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Editorial

Machine Learning in Electronic and Biomedical Engineering

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In recent years, machine learning (ML) algorithms have become of paramount importance in computer science research, both in the electronic and biomedical fields. Standard methods such as support vector machine (SVM), random forest (RF), k-nearest neighbor (kNN), and also more recent methods such as deep neural network, and specifically for images, convolutional neural networks (CNNs), are widely applied to solve a large variety of tasks (classification, regression, semantic segmentation, detection) in electronic and biomedical applications.

From the point of view of electronic engineering, a number of applications benefit from these methods (e.g., autonomous guide, industry, precision agriculture). A typical approach for ML applications involves offloading data acquired from IoT sensors and actuators to external computing systems (such as cloud servers) for further processing but this worsens latency, leads to increased communication costs, and adds to privacy concerns. In recent years, edge computation or edge AI has aimed to address this issue by processing the AI algorithms directly on the device where the data is generated, focusing on the operational aspects including compression techniques, dimensionality reduction, and parallel computations.

From the point of view of biomedical engineering, ML algorithms play a key role because they are capable of performing the analysis of complex data such as biological ones in a very efficient way. Recent advancements in wearable sensors for collecting biological data, such as ExG signals electrocardiography (ECG), electroencephalography (EEG), surface electromyography (sEMG), photopletysmography (PPG) and speech signals, and inertial data such as accelerometer and gyroscopic signals have led to complex, large and heterogeneous data processing. The human activity detection as well as the diagnosis and prognosis of patients based on manual investigation of data collected from these sensors are difficult and time consuming. Therefore, the implementation of knowledge-based decision-making intelligent decision systems is of great importance. Moreover, neuroimaging techniques such as structural magnetic resonance (sMRI), functional MRI, diffusion tensor imaging, positron emission tomography (PET), and single-photon emission computed tomography (SPECT), can be used to help in the diagnosis and prediction of the diseases. In particular, automatic computer-aided-diagnosis (CAD) systems for early detection and classification of diseases using these data are gaining popularity.

The aim of this Special Issue was to publish original research articles that cover recent advances in the theory and applications of machine learning for electronic and biomedical engineering. The Special Issue aimed to collect contributions from researchers involved in developing and using ML techniques applied to, but not limited to the following:

- Embedded systems for AI applications, in which the interest is on implementing these algorithms directly on the devices, thus reducing latency, communication costs, and privacy concerns.
- Edge computing where the aim is to process AI algorithms locally on the device, i.e., where the data is generated, by focusing on compression techniques, dimensionality reduction, and parallel computation.
- Wearable sensors utilized to collect biological data.

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- Human activity detection as well as the diagnosis and prognosis of patients based on the investigation of data collected from sensors.
- Intelligent decision systems and automatic computer-aided-diagnosis systems for the early detection and classification of diseases.
- Neuroimaging techniques such as magnetic resonance, ultrasound imaging, computed tomography, etc., to assist in the diagnosis and prediction of diseases.

This Special Issue features eight papers that present novel ML algorithms and applications in the field of electronic and biomedical engineering. These eight papers are described in the following sections.

Hevia-Montiel et al. [1] presented a novel pipeline that integrates temporal data acquisition from four modalities (electrocardiography signals, echocardiography images, Doppler spectrum, and ELISA antibody titers), multiple feature selection analyses, and an automatic classification strategy for the experimental diagnosis of a Chagas disease, caused by the *Trypanosoma cruzi* (*T. cruzi*) parasite, the third most common parasitosis worldwide. The variables of a murine experimental model of *T. cruzi* infection were derived from ECG signals, ECHO images, Doppler spectrum, and ELISA antibody titers. The authors proposed a unimodal analysis using correlation maps and a multimodal strategy using different feature selection approaches. Following this, a set of supervised classifiers were fed with different subsets of multimodal variables. The aim was to automatically classify *T. cruzi* infected animals from the murine experimental model for acute phase (control vs. infected), chronic phase (control vs. infected), and general infection groups (acute phase + chronic phase vs. controls). The most relevant multimodal attributes found were ELISA (IgGT, IgG1, IgG2a), electrocardiography (SR mean, QT and ST intervals), ascending aorta Doppler signals, and echocardiography (left ventricle diameter during diastole). Concerning automatic classification from selected features, the best accuracy of control vs. acute infection groups was $93.3 \pm 13.3\%$ for cross-validation and 100% in the final test; for control vs. chronic infection groups, it was 100% and 100%, respectively. Experimental results show that the proposed machine learning-based approach can be helpful when trying to obtain a robust and objective diagnosis in early *T. cruzi* infection stages.

Donisi et al. [2] investigated the feasibility of machine learning to classify subjects belonging to five categories of heart diseases (healthy, hypertension, myocardial infarction, congestive heart failure and heart transplanted) using ten unconventional quantitative parameters extracted from bidimensional and three-dimensional Poincaré maps. The implementation of ML-based tools in physiology, e.g., in the cardiovascular field, has attracted attention and is influencing the biomedical community. The introduction of parameters (i.e., those extracted from Poincaré maps) could represent a potential support for physiologists called to make specific decisions with the potential to save patients' lives. This analysis achieved interesting results in terms of evaluation metrics, as adaptive boosting and k-nearest neighbor achieved accuracies greater than 90%; and gradient boosting and k-nearest neighbor reached a 100% score in sensitivity and specificity, respectively. The study shows the proposed combination of unconventional features extracted from Poincaré maps and well-known machine learning algorithms represent a valuable approach to automatically classify patients with different cardiac diseases.

Mahum et al. [3] aimed to detect glaucoma at early stages with the help of deep learning-based feature extraction. Retinal fundus images were utilized for the training and testing of the proposed model. In the first step, images were pre-processed, before the region of interest (ROI) was extracted by employing segmentation. Then, features of the optic disc were extracted from the images containing optic cup utilizing the hybrid features descriptors, i.e., CNN, local binary patterns (LBP), histogram of oriented gradients (HOG), and speeded up robust features (SURF). Moreover, low-level features were extracted using HOG, whereas texture features were extracted using the LBP and SURF descriptors. Furthermore, high-level features were computed using CNN. Additionally, they employed a feature selection and ranking technique, i.e., the MR-MR method, to select the most representative features. In the end, multi-class classifiers, i.e., SVM, RF and kNN, were employed for the classification of fundus images as healthy or diseased. To assess the performance of the proposed system, various experiments were performed using combinations of the aforementioned algorithms that show the proposed model based on the RF algorithm with HOG, CNN, LBP, and SURF feature descriptors, providing $\leq$ 99% accuracy on benchmark datasets and 98.8% on k-fold cross-validation for the early detection of glaucoma.

Lee et al. [4] proposed a prediction model for the epidemic of viral hepatitis A, which is rapidly spreading in Korean society. The aim is to minimize the costs and damages involved in the prevention of epidemic outbreaks by predicting regional outbreaks of hepatitis A using publicly available data in Korea and recently developed deep machine learning algorithms. For this study, they gathered information from five organizations based on the open data policy, including the Korea Centers for Disease Control and Prevention, National Institute of Environmental Research, Korea Meteorological Agency, Public Open Data Portal, and Korea Environment Corporation. Patient information, water environment information, weather information, population information, and air pollution information were acquired and correlations were identified. To predict hepatitis A, they conducted a two-phase approach. (i) The first step was the correlated factor selection for learning for the prediction model, in which the irrelevant factors were separated from environmental factors through statistical analysis; (ii) the second step was disease outbreak prediction performed using preprocessed data and 3D LSTM (long short-term memory network). The experimental results were compared with various machine learning methods through RMSE.

Ferlin et al. [5] addressed the problem of automatic cerebral microbleeds (CMB) detection in magnetic resonance images. It is challenging due to difficulty in distinguishing a true CMB from its mimics; however, if successfully solved, it would streamline the radiologists work. To manage with this complex three-dimensional problem, the authors proposed a machine learning approach based on a 2D Faster RCNN network. The proposed approach obtained high precision (89.74%), sensitivity (92.62%), and F1 scores (90.84%). To achieve these results, the authors pointed out a number of pre- and post-processing techniques that increase the ability to detect CMBs and distinguish them from their mimics. Regarding pre-processing, enlargement of the images improved the network's ability to detect CMBs while providing information from the adjacent slices by skilful input structuring has led to a significant reduction in the false-positive rate. In terms of post-processing, they proposed a novel prediction post-processing algorithm to appropriately evaluate the model. This aided in the transition from two-dimensional to three-dimensional space of consideration and it made possible the reduction of false-positive predictions that are in fact CMBs. Moreover, it allowed for the detection of cerebral microbleeds not only on slices where they were labelled but also on the adjacent ones.

Guan et al. [6] proposed an advanced method of modeling radio-frequency (RF) devices based on deep learning. The S parameters of RF devices calculated by full-wave electromagnetic solvers along with the metallic geometry of the structure, permittivity and thickness of the dielectric layers of the RF devices were used partly for training and partly for testing data for the deep learning structure. To implement the training procedure efficiently, a novel selection method of training data considering critical points was introduced. In order to rapidly and accurately map the geometrical parameters of the RF devices to the S parameters, deep neural networks were used to establish the multiple non-linear transforms. The results illustrated that the deep neural network has good robustness and excellent generalization ability. Even for very wide frequency band prediction (0–100 GHz), the proposed method has a very small relative error (below 3%) in comparison to the brute-force full-wave results.

Nam et al. [7] presented an automated schematic design framework (GateRL) for digital logic gates, such as inverter, buffer, NAND, AND, NOR, and OR, at the backplane of complementary metal on semiconductor (CMOS) transistors, based on reinforcement learning. Although various ML algorithms were employed in many applications, the area of an automated circuit design has not been addressed yet. Thus, this paper demonstrated the first ML approach that automatically designs the circuit schematics. While most off-the-shelf applications are based on the supervised learning networks trained with a huge amount of data and labels, the GateRL employs the reinforcement learning (RL) because the schematic design makes it difficult to provide labels and only whether the resultant circuit works or not can be discerned. Nevertheless the proposed scheme has some limitations, the proposed GateRL paves the way to the complete ML frameworks of the schematic design over more complicated digital circuits, as well as analog circuits.

Saganowski [8] reviewed progress in sensors and machine learning methods and techniques that made it possible to move emotion recognition (ER) from the lab to the field in recent years. In particular, the commercially available sensors collecting physiological data, signal processing techniques, and deep learning architectures used to predict emotions were discussed.

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