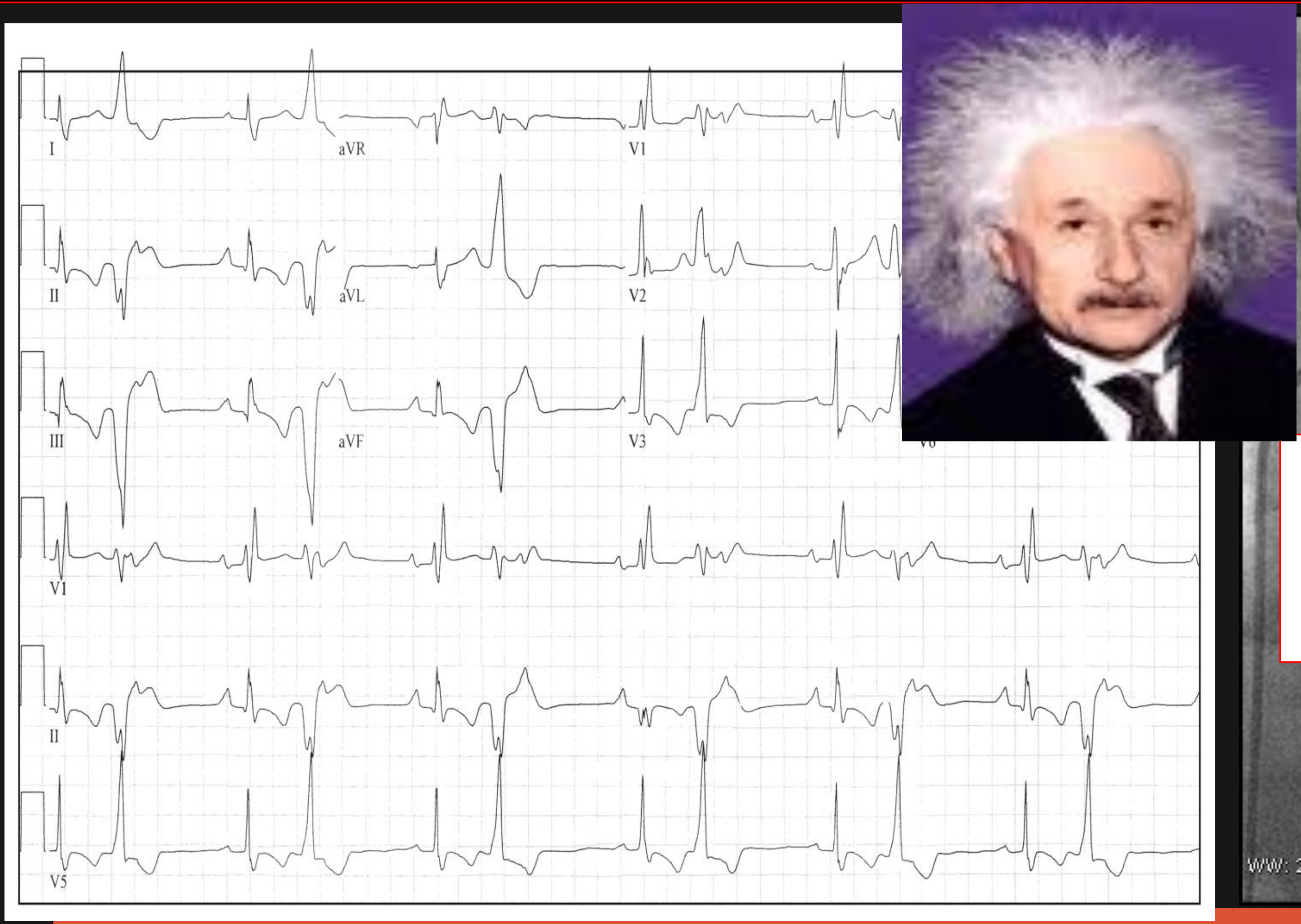
- **Infrastructure for AI**
  - Hardware
    - CPU Class
      - Intel based
    - GPU Class
      - Nvidia based

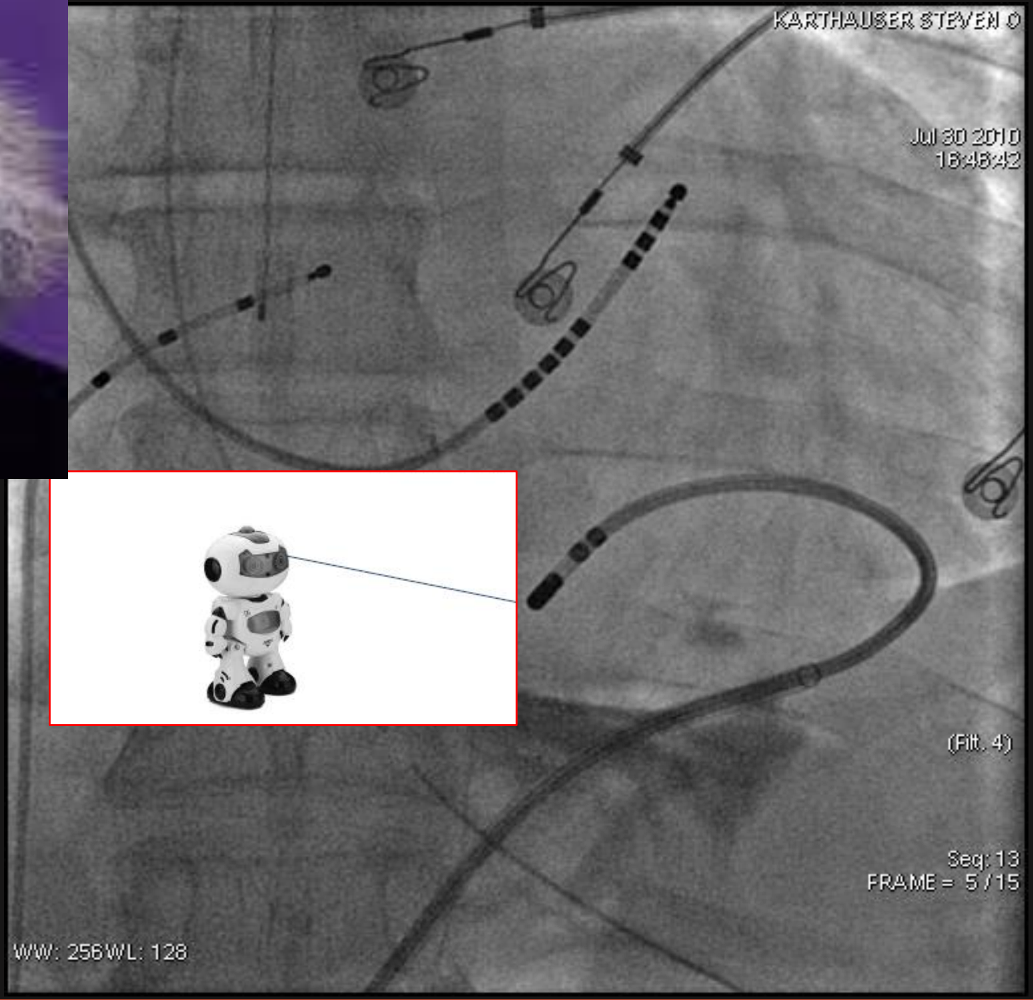
- **Training Platform**
  - Nvidia DIGITS
  - Microsoft CNTK
  - Google Tensor Flow

- **Containers**
  - Container 1..
    - Google – ConvNet
    - 2 Layers
  - Container 2
    - Microsoft – ResNet
      20 Layers
  - Container 3
    - >100 Layers

AI Features
- Data Analysis
- Training
- Image Recognition
- Signal Processing
- Inference
- Prediction

Prediction





Next Generation EP Solutions

Thank You

Next Generation EP Solutions

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