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List of Abbreviations

SN	Abbreviation	Definition
1	ADAM	Adaptive Learning Rate Optimization Algorithm
2	AI	Artificial Intelligence
3	AI-CAD	Artificial Intelligence-based Computer-Aided Diagnosis
4	AUC	Area-under-the-curve
5	BA	Bland-Altman's Plot
6	BP	Bacterial pneumonia
7	CAD	Computer Aided Diagnosis
8	CC	Coefficient of Correlation
9	CDP	Cumulative Distribution Plot
10	CE-loss	Cross Entropy Loss
11	CNN	Convolution neural network
12	COV	Coronavirus
13	CT	Computed tomography
14	CXR	Chest X-ray
15	DL	Deep learning
16	DNN	Deep neural network
17	ESD	Ensemble subspace discriminant
18	FC	Fully connected
19	GPU	Graphics processing unit
20	GT	Ground Truth
21	HDL	Hybrid Deep Learning
22	JPEG	Joint photographic expert group
23	ML	Machine learning
24	MRI	Magnetic Resonance Imaging
25	NasNet	Neural search architecture network
26	PNG	Portable network graphics
27	RAM	Random-access memory
28	ReLU	Rectified linear unit
29	ResNet	Residual neural network
30	RF	Resolution Factor
31	ROC	Receiver operating characteristic
32	RT-LAMP	Reverse transcription loop-mediated isothermal amplification
33	RT-PCR	Reverse transcriptase polymerase chain reaction
34	SARS-CoV-2	Severe acute respiratory syndrome coronavirus 2
35	TB	Tuberculosis
36	TMA	Transcription-mediated amplification
37	VGG	Visual geometry group
38	VP	Viral pneumonia
39	WHO	World health organization
40	2-D	2-dimensional