

## Recurrent Neural Network Based Model to Predict Different COVID-19 Patients Outcomes on Admission Based on their EHR Historical Data by Laila Rasmy

**Abstract:** With the increased number of COVID-19 cases, there is an increased need for tools to help identify patients at high risk of clinical deterioration. With the extensive use of electronic records and the availability of historical patient information, predictive models that can help identify patients at risk based on their history at an early stage can be a valuable adjunct to clinician judgment. Deep learning based models can help better predict patients' health outcomes using patients' clinical history information. We developed a model that can predict different health outcomes on admission including mortality risk, intubation, and prolonged length of stay.

We used the Cerner Real-world COVID-19 cohort which included information for 117,496 COVID patients from 62 health systems. Eligible patients had an emergency or inpatient encounter with a diagnosis code that could be associated with COVID exposure or infection or a positive result for a COVID laboratory test. For our study, we excluded all patients who have less than one day of information after their first COVID encounter as well as patients who had confusing dates like discharge dates before the hospitalization start date. Our cohort included 55,068 patients.

We defined mortality, intubation, and long stays outcomes as binary outcomes. We defined long stays (LOS) based on the median length of stay (LOS) in our cohort, Therefore hospitalizations longer than 3 days, are labeled as long stays. Our predictive model only used the data available at the time of the first COVID-19 encounter admission we refer to as the index date. We feed the model with all diagnoses, medication, laboratory results, and other clinical events information available before or on the index date. We kept the data preprocessing at a minimum for convenience and practicality.

Our model showed improved performance compared to logistic regression (LR). For in-hospital mortality, our model showed an AUROC of 89.5% versus 82.8% for LR for binary prediction. For ventilation, our model showed an AUROC of 90.6% versus 83.2% for LR for binary prediction. For prolonged LOS prediction, our model showed an AUROC of 84.3% versus 76.8% for LR.