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Supplementary information

Federated learning for predicting clinical outcomes in patients with COVID-19

In the format provided by the authors and unedited

Supplemental Table 1 | Number of PCR positive and negative cases across the sites

Site	*# Cases*	*# Pos. Cases*	*# Neg. Cases*	*% Pos. Cases*
1	2994	1057	1937	35.3%
2	2825	139	2686	4.9%
3	2697	258	2439	9.6%
4	1786	618	1168	34.6%
5	1065	347	718	32.6%
6	853	427	426	50.1%
7	724	168	556	23.2%
8	637	232	405	36.4%
9	565	342	223	60.5%
10	485	304	181	62.7%
11	400	400	0	100.0%
12	346	346	0	100.0%
13	213	114	99	53.5%
14	176	72	104	40.9%
15	102	102	0	100.0%
16	99	99	0	100.0%
17	74	49	25	66.2%
18	55	55	0	100.0%
19	28	28	0	100.0%
20	24	15	9	62.5%
Total	**16148**	**5172**	**10976**	**32.0%**

Supplemental Table 2 | p-values and 95% CI of ROC comparisons of local training to Federated Learning shown in Extended Data Fig. 1. We used the bootstrap method for the statistical test. The test is two-sided and is based on 1000 bootstrapped samples. The p-values, confidence intervals are noted in the table. These ROC comparisons are for three different cut-off values t of the EXAM risk score

p-values (95% CI improvement in AUC)	*t>=0.25*	*t>=0.5*	*t>=0.75*
Site 1	0.02674 (0.0103, 0.0134)	0.03455 (0.0096, 0.0222)	0.04015 (0.0457, 0.0122)
Site 4	4.866e-05 (0.0277, 0.0358)	1.08e-05 (0.0465, 0.0850)	3.92e-05 (0.0614, 0.1264)
Site 5	3.005e-06 (0.0329, 0.0403)	5.098e-05 (0.04428, 0.0786)	0.0001362 (0.0473, 0.0928)
Site 6	1.717e-14 (0.0782, 0.0938)	5.816e-08 (0.1044, 0.1678)	2.357e-05 (0.0953, 0.1882)
Site 8	2.872e-10 (0.0520, 0.0618)	3.19e-06 (0.0570, 0.0906)	5.872e-05 (0.0575, 0.1095)
Site 12	0.08332 (0.0401, 0.0565)	0.0507 (0.006, 0.891)	0.02664 (0.0235, 0.1633)

Supplemental Note #1 | Client-server based Federated Learning using the Federated Averaging algorithm [53,58] as implemented in NVIDIA Clara Train SDK[52]

Require: Number federated rounds T.
Require: Number of local training iterations n_k for client k.
procedure FEDERATEDAVERAGING
  Initialize model weights.
  for Round t of T **do**
    for client k of K **do** ▷ *Executed in parallel*
      Send current global model to client.
      Evaluate global model on local validation data.
      Initialize optimizer and momentums.
      Perform training on local data.
      Apply privacy-preserving scheme.
      Send weight updates and validation scores to server.
      Select locally best model based on validation score.
    end for
    Select best global model based on local validation scores.
    Aggregate the client weight updates.
    Update the global model weighted by local iterations n_k.
  end for
  Exchanged models and evaluate on each client.
  return Validation results.
  return Final global model.
  return Best global model.
  return Locally best model for each client.