Academic Paper

Project Name: Ventilator Weaning Assistant System (VWAS)

Term: Spring 2021

Team Name: VWAS

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1 BACKGROUND, SIGNIFICANCE, AND PROBLEM

Mechanical ventilation is a lifesaving technique that works by assisting or forcing respiration when a patient's own lungs are insufficient (Pham, Brochard, and Slutsky, 2017). However, there are many side effects, especially with prolonged use. A metanalysis by Damuth et al (2015) found that <50% of patients receiving two weeks or more of ventilation survived the next 12 months, regardless of if they were discharged. Even when factoring for the fact that ventilators are typically used on patients at risk of death, experiments on animal models have found noticeable barotrauma, lung shear, and other physical damage from mechanical ventilation (Beitler, Malhotra, and Thompson 2016), while minimizing Ventilator Induced Lung Injuries (VILI) has been found to improve outcomes(Pham, Brochard, and Slutsky, 2017).

Despite the benefits to minimizing ventilator use, doing it abruptly or too early can result in poor outcomes, especially given that ventilation was required to begin with (Mokhlesi et al, 2007). Exact protocols to determine when a patient is ready to be moved off ventilation and the procedures for doing so varies widely (Pham, Brochard, and Slutsky, 2017) and has to account for multiple factors, such as the duration of self breathing trials (Esteban et al, 1999) and the chance of a successful extubation (Mokhlesi et al, 2007), which determine if a patient is capable of breathing without a ventilator, and if the ventilator tubes in the lungs can be removed without issue, respectively. With this in mind, it is paramount to start self breathing trials and weaning protocols as soon as possible. However, constantly checking for the right conditions is taxing on ICU staff, who have many other things to check on while lives hang in the balance.

2 OUR SOLUTION

Our solution to this problem is the Ventilator Weaning Assistance System (VWAS), a robust web app that leverages interoperability standards to provide both ventilator patient monitoring and evidence based weaning clinical decision support. The app connects to a FHIR server and pulls patient and observation data for ICU patients on a ventilator, and uses this data to form two views: a Population View, and a Clinician view.

The Population View displays ICU wide resource monitoring, demographics, and aggregate data, to assist in ICU management. The Clinician view shows data on individual patients, which includes personal/contact info, ventilator settings and status, vitals readings, and CDS recommendations on if the patient is ready to start the weaning process. Our app has two CDS recommendation engines: a rule based recommender based on parameters known to be important in the literature, and a deep learning based model that draws from the same parameters but is trained against historical data for increased accuracy(Prasad et al 2017). For the latter, it's even possible to tune the model to produce decisions similar to a particular ICU's protocols or even a single attending physician, provided that there is enough data. This allows the attending to get pertinent notifications as if they were there, and also enables the rest of the ICU staff, such as physician assistants or nurses, to leverage their expertise.

The app uses vue.js, d3.js, jquery, and bootstrap on the frontend to create an intuitive interface with concise and informative visualizations. For the machine learning model, the app uses tensorflow.js and sharded models; combined with the other libraries and frameworks, this allows the entire application to be run client side, meaning that it can be statically hosted. Without the need for a full web server, the app can be run locally, or from fault tolerant cloud content delivery networks for rapid, cost effective, and robust deployment with low latency to many geographical locations.

3 COMPLEXITY AND EFFORT

Aside from the tools, libraries, and frameworks listed above, a modified version of Synthea was used to generate synthetic patient data to confirm that everything works, and to run our demo. Github pages and the HAPI FHIR server were also used to host our demo. Scikit-learn was used to explore the data, and later to verify that the data was being generated as expected, before switching to Tensorflow for neural nets.

Synthea is designed to simulate patient histories and populations, and not ICU ventilator records, so in stock form there are very few patients on ventilators like there would be in real life, and existing ventilator data generation is focused on showing a difference between survivors and nonsurvivors. To compensate for this we heavily modified the Covid-19 module made by Walonski et al (2020) to increase ICU ventilator patients to nearly 99% and adjusted data generation to add more ventilator parameters(e.g. PEEP) and increased variance over time to reflect recovering patients that are ready to wean. Further processing in python was used to generate model training data.

We tried many machine learning architectures and settled on a fairly straightforward deep neural network, due to overall effectiveness and ease of deployment via tf.js on the client. For inputs, we chose to train the model on Heart Rate, Systolic Blood Pressure, Arterial pH, Arterial O2 Saturation, Oxygen/Inspired gas setting Ventilator (FiO2), and Positive End Expiratory Pressure(PEEP), based primarily on the extracted model feature importance data in Prasad et al 2017, which was noted to mirror "typical protocol".

The public HAPI FHIR server (UHN_HAPI Server (R4 FHIR) used in our demo is subject to file size and rate limits, which precludes the use of unmodified JSON files straight from Synthea. To circumvent this we further processed the model training data to generate a minimal set of information relevant to our needs. Patient and observation resources of 20 patients were extracted and formatted into a FHIR bundle JSON data. Patient and observation JSON data are uploaded to HAPI FHIR server using API and server endpoint.

For research we consulted available literature, especially papers written using private datasets, or using machine learning. We requested access to some of the PhysioNet databases, but as of writing the application is still pending.

4 REFERENCES

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