Good morning. My name is Mel Sparks and I’m here today to present a project that could reduce the overall cost of ventilator use within our public health facilities.

**SLIDE**

Business Problem:

Since the onset of SARS-CoV-2 in March of 2020, ventilators have become a crucial component of critical care for emergency departments and intensive care units across the country. To understand the merits of this project we must first briefly discuss how ventilators work.

**SLIDE**

Ventilators are typically set to provide a patient with oxygen at a specific volume, which is based on the patient’s ideal bodyweight for their height. This has been and is still effective for short-term emergency aid – in fact many of our health practitioners have completed the training that would allow them to support up to four patients with one ventilator. However, as we grow closer to the second anniversary of the pandemic in the United States, we know that short-term solutions need to evolve into sustainable long-term solutions.

Ventilators are designed with a variety of settings to customize performance for nearly every individual, but the question then becomes: How do we discern who needs to have their ventilator functions altered vs false alarms. The current answer to this question is to have a healthcare worker – typically a nurse or respiratory therapist – thoroughly examine the patient, ventilator, and all connections between the two every time a ventilator alarm sounds. This process normally only takes approximately 5-10 minutes per occurrence. However, the daily average of ventilator alarms per bed is 30.9. This equates to 155-309 minutes per patient per day. Keep in mind metrics tell us that somewhere between 72 and 99% of alarms are false (aka, nothing is wrong with the patient).

**SLIDE**

We propose addressing this problem by reducing Type I errors by creating a model that will be used to build better simulated human lungs. This will ultimately result in the creation of better ventilators and better ventilator software – technology that decreases the number of Type I errors a machine produces. Best case scenario, we move forward with software updates for ventilators already in use, thereby reducing the overall cost to healthcare facilities in the long run.

**SLIDE**

Data Understanding and Preparation:

The data we will be working with is all quantitative, we will not be processing any qualitative data for this project. The variables include how restricted the airway is, how compliant the lung is, the control input for inspiratory solenoid valve, the input for the exploratory solenoid valve, and the airway pressure.

Normally I would have a lot more to say during this section of the presentation. However, the data we currently propose for this project has been provided by Princeton University and Google Brain. It is opensource and is ready for use – this means that we will not have to expend resources on acquiring data initially. However, as we move forward with the project, we will see the most success if we gather data from various health facilities. This will require allocating personnel to pull real world data, and they will then have to clean it. We would mostly likely prepare the data by dropping observations recorded during alarms and standardizing the data for uniformity.

Since this project is based on reducing false alarms, you may be wondering why we aren’t proposing analyzing that data. If time and resources allow, we will most certainly dig into that subset of data, but it will not be a priority line of effort at this time. We want to emulate a human lung so that ventilators under test are dealing with a controlled element that they’re expecting to see in the real world.

**SLIDE**

Moving on to how we will work with the data – research has shown that similar problem sets have been reliably solved using neural networks – specifically Long Short-Term Memory and Conv1d.

**SLIDE**: Long Short Term Memory is an advanced form of RNN. The primary difference between LSTM and RNN is that it has three “gates”. The first function is the “forget gate” where the model chooses which information from the previous iteration to forget. The second function is the “input gate” where it tries to learn new information from the current iteration. And the third function is the “output gate” where it passes updated information from the current iteration to the next iteration.

Conv1d on the other hand is a one-dimensional convolution neural network, which is a type of machine learning that works very well with time series, audio, and text information. We would be interested in something like how it is used with time-series data.

**SLIDE**: An example of this type of data is something like what accelerometers produce on the x, y, and z axes over time.

**SLIDE**

For evaluating the model, we will use accomplish this in three phases. In the first phase, we will use the testing dataset provided by Google Brain and Princeton University. In the second phase, we will seek to use real world data to check the mean standard error of the model. Finally, in the third phase, we will move into a “clinical trial” type of test where a simulated lung is made (or modified) to the desired specifications and tested with existing ventilators on the market.

**SLIDE**

Finally, for deployment, we’ll have two options. We can either share freely or sell the model specifications. Truthfully, there will be no requirement to profit on the model itself by selling it because outsourcing the process of creating and testing new ventilators to potential competitors relieves the resource and monetary burden from ourselves. We can still sell any lung simulators that we make to clients, but as you will see in our return on investment analysis the entirety of this is a moot point.

**SLIDE**

ROI:

Going back to what we said in the beginning of this presentation concerning the amount of additional care that must be provided to patients; we remember that 2.5-5 hours are spent per day per patient and that somewhere between 72 and 99% of alarms are false.

If we were to do some initial calculations to see how this impacts the budget, we have the following.

**SLIDE:** Firstly, we have the average number of ventilator alarms per day – 30.9

**SLIDE:** We will rule against what is beneficial to the optimal success of this project and assess on the lower percentage of occurrence for Type I errors (or false alarms) – that gives us 72%

**SLIDE:** We will also assume that Type I errors will take less time resolve – so 5 minutes

If 72% of the average ventilator alarms per day are false, the time taken to resolve them will be approximately 111 minutes.

If you have 10 patients on ventilators in your ICU, that equates to just over 18 and a half hours per day.

**SLIDE:** Taking into account the personnel who will most likely be responding to these alarms – nurses and travel nurses –

**SLIDE: Y**ou can see that in this scenario between $587 and $674 is spent per day on these alarms. This doesn’t seem like much initially, but if we convert that to how much we’re expending on average per month,

**SLIDE:** That comes to 17-20k per month, and finally,

**SLIDE:** Well over 200k per year. Which is the equivalent of employing three nurses for an entire year. **But let’s take this one step further.**

**SLIDE:** Let’s say we can’t modify our current stock of ventilators in house and we have to buy completely new equipment. Using the same scenario, we would want 10 ventilators for this hospital.

**SLIDE:** Ventilators can run between $25-50k per unit.

**SLIDE:** Setting the price of the ventilators at $50k, if we buy 10 ventilators that would be $500,000 total

**SLIDE:** With an estimated annual maintenance fee of $2000.

**SLIDE:** That seems like a lot until we look at the cost over time between buying these new ventilators vs buying none and leaving everything as is.

**SLIDE:** As you can see, this annual expenditure towards answering Type I ventilator errors quickly becomes more expensive than the buying of new equipment.

**SLIDE:** At around two and a half years, the cost of these errors surpasses the cost and upkeep of new ventilators. After 5 years, we will have spent over $1 million on these Type I errors. Over the course of the lifespan of a new ventilator – approximately 10 years – we would pay out approximately $2 million total.

In conclusion, hospitals will continue to pay an excess of 300% more than the value of new equipment if we do not seek to reduce Type I ventilator errors. Thank you for your time, I will now be taking questions.