

# Assessing Ventilator-Associated Pneumonia (VAP) in the PICU

#### Members:

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#### **Mentors:**

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Radiology Artificial Intelligence Lab

Clinical Collaborators: Dr. Jim Fackler Dr. Jules Bergmann Dr. Ferdinand Hui Dr. Haris Sair Dr. Paul Yi



# Background



Mechanical Ventilation – critical life sustaining ICU therapy There is still risk of further decompensation:

- Disease progression
- Latrogenic infection
- Ventilator injury



# Objective: Identify VAP Risk Early

Challenge: Can we identify VAP risk (at risk patients, early event warning)?

•Focus surveillance/interventions on high risk patients

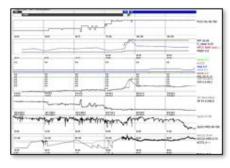
•Avoid unnecessary therapy in low risk patients

Multi-disciplinary team

•PICU – focus on identification of physiomarkers of increased VAP risk

•ID – focus on appropriate culture/antibiotic use

•Radiology – focus on early imaging changes associated with VAP risk





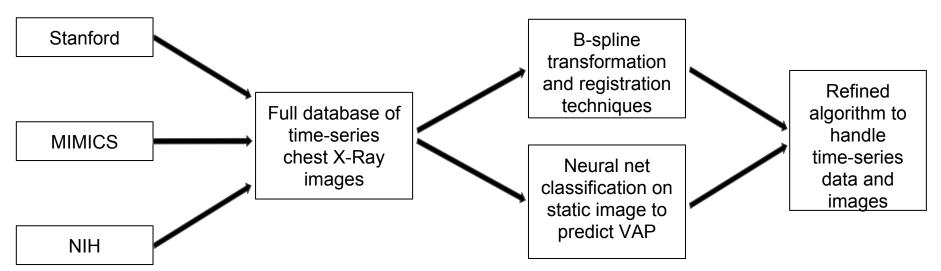




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# **Project Overview - Block Diagram**

#### **Public Datasets**



IRB Submission and Pending Approval for Pediatric Data from JHMI



### **Clinical Data Collection**

#### • Collected at many different hospitals

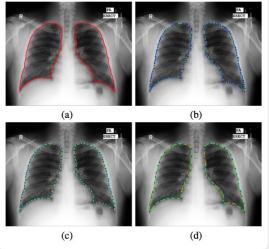
- Different lab techs performing
- Different orientation of patients
- Different machine/resolutions
- Image taken at inspiry vs expiry
- Every patient is different
  - Different IVs/tubes in the image
  - Young patients grow with every new image taken



# Technical Workflow - feature detection in time-series

• We need to be able to track the changes in important features of each time series

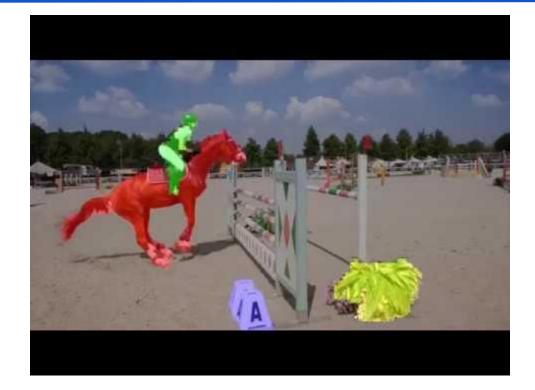
- To do this...
  - ο β- spline registration & transformation



S. Candemir, S. Jaeger, K. Palaniappan, J. P. Musco, R. Singh, Z. Xue, A. Karargyris, S. Antani, G. Thoma, and C. J. McDonald. Lung segmentation in chest radiographs using anatomical atlases with non-rigid registration. IEEE Trans. Medical Imaging, volume 33, issue 2, pages 577-590, 2014.



### **Technical Approach**





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## **Technical Workflow - Neural Net Classification**

- Goal: apply a prediction algorithm in order to predict characteristics of VAP
  - Start with a single chest X-ray image: predict effects
  - Potential models include:
    - VGG
    - Choose a Number
    - ResNet 52-102
    - DenseNet
  - $\circ$  Train and test model on multiple datasets  $\rightarrow$  reach set accuracy threshold
  - Final step: combine image transformation process with best-performing neural network to develop sophisticated algorithm that can serve as standalone tool for monitoring



### Workflow

01	Screen and Collect Working Data to Build Database of X-Ray Images	<ul> <li>Assemble packages from publicly available datasets (Stanford, MIMICS, NIH, etc.)</li> <li>Determine if time series data is applicable within specific cohorts         <ul> <li>If not, take different approach in training network</li> </ul> </li> <li>Screen for important characteristics if have time series data</li> </ul>
02	Assemble I/O Package for Analyzing Cohorts within the Database	<ul> <li>Normalize images so can perform accurate analysis         <ul> <li>Assume images are in the same physical extent</li> </ul> </li> <li>Establish landmarks to align to different images</li> <li>Analyze images to train model for baseline prediction         <ul> <li>Start with simple model (single images)</li> </ul> </li> </ul>
03	Develop Sophisticated Algorithm to Handle Complex Patterns within the Time Series Data	<ul> <li>Once model is trained to sufficient baseline, start testing new methods of classification         <ul> <li>E.g. Gaussian processes</li> </ul> </li> <li>Develop algorithm that can handle multiple images for feature analysis</li> </ul>



### Deliverables

#### Documentation:

- Python/MATLAB source code
- Code documentation
- Database of X-Ray cohorts
- Report describing methods and achievements

#### <u>Minimum</u>

- A database of X-ray cohorts and segment them based off patient type, time series characteristics, and other important features
- Algorithm that can identify physical landmarks on images and produce one image prediction

#### Expected

• Algorithm for working image alignment with subsequent classification

<u>Maximum</u>

• Sophisticated algorithm that handles arbitrary time series data for accurate prediction and monitoring



### Dependencies

Dependencies	Solution	Date			
Access to MIMICS Dataset	Complete Series of HIPAA Training Modules	2/20			
Access to Workbench with Significant GPU Processing Speed	Email Dr. Unberath and Request Access through RAIL	2/22			
Access to image processing neural networks	Download through internet and/or email Dr. Unberath	Ongoing			
IRB Approval for JHU Data	Submit through Dr. Unberath and Dr. Fackler	Ongoing			



### Schedule

	Feb. 15	Feb. 22	Mar. 1	Mar. 8	Mar. 15	Mar. 22	Mar. 29	Apr. 5	Apr. 12	Apr. 19	Apr. 26	May 3
Compile database of public data												
Normalize Data, Create Transformations												
Build I/O Module												
Refine Algorithm for Time Series												
		Current										

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### Key dates and Milestones

February 25 - full compilation of images

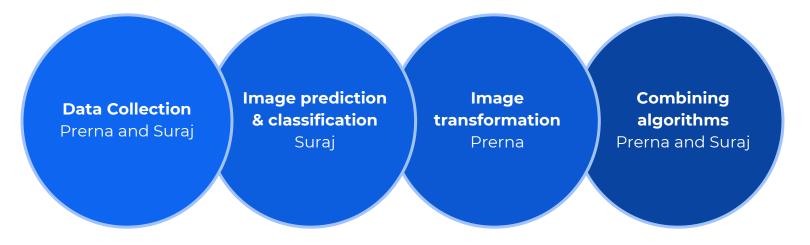
March 15 - images transformed and normalized

April 1 - I/O Module built

May 3 - Refine algorithm for time series input



## Responsibility





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### Management Plan

- Thursday weekly meetings with Dr. Unberath & RAIL (Radiology Artificial Intelligence Lab)
- Communication with Dr. Jules Bergmann and Dr. Jim Fackler (in coordination with Dr. Unberath)
  - Email and text
- Code on private github
- Data stored on work bench in Hackerman



# **Reading list**

Chen, Y., Pont-Tuset, J., Montes, A. and Van Gool, L. (2019). *Blazingly Fast Video Object Segmentation with Pixel-Wise Metric Learning*. [online] arXiv.org. Available at: https://arxiv.org/abs/1804.03131 [Accessed 18 Feb. 2019].

Yin Y, Hoffman EA, Ding K, Reinhardt JM, Lin CL. A cubic B-spline-based hybrid registration of lung CT images for a dynamic airway geometric model with large deformation. *Phys Med Biol*. 2010;56(1):203-18.

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep Residual Learning for Image Recognition. 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 770-778.

He, K., Zhang, X., Ren, S. and Sun, J. (2019). *Identity Mappings in Deep Residual Networks*. [online] arXiv.org. Available at: https://arxiv.org/abs/1603.05027 [Accessed 18 Feb. 2019].

Hatami, N., Gavet, Y. and Debayle, J. (2019). *Classification of Time-Series Images Using Deep Convolutional Neural Networks*. [online] arXiv.org. Available at: https://arxiv.org/abs/1710.00886 [Accessed 20 Feb. 2019].

