Supplementary Material

Addressing Label Noise for Electronic Health Records: Insights from Computer Vision for Tabular Data

Jenny Yang, Hagen Triendl, Andrew A. S. Soltan, Mangal Prakash, & David A. Clifton, 2024

A Software Packages and Implementation

Models implemented using Python (v3.6.9). Scikit Learn (v0.24.1) was used for standardization, imputation, and calculating performance metrics. Neural networks were implemented using PyTorch (v1.13.1). Models run using an Intel Xeon E-2146G Processor (CPU: 6 cores, 4.50 GHz max frequency).

NCR loss is implemented using: https://github.com/google-research/scenic/blob/main/scenic/projects/ncr/loss.py.

Labeling smoothing is implemented using: https://github.com/NVIDIA/DeepLearningExamples/blob/8d8b21a933fff3defb692e0527fca15532da5dc6/PyTorch/Classification/ConvNets/image_classification/smoothing.py#L18.

Mix-up is implemented using: https://github.com/facebookresearch/mixup-cifar10?tab=readme-ov-file.

B Model Architectures

Neural Network Model: The rectified linear unit (ReLU) activation function was used for the hidden layers and the softmax activation function was used in the output layer. For updating model weights, the Adaptive Moment Estimation (Adam) optimizer was used during training.

```
CovidClassifier(
  (hidden1): Linear(in_features=26, out_features=10, bias=True)
  (act1): ReLU()
  (hidden2): Linear(in_features=10, out_features=10, bias=True)
  (act2): ReLU()
  (hidden3): Linear(in_features=10, out_features=10, bias=True)
  (act3): ReLU()
  (hidden4): Linear(in_features=10, out_features=10, bias=True)
  (act4): ReLU()
  (output): Linear(in_features=10, out_features=2, bias=True)
  (act_output): Softmax(dim=None)
)
```

Supplementary Figure 1: Final neural network architecture used

C COVID-19 Data and Preprocessing

The following inclusions and exclusions are reproduced from previous studies (Soltan et al., 2022, Yang et al., 2022a, Yang et al., 2022b).

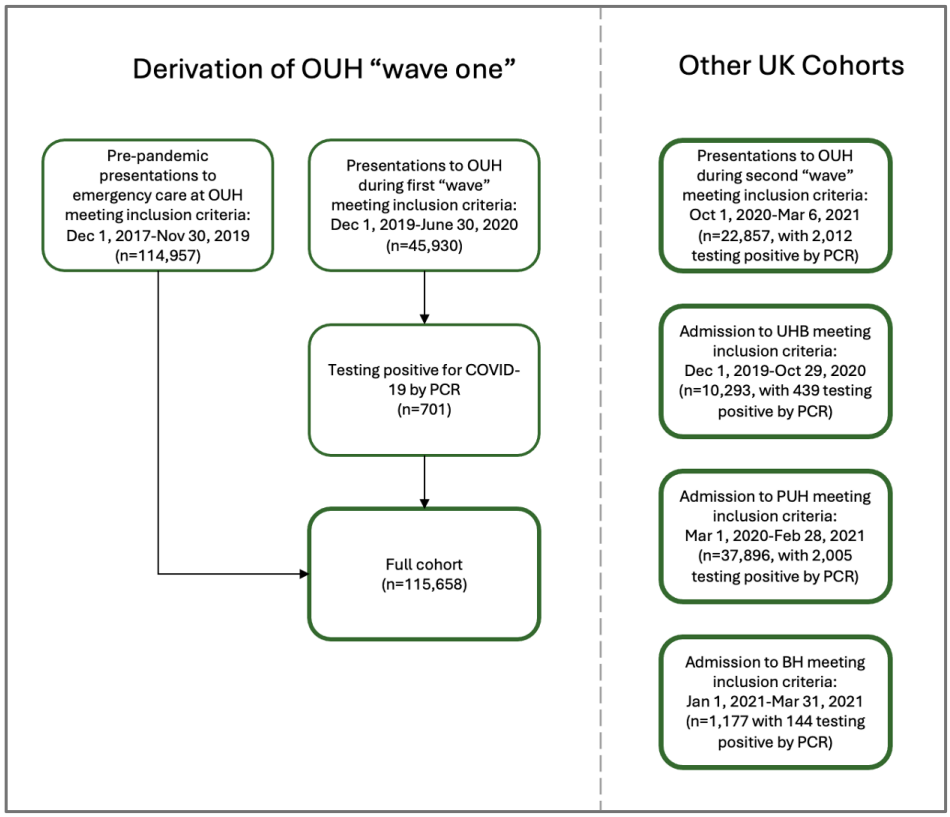
Oxford University Hospitals NHS Foundation Trust (OUH): We included all patients attending acute and emergency care settings at OUH who received routine blood tests on arrival, considering presentations before December 1, 2019, and thus before the pandemic, as the COVID-19-negative (control) cohort. We considered presentations during the 'first wave' of the UK COVID-19 pandemic (December 1, 2019 to June 30, 2020) with PCR confirmed SARS-CoV-2 infection as the COVID-19-positive (cases) cohort. We excluded patients who opted out of electronic health record (EHR) research and those who did not receive laboratory blood tests or were younger than 18 years of age. Due to incomplete penetrance of testing during the first wave of the pandemic, and imperfect sensitivity of the PCR test, there is uncertainty in the viral status of patients presenting during the pandemic who were untested or tested negative. We therefore selected a pre-pandemic control cohort during training to ensure absence of disease in patients labelled as COVID-19-negative. Clinical features extracted for each presentation included first-performed blood tests, blood gases, vital

signs measurements and PCR testing for SARS-CoV-2 (Abbott Architect [Abbott, Maidenhead, UK], TaqPath [Thermo Fisher Scientific, Massachusetts, USA] and Public Health England-designed RNA-dependent RNA polymerase assays).

Portsmouth Hospitals University NHS Foundation Trust (PUH): PUH considered all patients admitted to the Queen Alexandria Hospital, serving a population of 675,000 and offering tertiary referral services to the surrounding region, between March 1, 2020 and February 28, 2021. Confirmatory COVID-19 testing was by laboratory SARS-CoV2 RT-PCR assay, considering any positive PCR result within 48hrs of admission as a true positive.

University Hospitals Birmingham NHS Foundation Trust (UHB): UHB considered all patients admitted to The Queen Elizabeth Hospital, Birmingham, between December 01, 2019 and October 29, 2020. The Queen Elizabeth Hospital is a large tertiary referral unit within the UHB group which provides healthcare services for a population of 2.2 million across the West Midlands. Confirmatory COVID-19 testing was performed by laboratory SARS-CoV-2 RT-PCR assay.

Bedfordshire NHS Foundation Trust (BH): BH considered all patients admitted to Bedford Hospital between January 1, 2021 and March 31, 2021. BH provides healthcare services for a population of around 620,000 in Bedfordshire. Confirmatory COVID-19 testing was performed on the day of admission by point-of-care PCR based nucleic acid testing [SAMBA-II & Panther Fusion System, Diagnostics in the Real World, UK, and Hologic, USA].



Supplementary Figure 2: Overview of CURIAL datasets used.

Supplementary Table 1: Summary population characteristics for OUH training cohorts, prospective validation cohort of patients attending OUH, independent validation cohorts of patients admitted to three independent NHS Trusts. *indicates merging for statistical disclosure control.

	OUH (pre-pandemic & wave 1 cases, to 30/06/2020)		OUH	PUH	UHB	BH
Cohort	Pre-pandemic cohort	COVID-19-cases cohort	01/10/2020-06/03/2021	01/03/2020-28/02/2021	01/12/2019-29/10/2020	01/01/2021-31/03/2021
n, patients	114,957	701	22,857	37,896	10,293	1177
n, COVID positive	0	701	2,012 (8.80%)	2,005 (5.29%)	439 (4.27%)	144 (12.2%)
Sex:						
- Male (%)	53370 (46.43)	376 (53.64)	11409 (49.91)	20839 (54.99)	4831 (46.93)	627 (53.27)
- Female (%)	61587 (53.57)	325 (46.36)	11448 (50.09)	17054 (45.0)	5462 (53.07)	549 (46.64)
Age, yr (IQR)	60 (38-76)	72 (55-82)	67 (49-80)	69 (48-82)	63 (42-79)	68.0 (48-82)
Ethnicity:						
-White (%)	93921 (81.7)	480 (68.47)	17387 (76.07)	28704 (75.74)	6848 (66.53)	1024 (87.0)
-Not Stated (%)	13602 (11.83)	128 (18.26)	4127 (18.06)	8389 (22.14)	1061 (10.31)	$\leq$10
-South Asian (%)	2754 (2.4)	22 (3.14)	441 (1.93)	170 (0.45)	1357 (13.18)	71 (6.03)
-Chinese (%)	284 (0.25)	*	51 (0.22)	42 (0.11)	41 (0.4)	$\leq$10
-Black (%)	1418 (1.23)	25 (3.57)	279 (1.22)	187 (0.49)	484 (4.7)	36 (3.06)
-Other (%)	1840 (1.6)	34 (4.85)*	410 (1.79)	269 (0.71)	333 (3.24)	29 (2.46)
-Mixed (%)	1138 (0.99)	12 (1.71)	162 (0.71)	135 (0.36)	169 (1.64)	13 (1.1)

Supplementary Table 2: Clinical predictors considered for COVID-19 status prediction.

Category	**Features**
Vital Signs	Heart rate, respiratory rate, oxygen saturation, systolic blood pressure, diastolic blood pressure, temperature
Blood Tests	Haemoglobin, haematocrit, mean cell volume, white cell count, neutrophil count, lymphocyte count, monocyte count, eosinophil count, basophil count, platelets
Liver Function Tests & C-reactive protein	Albumin, alkaline phosphatase, alanine aminotransferase, bilirubin, C-reactive protein
Urea & Electrolytes	Sodium, potassium, creatinine, urea, estimated glomerular filtration rate

Supplementary Table 3: Summary of number of patients, COVID-19 positive cases, used in final model training and testing.

	Training	Validation	Test
Total patients	22,737 (1,182 positive)	7,579 (439 positive)	148,470 (4,226 positive)
PUH	22,737 (1,182 positive)	7,579 (439 positive)	7,580 (384 positive)
UHB	NA	NA	10,293 (439 positive)
BH	NA	NA	1,177 (144 positive)
OUH "wave 2"	NA	NA	22,857 (2,012 positive)
OUH "wave 1"	NA	NA	92,671 (701 positive)

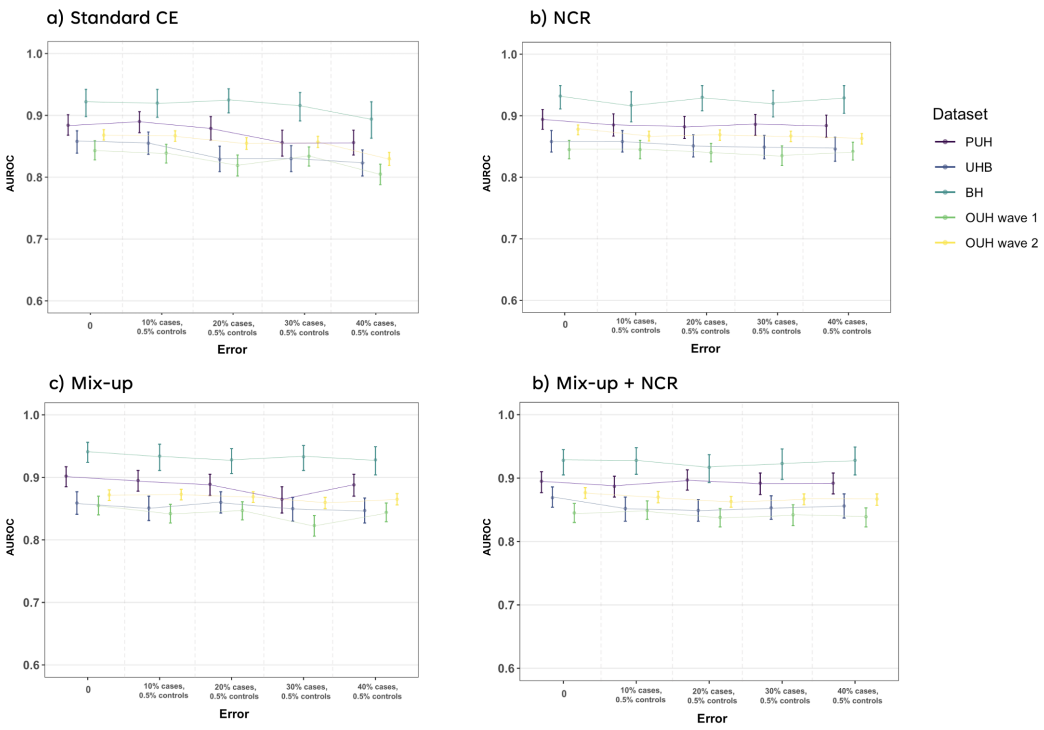
D Comparison of Methods

Supplementary Table 4: Hyperparameter values for final models presented in main text.

	0% Error	10% Error in Cases, 0.5% Error in Controls	20% Error in Cases, 0.5% Error in Controls	30% Error in Cases, 0.5% Error in Controls	40% Error in Cases, 0.5% Error in Controls
CE					
Epochs	100	100	100	100	100
Batch	2048	2048	2048	2048	2048
XGBoost					
Depth	3	3	3	3	3
Label Smoothing					
Epsilon	0.1	0.1	0.2	0.1	0.2
Mix-Up					
Probability of mix-up	0.3	0.3	0.3	0.3	0.3
Alpha	0.2	0.5	0.5	0.4	0.5
NCR					
Epochs	100	100	100	100	100
Batch	2048	2048	2048	2048	2048
NCR Starting Epoch	30	30	30	30	30
Hidden Layer (for NCR)	1	1	1	1	1
NCR weight	0.05	0.03	0.03	0.04	0.03
k	10	10	10	10	10

Supplementary Table 5: Comparison of mean AUROC performances (alongside standard deviation) for each test set, across different comparators. Red and blue values denote the best and second best performing methods for each test set, respectively.

Test Set	Baseline NN		XGBoost		Label Smoothing		Mix-up		Mix-up + NCR		NCR	
	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.	Mean	Std.
PUH	0.873	0.016	0.875	0.010	0.869	0.013	0.888	0.014	0.893	**0.004**	0.886	**0.005**
UHB	0.839	0.016	0.824	0.014	0.843	0.011	0.853	**0.006**	0.856	0.008	0.852	**0.005**
BH	0.915	0.012	0.896	0.014	0.923	0.012	0.933	**0.005**	0.925	**0.005**	0.926	**0.007**
OUH "wave 2"	0.855	0.015	0.844	0.011	0.859	0.010	0.868	**0.005**	0.869	**0.005**	0.869	**0.006**
OUH "wave 1"	0.828	0.016	0.805	0.031	0.838	0.012	0.842	0.012	0.843	**0.005**	0.841	**0.004**

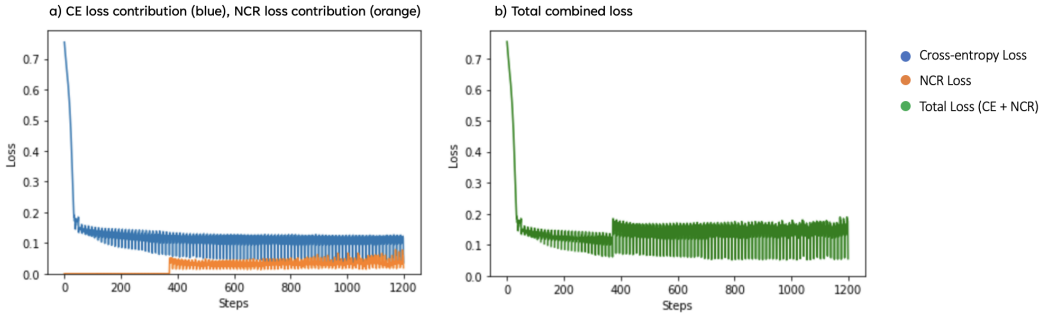


Supplementary Figure 3: Change in AUROC at different training error levels. Panel a) shows results when models are trained using standard cross-entropy, panel b) shows results when models were trained with NCR, panel c) shows results when models were trained with Mix-up, and panel d) shows results when models were trained using a combination of Mix-up and NCR.

Supplementary Table 6: p-values shown compare differences in performance between the Mix-up and Mix-up+NCR methods to the NCR model. p-values are obtained through 1,000 bootstrapped iterations.

Error in Training Set	Test Set	Mix-up	Mix-up+NCR
0	PUH	0.356	0.441
	UHB	0.007	0.056
	BH	0.095	0.314
	OUH2	0.131	0.072
	OUH1	0.032	0.378
10% cases, 0.5% controls	PUH	0.105	0.149
	UHB	0.072	0.278
	BH	0.208	0.27
	OUH2	<0.001	0.102
	OUH1	0.156	0.086
20% cases, 0.5% controls	PUH	0.024	0.442
	UHB	0.021	0.36
	BH	0.105	0.177
	OUH2	0.27	0.346
	OUH1	0.032	0.396
30% cases, 0.5% controls	PUH	0.031	0.019
	UHB	0.181	0.1
	BH	0.026	0.453
	OUH2	0.043	0.088
	OUH1	0.475	0.317
40%, cases 0.5% controls	PUH	0.089	0.38
	UHB	0.101	0.083
	BH	0.045	0.073
	OUH2	0.001	0.175
	OUH1	0.045	0.052

E Additional Results



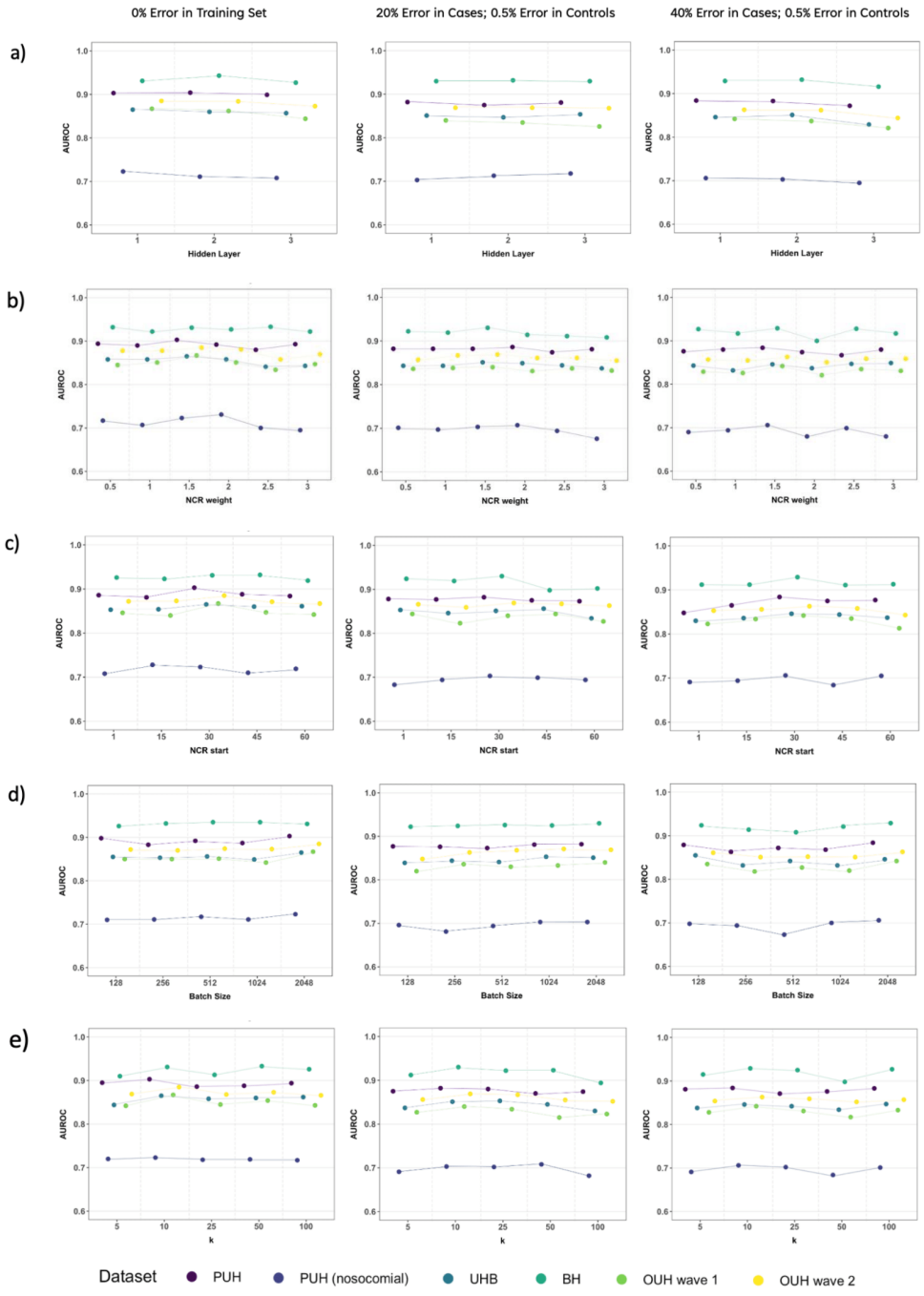
Supplementary Figure 4: Loss during NCR model training. Panel a) shows CE and NCR loss contributions separately (CE:NCR is about 10:3 ratio), and panel b) shows the combined total loss.

Supplementary Table 7: **AUROC comparison of different methods across different amounts of error (i.e. label corruption) for all considered test sets.** CV-based methods are highlighted in bold. In addition to label error in COVID-19 positive cases, there is also 0.5% label error in the negative controls. 0% error represents the original dataset, without any added label noise. Red and blue values denote the best and second best performing methods for each test set, respectively.

Test Set	Baseline NN	XGBoost	**Label Smoothing**	**Mix-up**	**NCR**	**Mix-up + NCR**
0% error						
PUH	0.884(0.868-0.901)	0.892(0.873-0.908)	0.877(0.858-0.895)	**0.902(0.885-0.917)**	0.894(0.878-0.91)	**0.895(0.877-0.91)**
UHB	0.858(0.839-0.875)	0.841(0.823-0.859)	0.854(0.834-0.873)	**0.859(0.841-0.877)**	0.858(0.841-0.876)	**0.869(0.854-0.886)**
BH	0.922(0.898-0.942)	0.914(0.89-0.933)	0.932(0.915-0.949)	**0.941(0.924-0.956)**	**0.932(0.911-0.949)**	0.928(0.905-0.945)
OUH "wave 2"	0.868(0.86-0.877)	0.856(0.847-0.865)	0.87(0.861-0.877)	0.872(0.863-0.88)	**0.878(0.869-0.885)**	**0.877(0.868-0.885)**
OUH "wave 1"	0.843(0.828-0.859)	**0.856(0.847-0.865)**	0.848(0.834-0.863)	**0.855(0.84-0.87)**	0.845(0.83-0.86)	0.845(0.83-0.86)
Error in 10% cases						
PUH	**0.89(0.872-0.906)**	0.872(0.852-0.892)	0.876(0.858-0.894)	**0.895(0.878-0.911)**	0.885(0.867-0.903)	0.887(0.87-0.903)
UHB	**0.855(0.837-0.873)**	0.838(0.819-0.854)	0.843(0.823-0.862)	0.851(0.831-0.87)	**0.858(0.841-0.876)**	0.852(0.832-0.87)
BH	0.92(0.897-0.942)	0.907(0.884-0.929)	0.924(0.902-0.944)	**0.934(0.911-0.953)**	0.917(0.89-0.939)	**0.928(0.906-0.948)**
OUH "wave 2"	0.867(0.858-0.875)	0.85(0.84-0.858)	0.858(0.848-0.867)	**0.873(0.864-0.881)**	0.867(0.858-0.875)	**0.87(0.861-0.879)**
OUH "wave 1"	0.839(0.823-0.853)	0.795(0.778-0.813)	0.83(0.815-0.846)	0.842(0.827-0.857)	**0.845(0.83-0.86)**	**0.849(0.835-0.864)**
Error in 20% cases						
PUH	0.879(0.86-0.898)	0.875(0.857-0.894)	0.876(0.857-0.893)	**0.889(0.871-0.905)**	0.882(0.863-0.899)	**0.897(0.881-0.913)**
UHB	0.829(0.809-0.85)	0.821(0.803-0.841)	0.836(0.816-0.855)	**0.86(0.843-0.877)**	**0.851(0.833-0.869)**	0.849(0.832-0.866)
BH	0.925(0.904-0.943)	0.895(0.871-0.917)	0.919(0.896-0.939)	**0.928(0.906-0.946)**	**0.93(0.908-0.949)**	0.917(0.893-0.937)
OUH "wave 2"	0.855(0.845-0.864)	0.85(0.84-0.858)	**0.864(0.855-0.873)**	**0.869(0.86-0.877)**	**0.869(0.86-0.877)**	0.863(0.854-0.871)
OUH "wave 1"	0.819(0.802-0.836)	0.807(0.791-0.824)	**0.846(0.832-0.861)**	**0.847(0.832-0.861)**	0.84(0.825-0.855)	0.838(0.823-0.852)
Error in 30% cases						
PUH	0.856(0.834-0.876)	0.867(0.848-0.887)	0.869(0.851-0.888)	0.865(0.843-0.885)	**0.886(0.868-0.902)**	**0.892(0.874-0.908)**
UHB	0.83(0.809-0.851)	0.809(0.789-0.828)	**0.855(0.838-0.872)**	0.85(0.83-0.868)	0.849(0.83-0.868)	**0.853(0.835-0.872)**
BH	0.916(0.891-0.937)	0.883(0.852-0.909)	**0.935(0.916-0.951)**	**0.933(0.911-0.951)**	0.92(0.898-0.941)	0.923(0.898-0.946)
OUH "wave 2"	0.857(0.848-0.866)	0.837(0.827-0.846)	0.858(0.849-0.867)	**0.86(0.85-0.868)**	**0.867(0.858-0.875)**	**0.867(0.858-0.875)**
OUH "wave 1"	0.834(0.818-0.849)	0.792(0.776-0.808)	**0.845(0.83-0.86)**	0.823(0.806-0.839)	0.835(0.819-0.851)	**0.842(0.825-0.858)**
Error in 40% cases						
PUH	0.856(0.836-0.876)	0.871(0.85-0.89)	0.847(0.823-0.869)	**0.888(0.87-0.905)**	0.884(0.865-0.901)	**0.892(0.875-0.908)**
UHB	0.823(0.802-0.844)	0.813(0.793-0.831)	0.829(0.807-0.849)	**0.847(0.827-0.867)**	0.846(0.826-0.865)	**0.856(0.837-0.875)**
BH	0.894(0.863-0.922)	0.882(0.854-0.908)	0.905(0.88-0.929)	**0.928(0.904-0.949)**	**0.929(0.904-0.949)**	**0.928(0.905-0.949)**
OUH "wave 2"	0.83(0.819-0.84)	0.828(0.818-0.837)	0.844(0.835-0.854)	**0.865(0.856-0.874)**	0.863(0.854-0.871)	**0.867(0.857-0.875)**
OUH "wave 1"	0.805(0.788-0.821)	0.773(0.756-0.792)	0.82(0.803-0.837)	**0.844(0.829-0.859)**	**0.842(0.828-0.857)**	0.839(0.823-0.853)

Supplementary Table 8: PPV and NPV comparison between baseline and NCR models, across different amounts of error and test sets. In addition to label error in COVID-19 positive cases, there is also 0.5% label error in the negative controls. 0% error represents the original dataset, without any added label noise.

Test Set	PPV		NPV	
	CE	CE+NCR	CE	CE+NCR
0% error				
PUH	0.139(0.133-0.145)	**0.203(0.193-0.213)**	0.988(0.986-0.991)	0.988(0.986-0.990)
UHB	0.096(0.092-0.099)	**0.118(0.113-0.123)**	0.990(0.988-0.992)	**0.990(0.988-0.991)**
BH	0.276(0.261-0.292)	**0.353(0.33-0.378)**	**0.986(0.978-0.992)**	0.983(0.975-0.989)
OUH "wave 2"	0.176(0.173-0.179)	**0.224(0.22-0.228)**	0.980(0.978-0.982)	0.980(0.978-0.981)
OUH "wave 1"	0.017(0.016-0.017)	**0.022(0.021-0.023)**	0.998(0.998-0.999)	0.998(0.998-0.998)
Error in 10% cases				
PUH	**0.150(0.144-0.157)**	0.126(0.121-0.131)	0.989(0.987-0.991)	**0.990(0.988-0.992)**
UHB	**0.106(0.102-0.11)**	0.098(0.095-0.101)	0.991(0.989-0.992)	**0.992(0.990-0.993)**
BH	**0.324(0.305-0.346)**	0.310(0.290-0.330)	0.984(0.977-0.991)	**0.985(0.978-0.992)**
OUH "wave 2"	**0.191(0.188-0.194)**	0.165(0.162-0.167)	0.980(0.978-0.982)	**0.981(0.979-0.983)**
OUH "wave 1"	**0.018(0.017-0.018)**	0.015(0.015-0.015)	0.998(0.998-0.998)	0.998(0.998-0.999)
Error in 20% cases				
PUH	**0.142(0.136-0.147)**	0.128(0.123-0.133)	0.989(0.987-0.991)	**0.991(0.988-0.993)**
UHB	**0.095(0.091-0.099)**	0.091(0.088-0.094)	0.989(0.987-0.991)	**0.992(0.990-0.993)**
BH	**0.310(0.291-0.331)**	0.302(0.284-0.320)	0.983(0.975-0.990)	**0.985(0.978-0.992)**
OUH "wave 2"	**0.174(0.171-0.177)**	0.160(0.157-0.162)	0.978(0.976-0.980)	**0.981(0.979-0.983)**
OUH "wave 1"	**0.016(0.016-0.016)**	0.015(0.015-0.016)	0.998(0.998-0.998)	0.998(0.998-0.999)
Error in 30% cases				
PUH	0.102(0.098-0.105)	**0.117(0.113-0.122)**	0.988(0.985-0.990)	**0.991(0.989-0.993)**
UHB	0.076(0.073-0.078)	**0.090(0.087-0.093)**	0.989(0.987-0.991)	**0.990(0.988-0.992)**
BH	0.231(0.219-0.242)	**0.296(0.278-0.314)**	**0.990(0.982-0.996)**	0.984(0.976-0.991)
OUH "wave 2"	0.150(0.148-0.153)	**0.153(0.151-0.155)**	0.980(0.978-0.982)	**0.982(0.980-0.983)**
OUH "wave 1"	0.014(0.013-0.014)	0.014(0.013-0.014)	0.998(0.998-0.999)	0.998(0.998-0.998)
Error in 40% cases				
PUH	0.093(0.09-0.097)	**0.115(0.111-0.119)**	0.987(0.985-0.99)	**0.989(0.987-0.992)**
UHB	0.082(0.079-0.085)	**0.088(0.085-0.091)**	0.989(0.986-0.991)	**0.991(0.989-0.993)**
BH	0.256(0.241-0.274)	**0.282(0.266-0.300)**	0.979(0.970-0.987)	**0.987(0.980-0.994)**
OUH "wave 2"	0.145(0.142-0.147)	**0.150(0.148-0.153)**	0.973(0.971-0.975)	**0.981(0.979-0.983)**
OUH "wave 1"	0.013(0.012-0.013)	**0.014(0.014-0.015)**	0.998(0.997-0.998)	**0.998(0.998-0.999)**



Supplementary Figure 5: Ablation study across varying hidden layer size, NCR weight, NCR starting epoch, batch size, and number of nearest neighbours (k). Results presented for 0% error, 20% error in cases and 0.5% error in controls, and 40% error in cases and 0.5% error in controls.

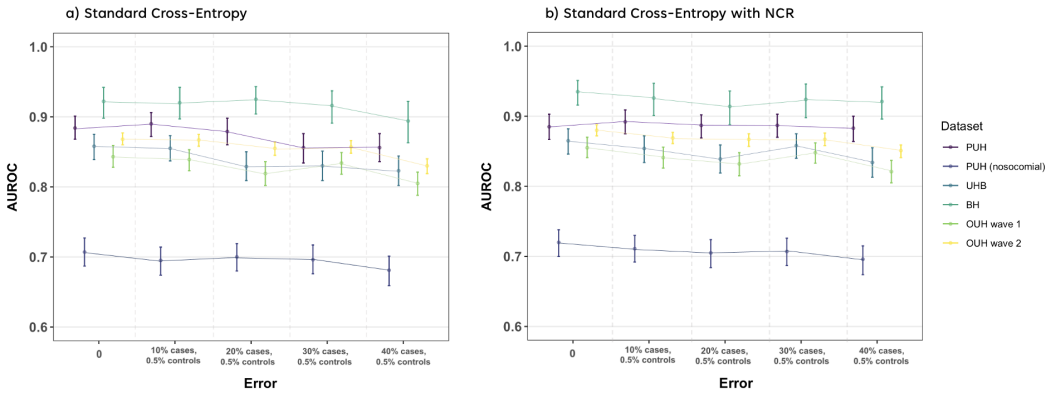
F Changing the Loss function

F.1 Jensen-Shannon Divergence

$$L_{NCR} := \frac{1}{m}\sum_{i=1}^{m} D_{JS}\left(\sigma(\mathbf{z_i}) \middle\| \sum_{j \epsilon NN_k} \frac{s_{i,j}}{\sum_k s_{i,k}} \sigma(\mathbf{z_j})\right) \tag{1}$$

Supplementary Table 9: AUROC, AUPRC, Sensitivity, and Specificity comparison between baseline and NCR models, across different amounts of error and test sets. In addition to label error in COVID-19 positive cases, there is also 0.5% label error in the negative controls. 0% error represents the original dataset, without any added label noise.

Test Set	AUROC		AUPRC		Sensitivity		Specificity	
	CE	CE+NCR	CE	CE+NCR	CE	CE+NCR	CE	CE+NCR
0% error								
PUH	0.884(0.868-0.901)	**0.885(0.867-0.903)**	0.538(0.494-0.583)	**0.588(0.546-0.630)**	**0.841(0.810-0.871)**	0.820(0.789-0.850)	0.722(0.713-0.731)	**0.810(0.803-0.817)**
UHB	0.858(0.839-0.875)	**0.865(0.846-0.882)**	0.309(0.278-0.34)	**0.417(0.375-0.461)**	**0.861(0.833-0.889)**	0.852(0.823-0.880)	0.638(0.629-0.646)	**0.717(0.710-0.725)**
BH	0.922(0.898-0.942)	**0.935(0.916-0.951)**	0.691(0.627-0.751)	**0.743(0.682-0.801)**	**0.931(0.894-0.961)**	0.910(0.872-0.949)	0.659(0.636-0.684)	**0.758(0.737-0.781)**
OUH "wave 2"	0.868(0.860-0.877)	**0.888(0.872-0.888)**	0.554(0.536-0.573)	**0.663(0.645-0.680)**	**0.875(0.862-0.887)**	0.854(0.839-0.867)	0.604(0.598-0.609)	**0.703(0.698-0.708)**
OUH "wave 1"	0.843(0.828-0.859)	**0.855(0.841-0.870)**	0.087(0.078-0.097)	**0.180(0.154-0.210)**	**0.859(0.837-0.882)**	0.810(0.785-0.836)	0.615(0.613-0.618)	**0.721(0.719-0.724)**
Error in 10% cases								
PUH	0.890(0.872-0.906)	**0.892(0.875-0.909)**	**0.572(0.529-0.617)**	0.526(0.478-0.580)	0.846(0.816-0.875)	**0.865(0.835-0.893)**	0.745(0.737-0.754)	**0.758(0.750-0.766)**
UHB	**0.855(0.837-0.873)**	0.854(0.834-0.872)	0.353(0.318-0.399)	0.353(0.319-0.396)	**0.854(0.825-0.882)**	0.836(0.805-0.865)	0.679(0.671-0.687)	**0.702(0.694-0.709)**
BH	0.920(0.897-0.942)	**0.926(0.901-0.947)**	0.693(0.630-0.760)	**0.713(0.649-0.774)**	0.917(0.874-0.954)	**0.924(0.885-0.959)**	0.734(0.712-0.756)	**0.771(0.748-0.792)**
OUH "wave 2"	0.867(0.858-0.875)	**0.869(0.861-0.877)**	**0.615(0.596-0.634)**	0.591(0.571-0.611)	0.865(0.851-0.877)	**0.866(0.853-0.878)**	0.647(0.641-0.652)	**0.653(0.647-0.658)**
OUH "wave 1"	0.839(0.823-0.853)	**0.841(0.826-0.856)**	**0.124(0.106-0.146)**	0.106(0.093-0.123)	**0.850(0.827-0.871)**	0.845(0.821-0.867)	0.642(0.639-0.645)	**0.653(0.650-0.656)**
Error in 20% cases								
PUH	0.879(0.860-0.898)	**0.887(0.869-0.902)**	0.471(0.427-0.519)	**0.495(0.453-0.545)**	0.854(0.823-0.883)	**0.880(0.852-0.906)**	**0.723(0.715-0.733)**	0.656(0.647-0.665)
UHB	0.829(0.809-0.850)	**0.839(0.819-0.859)**	0.272(0.243-0.305)	**0.322(0.289-0.364)**	0.834(0.803-0.863)	**0.841(0.810-0.869)**	**0.646(0.638-0.654)**	0.636(0.627-0.644)
BH	**0.925(0.904-0.943)**	0.914(0.888-0.936)	**0.679(0.614-0.74)**	0.649(0.582-0.725)	0.910(0.868-0.947)	**0.931(0.891-0.964)**	**0.718(0.695-0.741)**	0.711(0.688-0.735)
OUH "wave 2"	0.855(0.845-0.864)	**0.867(0.857-0.875)**	0.524(0.504-0.542)	**0.583(0.563-0.602)**	0.860(0.847-0.873)	**0.876(0.862-0.887)**	0.606(0.601-0.612)	**0.609(0.603-0.614)**
OUH "wave 1"	0.819(0.802-0.836)	**0.832(0.815-0.848)**	0.065(0.058-0.072)	**0.108(0.095-0.123)**	0.840(0.818-0.863)	**0.846(0.824-0.869)**	**0.607(0.605-0.610)**	0.594(0.592-0.597)
Error in 30% cases								
PUH	0.856(0.834-0.876)	**0.887(0.87-0.903)**	0.493(0.448-0.544)	**0.527(0.482-0.578)**	0.865(0.834-0.891)	**0.885(0.858-0.912)**	0.593(0.583-0.602)	**0.628(0.619-0.637)**
UHB	0.830(0.809-0.851)	**0.858(0.84-0.875)**	**0.315(0.281-0.356)**	0.312(0.280-0.353)	0.868(0.84-0.892)	**0.911(0.889-0.933)**	**0.527(0.519-0.536)**	0.524(0.515-0.532)
BH	0.916(0.891-0.937)	**0.924(0.898-0.946)**	0.675(0.605-0.74)	**0.697(0.626-0.770)**	**0.958(0.928-0.985)**	0.938(0.902-0.969)	0.555(0.530-0.581)	**0.622(0.598-0.649)**
OUH "wave 2"	0.857(0.848-0.866)	**0.867(0.858-0.876)**	**0.581(0.560-0.60)**	0.576(0.555-0.598)	0.891(0.879-0.902)	**0.911(0.900-0.921)**	**0.514(0.509-0.520)**	0.469(0.463-0.474)
OUH "wave 1"	0.834(0.818-0.849)	**0.848(0.833-0.862)**	**0.121(0.104-0.142)**	0.082(0.072-0.095)	0.880(0.858-0.899)	**0.910(0.893-0.928)**	**0.511(0.508-0.514)**	0.496(0.493-0.499)
Error in 40% cases								
PUH	0.856(0.836-0.876)	**0.883(0.864-0.900)**	0.488(0.443-0.543)	**0.544(0.501-0.592)**	0.870(0.841-0.898)	**0.901(0.876-0.925)**	0.548(0.539-0.558)	**0.577(0.567-0.586)**
UHB	0.823(0.802-0.844)	**0.834(0.813-0.855)**	**0.352(0.313-0.399)**	0.318(0.283-0.356)	0.852(0.823-0.879)	**0.877(0.850-0.905)**	**0.576(0.568-0.585)**	0.546(0.538-0.554)
BH	0.894(0.863-0.922)	**0.921(0.896-0.942)**	0.701(0.640-0.760)	**0.712(0.640-0.776)**	0.903(0.859-0.941)	**0.938(0.903-0.969)**	**0.634(0.612-0.660)**	0.597(0.572-0.623)
OUH "wave 2"	0.830(0.819-0.840)	**0.851(0.841-0.859)**	0.553(0.532-0.572)	**0.554(0.533-0.573)**	0.852(0.839-0.865)	**0.901(0.889-0.912)**	**0.514(0.508-0.519)**	0.460(0.454-0.465)
OUH "wave 1"	0.805(0.788-0.821)	**0.821(0.805-0.837)**	**0.122(0.105-0.144)**	0.094(0.082-0.107)	0.840(0.818-0.863)	**0.874(0.853-0.894)**	**0.497(0.494-0.500)**	0.460(0.457-0.463)



Supplementary Figure 6: Change in performance (AUROC) at different training error levels. Panel a) shows results when models are trained using standard cross-entropy, and panel b) shows results when models were trained with NCR.

Supplementary Table 10: Comparison of mean AUROC performance across different training set error levels.

Test Set	CE		CE + NCR	
	Mean	Std.	Mean	Std.
PUH	0.873	0.016	**0.887**	**0.003**
UHB	0.839	0.016	**0.850**	**0.013**
BH	0.915	0.012	**0.924**	**0.008**
OUH "wave 2"	0.855	0.015	**0.867**	**0.010**
OUH "wave 1"	0.828	0.016	**0.839**	**0.013**

Supplementary Table 11: Hyperparameter values for final models (NCR term based on JS divergence) presented in main text.

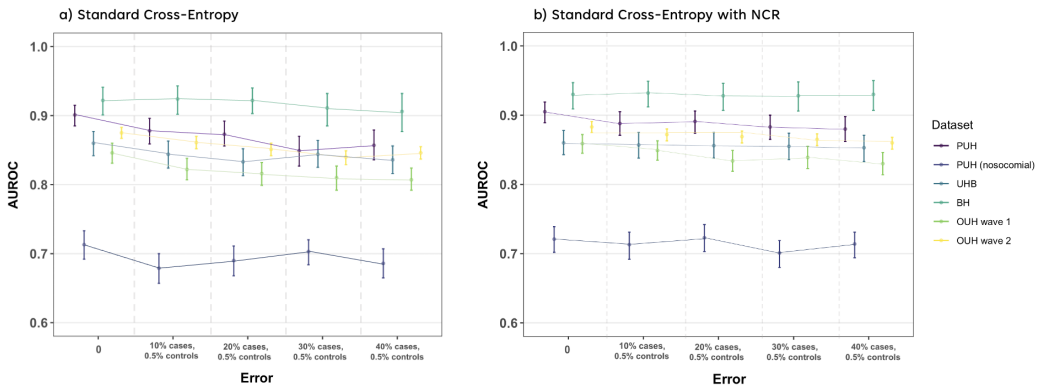
Loss Function	CE	CE + NCR				
Error in Training Labels	0% Error	0% Error	10% Error in Cases, 0.5% Error in Controls	20% Error in Cases, 0.5% Error in Controls	30% Error in Cases, 0.5% Error in Controls	40% Error in Cases, 0.5% Error in Controls
Epochs	100	100	100	100	100	100
Batch	2048	2048	2048	2048	2048	2048
NCR Starting Epoch	NA	30	30	30	30	30
Hidden Layer (for NCR)	NA	3	3	1	1	1
NCR weight	NA	0.3	0.5	0.8	0.8	0.8
k	NA	10	10	10	10	10

F.2 Mean Absolute Error

$$L_{NCR} := \frac{1}{m}\sum_{i=1}^{m} abs\left(\sigma(\mathbf{z_i}) - \sum_{j \epsilon NN_k} \frac{s_{i,j}}{\sum_k s_{i,k}} \sigma(\mathbf{z_j})\right) \tag{2}$$

Supplementary Table 12: AUROC, AUPRC, Sensitivity, and Specificity comparison between baseline and NCR models, across different amounts of error and test sets. In addition to label error in COVID-19 positive cases, there is also 0.5% label error in the negative controls. 0% error represents the original dataset, without any added label noise.

Test Set	AUROC		AUPRC		Sensitivity		Specificity	
	CE	CE+NCR	CE	CE+NCR	CE	CE+NCR	CE	CE+NCR
0% error								
PUH	0.901(0.885-0.915)	**0.905(0.889-0.919)**	0.568(0.521-0.614)	**0.580(0.539-0.625)**	0.812(0.778-0.846)	**0.839(0.807-0.869)**	0.839(0.832-0.846)	**0.844(0.837-0.852)**
UHB	0.860(0.842-0.877)	0.860(0.843-0.878)	**0.350(0.313-0.391)**	0.344(0.311-0.386)	0.818(0.787-0.848)	**0.820(0.789-0.850)**	0.751(0.744-0.758)	**0.757(0.75-0.764)**
BH	0.922(0.901-0.941)	**0.93(0.909-0.947)**	0.706(0.638-0.765)	**0.738(0.682-0.800)**	**0.889(0.844-0.928)**	0.882(0.833-0.924)	0.777(0.755-0.799)	0.777(0.758-0.799)
OUH "wave 2"	0.875(0.867-0.883)	**0.883(0.875-0.891)**	0.605(0.585-0.625)	**0.624(0.604-0.642)**	0.834(0.819-0.848)	**0.847(0.833-0.860)**	**0.740(0.735-0.745)**	0.734(0.729-0.739)
OUH "wave 1"	0.846(0.831-0.860)	**0.859(0.845-0.872)**	0.096(0.084-0.111)	**0.112(0.097-0.128)**	0.792(0.766-0.817)	**0.812(0.787-0.837)**	**0.749(0.747-0.751)**	0.742(0.740-0.744)
Error in 10% cases								
PUH	0.878(0.859-0.896)	**0.888(0.871-0.905)**	**0.559(0.512-0.606)**	0.558(0.514-0.604)	0.833(0.801-0.863)	**0.854(0.823-0.884)**	0.716(0.707-0.724)	**0.74(0.732-0.749)**
UHB	0.844(0.824-0.863)	**0.857(0.838-0.875)**	**0.328(0.292-0.372)**	0.320(0.285-0.363)	0.845(0.815-0.872)	**0.866(0.837-0.892)**	0.659(0.652-0.667)	**0.660(0.652-0.668)**
BH	0.924(0.902-0.943)	**0.932(0.912-0.949)**	**0.720(0.654-0.782)**	0.694(0.632-0.767)	0.917(0.876-0.951)	**0.938(0.901-0.970)**	**0.689(0.665-0.713)**	0.684(0.661-0.709)
OUH "wave 2"	0.861(0.852-0.870)	**0.872(0.863-0.880)**	**0.613(0.595-0.631)**	0.589(0.570-0.610)	0.851(0.838-0.863)	**0.881(0.869-0.893)**	**0.645(0.640-0.650)**	0.613(0.608-0.618)
OUH "wave 1"	0.822(0.807-0.838)	**0.849(0.835-0.863)**	**0.104(0.089-0.123)**	0.101(0.088-0.120)	0.833(0.810-0.856)	**0.863(0.842-0.885)**	**0.635(0.632-0.637)**	0.615(0.612-0.617)
Error in 20% cases								
PUH	0.873(0.856-0.892)	**0.891(0.874-0.906)**	0.503(0.457-0.553)	**0.557(0.514-0.601)**	**0.883(0.856-0.909)**	0.880(0.851-0.907)	0.579(0.569-0.588)	**0.645(0.636-0.655)**
UHB	0.833(0.813-0.852)	**0.856(0.838-0.875)**	0.313(0.278-0.356)	**0.366(0.328-0.411)**	0.859(0.831-0.886)	**0.891(0.866-0.915)**	**0.593(0.584-0.601)**	0.563(0.555-0.571)
BH	0.922(0.903-0.94)	**0.928(0.907-0.946)**	0.683(0.614-0.75)	**0.700(0.632-0.764)**	0.938(0.901-0.969)	**0.965(0.939-0.987)**	**0.642(0.618-0.667)**	0.614(0.590-0.638)
OUH "wave 2"	0.851(0.842-0.86)	**0.869(0.86-0.877)**	0.574(0.554-0.593)	**0.607(0.588-0.626)**	0.891(0.879-0.902)	**0.916(0.905-0.926)**	**0.498(0.492-0.503)**	0.492(0.487-0.498)
OUH "wave 1"	0.816(0.799-0.832)	**0.834(0.819-0.849)**	0.104(0.089-0.122)	**0.111(0.095-0.131)**	0.862(0.839-0.882)	**0.887(0.868-0.906)**	0.499(0.496-0.502)	**0.506(0.503-0.508)**
Error in 30% cases								
PUH	0.849(0.827-0.870)	**0.883(0.865-0.900)**	0.474(0.428-0.520)	**0.502(0.457-0.553)**	0.865(0.835-0.893)	**0.870(0.840-0.898)**	0.543(0.533-0.553)	**0.640(0.631-0.649)**
UHB	0.844(0.825-0.864)	**0.855(0.836-0.874)**	**0.330(0.294-0.375)**	0.310(0.280-0.351)	0.870(0.844-0.896)	**0.891(0.866-0.914)**	**0.587(0.579-0.596)**	0.578(0.569-0.586)
BH	0.911(0.885-0.932)	**0.928(0.906-0.948)**	0.704(0.641-0.761)	**0.721(0.655-0.789)**	0.938(0.902-0.967)	0.938(0.901-0.969)	0.592(0.568-0.616)	**0.668(0.643-0.692)**
OUH "wave 2"	0.840(0.829-0.849)	**0.865(0.856-0.873)**	**0.552(0.531-0.572)**	0.542(0.521-0.563)	0.871(0.858-0.884)	**0.898(0.886-0.908)**	0.512(0.506-0.517)	**0.520(0.514-0.525)**
OUH "wave 1"	0.810(0.792-0.827)	**0.839(0.823-0.855)**	**0.112(0.097-0.131)**	0.083(0.072-0.095)	0.857(0.835-0.879)	**0.882(0.861-0.902)**	0.480(0.477-0.482)	**0.521(0.518-0.524)**
Error in 40% cases								
PUH	0.857(0.836-0.879)	**0.880(0.862-0.898)**	0.488(0.441-0.534)	**0.489(0.446-0.539)**	0.883(0.856-0.908)	**0.911(0.887-0.936)**	0.531(0.521-0.541)	**0.563(0.553-0.573)**
UHB	0.836(0.816-0.856)	**0.853(0.833-0.871)**	0.268(0.240-0.298)	**0.354(0.318-0.400)**	0.886(0.861-0.910)	**0.900(0.874-0.922)**	0.506(0.497-0.514)	**0.517(0.508-0.525)**
BH	0.906(0.877-0.932)	**0.930(0.907-0.950)**	0.640(0.578-0.703)	**0.703(0.637-0.765)**	0.938(0.901-0.969)	**0.965(0.938-0.987)**	**0.541(0.517-0.568)**	0.517(0.494-0.544)
OUH "wave 2"	0.846(0.837-0.855)	**0.860(0.851-0.868)**	0.477(0.459-0.494)	**0.547(0.526-0.568)**	0.899(0.887-0.909)	**0.908(0.897-0.918)**	0.456(0.451-0.462)	**0.465(0.459-0.471)**
OUH "wave 1"	0.807(0.792-0.824)	**0.830(0.814-0.846)**	0.052(0.046-0.057)	**0.098(0.085-0.114)**	0.876(0.855-0.897)	**0.887(0.866-0.907)**	**0.453(0.451-0.456)**	0.447(0.445-0.450)



Supplementary Figure 7: Change in performance (AUROC) at different training error levels. Panel a) shows results when models are trained using standard cross-entropy, and panel b) shows results when models were trained with NCR.

Supplementary Table 13: Comparison of mean AUROC performance across different training set error levels.

Test Set	CE		CE + NCR	
	Mean	Std.	Mean	Std.
PUH	0.872	0.020	**0.889**	**0.010**
UHB	0.843	0.010	**0.856**	**0.003**
BH	0.917	0.008	**0.930**	**0.002**
OUH "wave 2"	0.855	0.014	**0.870**	**0.009**
OUH "wave 1"	0.820	0.016	**0.842**	**0.012**

Supplementary Table 14: Hyperparameter values for final models (NCR term based on MAE) presented in main text.

Loss Function	CE	CE + NCR				
Error in Training Labels	0% Error	0% Error	10% Error in Cases, 0.5% Error in Controls	20% Error in Cases, 0.5% Error in Controls	30% Error in Cases, 0.5% Error in Controls	40% Error in Cases, 0.5% Error in Controls
Epochs	100	100	100	100	100	100
Batch	2048	2048	2048	2048	2048	2048
NCR Starting Epoch	NA	30	30	30	30	30
Hidden Layer (for NCR)	NA	1	1	1	1	1
NCR weight	NA	0.05	0.03	0.03	0.04	0.03
k	NA	10	10	10	10	10

G Previous Studies Using Same COVID-19 Cohorts

Supplementary Table 15: Previously published COVID-19 status prediction results. using same datasets and patient cohorts. Sensitivity, specificity, and AUROC shown, alongside 95% confidence intervals, unless otherwise specified.

Test Set	Sensitivity	Specificity	AUROC
Soltan et al., 2022.			
Method: XGBoost + SMOTE + Threshold Adjustment (0.9)			
OUH	0.857 (SD 0.009)	0.686 (SD 0.022)	0.878 (SD 0.001)
PUH	0.841 (0.825-0.857)	0.713 (0.709 -0.718)	0.872 (0.863 -0.882)
UHB	0.788 (0.748-0.824)	0.747 (0.738 -0.755)	0.858 (0.838 -0.878)
BH	0.743 (0.666-0.807)	0.848 (0.825 0. 869)	0.881 (0.851- 0.912)
Yang et al., 2022.			
Method: Neural Network + SMOTE + Threshold Adjustment (0.85)			
OUH	0.844 (0.828-0.860)	0.710 (0.704-0.717)	0.777 (0.765-0.789)
PUH	0.857 (0.842-0.873)	0.672 (0.667-0.677)	0.765 (0.752-0.777)
UHB	0.847 (0.814-0.881)	0.716 (0.708-0.725)	0.782 (0.756-0.808)
BH	0.847 (0.789-0.906)	0.822 (0.799-0.845)	0.835 (0.793-0.876)
Yang et al., 2022.			
Method: Neural Network + Threshold Adjustment (0.85)			
OUH	0.762 (0.744-0.781)	0.844 (0.839-0.849)	0.878 (0.868-0.888)
PUH	0.633 (0.585-0.681)	0.903 (0.897-0.910)	0.861 (0.837-0.885)
UHB	0.714 (0.621-0.807)	0.854 (0.839-0.870)	0.878 (0.832-0.924)
BH	0.724 (0.561-0.887)	0.908 (0.869-0.948)	0.880 (0.798-0.963)

H Additional Case Studies

H.1 Data Availability

The eICU Collaborative Research Database is available online at `https://www.physionet.org/content/eicu-crd/2.0/`. The eICU Collaborative Research Database (eICU-CRD) is a publicly-available, anonymized database with pre-existing institutional review board (IRB) approval. The database is released under the Health Insurance Portability and Accountability Act (HIPAA) safe harbor provision. The re-identification risk was certified as meeting safe harbor standards by Privacert (Cambridge, MA) (HIPAA Certification no. 1031219-2).

The Adult (Census Income) Dataset is available online at `https://archive.ics.uci.edu/ml/datasets/Adult/`

H.2 Creating Noisy Labels

For ICU acute event prediction and income prediction, we randomly added incorrect labels at different noise ratios.

H.3 eICU Collaborative Research Database

Addressing the clinical applications of AI, the diagnosis of patients holds significant importance as it directly impacts clinical decision-making, allocation of resources, and healthcare expenditures. Thus, further analysis was performed using the eICU Collaborative Research Database (eICU-CRD) (Pollard et al., 2018) which is publicly available through PhysioNet (Goldberger et al., 2000).

In our experiments, we predict which acute condition might be developed by a patient during the course of an ICU stay, as defined through International Classification of Diseases, 9th Revision (ICD-9) codes. These are a system of alphanumeric codes used to classify and code diagnoses and procedures in medical billing and healthcare documentation. Previously, a similar undertaking involving both acute and chronic conditions was examined using the eICU-CRD dataset. In this study, 767 ICD-9 codes were grouped into 25 comprehensive diagnoses, which were then predicted using a BiLSTM model (Sheikhalishahi et al., 2020). Another study further grouped these diagnoses into

their relevant systems and clinical specialties, before training a reinforcement learning model (Yang et al., 2022). Using consistent inclusion and exclusion criteria as these studies, we obtained three labels we aim to classify: acute cardiovascular event, acute respiratory event, and acute gastrointestional event. This grouping was selected to reflect clinic reality, where an emergency physician might consult with a system specialist to rule out a severe condition before admission to ICU, and to account for the relatedness of diagnoses within a system. For example, pneumonia is a leading cause of respiratory failure, and combining both diagnoses into a single "acute respiratory event" category reflects the systemic nature of the disease.

H.3.1 Inclusion and Exclusion Criteria

We selected adult patients (age > 18) with a minimum of 15 ICU records, grouped them into 1 hour windows, and asked our clinical team to reviewed the list of 25 diagnoses, removed 13 diagnoses considered chronic, non-acute, or poorly defined, and grouped the remaining 12 diagnoses into their relevant system and clinical specialties. We removed any samples that did not have a differentiable ICD9 code, or did not belong to any of the curated groups.

Supplementary Table 16: Acute event groups

Label	Events
Acute cardiovascular event	Acute myocardial infarction, acute cerebrovascular disease
Acute respiratory event	Respiratory failure, insufficiency, arrest, pneumonia, pleurisy, pneumothorax, pulmonary collapse, other upper respiratory disease, other lower respiratory disease
Acute gastrointestinal event	Gastrointestinal hemorrhage

Supplementary Table 17: Clinical predictors considered for predicting acute event diagnosis.

Category	Features
Demographic features	Gender, age, ethnicity, height, weight
Measurements at hospital admission	Non-invasive systolic blood pressure, non-invasive diastolic blood pressure, non-invasive mean arterial pressure, heart rate, Supporting oxygen used at admission, blood oxygen saturation, Glasgow coma score, diagnosis at admission
Measurements at ICU admission	Glucose

Supplementary Table 18: Summary of number of patients, COVID-19 positive cases, and ethnicity distribution for training, validation, and external test set cohorts included in the ethnicity debiasing task.

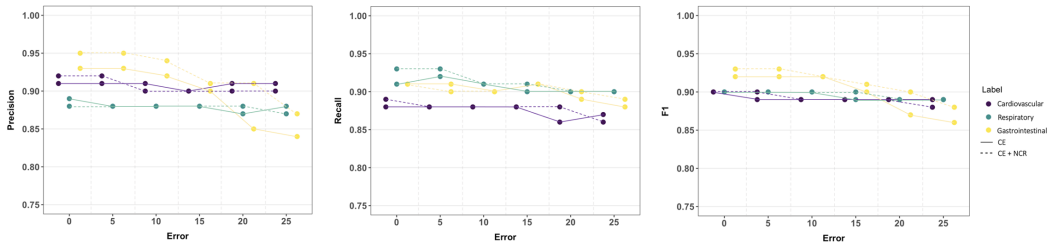
	Training	Test
n, patients	12,870	4,301
Acute Cardiovascular	5,214	1,776
Acute Respiratory	6,085	2,010
Acute Gastrointestinal	1,571	515

H.3.2 Acute Event Diagnosis Using NCR

To further evaluate the effectiveness of NCR, we demonstrate it's utility on an different task, using data from the eICU Collaborative Research Database (eICU-CRD) (Pollard et al., 2018; Goldberger et al., 2000). Our objective was to predict the occurrence of three acute events (cardiovascular,

respiratory, gastrointestinal) during patients' stays in hospital intensive care units (ICUs). This task allowed us to evaluate the applicability of our model for a multi-class classification problem, which is commonly encountered in real-world applications.

In Supplementary Figure 8, we observed that the model trained with NCR performs similarly to the model trained with standard cross entropy for cardiovascular and respiratory events. However, for gastrointestinal events, the model trained with NCR exhibits greater improvement in classification precision ($p<0.001$). This observation aligns with our expectations since gastrointestinal events have the lowest representation in the dataset, making this category more susceptible to the presence of noise. Consequently, NCR demonstrates its greatest positive impact on this specific group, effectively mitigating the model's tendency to overfit to noise.



Supplementary Figure 8: Change in performance at different training error levels. Results presented as precision, recall, and F1 using a one-vs-rest method.

Supplementary Table 19: Comparison of mean AUROC (alongside standard deviation) performances across different training set error levels.

Test Set	Precision		Recall		F1		p-value
	CE	CE+NCR	CE	CE+NCR	CE	CE+NCR	
0% Error							
Cardiovascular	0.91	**0.92**	**0.89**	0.88	0.9	0.9	p<0.001
Respiratory	**0.89**	0.88	0.91	**0.93**	0.9	0.9	p<0.001
Gastrointestinal	0.93	**0.95**	0.91	**0.91**	0.92	**0.93**	p<0.001
5% Error							
Cardiovascular	0.91	**0.92**	0.88	0.88	0.89	**0.9**	p<0.001
Respiratory	0.88	0.88	0.92	**0.93**	0.9	0.9	p<0.001
Gastrointestinal	0.93	**0.95**	**0.91**	0.9	0.92	**0.93**	p<0.001
10% Error							
Cardiovascular	**0.91**	0.9	0.88	0.88	0.89	0.89	p<0.001
Respiratory	0.88	0.88	0.91	0.91	0.9	0.9	p<0.001
Gastrointestinal	0.92	**0.94**	0.9	0.9	0.92	0.92	p<0.001
15% Error							
Cardiovascular	0.9	0.9	0.88	0.88	**0.89**	0.89	p<0.001
Respiratory	0.88	0.88	0.9	**0.91**	0.89	**0.9**	p<0.001
Gastrointestinal	0.9	**0.91**	0.91	0.91	0.9	**0.91**	p<0.001
20% Error							
Cardiovascular	**0.91**	0.9	0.86	**0.88**	0.89	0.89	p<0.001
Respiratory	0.87	**0.88**	0.9	0.9	0.89	0.89	p<0.001
Gastrointestinal	0.85	**0.91**	0.89	**0.9**	0.87	**0.9**	p<0.001
25% Error							
Cardiovascular	**0.91**	0.9	**0.87**	0.86	**0.89**	0.88	p<0.001
Respiratory	**0.88**	0.87	0.9	0.9	0.89	0.89	p<0.001
Gastrointestinal	0.84	**0.87**	0.88	**0.89**	0.86	**0.88**	p<0.001

H.4 UCI Adult Dataset

The UCI Adult dataset is a widely used dataset in ML and data mining for classification tasks. It contains demographic and employment-related features of individuals, such as age, education level, marital status, occupation, and income, along with a binary label indicating whether the individual's income exceeds $50,000 per year.

H.4.1 Income Prediction Using NCR

We additionally evaluate NCR for income prediction, where the goal is to classify individuals into two income groups: those with income greater than $50,000 per year and those with income less than or equal to $50,000 per year. This data is also in tabular form, containing demographic and employment-related features of individuals, such as age, education level, marital status, occupation.

Supplementary Table 20 presents the AUROC and AUPRC scores achieved by models trained using standard cross entropy and models trained with the inclusion of NCR, considering different ratios of noisy labels. When compared to the standard baseline model, our approach significantly enhances performance, with improvements of up to 1.3% across all noise ratios ($p < 0.001$). Moreover, we demonstrate that utilizing NCR yields comparable, and slightly better, performance than standard cross entropy when there is no noise present ($p < 0.001$), further suggesting the general regularization effect of NCR. Additionally, we observe lower error rates at lower noise levels and a reduced improvement when NCR is incorporated (compared to the COVID-19 diagnosis task). This can be attributed to the utilization of a shallower neural network model for this prediction task, resulting in less error at lower noise levels and reduced susceptibility to overfitting to noise in general.

Supplementary Table 21 displays the mean AUROC and AUPRC (with standard deviation) obtained across different noise ratios. NCR consistently outperformed the baseline method, achieving the highest mean AUROCs on the held-out test set. Moreover, models trained with NCR exhibited lower standard deviations, indicating more consistent classification performance across various noise ratios. This suggests that the detrimental impact of increasing noise on performance was reduced compared to the baseline method.

Supplementary Table 20: AUROC and AUPRC comparison between baseline and NCR models, across different amounts of error. 0% error represents the original dataset, without any added label noise.

Error (%)	AUROC		AUPRC		p
	CE	CE+NCR	CE	CE+NCR	
0	0.896(0.890-0.903)	**0.898(0.891-0.904)**	0.754(0.739-0.769)	**0.755(0.739-0.770)**	p<0.001
5	**0.898(0.892-0.904)**	0.897(0.891-0.903)	0.751(0.736-0.766)	**0.756(0.741-0.771)**	p<0.001
10	0.894(0.887-0.900)	**0.898(0.892-0.904)**	0.750(0.735-0.766)	**0.755(0.741-0.770)**	p<0.001
15	0.889(0.883-0.896)	**0.895(0.888-0.902)**	0.743(0.728-0.759)	**0.758(0.744-0.774)**	p<0.001
30	0.887(0.880-0.893)	**0.889(0.882-0.895)**	0.735(0.719-0.751)	**0.746(0.731-0.761)**	p<0.001
45	0.877(0.870-0.885)	**0.890(0.883-0.897)**	0.728(0.712-0.744)	**0.745(0.729-0.761)**	p<0.001
60	0.870(0.862-0.877)	**0.883(0.876-0.890)**	0.718(0.702-0.735)	**0.731(0.716-0.747)**	p<0.001

Supplementary Table 21: Comparison of mean AUROC and AUPRC (alongside standard deviation) performances across different training set error levels.

Metric	CE		CE + NCR	
	Mean	Std.	Mean	Std.
AUROC	0.887	0.010	**0.893**	**0.006**
AUPRC	0.740	0.013	**0.749**	**0.010**

Supplementary Table 22: Hyperparameter values for final models (NCR term based on KL divergence) presented in main text.

Loss Function	CE	CE + NCR						
Error (%) in Training Labels	0	0	5	10	15	30	45	60
Epochs	100	100	100	100	100	100	100	100
Batch	2048	2048	2048	2048	2048	2048	2048	2048
NCR Starting Epoch	NA	30	30	30	30	10	10	10
Hidden Layer (for NCR)	NA	1	1	1	1	1	1	1
NCR weight	NA	0.2	0.25	0.25	0.4	0.3	0.3	0.5
k	NA	10	10	10	10	10	10	10

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