



Machine learning in biomedical engineering

Cheolsoo Park¹ · Clive Cheong Took² · Joon-Kyung Seong³

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Machine learning, which was first paraphrased by Arthur Samuel, can be defined as a field of computer science that gives computers the ability to learn without being explicitly programmed [1]. Having evolved from the study of pattern recognition and computational learning theory in artificial intelligence [2], machine learning creates algorithms that can learn from a large body of data and make predictions on the data [3]. Machine learning is applied to a wide range of computing tasks, such as email filtering, detection of network intruders or malicious insiders working towards a data breach, optical character recognition, learning to rank, and computer vision. In many such areas, where designing explicit algorithms with good performance is difficult or infeasible, machine learning has been successfully employed with outstanding performances.

Among the various applications of machine learning, computer vision is one of the core branches of computer science that can function exclusively when combined with the machine learning technologies. Machine learning can solve a wide variety of problems in computer vision including image recognition, object detection and tracking, automatic document analysis, face detection and recognition, computational photography, augmented reality, 3D reconstruction, and medical image processing, to name a few. Recently, the rapid developments in advanced computing and imaging systems in biomedical engineering

areas have given rise to a new research dimension, and the increasing size of biomedical data requires precise machine learning-based data mining algorithms.

This special issue “Machine Learning in Biomedical Engineering” tries to capture the scope of various applications of machine learning in the biomedical engineering field, with a special emphasis on the most representative machine learning techniques, namely deep learning-based approaches. Machine learning tasks are typically classified into two broad categories, depending on whether there is a learning “label” or “feedback” available to a learning system: supervised learning and unsupervised learning. This special issue also introduces various types of machine learning tasks in the biomedical engineering field from classification (supervised learning) to clustering (unsupervised learning).

Recently, researchers have shifted their focus towards applying digital image processing techniques to extract, analyze, and categorize brain tumors from Magnetic Resonance Imaging (MRI). The first paper entitled “Computer-Assisted Brain Tumor Type Discrimination using Magnetic Resonance Imaging Features” by Iqbal et al. [4] provides a comprehensive review of recent researches on brain tumor multiclass classification using MRI. A set of common parameters from the reviewed works is extracted and compared to highlight the merits and demerits of individual works. The present review paper provides a set of recommendations for researchers and professionals working in the area of brain tumor classification. The second paper entitled “Performance of Machine Learning Methods in Diagnosing Parkinson’s Disease based on Dysphonia Measures” by Lahmiri et al. [5] evaluates the performance of machine learning-based techniques for Parkinson’s disease (PD) diagnosis based on dysphonia symptoms. PD is a widespread degenerative syndrome that affects the nervous system. Its early symptoms include tremor, rigidity, and vocal impairment (dysphonia). In this review article, several machine-learning techniques were considered and trained with the same data set to classify healthy and PD patients. These machine learning techniques included linear discriminant analysis (LDA), k

✉ Joon-Kyung Seong
joon.swallow@gmail.com

Cheolsoo Park
parkcheolsoo@kw.ac.kr

Clive Cheong Took
c.cheongtook@surrey.ac.uk

¹ Department of Computer Engineering, Kwangwoon University, Nowon-gu, Seoul, Korea

² Department of Computer Science, University of Surrey, Guildford GU2 7XH, UK

³ School of Biomedical Engineering, Korea University, 145, Anam-ro, Anam-dong 5-ga, Seongbuk-gu, Seoul 02841, Korea

nearest-neighbors (k-NN), Naïve Bayes (NB), regression trees (RT), and support vector machine (SVM). The experimental results showed that the SVM classifier achieved higher average performance than all the other classifiers in terms of overall accuracy, G-mean, and area under the curve (AUC) of the receiver operating characteristic (ROC) plot.

This special issue also introduces machine-learning techniques that were developed for retinal image analysis. The third paper entitled “Deep-Learning-Based Automatic Computer-Aided Diagnosis System for Diabetic Retinopathy” by Romany F. Mansour deals with a classification problem in diabetic retinopathy [6]. Specifically, the paper proposes the use of AlexNet deep neural networks (DNNs), which function on the basis of convolutional neural network (CNN), to enable an optimal diabetic retinopathy computer-aided diagnosis solution. The experimental results with standard KAGGLE fundus datasets reveal that the proposed AlexNet DNN-based system exhibits a better performance with LDA feature selection, where it exhibits a classification accuracy of 97.93%. With the high accuracy, the proposed algorithm enables early disease detection and diagnosis decision in diabetic retinopathy. The fourth paper entitled “Multiscale Self-Quotient Filtering for an Improved Unsupervised Retinal Blood Vessels Characterisations” by D. Relan and R. Relan presents an unsupervised retinal vessel classification approach, which utilizes multi-scale self-quotient filtering to pre-process the input image before extracting the discriminating features [7]. The proposed method uses the squared-loss mutual information clustering method for the unsupervised classification of retinal vessels. The proposed vessel classification method was evaluated using the publicly available DRIVE and INSPIRE-AVR databases with accuracies of 93.2 and 889%, respectively. The proposed method outperformed the other tested methods available in literature. Machine learning techniques can also be applied to endoscopic image analysis. The fifth paper entitled “Gastrointestinal Polyp Detection in Endoscopic Images using an Improved Feature extraction Method” by Billah et al. [8] proposes an improved computer aided polyp detection method that can reduce the polyp miss detection rate and assist doctors in finding the most important regions to pay attention. In the proposed method, the color wavelet features and CNN features are extracted from endoscopic images, which are then used for training an SVM. Experimental results show that the color wavelet and CNN features together construct highly representative endoscopic polyp images, and evaluations on standard public databases show that the proposed system outperforms state-of-the-art methods, with an accuracy of 98.23%.

The sixth paper entitled “Automatic Heart Activity Diagnosis based on Gram Polynomials and Probabilistic Neural Networks” by Beritelli et al. [9] proposes a method to diagnose heart disease using machine-learning algorithms such as neural networks. Normal and abnormal heart sounds (phonocardiogram) from over 3000 data samples were separated by probabilistic neural networks using features extracted by Gram polynomials. Machine-learning algorithms have been often applied to sleep analysis such as automatic sleep staging and diagnosis of sleep disorders. The seventh paper by Wei et al. [10], entitled “The Research of Sleep Staging Based on Single-lead Electrocardiogram and Deep Neural Network” utilizes a deep neural network (DNN) model implemented using a stacked autoencoder. The DNN structure classifies three sleep stages, wake, REM, and Non-REM, using only one channel electrocardiogram (ECG) signal. In the eighth paper entitled “Obstructive Sleep Apnoea Detection using convolutional neural network based deep learning framework,” Dey et al. [11] proposes an end-to-end framework of convolutional neural network (CNN) to detect obstructive sleep apnoea (OSA) using a single-lead ECG signal. While the second paper by Wei et al. extracted the features of raw ECG using conventional methods before the DNN classifier, Dey et al. directly feeds the raw ECG signal into CNN and lets the algorithm define the feature and class outputs simultaneously.

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