Appendix 1

1 General search term

("deep learning" OR "deep neural network" OR
“cnn” OR "convolutional neural network" OR
“rnn” OR "recurrent neural network" OR
“dbn” OR "deep belief network" OR
“lstm” OR “long short term memory” OR
“autoencoder”)
AND
(“biosignal” OR "biomedical signal" OR "physiological signal" OR
“ecg” OR “electrocardiography” OR “electrocardiogram” OR
“emg” OR “electromyography” OR “electromyogram” OR
“ppg” OR “photoplethysmography” OR "photoplethysmogram" OR
“pcg” OR “phonocardiography” OR “phonocardiogram” OR
“bcg” OR “ballistocardiography” OR “ballistocardiogram” OR
“scg” OR “seismocardiography” OR “seismocardiogram” OR
“eog” OR “electrooculography” OR “electrooculogram” OR
“eda” OR "electrodermal activity" OR “Respiration” OR “Blood Pressure”)
AND NOT (images[Title] OR image[Title])
AND ("2010/01/01"[PDAT] : "2017/12/31"[PDAT])

2 PubMed search query

(("deep learning"[All Fields] OR "deep neural network"[All Fields] OR "cnn"[All Fields] OR "convolutional neural network"[All Fields] OR "rnn"[All Fields] OR "recurrent neural network"[All Fields] OR "dbn"[All Fields] OR "deep belief network"[All Fields] OR "lstm"[All Fields] OR "long short term memory"[All Fields] OR "autoencoder"[All Fields]) AND ("biosignal"[All Fields] OR "biomedical signal"[All Fields] OR "physiological signal"[All Fields] OR "ecg"[All Fields] OR "electrocardiography"[All Fields] OR "electrocardiogram"[All Fields] OR "emg"[All Fields] OR "electromyography"[All Fields] OR "electromyogram"[All Fields] OR "ppg"[All Fields] OR "photoplethysmography"[All Fields] OR "photoplethysmogram"[All Fields] OR "pcg"[All Fields] OR "phonocardiography"[All Fields] OR "phonocardiogram"[All Fields] OR "bcg"[All Fields] OR "ballistocardiography"[All Fields] OR "ballistocardiogram"[All Fields] OR "scg"[All Fields] OR "seismocardiography"[All Fields] OR "seismocardiogram"[All Fields] OR "eog"[All Fields] OR "electrooculography"[All Fields] OR "electrooculogram"[All Fields] OR "eda"[All Fields] OR "electrodermal activity"[All Fields] OR "Respiration"[All Fields] OR "Blood pressure"[All Fields])) NOT (images[Title] OR image[Title]) AND ("2010/01/01"[PDAT] : "2017/12/31"[PDAT])

3 Scopus search query

(TITLE-ABS-KEY (("deep learning" OR "deep neural network" OR "cnn" OR "convolutional neural network" OR "rnn" OR "recurrent neural network" OR "dbn" OR "deep belief network" OR "lstm" OR "long short term memory" OR "autoencoder")) AND TITLE-ABS-KEY (("biosignal" OR "biomedical signal" OR "physiological signal" OR "ecg" OR "electrocardiography" OR "electrocardiogram" OR "emg" OR "electromyography" OR "electromyogram" OR "ppg" OR "photoplethysmography" OR "photoplethysmogram" OR "pcg" OR "phonocardiography" OR "phonocardiogram" OR "bcg" OR "ballistocardiography" OR "ballistocardiogram" OR "scg" OR "seismocardiography" OR "seismocardiogram" OR "eog" OR "electrooculography" OR "electrooculogram" OR "eda" OR "electrodermal activity" OR "blood pressure" OR "Respiration")) AND NOT TITLE (images OR image) AND NOT TITLE-ABS-KEY (conference AND proceedings)) AND PUBYEAR > 2009 AND PUBYEAR < 2018

4 ACM search query

"query": {{("deep learning" "deep neural network" "cnn" "convolutional neural network" "rnn" "recurrent neural network" "dbn" "deep belief network" "lstm" "long short term memory" "autoencoder") AND ("biosignal" "biomedical signal" "physiological signal" "ecg" "electrocardiography" "electrocardiogram" "emg" "electromyography" "electromyogram" "ppg" "photoplethysmography" "photoplethysmogram" "pcg" "phonocardiography" "phonocardiogram" "bcg" "ballistocardiography" "ballistocardiogram" "scg" "seismocardiography" "seismocardiogram" “eog” "electrooculography" "electrooculogram" "eda" "electrodermal activity" "blood pressure" "respiration") AND acmdlTitle:(-images -image) } "filter": {"publicationYear":{ "gte":2010, "lte":2017 }}

Appendix 2

Performance of DNN for Biosignal Analysis

Ref. No.	Architecture used	Optimizer/Regularizers	Database / Experiment	Performance Accuracy(acc), Sensitivity(sen), Specificity(spe)
44	SDAE	• Ranking Criteria: ▪ Entropy ▪ Breaking Ties	MIT-BIH, INCART	• BT (acc: 98.77%; sen: 86.39%; spe: 99.64%) • Entropy(acc: 98.16%; sen: 78.28%; spe: 99.55%)
50	AE	• Split Bregmann Technique	MIT-BIH, BONN	• acc: 90.20%; sen: 99.70%;spe: 99.30%"
51	SDAE		DAISY	• For Compress ration (93.5): 21.99 SNR
52	DAE	• Wavelet transform with scale-adaptive thresholding	MIT-BIH	• SNR: 21.56 - 22.96 dB • RMSE: <0.03
61	DCNN	• Fine tuning of Weights • Performance of the Deep feature tested with conventional classifier	PAF	• Precision: ▪ End-to-end CNN: 93.60% ▪ CNN - kNN: 90.79% ▪ CNN - Linear: 87.58% ▪ CNN - Gaussian SVM: 92.96% ▪ CNN - MLP: 90.65%"
12	LCNN, LSTM	• LCNN and LSTM with rule inference • Fusion of decision from two network	MIT-BIH, CCDD	• acc: 99.40%; sen: 97.59%; spe: 99.54%
53	DAE	• Stacked Contractive de-noising AE	MIT-BIH	• RMSE: 0.075 - 0.350 • SNR: 2.40dB improvement
56	CNN	• Lead Asymmetric pooling layer	PTB	• acc: 96.00%
64	CNN	• Rule inference • Bayesian feature fusion	CCDD	• acc: 86.22%
70	DBN	• Stack of two different RBM is used • RBM parameters are adjusted using	MIT-BIH	• acc: 90.20%; sen: 99.70%; spe: 99.30%

		Persistent Contrastive divergence		
69	SAE,DBN	• Robust Dictionary Learning used	MIT-BIH	• acc: 97.00%; sen: 100.00%; spe: 67.20%
71	DBN		MIT-BIH	Acc: 75% - 95% based on the signal contamination level
30	1-D CNN	• Wavelet transform (WT) • Each component of WT is input to 1-D-CNN	CEBSDB, WECG, FANTASIA, NSRDB, STDB, MITDB, AFDB, VFDB	• Individual identification rate: 93.50% • acc (Normal: 96.50%; Abnormal :90.50%)
83	DAE	• DAE is used to extract feature • DNN for classification	• MIT-BIH • Experiment	• Recognition rate ▪ ECG: 94.39% ▪ Pressure data: 95.67% ▪ Emotion (Calm) data: 98.10
87	CNN	• Heart model is used	Experiment	• Localization of PVC in heart model: 78% • Classification of Epicardium and endocardium region: 90.00%
90	DNN	• DNN with pre-training	Experiment	• acc: 85.52%; sen: 91.76%; spe: 78.27%
45	CNN	• Feature fusion	PTB	• acc : 99.33%
46	DCNN		PTB	• acc: 95.22%; sen: 95.49%; spe: 94.19%
19	CNN	• Models are used ▪ to generate abnormal heartbeat ▪ For training	MIT-BIH	Personalized patient specific Design
58	CNN		MIT-BIH	• acc: 94.03%; sen: 96.71%; spe: 91.54%
72	Sparse AE	• Sparseness and feature learning	MIT-BIH	• acc: 71.39% ; sen: 39.97%; spe: 89.97%
60	1-D CNN	• Adaptive 1-D-CNN implementation	MIT-BIH	• acc: 99.00%; sen: 93.90%; spe: 98.90%
47	CNN	• 1-D CNN	MIT-BIH	• acc: 99.93%; sen: 99.81%

48	CNN		Fantasia	• For 2 Sec Segment ▪ acc: 94.95%; sen: 99.37%; spe: 95.81% • For 5 Sec Segment ▪ acc: 95.11%; sen: 91.13%; spe: 95.88%
49	CNN		MIT-BIH	• For 2 Sec Segment ▪ acc: 92.50%; sen: 98.09%; spe: 93.13% • For 5 Sec Segment ▪ acc: 94.90%; sen: 99.13%; spe: 81.44%
59	CNN		MIT-BIH	• acc: 92.70%
62	RNN	• Equal Error rate used to check training performance	ECG ID and MIT-BIH	• Better Recognition rate
63	RNN	• Deep LSTM RNN Model, Dropout	Synthetic signal	• Percent Root Mean square difference : 2.42%
75	SDAE	• Spectrogram input	MIT-BIH	• Disease: ▪ acc: 97.50%; sen: 99.00%; spe: 85.90% • Beat Recognition: ▪ acc: 98.80%; sen: 99.80%; spe: 71.40%
74	LSTM-RNN		Physionet-Sleep	• Classification of arrhythmias : 99.00%
66	DBN	• Feature extracted from ECG signals is fed as input	Experiment	• sen: 80.00%; spe: 50.00%
72	DBN	• Signal Quality Assessment	MIT-BIH	• acc: 75% – 95% based on signal quality
68	DBN	• Signal quality assessment	• MIT-BIH AFDB	• acc: 87.00% (clean Signal) • Noise level (-20dB): 58.70%
77	CNN	• Multi-scale CNN	• LTAFDB, AFDB, HEDB, LTAFDB, AFDB	• acc: 98.18%; sen: 98.22%; spe: 98.11%
94	CNN		MIT-BIH	• Recognition Rate: 98.51% • Classification acc: 92 %
80	DNN		MIT-BIH	• acc: 99.41%; sen: 96.80%

93	CNN	• Spectrogram are fed as input	MIT-BIH	• STFT: ▪ acc: 98.29%; sen: 98.34%; spe: 98.24% • SWT: ▪ acc: 98.63%; sen: 98.79%; spe: 97.87%
78	DBN		Experiment	• acc: ▪ With calibration: 85.30% ▪ Without calibration: 97.60%
81	CNN		• NinaPro • Experiment	• Acc: ▪ Dataset-1: 66.59%; Dataset-2: 60.27%; Amputees: 38.09%
84	DBN	• Split and merge DBN	Experiment	• acc: 89.29%; sen: 89.39%; spe: 2.88%
85	DBN	• Greedy learning algorithm	Experiment	• acc: 88.60%
88	CNN, RNN	• Ensemble Learning • Transformed input is used	Experiment	• Ratio of MSE: 90.30%
91	CNN	• Spectrograms are used	University of Copenhagen	• Spectrogram: ▪ acc: 96.69%; sen: 94.24%; spe: 97.59% • SPWD: ▪ acc: 81.92%; sen: 99.71%; spe: 75.37% • CWT: ▪ acc: 96.80%; sen: 94.80%; spe: 98.80%
95	CNN	• Transfer learning	Experiment	• acc: 97.81
97	CNN	• Multilead Stream Signal	• NinaPro, csl-hdemg, CapgMyo	• acc: 99.70%
67	RNN	• Gated RNN	2016 Physionet Challenge	• acc : 89.00%
65	CNN		2016 Physionet Challenge	• acc: 79.50%; sen: 70.80%
73	RNN		MITHSDB	• acc: 74.90%

54	DBN		TROIKA	• acc: 96.10%
57	CNN		Experiment	• acc: 95.00%
23	SAE	• Sparse AE	Experiment	• acc: ▪ Valence: 73.60%; Arousal: 80.78%
79	CNN	• Adam Optimizer	Simulated signals	• acc: 77.5%
76	CNN		Experiment	• Correlation Coefficient : 0.73
82	DAE	• DNN based DAE	MIT-BIH	• Recognition Rate: 94.39% • Classification Acc: 95.67 %
86	DNN	• Input: features from signals	Experiment	• acc: 91.12%
89	CNN		Experiment	• acc: 80.20%
92	DCNN	• Split flag on CNN weights	Physionet- PPG	• acc: 84.15%
96	DBN-DNN	• Bootstrap Optimization • Ensemble learning	Experiment	• Estimation Acc: 99.29%
98	CNN	• LeNET-5 and AlexNet	Physionet	• acc: 97.00%; sen: 93.20%; spe: 95.12%
99	CNN	• Mel spectral coefficient based spectrogram as input	2016 Physionet Challenge	• acc: 84.80%; sen: 76.50%; spe: 93.10%
100	CNN	• Mel spectral coefficient based spectrogram • Power spectral density	2016 Physionet Challenge	• acc: 81.30%
101	DNN	• GRU Block used	MIT-BIH	• RMSE to reconstruct Biosignals
102	DBN	• DBN with Sparse Coding	UCDDB	• Class wise acc: ▪ Wake: 98.49%; S1: 80.05%; S2: 91.20%; SWS: 98.22%; REM: 95.31%
10	DBN, CNN, SAE		Maze-Ball	• Proposed approach better than previous methods

103	CNN		Experiment	• Acc: ▪ ECG: 71.65%; EDA: 71.33%
104	DAE	• Input: features from signals	DEAP	• Overall performance is better than previous approach
105	SAE	• Input: features from signals	DEAP	• Classification rate improved by: 5.60%
106	DBN		Experiment	• Rapid Artefacts elimination
107	CNN	• Spectrogram as input	Experiment	• Significance of study is discussed
108	DBN-DNN	• Artificial features are generated	Experiment	• Efficient for low number of samples • Better than previous approach
109	DBN-DNN	• Mimic features generated	Experiment	• Efficient for low number of samples • Better than previous approach