# Harnessing Machine Learning Models to Predict Outcomes in Patients Supported with Extracorporeal Membrane Oxygenation

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## Introduction and Purpose:

Extracorporeal membrane oxygenation (ECMO) machines are miniaturized heart lung bypass machines that are increasingly used to support patients with refractory respiratory failure or cardiogenic shock[1,2]. Parameters of ECMO support are adjusted by clinicians to the specific pathophysiology of the patient. The interplay between patient and machine is captured by continuously collected perfusion data[3].

We present evidence that a Long-Short-Term Memory (LSTM) Recurrent Neural Network model can predict successful vs unsuccessful decannulation based on perfusion data. This prediction is improved by the addition of laboratory values to the data set

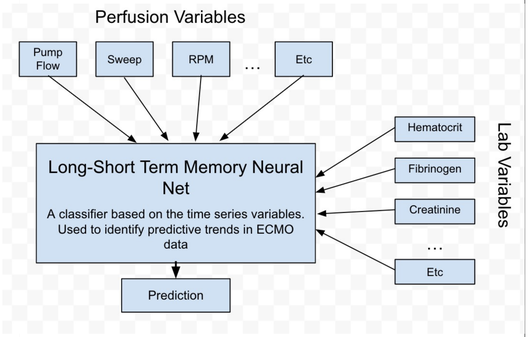


**Figure 1. The Overall Architecture for the Combined LSTM**
The overall design of the LSTM is shown. The upper variables are examples of the perfusion set, whereas the rightward variables are examples of the lab values data set.

## Methods and Data Processing:

Data was extracted from 36 COVID-19 patients who underwent ECMO cannulation. To create the data set, twelve perfusion variables and seventeen lab values were collected. Perfusion data included oxygenator ventilation (called sweep gas), pump flow, pump head revolutions per minute (RPM) and pressure gradients across device modules. This data was nearly continuous with a majority of time points less than 100 seconds apart. The number of time points was standardized between patients, and each variable was normalized between 0-1. For the first LSTM, this was the only data included.

Clinical laboratory values included complete blood count, basic metabolic panel, arterial blood gases and coagulation assays. These data were sparse, meaning that time between measurements was long. In addition, not all patients had all lab values, and six had no lab values (one unsuccessful decannulation, five successful). For many machine learning models, this would prove impossible to solve, but previous studies have demonstrated that LSTMs can handle data sparsity[4]. Lab data was not normalized.

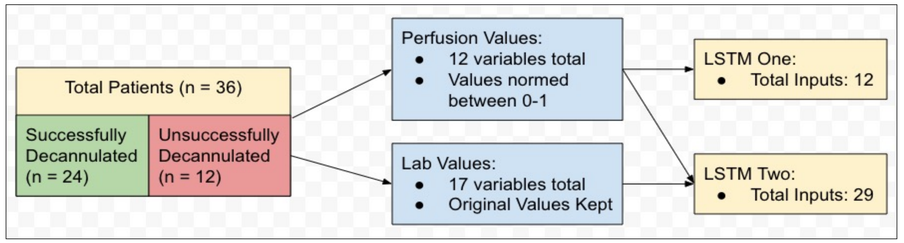


**Figure 2. Data Pipeline into the two LSTMs**
Original data set contained 36 patients and 29 variables. First LSTM took only perfusion variables, whereas the second model analyzed both perfusion and lab variables.

## Methods of Testing the Model

The two LSTMs were tested on discriminatory power and predictive power. We define the discriminatory power as the model's performance when given all time points for patients. Predictive power is the model's performance when given limited data. For this test, the data were also split into four time periods: All time points on ECMO, 1 Week on ECMO, 2 Weeks on ECMO, and 3 Weeks on ECMO. These are applied to all patients.

## Results

The main aim of this project was twofold. The first was to demonstrate that an LSTM can accurately discriminate between successful and unsuccessful ECMO decannulation, given only the perfusion data. The second was to improve the predictive power of the LSTM with laboratory values. The evaluation metric used was the area under the receiver operator characteristic (AUC).

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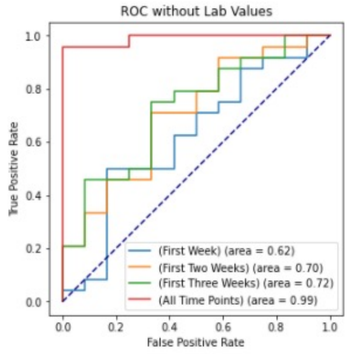


3B)

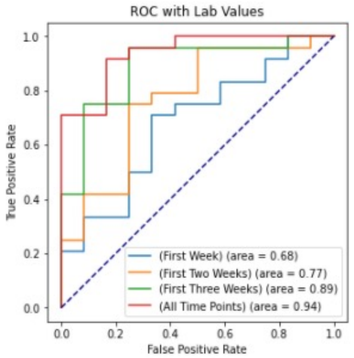


**Figure 3. Results of the two LSTMs**
Figure 3A is the LSTM that was only given the perfusion variables. When given all time points for every patient, it achieves an AUC of 0.99. Figure 3B is the LSTM given the perfusion variables and the lab variables. It shows improvement in all truncated time periods.

## Conclusion:

Continuous perfusion data recorded by ECMO machines offers an opportunity to predict patient outcomes. We show a LSTM recurrent neural network can reliably detect these clues. If given the entire run, our model is almost perfectly discriminatory, having an AUC of 0.99. This high accuracy validates the appropriateness of the LSTM for this classification problem.

When the data are truncated, the model's predictive power weakens. This is intuitive considering there is less information about later parts of the ECMO run. However, the LSTM with only laboratory values is still more accurate than random chance, even just considering one week in. When laboratory values are added, accuracy increases significantly. Two weeks of perfusion and laboratory data has even more diagnostic power than perfusion data alone. This signals that the LSTM can incorporate sparse information into its classification, further demonstrating its usefulness as a clinically predictive tool.

We intend to expand this dataset to more patients and incorporate more variables including ventilator settings and vital signs. One imagines that with sufficient accuracy, a successful or unsuccessful ECMO run could be predicted weeks in advance.

## References

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