ADVANCED DEEP LEARNING APPROACHES FOR BIOSIGNALS APPLICATIONS

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Certificate of Original Authorship

I, Marwa Farouk Ibrahim, certify that the work in this thesis has not previously been submitted for a degree nor has it been submitted as part of requirements for a degree except as fully acknowledged within the text.

I also certify that the thesis has been written by me. Any help that I have received in my research work and the preparation of the thesis itself has been acknowledged.

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List of Abbreviations

ANN	Artificial neural network
ANOVA	Analysis of variance
AR	Autoregressive
AW-ELM	Adaptive wavelet extreme learning machine
CNN	Convolutional neural network
CDF	Cumulative distribution function
CMC	Carpometacarpal
CPD	Canonical polyadic decomposition
CTC	Connectionist temporal classification
DA	Discriminant analysis
DCS	Dynamic classifier selection
DCS-LA	Dynamic classifier selection local accuracy
DFT	Discrete Fourier transform
DTNN	Deep tensor neural network
ECG	Electrocardiogram
ECOG	Electrocorticographic
ECRB	Extensor carpi radialis brevis
ECRL	Extensor carpi radialis longus
ECU	Extensor carpi ulnaris
EDA	Electrodermal activity
EEG	Electroencephalogram
ELM	Extreme learning machine
EMG	Electromyography
EOG	Electrooculography
FCU	Flexor carpi ulnaris
FFT	Fast Fourier transform

FLDA	Fuzzy LDA
FLN	Functional-link net
FNN	Feed-forward neural networks
FNPA	Fuzzy neighbourhood preserving analysis
FP	Feature projection
FS	Feature selection
FT	Fourier transform
GSR	Galvanic skin response
HME	Hierarchical mixture of experts
HMM	Hidden Markov model
HTD	Hjorth time domain
ICA	Independent component analysis
KNN	k nearest neighbourhood
K-SVD	K-singular value decomposition
LDA	Linear discriminant analysis
LIBSVM	Library support vector machine
LinELM	Linear extreme learning machine
LLE	Local linear embedding
LPM	Linear programming machine
LPP	Locality preserving projection
LS-SVM	Least-square SVM
LSTM	Long Short-Term Memory
MAV	Mean absolute value
MAVs	Mean absolute value slope
MC	Markov chain
MCA	Mutual components analysis
MCE	Misclassification error
MCMC	Markov chain Monte Carlo

MDF	Median frequency
MDP	Markov decision process
MEG	Magnetoencephalogram
MES	Myoelectric signal
MI	Mutual information
MLP	Multilayer perceptron
MMG	Mechanomyogram
MNF	Mean frequency
NB	Naive bayes
NMF	Nonnegative matrix Factorization
OFNDA	Orthogonal fuzzy neighbourhood discriminant analysis
OLDA	Orthogonal LDA
OS-ELM	Online sequential extreme learning machine
PCA	Principal component analysis
PNN	Probabilistic neural network
Poly-ELM	Polynomial extreme learning machine
PSO	Particle swarm optimization
QDA	Quadrature discriminant analysis
QPC	Quadratic phase coupling
RBF	Restricted Boltzmann machine
RBN	Radial basis network
RegTree	Regression Tree
ReLU	Rectified linear unit
RF	Random forest
RGB	Red Green Blue
RLDA	Regularised linear discriminant analysis
RMS	Root mean square

RVFLN	Random vector functional-link net
SA-EELM	Self-adaptive evolutionally extreme learning machine
SA-SVM	Self-advising SVM
Sig-ELM	Sigmoid extreme learning machine
SFLNs	Single-hidden-layer feed-forward networks
SL	Softmax layer
SOM	Self-organising map
SPCA	Sparse PCA
SR	Spectral regression
SS	Sample skewness
SSC	Slope sign changes
SRDA	Spectral regression discriminant analysis
STFT	Short-time Fourier transform
SVD	Singular value decomposition
SVM	Support vector machine
TD	Time domain
TDD	Time-domain descriptors
TDNN	Time delay neural network
ULDA	Uncorrelated linear discriminant analysis
USELM	Unsupervised extreme learning machine
WAMP	Willison amplitude
W-ELM	Wavelet extreme learning machine
WHO	World health organisation
WL	Waveform length
WPT	Wavelet packet transform
WT	Wavelet transform
ZC	Zero crossing

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Abstract

A wide gap exists between clinical application results and those from laboratory observations concerning hand rehabilitation devices. In most instances, laboratory observations show superior outcomes the real-time applications demonstrate poor consequences. The robust nature of the electromyography signal and limited laboratory applications are the principal reasons for the gap. This thesis aims to introduce and develop a deep learning model that is capable of learning features from biosignals.

The deep learning model is expected to tame the variable nature of the electromyography signal which will lead to the best available outcomes. Furthermore, the suggested deep learning scheme will be trained to be skilled in learning the best features that match the biosignal application regardless of the number of classes. Moreover, traditional feature extraction is time consuming and extremely reliant on the user's experience and the application. The objective of this research is accomplished via the following four implemented models.

1. Developing a deep learning model via implementing a two-stage autoencoder along with applying different signal representations like spectrogram, wavelet and wavelet packet to tame variations of the electromyography signal. Support vector machine, extreme learning machine with two activation functions (sigmoid and radial basis function) and softmax layer were used for classifications. Moreover, the classifier fusion layer achieved testing accuracy of more than 92% and training attained more than 98%. The same dataset was implemented for superimposed signal representations for two stages autoencoder and softmax layer, support vector machine, k-nearest neighbor and discriminant analysis for classification besides the classifier fusion which led to testing accuracy of more than 90%.
2. Presenting principal component analysis and independent component analysis for feature learning purposes after applying different signal representations algorithms such as spectrogram, wavelet and wavelet packet. Discriminant analysis, extreme learning machine and support vector machine were used for classification. Furthermore, the two proposed models showed acceptable accuracy along

with shorter simulation time. The testing accuracy achieved more than 90% by implementing a classifier fusion layer. Manhattan index was estimated for all features and only the top 50 Manhattan index features were included to decrease the simulation time while attaining acceptable accuracy values.

3. Introducing a self-organising map for deep learning whereby the biosignal was represented by spectrograms, wavelet and wavelet packet. The presented biosignal was introduced to a layer of self-organising map then the suggested system performance was evaluated by extreme learning machine, self-adaptive evolutionally extreme learning machine, discriminant analysis and support vector machine for classification. Adding a classifier fusion layer increased the testing accuracy to 96.60% for ten-finger movements and 99.73% for training. The proposed system showed superior behavior regarding accuracy and simulation time.
4. Presenting a deep learning model where 1) the data was augmented after representing the biosignal by a spectrogram, 2) the augmented signal was represented by a tensor, and finally 3) The signal was introduced to the two-stage autoencoder. The same dataset was used with traditional pattern recognition for comparison purposes. Classifier fusion layer was executed in deep learning scheme whereby the ten-finger movements achieved 90.25% and 87.11% attained by pattern recognition. Besides, the six finger movement dataset was acquired from amputee participants and accomplished 91.85% for deep learning and reached 89.64% for traditional pattern recognition. Furthermore, different datasets for different applications were tested using the recommended deep learning model. Eventually, feeding the deep learning model with various datasets for different applications afforded the model with higher fidelity, combined with real outcomes and generalization.