Supplementary Online Content

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This supplementary material has been provided by the authors to give readers additional information about their work.

eTable 1. Description of Rubric Categories Evaluated

Rubric Category	**Potential Values**	**Description**
Key Words	Free Text	Determined by author submission and reviewer determination.
Clinician Involvement	Main Authors, Authors, Consultants, None	Check if primary authors are clinicians. If not, check any other authors. If none, search for mentions of physician, clinician, doctor in text to see if collaborators consulted. If not, choose none.
Research Area	Biomedical Research, Clinical Operations, Clinical Practice, Policy, Core Methods Development, Other	Which area is the research aimed at improving?
Conditions Studied	Free Text	Which medical conditions were studied? (if any)
Clinical Tasks	Diagnostician, Prognostication, Subtyping, Biomarker Discovery, Treatment Planning, Other (with text description), NA	If a clinical task was performed, what was its purpose?
Machine Learning Task	Classification, Regression, Clustering, Representation Learning (Encoding / Embedding), Autoregressive Forecasting, Imputation, Generative Model (GAN, VAE or other), Causal Analysis, Other	What was the machine learning task performed?

Machine Learning Methodology	Convolutional Neural Network, Long-short term memory network, Gated recurrent unit, Multilayer Perceptron, Other Recurrent Neural Network, Other Neural Network, Generative Adversarial Network, Linear Model, Tree-based Model, Nearest Neighbor Model, Gaussian Processes, Hidden Markov Model	What types of models / architectures were used to perform the task?
Develops New Machine Learning Methodology	Yes, No	Does the work develop a new machine learning methodology or apply an existing method?
Are the methods designed to address a particular common issue in using Machine Learning for Health?	No, Class Imbalance, Limited Training Data, Domain Adaptation, Weak Labels, Missing Data, Confounding, Other (with text description)	Are the methods designed to achieve better results using machine learning under conditions common to healthcare?
Were state of the art comparisons used (vs. strawman?)	Yes, No	Did the work compare results to state of the art methods and/or human performance? Or were only strawman comparisons made (if any)?
Datasets	Free Text	What datasets were used in the work?
Dataset Access	None, Public, Public Apply for Access, Institutionally Gated Apply for Access, Private, Self-Collected	Can others access the data used in the work?
Datatype	**Structured, Speech, Image, Video, Text, Genetic (and other structured biomarker), ECG, EEG**	**What type of data was used in the project?**

Structured Covariates	Free Text	Were additional covariates provided for the dataset?
Sample Size	Free Text	How many samples were included in the dataset?
Feature Count	Free Text	How many features were present per sample?
Examined Multiple Datasets	Yes, No	Did the work analyze multiple datasets? (either through integration or evaluation)
Separate Evaluation Dataset	None, Test Set from Same Dataset, Test Set from External Dataset	Did the work evaluate results using a separate external dataset?
Interpretability Analyses Performed	Yes, No	Were any interpretability analyses performed?

eTable 2. Data Sets That Are Either Publicly Available or Available After Registration

Category	**Datasets**
Image	Alzheimer's Disease Neuroimaging Initiative [1], Dermnet Skin Disease Atlas [2], Broad Bioimage Benchmark Collection [3], Chest X-Ray8 [4], ISBI-ISIC 2017 melanoma classification challenge [5], ImageCLEF Medical Image Retrieval Task Test Collection [6], Montgomery County X-ray Set [7], Japanese Society of Radiological Technology [8] Cancer Genome Atlas (MRI Collections) [9], LITS: Leveraging Liver Tumor Segmentation Challenge [10], Open Access Series of Imaging Studies (OASIS) Brains [11], MIMC-CXR [12], Indiana University Chest X-Ray [13], Indian diabetic retinopathy image dataset (IDRiD) [14]
Structured (EMR, Registry, Claims etc)	MIMIC-III [15], eICU [16], Alzheimer's Disease Neuroimaging Initiative [1], CDC Linked birth and infant death data [17] , MAGGIC [18], Prostate, Lung, Colorectal and Ovarian Cancer (PLCO) [19], Surveillance Epidemiology, and End Results (SEER) [20], International Stroke Trial [21], The Cancer Genome Atlas [22] PRO-ACT Database [23] MIMIC-CXR [12]
Text	i2b2 2010 challenge [24], UK Biobank [25], MIMIC-III [15], eICU [16], Framingham heart study [26], Medline [27], AskAPatient [28], CADEC corpus [29], FB15k-237 knowledge base completion [30], NHANES [31], The Cancer Genome Atlas [22], CIHI [32]
Genetic	UK Biobank [25], DeepArg [33], Alzheimer's Disease Neuroimaging Initiative [1], METABRIC [34], The Cancer Genome Atlas [22],

	PsychENCODE [35] Pan-Cancer Analysis of Whole Genomes [36]
ECG	MIT-BIH [37], Capture-24 [38]
EEG	The Human Connectome Project [39–41], Temple University Hospital Seizure Detection Corpus [42], UCI-EEG [43], MIT-EEG [44], Sleep-EDF [45]
Video	Parkinson@Home [46]
Protein	BindingDB [47]
Speech	Google Speech Commands [48]

eTable 3. Clinical Tasks

Clinical task	**Paper Count (Percentage of total)**
Diagnostication	57 (34.3%)
Prognostication	16 (9.6%)
Subtyping	13 (7.8%)
Treatment Planning	10 (6.0%)
Biomarker Discovery	3 (1.8%)
Other	6 (3.6%)
NA	61 (36.8%)

Each paper can only be in one category. Percentage of the total number of papers shown in parentheses.

eTable 4. Primary Machine Learning Tasks

ML Task	**Paper Count (Percentage of Total)**
Classification	86 (51.81%)
Clustering	11 (6.63%)
Regression	8 (4.82%)
Representation Learning	8 (4.82%)
Generative Model	6 (3.61%)
Forecasting	4 (2.41%)
Causal Analysis	4 (2.41%)
Survival Analysis	3 (1.81%)
Policy Learning	2 (1.2%)
Segmentation	2 (1.2%)
Imputation	2 (1.2%)
Multiple	9 (5.42%)
Other (feature selection, multiple instance learning, synthesis of minority class, image reconstruction, mixed effect modeling, summarization, dialogue tasks, concept normalization, automated measurement, NLP mapping, association tests.)	21 (12.65%)

Each paper can only be in one category. Percentage of the total number of papers shown in parentheses.

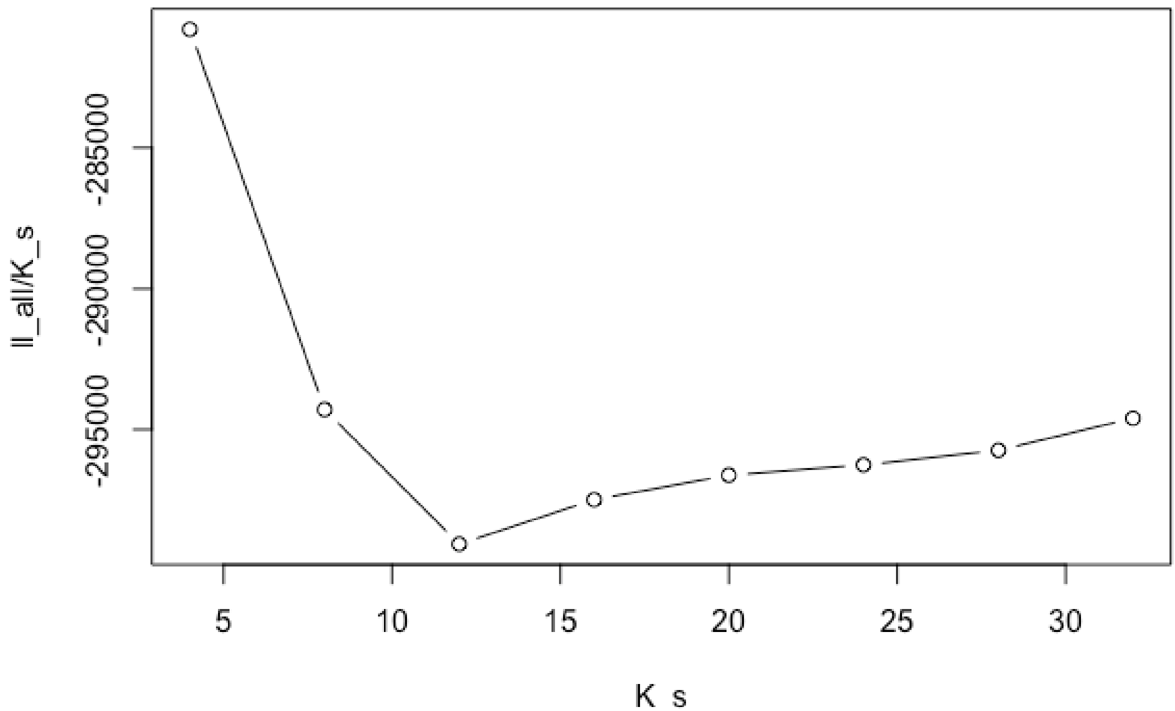
eTable 5. Primary Machine Learning Method Used

ML Methodology	**Paper Count (Percentage of Total)**
CNN	39 (23.49%)
MLP	2 (1.2%)
Other NN	30 (18.07%)
LSTM	16 (9.64%)
GRU	4 (2.41%)
Other RNN	5 (3.01%)
GAN	8 (4.82%)
HMM	5 (3.01%)
Other Graphical Model	2 (1.2%)
Tree-based Model	8 (4.82%)
Linear Model	7 (4.22%)
SVM	2 (1.2%)
Gaussian Processes	6 (3.61%)
LVM	4 (2.41%)
Nearest Neighbor Model	5 (3.01%)
Reinforcement Learning	2 (1.2%)
Transfer Learning	2 (1.2%)

Other (prototypical clustering networks, generalized low-rank models, Bayesian simulation, deep Q learning, kernel methods, mutual information-based methods, multiple instance learning, statistical methods, Gibbs sampling)	19 (11.45%)

Each paper can only be in one category. Percentage of the total number of papers shown in parentheses.

eFigure. Number of Topics (k) vs Perplexity as Measured on a Hold-out Set of 10% (n=17) of the Papers Showing Perplexity Minimized at k=12



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